Is there volatility information trading in the Chinese stock options market?

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Abstract

This paper investigates the volatility information trading in the Chinese index options market. Specially, we apply the VPIN metric proposed by Easley et al. (2012) and the Volatility Demand proposed by Ni, Pan and Poteshman (2008) to measure the informed trading and compare their performance in predicting future volatility. We find that the VPIN metric has significant and positive impact on future realized volatility while the volatility demand measure is not significant. And the VPIN metric also has a positive predictive power for future implied volatility. More important, using the unique volume-time feature of the VPIN, we document that it captures the volatility information trading during the 2015 Chinese stock crash period as well.

Keywords: SSE 50 ETF options; VPIN; Implied volatility; Realized volatility

1. Introduction

It is well-known that option trading is informative for future stock returns and volatility.[1] For example, Easley et al. (1998) and Pan and Poteshman (2006) find that trading volume of particular options can predict future stock returns, while Ni, Pan and Poteshman (2008) establish the net demand for volatility, constructed from equity options, forecasting future realized volatility for at least next 5 trading days. However, these papers focus on individual stock options and there is seldom research on index options. Two exceptions are Chen et al. (2017) and Chordia et al. (2017). Specifically, Chen et al. (2017) show that volume of deep OTM S&P 500 index put options has strong negative information on future monthly index returns. Chordia et al. (2017) find that both net buying and selling pressure in S&P 500 index put options are positively informative about future weekly index returns, indicating that index options play an important informational role as well. Nevertheless, there is no study on volatility information trading in index options markets.

In this paper, we try to fill this gap by investigating newly launched Chinese index options market. [2] As a matter of fact, there is a fast growth in trading volume of Chinese index options since its inception on Feb 9, 2015. The monthly trading volume increases from 2.86 million in July 2015 to 19.26 million in July 2017. To our best knowledge, we are among the first to study volatility information trading in this market. In particular, we ask an essential question: Does volatility information trading exist in Chinese index

[1]There is a large literature on this topic. An incomplete list is Manaster and Rendleman (1982), Anthony (1988), Vijh (1988), Stephan and Whaley (1990), Easley et al. (1998), Pan and Poteshman (2006), Ni, Pan and Poteshman (2008) and An et al. (2014).

[2] Till now, the SSE 50 ETF option is the only product of the Chinese index option market.

options market? We answer this question by taking advantage of tick data on the index option and constructing two measures based on option trading volume, i.e., the net volatility demand proposed by Ni, Pan and Poteshman (2008) and volume-synchronized probability of informed trading (VPIN) metric suggested by Easley et al. (2012). Then, we compare the performance of the two measures by forecasting future realized volatility and implied volatility. In addition, we decompose the realized volatility into its continuous and jump components and examine the forecasting power of the two measures in more detail. Furthermore, using the unique feature of VPIN metric, we conduct volume-time regressions to predict realized volatility and implied volatility. More important, we consider both the whole sample period and the 2015 melt down period, which allows us to explore the volatility information trading in highly uncertain period and verify whether the VPIN metric still valid. We do obtain some different results for the two sample periods.

We have several main findings. First, the net volatility demand has no information about future realized volatility while the VPIN metric has significantly positive impact on 1-day, 4-day and 5-day ahead realized volatilities. It is notable that these results are obtained when five lags of realized volatilities are included, indicating that VPIN has incremental information for future volatility. Furthermore, when the realized volatility is decomposed into continuous and jump components, it turns out that the VPIN metric positively predicts 1-day, 3-day, 4-day and 5-day ahead jump components of realized volatility while the net volatility demand is still invalid. As for continuous component, the VPIN metric is positively significant at 1% level in forecasting 1-day ahead continuous component while the net volatility demand is not significant.

