Volatility Information and Derivatives Trading

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ABSTRACT

We investigate the order flows of S&P 500 index and VIX options and find that the volatility information generated from directional trades of these two options provides consistently effective volatility prediction for the S&P 500 index returns, whereas volatility information generated from volatility trades of S&P 500 index options does not. In addition, our results show that the volatility information from S&P 500 index options is more useful when the options market is dominated by volatility-informed traders, especially after the introduction of VIX derivatives, which, in general, weakens the predictive power of the volatility information from S&P 500 index options.

Keywords: S&P 500, VIX, options, order imbalance, volatility forecasting

JEL Classification: G13, G14

1. Introduction

The trading of derivatives is well known to contain forward-looking information of the price dynamics of the underlying asset.[1] As such, informed traders are likely to initiate their realization of private information by trading derivatives.[2] A number of studies have explored the information content of option-implied information for future price dynamics of the underlying asset. While a particularly large body of literature focuses on the association between implied volatility and both the future returns and the future volatility of the underlying asset prices,[3] some studies investigate the informativeness of option trading activities for the future price dynamics of the underlying asset.[4] These studies generally support the predictive ability of option-implied information. In particular, the prediction of volatility from option-implied information is especially successful due to the stylized facts of volatility, such as persistence and mean-reversion, which make volatility highly predictable.

Because the price of an option is a function of not only the price of the underlying asset but also the volatility of returns, the trading of options can be motivated by an investor's expectation of or information on the price or the volatility. While generating volatility

[1] Some studies focus particularly on trading activities. See, for example, Anthony (1988), Pan and Poteshman (2006), Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), and Hu (2014). On the other hand, some studies focus on derivative prices including Chakravarty, Gulen, and Mayhew (2004), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), and An, Ang, Bali, and Cakici (2014).

[2] See, for example, Manaster and Rendleman (1982), Diamond and Verrecchia (1987), Sheikh and Ronn (1994), Amin and Lee (1997), and Easley, O'Hara, and Srinivas (1998).

[3] Classical references include Whaley (2000), Giot (2005), Guo and Whitelaw (2006), and Banerjee, Doran, and Peterson (2007) for the prediction of returns, and Canina and Figlewski (1993), Lamoureux and Lastrapes (1993), Xu and Taylor (1995), Christensen and Prabhala (1998), Fleming (1998), Blair, Poon, and Taylor (2001), Poon and Granger (2003), Jiang and Tian (2005) and Busch, Christensen, and Nielsen (2011) focus on volatility forecasting.

[4] In particular, Amin and Lee (1997), Cao, Chen, and Griffin (2005), and Pan and Poteshman (2006) report the usefulness of the measures compiled from option trading activities although in different ways.

information, such as implied volatility, using the prices of options is fairly straightforward, how to properly generate volatility information from the trading activities of options remains a very important empirical issue. Because prior research finds that the implied volatility of the CBOE VIX index is the best predictor of the volatility of S&P 500 index returns, we focus on generating a sensible proxy of volatility information from the order flows of S&P 500 index options to enhance the volatility prediction of the index returns.

Because both call and put prices are positively associated with volatility, investors buying (selling) calls and puts benefit from an increase (decrease) in the volatility. If most investors trade options due to an expectation of or information on the volatility level of the underlying asset returns, we expect the order flows of both buying (selling) calls and puts to be linked to an increase (decrease) in future volatility. This direct hypothesis is adopted in most of previous studies.[5]

By contrast, if most investors trade options based on their expectation of or information on the price level of the underlying asset, the order flows of both buying (selling) calls and selling (buying) puts result in an increase (decrease) in the price of the underlying asset because the call (put) price is positively (negatively) related to the price of the underlying asset. However, according to the definition of volatility, both an increase and a decrease in price raise volatility. Therefore, we expect the order flows of both buying and selling call or

[5] See, for example, Bollen and Whaley (2004), Ni, Pan, and Poteshman (2008), and Fahlenbrach and Sandås (2010).

put options to be linked to an increase in future volatility. This indirect hypothesis is driven by investors' expectation of or information on future price rather than the volatility level.

Because each trade requires a buyer and a seller, we use the algorithm proposed by Lee and Ready (1991) to identify whether an option transaction is buyer or seller initiated for all trades of the S&P 500 index options and then aggregate the numbers of contracts within a day for the four categories: namely, buyer- and seller-initiated calls and puts. Using these four categories of proxies for the trading activities in the S&P 500 index options market, we provide an insightful analysis on how to generate sensible volatility information from the options market by investigating their information content for future volatility of the underlying asset returns.

However, for the S&P 500 index, investors can process volatility information by trading not only S&P 500 index options but also VIX options, with the latter being a more straightforward venue. Wang (2013) shows that the trading volume of both S&P 500 index options and VIX options provides useful information for volatility forecasting of the S&P 500 index returns, with the latter being more informative than the former. Therefore, we revisit the predictive power of trading activities of VIX options in terms of order flows and then take an additional step to explore the relative usefulness of the trading activities in these two options markets to improve the volatility prediction of the S&P 500 index returns. Because the underlying asset of VIX options is the VIX index, which is the best predictor for the realized volatility of the S&P 500 index returns, we expect the order flows of buying (selling) calls and selling (buying) puts to be positively correlated to the future volatility of the index returns. Our expectation follows the same reasoning as the indirect hypothesis of S&P 500 index options, as previously discussed.

Our main empirical results are summarized as follows. First, the volatility information generated from directional trades of S&P 500 index options results in consistently effective volatility forecasting for the S&P 500 index returns, while that generated from volatility trades does not. Second, the volatility information compiled from the directional trades of VIX options also provides consistently useful information to determine the future volatility of S&P 500 index returns. These results suggest that investors should compile the volatility information indirectly from directional trades of S&P 500 index options rather than directly from volatility trades because S&P 500 index options are more commonly used to trade on directional expectation or information, especially after the introduction of VIX derivatives.

Given that the trading activities of S&P 500 index options are informative for the future volatility of index returns, we conduct additional analyses, which result in four main findings. First, the volatility information generated from S&P 500 index options provides better predictive power for the realized volatility of index returns when volatility-informed traders dominate directionally informed traders in the options market. Second, information is efficiently transferred between the S&P 500 index and VIX options markets. Third, the introduction of VIX derivatives weakens the predictive power of the volatility information generated from S&P 500 index options. Finally, after the introduction of VIX options, the volatility information from S&P 500 index options provide useful information for volatility forecasting only when volatility-informed traders dominate the options market.

This study contributes to prior literature on the information content of trading activities of derivatives for the future dynamics of the underlying asset price not only by developing an effective information proxy from the trading activities of S&P 500 index and VIX options to predict the future volatility of S&P 500 index returns but also by providing insights on the relative role of the trading activities of S&P 500 index and VIX options in determining the future volatility of S&P 500 index returns.

The remainder of this paper is organized as follows. Section 2 develops the main hypotheses for the empirical tests. Section 3 describes the method for the identification of transactions, followed by the description of data and empirical models in Section 4. Section 5 presents the main empirical results. Section 6 provides additional relevant empirical discussions, followed by robustness analyses in Section 7. Finally, Section 8 offers concluding remarks.

2. Hypotheses

Across all option pricing theories, a call price is a positive function of both the price of the underlying asset and the volatility of returns, and a put price is a negative function of the price but a positive function of the volatility. Therefore, investors can trade options to make profits based on their expectation of or information on the change of the underlying asset price or volatility of returns. Although previous research investigates the information content of trading activities of options on the future returns of the underlying asset price,[6] the information role of the trading activities of options on the future volatility of returns has not been fully explored.[7]

When investors trade options to realize their expectation of or information on future volatility of returns based on the positive relation between option prices and the volatility, expressed as

$$Vega(C) = \frac{dC}{d\sigma} > 0 \;\&\; Vega(P) = \frac{dP}{d\sigma} > 0, \tag{1}$$

we expect a positive (negative) relation between the future volatility of returns and the trading activities of buying (selling) calls and puts. We refer to this type of transaction as a volatility trade. Therefore, we form our first hypothesis as follows:

> *Hypothesis 1 (Direct Hypothesis): Volatility trades of options effectively generates volatility information of the underlying asset; therefore, trading activity related to buying (selling) calls and puts positively (negatively) predicts the volatility of returns.*

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[6] Classical literature includes Stephan and Whaley (1990), Amin and Lee (1997), Easley, O'Hara, and Srinivas (1998), Chan, Chung, and Fong (2002), and Pan and Poteshman (2006). In recent literature, Roll et al. (2010), Johnson and So (2012), and Hu (2014) focus on predicting returns of the underlying asset by option-implied trading measures.

[7] See, for example, Ni et al. (2008) and Wang (2013) using the singed and unsigned trading activities to investigate the volatility prediction, respectively.

Alternatively, when most investors trade options to realize their expectation of or information on future returns of the underlying asset based on the positive (negative) relation between call (put) prices and the prices of the underlying asset, expressed as

$$Delta(C) = \frac{dC}{dS} > 0 \; \& \; Delta(P) = \frac{dP}{dS} < 0, \tag{2}$$

we expect a positive (negative) relation between the future returns of the underlying asset and the trading activities of buying (selling) calls and selling (buying) puts. We refer to this type of transaction as a directional trade. Because price changes are a source of volatility and both positive and negative changes contribute to the formation of volatility, directional options trading affects the volatility of returns. In other words, the trading activities of all types of option trades—that is, both buying and selling calls and buying and selling puts—positively affects the future volatility of returns. Therefore, we form our second hypothesis as follows:

> *Hypothesis 2 (Indirect Hypothesis): The directional trading of options effectively generates volatility information of the underlying asset; therefore, the trading activities of all types of option trades positively predict the volatility of returns.*

3. Identification and Aggregation of Option Transactions

Because each transaction involves a buyer and a seller, we adopt the procedure proposed by Lee and Ready (1991) to identify each transaction as buyer or seller initiated. We implement this procedure in two steps. First, we classify transactions occurring above (below) the midpoint of the bid and ask prices of the last efficient quote records as buyer-initiated (seller-initiated) transactions. Second, we first classify transactions occurring at the midpoint of the bid and ask prices of the last efficient quote records using a tick test that compares the last different trade price of the previous transactions. Therefore, we define all transactions within one of four categories: buyer-initiated call, seller-initiated call, buyer-initiated put, or seller-initiated put. Second, we sum the trading volumes of the transactions day by day for each contract with the same category. Specifically, for strike K_i and maturity T_i at day *t*, $CB_t^{SPX}(K_i, T_i)$, $CS_t^{SPX}(K_i, T_i)$, $PB_t^{SPX}(K_i, T_i)$, and $PS_t^{SPX}(K_i, T_i)$ denote the daily trading volumes of the buyer-initiated call, sell-initiated call, buyer-initiated put, and seller-initiated put trades, respectively. Following the same procedure for VIX options, we use $CB_t^{VIX}(K_i, T_i)$, $CS_t^{VIX}(K_i, T_i)$, $PB_t^{VIX}(K_i, T_i)$, and $PS_t^{VIX}(K_i, T_i)$ to denote the daily trading volumes of the same four categories, respectively.

After obtaining the daily order flows for each contract, we use the method suggested by Holowczak, Hu, and Wu (2014) to aggregate transactions across contracts for each day. Holowczak et al. suggest that an effective method for the information aggregation in option transactions must account for each contract's different exposure to the price and volatility movements of the underlying asset. In other words, for the aggregation of transactions to extract information about the price movement of the underlying asset, the order flows of buying a call (put) and selling a put (call) option must have a positive (negative) weight.

Similarly, for the aggregation to extract information about the volatility movement of the underlying asset returns, the order flows of buying (selling) both a call and a put option must have a positive (negative) weight.

To test Hypothesis 1 for the S&P 500 index—namely, that volatility trades of the S&P 500 index options effectively generates volatility information of the S&P 500 index returns—we construct five variables to proxy for the volatility information as

$$NetCall_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i, T_i)\Big(CB_t^{SPX}(K_i, T_i) - CS_t^{SPX}(K_i, T_i)\Big) \tag{3}$$

$$NetPut_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i, T_i)\Big(PB_t^{SPX}(K_i, T_i) - PS_t^{SPX}(K_i, T_i)\Big) \tag{4}$$

$$Buy_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i, T_i)\Big(CB_t^{SPX}(K_i, T_i) + PB_t^{SPX}(K_i, T_i)\Big) \tag{5}$$

$$Sell_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i, T_i)\Big(CS_t^{SPX}(K_i, T_i) + PS_t^{SPX}(K_i, T_i)\Big) \tag{6}$$

$$VTotal_t^{SPX}(K_i, T_i) = NetCall_t^{SPX} + NetPut_t^{SPX} = Buy_t^{SPX} - Sell_t^{SPX} \tag{7}$$

where $Vega_{i,t} = n\big(d_{i,t}\big)S_t\sqrt{T_i}$, $n(.)$ is the density function of a standard normal variable, $w_t(K_i, T_i) = exp\left(-\frac{m_i^2}{2} - (M_i - 1)^2\right)$, $m_i = \left(\frac{K_i}{S_t} - 1\right)$ measures the moneyness of the option contract, $M_i = max(1, T_i \times 12)$ is the maturity in months and at least being one-month, $d_{i,t} = \frac{ln\left(\frac{F_t}{K_i}\right) + \frac{1}{2}\sigma_t^2 T_i}{\sigma\sqrt{T_i}}$, S_t is the S&P 500 index at time t, F_t is the forward price of *S&P 500* index at tune t, and σ_t^2 is the average implied volatility of the same contract in previous day ($t - 1$). These variables take into account not only the exposure to volatility by $Vega_{i,t}$ but also the weighting system across maturities and moneyness by $w_t(K_i, T_i)$ with the current month at-the-money contract taking the largest weight. When $w_t(K_i, T_i)$ is set to 1, the variables are equally weighted across maturities and strikes.

We expect both measures of order imbalance, $NetCall_t^{SPX}$ and $NetPut_t^{SPX}$, respectively grouped by calls and puts, to positively predict the volatility of S&P 500 index returns because the buyers (sellers) of both calls and puts benefit from an increase (decrease) in volatility. In addition, we expect Buy_t^{SPX} ($Sell_t^{SPX}$), grouped by buying (selling), to positively (negatively) predict volatility. Finally, combining all trading activities, we expect $VTotal_t^{SPX}$ to positively predict volatility.