Second, the VPIN metric has positive impact on 1-day and 5-day ahead implied volatilities while the net volatility demand has negative impact on 1-day ahead implied volatility when five lagged implied volatilities are included. Third, when volume-time regression is employed for the VPIN metric, we compare its performance for the whole sample and the 2015 melt down periods. In forecasting future realized volatility, we find that the VPIN metric is positively significant at 1% level for next five volume-times for the whole sample period. However, the VPIN metric only has positive impacts on next three volume-times for the 2015 melt down period. Also, both magnitudes of regression coefficients and statistical significance levels decrease. These results may indicate that it is too uncertain to trade on information about index volatility during the 2015 melt down period. Different results are obtained when the continuous and jump components of realized volatility are considered. For example, the VPIN metric is positively significant at 5% level for next five volume-times' jump components for the whole sample period while is only positively significant at 10% level for next 1 volume-time jump component for the 2015 melt down period. However, the VPIN metric has positive impact on next five volume-times' continuous components at 1% significance level for the whole sample period while has no predictive power for future continuous components for the 2015 melt down period. In predicting future implied volatility, we note that the VPIN metric is positively significant at 1% level for next five volume-times for the whole sample period while has positive impacts on next three volume-times with lower significant level for the 2015 melt down period.

We make several contributions to the literature on volatility information trading. First of all, we document that there is volatility information trading in the Chinese index option market. Second, we demonstrate that different measurements may have different performance in this issue, that VPIN is more suitable for the newly developed Chinese index option market. Third, we show that the VPIN is an effective measure in capturing volatility information trading in the 2015 volatile period, making it a great indicator for the market regulators to consider in their risk management and supervisory activities.

The rest of the paper is structured as follows. Section 2 introduces the data and methodology. Section 3 presents the daily forecasting performance of the VPIN and volatility demand of options market for future stock price volatility. Section 4 further explore the forecasting power of VPIN in volume-time and during the 2015 melt down of the Chinese stock market, and section 5 concludes.

2.Data and Methodology

2.1 The VPIN Metric

The volume-synchronized probability of informed trading (VPIN) metric is produced by a series of work of Easley et al. (2010, 2011, 2012). It measures the order imbalance in the high frequency market based on volume imbalance and trading intensity, making it possible to be free from estimating non-observable parameters and applying numerical methods, which is the main limitation of the traditional PIN method.

The core of the VPIN is its volume-time classification pattern. In order to calculate VPIN, we first define the time bar as 1 minute and calculate the trade volume per time bar ($V_{\tau i}$) and the price change per time bar ($P_i - P_{i-1}$). Then all the trades are categorized into equal volume buckets V to create volume-time series, where V is 1/50 of the average daily volume following Easley et al. (2012). The extra volume larger than V is put into the next bucket and we delete the last bucket of the whole sample if its volume is less than V. And then the volume is classified as buyer or seller initiated by multiplying the trade volume by the normal distribution evaluated at the standardized price change:

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_{\tau i} \cdot Z(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}) \tag{1}$$

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_{\tau i} \cdot \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B \tag{2}$$

Where V_τ^B and V_τ^S is the buy and sell volume respectively. $t(\tau)$ is the last time bar included in the τth volume bucket, $V_{\tau i}$ is the trading volume of the ith 1-minute time bar, Z is the cumulative distribution function (CDF) of the standard normal distribution, and $\sigma_{\Delta P}$ is the estimate of the standard derivation of price changes between time bars.

Finally, the volume-synchronized probability of informed trading (VPIN) can be established by the values computed above:

$$VPIN = \frac{\sum_n^{\tau=1} |V_\tau^B - V_\tau^S|}{nV} \tag{3}$$

where n is the number of buckets used to estimate the approximate trading imbalance. Following Easley et al. (2012), we choose n=50, calculating VPIN over a fifty-bucket rolling window.

2.2 The Volatility Demand

We also apply another volume-based measure of the informed trading in the options market, the Volatility Demand proposed by Ni, Pan and Poteshman (2008). It constructs the demand for volatility from the market maker’s perspective and separate trading volume into non-market maker buys and sells of call and put options:

$$D_t^{\sigma} = \sum_{K}\sum_{T} \frac{\partial \ln C_t^{K,T}}{\partial \sigma_t}\left(\mathrm{BuyCall}_t^{K,T} - \mathrm{SellCall}_t^{K,T}\right) +$$

$$\sum_{K}\sum_{T} \frac{\partial \ln P_t^{K,T}}{\partial \sigma_t}\left(\mathrm{BuyPut}_t^{K,T} - \mathrm{SellCall}_t^{K,T}\right) \tag{4}$$