To test Hypothesis 2 for the S&P 500 index—namely, that directional trades of the S&P 500 index options effectively generates the volatility information of S&P 500 index returns—we construct five variables to proxy for the volatility information as

$$ANetCall_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i,T_i)|CB_t^{SPX}(K_i,T_i) - CS_t^{SPX}(K_i,T_i)| \tag{8}$$

$$ANetPut_t^{SPX} = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i,T_i)|PB_t^{SPX}(K_i,T_i) - PS_t^{SPX}(K_i,T_i)| \tag{9}$$

$$Up_t^{SPX}(K_i,T_i) = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i,T_i)\left(CB_t^{SPX}(K_i,T_i) + PS_t^{SPX}(K_i,T_i)\right) \tag{10}$$

$$Down_t^{SPX}(K_i,T_i) = \sum_{i=1}^{N_t} Vega_{i,t} * w_t(K_i,T_i)\left(CS_t^{SPX}(K_i,T_i) + PB_t^{SPX}(K_i,T_i)\right) \tag{11}$$

$$DTotal_t^{SPX}(K_i,T_i) = Up_t^{SPX}(K_i,T_i) + Down_t^{SPX}(K_i,T_i) \tag{12}$$

For directional trades, we expect the positive and negative order imbalance of call (put) options to be positively (negatively) and negatively (positively) related to future returns of the S&P 500 index, respectively. Because both positive and negative returns contribute to the formation of volatility, we use the absolute value of order imbalance to predict volatility.

Therefore, we expect both $ANetCall_t^{SPX}$ and $ANetPut_t^{SPX}$ to positively predict the volatility of S&P 500 index returns. In addition, we expect Up_t^{SPX} ($Down_t^{SPX}$), grouped by the expectation of an increase (decrease) in the S&P 500 index level to positively predict volatility. Combining all trading activities, we expect $DTotal_t^{SPX}$ to positively predict volatility.

Following the same rules as previously discussed to compile directional information variables from directional trades of the S&P 500 index options, we construct five variables to proxy for the volatility information of the S&P 500 index returns from the trading activities of VIX options as

$$NetCall_t^{VIX}(K_i,T_i) = \sum_{i=1}^{N_t} CDelta_{i,t} * w_t(K_i,T_i)\left(CB_t^{VIX}(K_i,T_i) - CS_t^{VIX}(K_i,T_i)\right) \quad (13)$$

$$NetPut_t^{VIX}(K_i,T_i) = \sum_{i=1}^{N_t} PDelta_{i,t} * w_t(K_i,T_i)\left(PB_t^{VIX}(K_i,T_i) - PS_t^{VIX}(K_i,T_i)\right) \quad (14)$$

$$Up_t^{VIX}(K_i,T_i) = \sum_{i=1}^{N_t} w_t(K_i,T_i)\left(CDelta_{i,t} * CB_t^{VIX}(K_i,T_i) + PDelta_{i,t} * PS_t^{VIX}(K_i,T_i)\right) \quad (15)$$

$$Down_t^{VIX}(K_i,T_i) = \sum_{i=1}^{N_t} w_t(K_i,T_i)\left(CDelta_{i,t} * CS_t^{VIX}(K_i,T_i) + PDelta_{i,t} * PB_t^{VIX}(K_i,T_i)\right) \quad (16)$$

$$Total_t^{VIX}(K_i,T_i) = Up_t^{VIX}(K_i,T_i) - Down_t^{VIX}(K_i,T_i) \quad (17)$$

where $CDelta_{i,t} = N(d_{i,t})$, $PDelta_{i,t} = 1 - N(d_{i,t})$, $N(.)$ is the distribution function of a standard normal variable, and the definitions of the other variables are the same as those for the S&P 500 index options, replacing the underlying asset with the VIX level. Because the underlying asset of VIX options is the VIX index, which is the best predictor of realized volatility, we use Delta to measure the exposure to volatility.

We expect $NetCall_t^{VIX}$ ($NetPut_t^{VIX}$), grouped by calls (puts), to positively (negatively) predict the volatility of S&P 500 index returns. We expect Up_t^{VIX} ($Down_t^{VIX}$), grouped by the expectation of an increase (decrease) in the VIX level, to positively (negatively) predict the volatility, respectively. Finally, combining all trading activities, we expect $VTotal_t^{VIX}$ to positively predict volatility.

4. Data and Empirical Method

4.1. Data

To compile the variables to proxy for the volatility information of the S&P 500 index returns from the trading activities of S&P 500 index and VIX options, we obtain the tick data of S&P 500 index and VIX options from the CBOE DataShop. To estimate the realized volatility of the S&P 500 index returns, we obtain the intraday data of the S&P 500 index from OlsenData and TickData. We follow Andersen, Bollerslev, Diebold, and Ebens (2001) to calculate realized volatility as the square root of the sum of the five-minute squared returns. In addition, we obtain intraday VIX levels from the CQG Data Factory. The sample period runs from January 1, 1998 to April 30, 2016 for all data except VIX options, which does not begin until January 1, 2008 due to data availability.

Following the suggestions of Hu (2014), we exclude the trade records (a) taken before 8:45 AM Central Standard Time (the first 15 minutes) or after 3:10 PM Central Standard Tim (the last 5 minutes) each day, (b) of options with maturity within ten calendar days, and (c) with trivial errors such as zero strike prices.

4.2. Empirical Method

Using the variables of volatility information, we investigate the information content for future realized volatility of S&P 500 index returns. Because the prior literature commonly finds that the logarithmic realized volatility is approximately normal,[8] we implement the regression model to tests our hypotheses using the logarithmic form of volatility as

$$logRV_{t+1} = \alpha + \sum_{i=1}^{m} \beta_i X_{i,t} + \sum_{j=1}^{n} \theta_j Y_{j,t} + \varepsilon_t, \tag{18}$$

where RV_t denotes realized volatility, $X_{i,t}$ represents the *i*th proxy of volatility information generated, and $Y_{j,t}$ represents the *j*th control variable generated at time *t*. Due to the well-reported success in the volatility prediction made by the VIX index and the well-known stylized facts of volatility (i.e., volatility persistence), the control variables include the logarithms of the current (time *t*) VIX level and the current and lagged realized volatility values of four days. This model allows us to explore the individual, relative, and joint performance of the variables of volatility information extracted from the two option markets on the volatility prediction of S&P 500 index returns.

5. Main Empirical Results

5.1. Volatility Information from Volatility Trades of S&P 500 Index Options

To test for Hypothesis 1, we run the regression model with the variables of volatility

[8] See Andersen, Bollerslev, Diebold, and Labys (2000, 2001), Andersen, Bollerslev, Diebold, and Ebens (2001), and Areal and Taylor (2002).

information generated from the volatility trades of S&P 500 index options (i.e., $NetCall_t^{SPX}$, $NetPut_t^{SPX}$, Buy_t^{SPX}, $Sell_t^{SPX}$, and $VTotal_t^{SPX}$). Table 1 provides the regression results.

<Insert Table 1 about here>

If the trading activity of volatility trades of S&P 500 index options is informative to the future volatility of returns, the β_1 coefficients for $NetCall_t^{SPX}$ and $NetPut_t^{SPX}$ should be significantly positive. However, Models 1 and 2 of Table 1 show that the β_1 coefficients of $NetCall_t^{SPX}$ and $NetPut_t^{SPX}$ are both negative, which contradicts the prediction by Hypothesis 1.

Similarly, in line with our predictions, the β_1 coefficient for Buy_t^{SPX} ($Sell_t^{SPX}$) should be significantly positive (negative). Model 3 of Table 1 show that, consistent with Hypothesis 1, the β_1 coefficient of Buy_t^{SPX} is significantly positive. However, the β_1 coefficient for $Sell_t^{SPX}$ is not significantly negative, and thus the result does not support Hypothesis 1. Furthermore, the estimate of the β_1 coefficient of $VTotal_t^{SPX}$ should be positive, but Model 5 shows that the coefficient is negative and thus also not in line with our expectations.

In sum, the empirical results for the variables of volatility information obtained from the volatility trades of the S&P 500 index options do not, in general, support Hypothesis 1. In other words, the volatility information generated from volatility trades of S&P 500 index options do not effectively or reasonably predict the volatility of S&P 500 index returns.

5.2. Volatility Information from Directional Trades of S&P 500 Index Options

To test Hypothesis 2, we run the regression model with the variables of volatility information generated from the directional trades of S&P 500 index options (i.e., $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$). Table 2 reports the regression results with the control variables.

<Insert Table 2 about here>

If the trading activity of directional trades of S&P 500 index options is informative to the future volatility of returns, the β_1 coefficient for all variables of order flows should be significantly positive. Table 2 shows that, in line with the prediction of Hypothesis 2, the β_1 coefficient is positively significant at the 10% level or less across all models. In addition, the results do not depend on how the trading activities are grouped.

Given the consistent predictive power of the VIX level, which is supported by the highly positively significant γ_1 coefficient, the variables of volatility information indirectly compiled from the directional trades of S&P 500 index options consistently and reasonably predict the volatility of the S&P 500 index returns. In other words, our results indicate that, in general, investors use S&P 500 index options for directional trading although the use of volatility trades is also plausible. Therefore, we conclude that the channel of directional trading indirectly affects the impact of trading activity of S&P 500 index options on the future volatility of the S&P 500 index returns.

5.3. Volatility Information from Directional Trades of VIX Options

According to our previous results, S&P 500 index options are not an effective venue for volatility trades. Because the underlying asset of VIX options is a volatility measure, trading VIX options may be a more direct and effective channel to realize investors' expectation of or information on the volatility of S&P 500 index returns. To test this conjecture, we run the regression model with the variables of volatility information generated from the directional trades of VIX options (i.e., $NetCall_t^{VIX}$, $NetPut_t^{VIX}$, Up_t^{VIX}, $Down_t^{VIX}$, and $Total_t^{VIX}$). Table 3 provides the regression results with the control variables.

<Insert Table 3 about here>

If the trading activity of directional trades of VIX options is informative to the future volatility of S&P 500 index returns, the β_1 coefficients for $NetCall_t^{VIX}$, Up_t^{VIX}, and $Total_t^{VIX}$ should be significantly positive, and the β_1 coefficient for $NetPut_t^{VIX}$ and $Down_t^{VIX}$ should be significantly negative. Table 3 shows that the signs of all variables are consistent with our predictions. With the exception for $Down_t^{VIX}$, all variables are significant at the 10% level or less; of particular note, $NetCall_t^{VIX}$ and $Total_t^{VIX}$ are significant at the 1% level.

In sum, the results from the variables compiled from the directional trades of VIX options show that trading VIX options is an effective way to realize volatility expectation of or information on the volatility of S&P 500 index returns.

6. Further Discussions

According to our main empirical results, investors should generate the volatility information of the S&P 500 index returns indirectly from directional trades, instead of the volatility trades of S&P 500 index options, although investors can also trade the options to realize their expectation of or information on the volatility. Because the underlying asset of VIX options is a volatility measure, useful volatility information can be straightforwardly generated from the directional trades of VIX options. Given these empirical findings, we next explore associated relevant issues.

6.1. The Impact of Informed Trading

If the degree of informed trading is higher, the trading of derivatives should be more informative to the future dynamics of the underlying asset price. Informed traders can be motivated to trade options on both directional (Black, 1975; Diamond & Verrecchia, 1987) and volatility information (Back, 1993; Ni et al., 2008). Assuming that informed traders are either directionally or volatility informed, Han, Kim, and Byun (2017) extend the analytical framework of Easley et al. (1998) to link the predictive power of option-implied information for the returns of the underlying asset with the relative dominance of directionally or volatility informed traders in the options market. Empirically, they find that the dominance of directionally informed traders—proxied by the slope of the implied volatility function (i.e., the volatility skew defined as the difference between the implied volatilities of an out-of-the-money [OTM] put and an at-the-money [ATM] call)—strengthens the negative relation between options volume and future stock returns.[9]

Following Han et al. (2017), we investigate whether the predictive power of volatility information compiled from the order flows of S&P 500 index options increases when volatility-informed traders dominate directionally informed traders in the options market. To do so, we construct a regression model with the variables used to test Hypothesis 2, defined as

$$logRV_{t+1} = \alpha + \beta_1 X_t + \beta_2 D_{1,t} X_t + \beta_3 D_{2,t} X_t + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t, \quad (19)$$

where X_t is $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, or $DTotal_t^{SPX}$. $D_{1,t}$ ($D_{2,t}$) equals 1 when the volatility skew of S&P 500 index options is smaller (larger) than the 10% (90%) quantile at day *t*, and zero otherwise. Namely, $D_{1,t}$ ($D_{2,t}$) indicates the dominance of volatility (directionally) informed traders in the options market at day *t*. Table 4 shows the regression results.

<Insert Table 4 about here>

Table 4 shows that the β_2 coefficient is positively significant at the 1% level across all information variables. Given that all variables positively affect future realized volatility, the predictive power of the volatility information generated from the S&P 500 index options market is stronger when volatility-informed traders dominate directionally informed traders.

[9] See Xing et al. (2010). An OTM put option has a moneyness (defined as the strike price divided by the closing underlying stock price for a day) lower than and closest to 0.95, and an ATM call option has a moneyness between 0.95 and 1.05 and closest to 1.

The β_3 coefficient for all information variables is negative, at varying levels of significance. Thus, predictive power is lower when directionally informed traders dominate volatility-informed traders.

6.2. The Link between the S&P 500 Index and VIX Options Markets

In the previous section, we use the trading activities of S&P 500 index options to determine the volatility skew as a proxy for the relative dominance of directionally and volatility-informed traders. If the interaction between the S&P 500 index and VIX options markets is positive, the volatility skew should be associated with the predictive power of the volatility information generated from the trading activities of VIX options. To investigate the issue, we run the previous regression model with the variables of volatility information compiled from the trading of VIX options respectively (i.e., $NetCall_t^{VIX}$, $NetPut_t^{VIX}$, Up_t^{VIX}, $Down_t^{VIX}$, and $Total_t^{VIX}$). Table 5 shows the regression results.

<Insert Table 5 about here>

According to the sign of the β_1 coefficient, which represents the direction of the volatility information variable, if the two options markets interact, the β_2 (β_3) coefficient for $NetCall_t^{VIX}$, Up_t^{VIX}, and $Total_t^{VIX}$ should be significantly positive (negative), and the β_2 (β_3) coefficient for $NetPut_t^{VIX}$ and $Down_t^{VIX}$ should be significantly negative (positive). Table 5 shows that, with the exception of $NetPut_t^{VIX}$ and $Down_t^{VIX}$, the signs for the β_2 coefficients confirm the existence of a market interaction. In addition, all β_3

coefficients support market linkage but are statistically insignificant.

In sum, our empirical results do not provide overwhelmingly strong evidence of the informational link between the S&P 500 index and VIX options markets. However, results shows that the two options markets share volatility information to a certain degree.

6.3. The Introduction of VIX Futures and Options

Investors can, indirectly, trade on their volatility expectation of or information on the S&P 500 index returns through S&P 500 index derivatives. The introduction of VIX derivatives provides a direct and effective alternative to execute volatility trades because their underlying asset is a volatility measure. Therefore, we explore whether the introduction of VIX futures and options alter the usefulness of the volatility information generated from the S&P 500 index options market for volatility forecasting. To do so, we run the following regression with the variables used to test for Hypothesis 2:

$$logRV_{t+1} = \alpha + \beta_1 X_t + \beta_2 D_{1,t} X_t + \beta_3 D_{2,t} X_t + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t, \quad (20)$$

where X_t *is* $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, or $DTotal_t^{SPX}$. $D_{1,t}$ ($D_{2,t}$) equals 1 for the observations post the introduction of VIX futures (options) in January 2004 (February 2006), and zero otherwise. Table 6 provides the results.

<Insert Table 6 about here>

Table 6 reports that the β_2 and β_3 coefficients are negatively significant at the 1% level for the information variables Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$. These results indicate that the introduction of VIX futures and options weakens the predictive power of the volatility information generated from the S&P 500 index options. Conversely, the variables $ANetCall_t^{SPX}$ and $ANetPut_t^{SPX}$ provide no significant results. In general, these results suggest that the introduction of VIX weakens the informativeness of volatility information implied in the S&P 500 index options.

6.4. Comparison between the Information from S&P 500 index and VIX options

Our previous findings show that the volatility information generated from the trading activities of both the S&P 500 index and VIX options markets are useful for volatility forecasting of the S&P 500 index returns and that the VIX options market is an effective alternative to trade on the volatility information. Therefore, we next investigate the relative roles of the volatility information from these two options markets in the determination of future volatility of the index returns. To do so, we select the common sample period of S&P 500 index and VIX options and run a regression model with $DTotal_t^{SPX}$ and $Total_t^{VIX}$ because prior studies show that these two aggregation variables are highly significant for volatility forecasting. We construct the model as

$$logRV_{t+1} = \alpha + \beta_1 Total_t^{VIX} + \beta_2 DTotal_t^{SPX} + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t, \quad (21)$$

Table 7 provides the results.

<Insert Table 7 about here>

The results in Model 1 of Table 7 confirm that the predictive power of $Total_t^{VIX}$ is highly significantly. However, the β_2 coefficient for $DTotal_t^{SPX}$ in Model 2 is statistically insignificant for the sample period after the introduction of VIX options. When we include both $DTotal_t^{SPX}$ and $Total_t^{VIX}$ in Model 3, the significance of the β_1 coefficient is much stronger than that of the β_2 coefficient. In other words, the predictive power of the volatility information generated from VIX options dominates that from S&P 500 index options. These findings are in line with our previous finding that the predictive power of the volatility information generated from S&P 500 index options becomes weaker after the introduction of VIX derivatives.

Next, we examine whether the predictive power of the volatility information generated from S&P 500 index options improves when volatility-informed traders dominate directionally informed traders in the S&P 500 index options market. We add $\beta_3 D_{1,t} DTotal_t^{SPX}$ to the regression model, where $D_{1,t}$ equals to 1 when the volatility skew of S&P 500 index options is smaller than the 10% quantile at day *t*, and zero otherwise.[10] In Model 4 of Table 7, the β_2 estimate is 0.52 and statistically insignificant, but the β_3 estimate is 3.02 and significant at the 1% level. In other words, the volatility information generated from S&P 500 index options still plays an important role for volatility forecasting when the options market is relatively dominated by volatility-informed traders, even after the introduction of VIX derivatives.

[10] Previous results indicate that $D_{1,t}$ is more informative than $D_{2,t}$, which is equals 1 when the volatility skew of S&P 500 index options is larger than the 90% quantile.

7. Robustness Analysis

7.1. Weighting Scheme across Option Contracts

For our main analysis, in addition to taking accounting for the exposure to volatility, we adopt a weighting scheme in which the weight is negatively associated with the length of maturity and the depth of moneyness. Now we re-examine Hypotheses 1 and 2 with the variables compiled with an equally weighting scheme across maturity and moneyness. Table 8 summarizes the regression results.

<Insert Table 8 about here>

Panel A of Table 8 shows that the signs and significance of the β_1 coefficients for Hypothesis 1 are insistent with expectations, and Panel B shows that all β_1 coefficients are significantly positive for Hypothesis 2. These results are in line with those of our main analysis: The volatility information variables generated from the directional trades of S&P 500 index options consistently produce effective forecasting, while those generated from the volatility trades do not.

7.2. The Effect of Maturity and Moneyness

Because the OTM options have higher leverage than the ATM and in-the-money options and the near-month contracts usually have better liquidity, informed traders may prefer to trade the near-month OTM options to realize their private information. Therefore, we re-examine Hypotheses 1 and 2 with the variables compiled from the near-month OTM S&P 500 index options.[11] Table 9 provides the regression results.

<Insert Table 9 about here>

The results in Table 9 are, in general, consistent with our main findings. Specifically, the signs and significance of the β_1 coefficients for Hypothesis 1 (Panel A) are inconsistent with our expectations, and all β_1 coefficients for Hypothesis 2 (Panel B) are significantly positive. In other words, the information content of the variables compiled from near-month OTM options is, in general, equivalent to that of the variables compiled from all options.

8. Concluding Remarks

We adopt the algorithm proposed by Lee and Ready (1991) to identify each transaction of S&P 500 index and VIX options to compile volatility information variables from the order flows of these two options. Based on differing trading motivations of S&P 500 index options, we form variables of volatility information from directionally and volatility-motivated trades. We find that the information generated from directional trades provide consistently effective forecasting for the S&P 500 index returns, while the information generated from volatility trades does not.

In addition to our main finding, we provide several other results. First, the dominance of volatility-informed traders in the options market increases the predictive power of the volatility information generated from S&P 500 index options. Second, information between

[11] Contracts are aggregated without the consideration of maturity and moneyness because only the current-month OTM options are included.

the S&P 500 index and VIX options markets is closely linked, with the order flows of the VIX options market also providing useful information to determine the future volatility of the index returns. Third, the introduction of VIX derivatives weakens the predictive power of the volatility information generated from S&P 500 index options. Finally, even after the introduction of VIX derivatives, S&P 500 index options provide useful information for volatility forecasting when volatility-informed traders dominate the options market.

References

Amin, K. I., & Lee, C. (1997). Option trading, price discovery, and earnings news dissemination. Contemporary Accounting Research, 14(2), 153-192.

An, B. J., Ang, A., Bali, T. G., & Cakici, N. (2014). The joint cross section of stocks and options. The Journal of Finance, 69(5), 2279-2337.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. Journal of Financial Economics, 61(1), 43-76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2000). Exchange rate returns standardized by realized volatility are (nearly) Gaussian. Retrieved from

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. Journal of the American statistical association, 96(453), 42-55.

Anthony, J. H. (1988). The Interrelation of Stock and Options Market Trading-Volume Data. The Journal of Finance, 43(4), 949-964.

Areal, N. M., & Taylor, S. J. (2002). The realized volatility of FTSE-100 futures prices. Journal of Futures Markets, 22(7), 627-648.

Back, K. (1993). Asymmetric information and options. The Review of Financial Studies, 6(3), 435-472.

Banerjee, P. S., Doran, J. S., & Peterson, D. R. (2007). Implied volatility and future portfolio returns. Journal of Banking & Finance, 31(10), 3183-3199. doi:10.1016/j.jbankfin.2006.12.007

Black, F. (1975). Fact and fantasy in the use of options. Financial Analysts Journal, 31(4), 36-41.

Bollen, N. P., & Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions? The Journal of Finance, 59(2), 711-753.

Busch, T., Christensen, B. J., & Nielsen, M. Ø. (2011). The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. Journal of Econometrics, 160(1), 48-57.

Canina, L., & Figlewski, S. (1993). The informational content of implied volatility. The Review of Financial Studies, 6(3), 659-681.

Cao, C., Chen, Z., & Griffin, J. M. (2005). Informational content of option volume prior to takeovers. The Journal of Business, 78(3), 1073-1109.

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and option markets. The Journal of Finance, 59(3), 1235-1257.

Chan, K., Chung, Y. P., & Fong, W.-M. (2002). The informational role of stock and option volume. The Review of Financial Studies, 15(4), 1049-1075.

Christensen, B. J., & Prabhala, N. R. (1998). The relation between implied and realized volatility. Journal of Financial Economics, 50(2), 125-150.

Cremers, M., & Weinbaum, D. (2010). Deviations from put-call parity and stock return predictability. Journal of Financial and Quantitative Analysis, 45(2), 335-367.

Diamond, D. W., & Verrecchia, R. E. (1987). Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics, 18(2), 277-311.

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.

Fahlenbrach, R., & Sandås, P. (2010). Does information drive trading in option strategies? Journal of Banking & Finance, 34(10), 2370-2385.

Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices. Journal of Empirical Finance, 5(4), 317-345.

Giot, P. (2005). Relationships between implied volatility indexes and stock index returns. The Journal of Portfolio Management, 31(3), 92-100.

Guo, H., & Whitelaw, R. F. (2006). Uncovering the risk–return relation in the stock market. The Journal of Finance, 61(3), 1433-1463.

Han, J., Kim, D. H., & Byun, S. J. (2017). Informed trading in the options market and stock return predictability. Journal of Futures Markets, 37(11), 1053-1093.

Holowczak, R., Hu, J., & Wu, L. (2014). Aggregating information in option transactions. The Journal of Derivatives, 21(3), 9-23.

Hu, J. (2014). Does option trading convey stock price information? Journal of Financial Economics, 111(3), 625-645.

Jiang, G. J., & Tian, Y. S. (2005). The model-free implied volatility and its information content. The Review of Financial Studies, 18(4), 1305-1342.

Johnson, T. L., & So, E. C. (2012). The option to stock volume ratio and future returns. Journal of Financial Economics, 106(2), 262-286.

Lamoureux, C. G., & Lastrapes, W. D. (1993). Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities. The Review of Financial Studies, 6(2), 293-326.

Lee, C., & Ready, M. J. (1991). Inferring trade direction from intraday data. The Journal of Finance, 46(2), 733-746.

Manaster, S., & Rendleman, R. J. (1982). Option prices as predictors of equilibrium stock prices. The Journal of Finance, 37(4), 1043-1057.

Ni, S. X., Pan, J., & Poteshman, A. M. (2008). Volatility information trading in the option market. The Journal of Finance, 63(3), 1059-1091.

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. Review of Financial Studies, 19(3), 871-908.

Poon, S.-H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review.

Journal of economic literature, 41(2), 478-539.

Roll, R., Schwartz, E., & Subrahmanyam, A. (2010). O/S: The relative trading activity in options and stock. Journal of Financial Economics, 96(1), 1-17.

Stephan, J. A., & Whaley, R. E. (1990). Intraday price change and trading volume relations in the stock and stock option markets. The Journal of Finance, 45(1), 191-220.

Wang, Y. H. (2013). Volatility information in the trading activity of stocks, options, and volatility options. Journal of Futures Markets, 33(8), 752-773.

Whaley, R. E. (2000). The investor fear gauge. The Journal of Portfolio Management, 26(3), 12-17.

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.

Xu, X., & Taylor, S. J. (1995). Conditional volatility and the informational efficiency of the PHLX currency options market. Journal of Banking & Finance, 19(5), 803-821.

Table 1 The regression results for the volatility information from the order flows of volatility trades of S&P 500 index options

This table presents the results based on the following regression model:

$$log\, RV_{t+1} = \alpha + \beta_1 X_t + \sum_{i=0}^{4} \theta_i \, log\, RV_{t-i} + \gamma_1 \, log\, VIX_t + \epsilon_{t+1},$$

where $log\, RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; X_t denotes one of the variables of volatility information generated from the order flows of volatility trades of S&P 500 index options (i.e., $NetCall_t^{SPX}$, $NetPut_t^{SPX}$, Buy_t^{SPX}, $Sell_t^{SPX}$, and $VTotal_t^{SPX}$); $log\, VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$NetCall$	$NetPut$	Buy	$Sell$	$VTotal$
Coeff. \ X	(1)	(2)	(3)	(4)	(5)
β_1	–4.56**	–0.82	7.29***	6.96***	–2.70*
	(–2.08)	(–0.43)	(12.03)	(12.11)	(–1.78)
θ_0	0.21***	0.21***	0.19***	0.19***	0.21***
	(14.38)	(14.37)	(13.50)	(13.42)	(14.34)
θ_1	0.13***	0.13***	0.13***	0.13***	0.13***
	(8.96)	(8.97)	(8.72)	(8.71)	(8.96)
θ_2	0.05***	0.05***	0.05***	0.05***	0.05***
	(3.43)	(3.47)	(3.54)	(3.39)	(3.42)
θ_3	0.02	0.02	0.02	0.02	0.02
	(1.13)	(1.08)	(1.07)	(1.09)	(1.09)
θ_4	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.04)	(0.26)	(0.27)	(0.05)
γ_1	0.73***	0.73***	0.74***	0.74***	0.73***
	(29.10)	(29.07)	(29.89)	(30.03)	(29.13)
α	–0.63***	–0.63***	–0.67***	–0.68***	–0.63***
	(–16.33)	(–16.34)	(–17.65)	(–17.71)	(–16.38)
No. of Obs.	4,593	4,593	4,593	4,593	4,593
Adj. R^2	0.704	0.704	0.713	0.713	0.704

Table 2 The regression results for the volatility information from directional trades of S&P 500 index options

This table presents the results based on the following regression model:

$$log\,RV_{t+1} = \alpha + \beta_1 X_t + \sum_{i=0}^{4} \theta_i\, log\,RV_{t-i} + \gamma_1\, log\,VIX_t + \epsilon_{t+1},$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; X_t denotes one of the variables of volatility information generated from the order flows of directional trades of S&P 500 index options (i.e., $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$); ad$log\,VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$ANetCall$	$ANetPut$	Up	$Down$	$DTotal$
Coeff. \ X	(1)	(2)	(3)	(4)	(5)
β_1	4.46*	12.16***	6.85***	7.26***	3.70***
	(1.72)	(5.04)	(11.72)	(12.31)	(12.32)
θ_0	0.21***	0.21***	0.19***	0.19***	0.19***
	(14.38)	(14.29)	(13.44)	(13.49)	(13.42)
θ_1	0.13***	0.13***	0.13***	0.13***	0.13***
	(8.97)	(8.88)	(8.73)	(8.71)	(8.71)
θ_2	0.05***	0.05***	0.05***	0.05***	0.05***
	(3.50)	(3.45)	(3.47)	(3.46)	(3.46)
θ_3	0.02	0.02	0.01	0.02	0.02
	(1.07)	(1.13)	(1.02)	(1.15)	(1.08)
θ_4	–0.00	0.00	0.00	0.00	0.00
	(–0.01)	(0.07)	(0.30)	(0.23)	(0.28)
γ_1	0.73***	0.73***	0.74***	0.74***	0.74***
	(29.11)	(29.24)	(29.97)	(29.94)	(30.00)
α	–0.64***	–0.65***	–0.68***	–0.67***	–0.68***
	(–16.42)	(–16.74)	(–17.68)	(–17.65)	(–17.74)
No. of Obs.	4,593	4,593	4,593	4,593	4,593
Adj. R^2	0.704	0.705	0.712	0.713	0.713

Table 3 The regression results for the volatility information from directional trades of VIX options

This table presents the results based on the following regression model:

$$log\, RV_{t+1} = \alpha + \beta_1 X_t + \sum_{i=0}^{4} \theta_i \, log\, RV_{t-i} + \gamma_1 \, log\, VIX_t + \epsilon_{t+1},$$

where $log\, RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day *t*; X_t denotes one of the variables of volatility information generated from the order flows of directional trades of VIX options ($NetCall_t^{VIX}$, $NetPut_t^{VIX}$, Up_t^{VIX}, $Down_t^{VIX}$, and $Total_t^{VIX}$); and $log\, VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 2008 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$NetCall$	$NetPut$	Up	$Down$	$Total$
Coeff. \ X	(1)	(2)	(3)	(4)	(5)
β_1	1.50*	–3.48***	1.18***	0.45	2.12***
	(1.74)	(–3.03)	(3.00)	(1.14)	(3.15)
θ_0	0.20***	0.20***	0.19***	0.20***	0.20***
	(8.73)	(8.68)	(7.94)	(8.43)	(8.64)
θ_1	0.15***	0.15***	0.14***	0.15***	0.15***
	(6.51)	(6.55)	(6.27)	(6.37)	(6.56)
θ_2	0.06**	0.06***	0.06**	0.06**	0.06**
	(2.53)	(2.58)	(2.48)	(2.51)	(2.54)
θ_3	0.00	–0.00	0.00	0.00	0.00
	(0.03)	(–0.02)	(0.12)	(0.00)	(0.06)
θ_4	–0.01	–0.02	–0.01	–0.01	–0.01
	(–0.70)	(–0.72)	(–0.58)	(–0.66)	(–0.70)
γ_1	0.78***	0.78***	0.81***	0.79***	0.78***
	(16.76)	(16.73)	(17.00)	(16.53)	(16.77)
α	–2.15***	–2.14***	–2.26***	–2.19***	–2.14***
	(–16.52)	(–16.46)	(–16.67)	(–16.10)	(–16.52)
No. of Obs.	2,092	2,092	2,092	2,092	2,092
Adj. R^2	0.698	0.699	0.699	0.698	0.699

Table 4 The impact of informed trading

This table presents the results based on the following regression model:

$$logRV_{t+1} = \alpha + \beta_1 X_t + \beta_2 D_{1,t} X_t + \beta_3 D_{2,t} X_t + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t,$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; X_t denotes one of the variables of volatility information generated from the order flows of directional trades of S&P 500 index options ($ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$); $D_{1,t}$ ($D_{2,t}$) equals 1 when the volatility skew of S&P 50 index options is smaller (larger) than the 10% (90%) quantile at day t, and zero otherwise; and $log\,VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$ANetCall$		$ANetPut$		Up		$Down$		$DTotal$	
Coeff. \ X	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_1	2.43	24.22***	9.81***	20.63***	6.24***	8.02***	6.70***	9.42***	3.40***	4.51***
	(0.93)	(2.92)	(3.98)	(3.25)	(10.42)	(6.94)	(11.13)	(7.89)	(11.07)	(7.60)
β_2	47.65***		31.85***		5.70***		6.19***		2.99***	
	(4.81)		(4.49)		(4.45)		(4.60)		(4.52)	
β_3		–21.11**		–9.31		–1.34		–2.46**		–0.92
		(–2.51)		(–1.44)		(–1.17)		(–2.08)		(–1.57)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α	–0.62***	–0.63***	–0.63***	–0.64***	–0.66***	–0.67***	–0.66***	–0.67***	–0.66***	–0.67***
	(–16.15)	(–16.38)	(–16.34)	(–16.68)	(–17.09)	(–17.59)	(–17.14)	(–17.51)	(–17.18)	(–17.62)
No. of Obs.	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593
Adj. R^2	0.705	0.704	0.707	0.706	0.714	0.712	0.715	0.714	0.715	0.713

Table 5 The interaction between S&P 500 index and VIX options markets

This table presents the results based on the following regression model:

$$logRV_{t+1} = \alpha + \beta_1 X_t + \beta_2 D_{1,t} X_t + \beta_3 D_{2,t} X_t + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t,$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day *t*; X_t denotes one of the variables of volatility information generated from the order flows of directional trades of VIX options ($NetCall_t^{VIX}$, $NetPut_t^{VIX}$, Up_t^{VIX}, $Down_t^{VIX}$, or $Total_t^{VIX}$); $D_{1,t}$ ($D_{2,t}$) equals 1 when the volatility skew of S&P 50 index options is smaller (larger) than the 10% (90%) quantile at day *t*, and zero otherwise; and $log\,VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$NetCall$		$NetPut$		Up		$Down$		$Total$	
Coeff. \ X	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_1	1.20	1.74*	–3.98***	–3.83***	0.72*	1.24***	–0.05	0.39	2.06***	2.36***
	(1.38)	(1.90)	(–3.21)	(–3.21)	(1.72)	(2.94)	(–0.11)	(0.94)	(3.03)	(3.45)
β_2	9.82**		3.53		2.59***		2.93***		0.47	
	(1.97)		(1.07)		(3.25)		(3.60)		(0.20)	
β_3		–2.04		4.73		–0.25		0.36		–2.61
		(–0.76)		(1.08)		(–0.36)		(0.48)		(–1.21)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α	–2.14***	–2.15***	–2.14***	–2.13***	–2.24***	–2.27***	–2.16***	–2.19***	–2.14***	–2.14***
	(–16.50)	(–16.52)	(–16.46)	(–16.45)	(–16.46)	(–16.67)	(–15.90)	(–16.08)	(–16.52)	(–16.51)
No. of Obs.	2,092	2,092	2,092	2,092	2,092	2,092	2,092	2,092	2,092	2,092
Adj. R^2	0.698	0.698	0.699	0.699	0.700	0.699	0.700	0.698	0.699	0.699

Table 6 The introduction of VIX futures and options

This table presents the results based on the following regression model:

$$logRV_{t+1} = \alpha + \beta_1 X_t + \beta_2 D_{1,t} X_t + \beta_3 D_{2,t} X_t + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t,$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; X_t denotes one of the variables of volatility information generated from the order flows of directional trades of S&P 500 index options (i.e., $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$); $D_{1,t}$ ($D_{2,t}$) equals 1 for the observations post the introduction of VIX futures (options) in January 2004 (February 2006), and zero otherwise; and $log\,VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	$ANetCall$		$ANetPut$		Up		$Down$		$Total$	
Coeff. \ X	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_1	–11.16	3.00	–1.45	12.39***	33.73***	32.64***	42.11***	34.96***	22.23***	18.73***
	(–0.91)	(1.07)	(–0.12)	(5.00)	(7.87)	(13.10)	(9.59)	(14.02)	(9.65)	(14.44)
β_2	15.73		13.38		–24.81***		–32.20***		–17.01***	
	(1.31)		(1.13)		(–6.33)		(–8.01)		(–8.11)	
β_3		–3.27		0.82		–23.28***		–25.06***		–13.48***
		(–1.33)		(0.40)		(–10.64)		(–11.42)		(–11.90)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
α	–0.64***	–0.63***	–0.65***	–0.65***	–0.62***	–0.77***	–0.59***	–0.76***	–0.59***	–0.78***
	(–16.42)	(–16.37)	(–16.65)	(–16.72)	(–15.68)	(–19.77)	(–14.96)	(–19.88)	(–15.05)	(–20.20)
No. of Obs.	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593	4,593
Adj. R^2	0.704	0.704	0.705	0.705	0.715	0.719	0.717	0.721	0.717	0.722

Table 7 Comparison between S&P 500 index and VIX options

This table presents the results based on the following regression model:

$$logRV_{t+1} = \alpha + \beta_1 Total_t^{VIX} + \beta_2 DTotal_t^{SPX} + \beta_3 D_{1,t} DTotal_t^{SPX} + \sum_{i=0}^{4} \theta_i logRV_{t-i} + \gamma_1 logVIX_t + \varepsilon_t,$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day *t*; $DTotal_t^{SPX}$ and $Total_t^{VIX}$, respectively, denote the variables of volatility information generated from the order flows of S&P 500 index and VIX options; $D_{1,t}$ equals 1 when the volatility skew of S&P 50 index options is smaller than the 10% quantile at day *t*, and zero otherwise; and $log\,VIX_t$ is the logarithmic VIX level at day t. The sample period runs from January 1, 2008 to 30 April 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Coeff.	(1)	(2)	(3)	(4)
β_1	2.12***		2.18***	2.06***
	(3.15)		(3.23)	(3.06)
β_2		1.06	1.16*	0.52
		(1.55)	(1.71)	(0.74)
β_3				3.02***
				(4.35)
Controls	YES	YES	YES	YES
α	–2.14***	–2.18***	–2.18***	–2.15***
	(–16.52)	(–16.42)	(–16.48)	(–16.33)
No. of Obs.	2,092	2,090	2,090	2,090
Adj. R^2	0.699	0.698	0.699	0.702

Table 8 The regression results for the variables compiled with an alternative weighting scheme

This table presents the results based on the following regression model:

$$log\,RV_{t+1} = \alpha + \beta_1 X_t + \sum_{i=0}^{4} \theta_i\, log\,RV_{t-i} + \gamma_1\, log\,VIX_t + \epsilon_{t+1},$$

where $log\,RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; $log\,VIX_t$ is the logarithmic VIX level at day t. X_t denotes one of the variables of volatility information generated from the order flows of S&P 500 index options: $NetCall_t^{SPX}$, $NetPut_t^{SPX}$, Buy_t^{SPX}, $Sell_t^{SPX}$, and $VTotal_t^{SPX}$ for Hypothesis 1 (Panel A) and $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$ for Hypothesis 2 (Panel B). The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Hypothesis 1					
Coeff. \ X	$NetCall$	$NetPut$	Buy	$Sell$	$VTotal$
	(1)	(2)	(3)	(4)	(5)
β_1	–3.66**	–0.98	4.13***	4.04***	–2.27**
	(–2.40)	(–0.80)	(12.34)	(12.59)	(–2.25)
Panel B: Hypothesis 2					
Coeff. \ X	$ANetCall$	$ANetPut$	Up	$Down$	$DTotal$
	(1)	(2)	(3)	(4)	(5)
β_1	4.62**	7.53***	3.94***	4.18***	2.10***
	(2.44)	(4.76)	(12.16)	(12.69)	(12.64)

Table 9 The regression results for the variables compiled with OTM options

This table presents the results based on the following regression model:

$$log\, RV_{t+1} = \alpha + \beta_1 X_t + \sum_{i=0}^{4} \theta_i \, log\, RV_{t-i} + \gamma_1 \, log\, VIX_t + \epsilon_{t+1},$$

where $log\, RV_t$ is the logarithmic realized volatility calculated from the five-minute S&P 500 index returns at day t; $log\, VIX_t$ is the logarithmic VIX level at day t. X_t denotes one of the variables of volatility information generated from the order flows of S&P 500 index options: $NetCall_t^{SPX}$, $NetPut_t^{SPX}$, Buy_t^{SPX}, $Sell_t^{SPX}$, and $VTotal_t^{SPX}$ for Hypothesis 1 (Panel A) and $ANetCall_t^{SPX}$, $ANetPut_t^{SPX}$, Up_t^{SPX}, $Down_t^{SPX}$, and $DTotal_t^{SPX}$ for Hypothesis 2 (Panel B). All variables are compiled from out-of-the-money options only. The sample period runs from January 1, 1998 to April 30, 2016. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Hypothesis 1					
Coeff. \ X	$NetCall$	$NetPut$	Buy	$Sell$	$VTotal$
	(1)	(2)	(3)	(4)	(5)
β_1	–4.77***	–1.32	2.85***	2.92***	–2.13***
	(–3.09)	(–1.57)	(7.85)	(8.64)	(–2.87)
Panel B: Hypothesis 2					
Coeff. \ X	$ANetCall$	$ANetPut$	Up	$Down$	$DTotal$
	(1)	(2)	(3)	(4)	(5)
β_1	5.68***	4.56***	2.86***	2.91***	1.53***
	(3.30)	(4.72)	(8.20)	(8.30)	(8.50)