Where $C_t^{K,T}$ ($P_t^{K,T}$) is the price of the call (put) option at time t with strike price K and maturity T, $\mathrm{BuyCall}_t^{K,T}$ ($\mathrm{BuyPut}_t^{K,T}$) is the number of call (put) contracts purchased by non-market makers on day t with strike price K and maturity T, and $\mathrm{SellCall}_t^{K,T}$ ($\mathrm{SellPut}_t^{K,T}$) is the number of call (put) contracts shorted by non-market makers on day t with strike price K and maturity T. In the empirical work, $\partial \ln C_t^{K,T} / \partial \sigma_t$ is approximated with ($1/C_t^{K,T}$) $\mathrm{BlackScholesCallVega}_t^{K,T}$ (and similarly for $\partial \ln P_t^{K,T} / \partial \sigma_t$), where the Black-Scholes vega is computed with the volatility of the underlying stock set to the sample volatility from the 60 trading days of returns leading up to day t. For the information of buy and sell orders is unobservable, we empirically use quotation and transaction data in conjunction with the Lee and Ready (1991) algorithm to classify option volume as buyer- or seller-initiated.

When calculating the volatility demand, we only include the contracts that meet the following conditions: a) the time to expiration is between 5 to 120 days, and b) the ratio of the strike price to the closing underlying price is between 0.8 to 1.2.

2.3 Realized volatility and its jump and continuous components

We employ the realized volatility to portray the volatility movement of the stock index:

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{5}$$

Where RV_t is the realized volatility of the index calculated by the quadratic sum of the index return for the SSE 50 index on day t, M = 1/Δ, and the Δ-period intraday return is defined by $r_{t,i} = \log(P_{t-1+i\Delta}) - \log(P_{t-1+(i-1)\Delta})$.

Moreover, following Bollerslev et al. (2016), we further decompose RV into its continuous (BPV) and discontinuous (Jump) variations using the Bi-Power Variation (BPV) measure of Barndorff-Nielsen and Shephard (2004):

$$BPV_t = \mu_1^{-2} \sum_{i=1}^{M-1} |r_{t,i}|\,|r_{t,i+1}| \tag{6}$$

$$J_t = \max[RV_t - BPV_t, \quad 0] \tag{7}$$

Where RV_t is the realized volatility of the index calculated by the quadratic sum of the index return for the SSE 50 index on day t, BPV_t is the continuous part of the realized volatility, $\mu_1 = \sqrt{2/\pi} = E(|Z|)$ (Z is a standard normally distributed random variable), $r_{t,i}$ is the Δ-period intraday return, and J_t is the Jump variation of the realized volatility.

2.4 Data

The intraday tick by tick data of the Chinese SSE 50 ETF options, the SSE 50 index and China Volatility Index (IVX) from February 2015 to March 2016 is used to examine the relationship between the informed trading in the options market and future stock price volatility. The tick data are obtained from the China Stock Market & Accounting Research (CSMAR) Database.

After calculating the VPIN and the volatility demand of the SSE 50ETF options, and the realized volatility of the SSE 50 index, we plot the daily time series of them in figure 1 (the last VIPIN of the day is selected as the daily VPIN value and all the data are standardized), from which we can roughly see that RV and VPIN series are highly correlated. Most of the time, they go up and down together, and during the 2015 melt down and the crash in early 2016, they both jumps sharply. However, the volatility demand moves quite independently with the other two, showing more noises.

<Insert Figure 1>

The monthly trading volume of SSE 50 ETF options is plotted in figure 2, which shows that the trading volume of 50 ETF options has increased dramatically during the first year of its launch, from less than 1 million contracts in the first four months to more than 5 million a month one year later. But there are three low points in September and October 2015 and February 2016, which are related with the rolling of the contracts and may account for the relatively low value of volatility demand in these periods presented in figure 1.

<Insert Figure 2>

And the VPIN series is further plotted in volume-time with the RV series during the whole sample period in figure 3 and during the 2015 melt down in figure 4. We can see that during the full sample, the volume-time VPIN and RV are highly synchronized. They both have three distinct ascending periods: around the beginning of the 2015 melt down in June, 2015, near the end of the 2015 melt down in late August, and during another slump of the stock market in January, 2016. And to some extent, VPIN all begins to increase slightly before the RV during these three periods, indicating its possible early warning ability for risks. While figure 4 shows more specifically the condition during the 2015 crisis. It seems that during the crisis, the differentiation of the VPIN and RV increases, but they still generally have the same trend.

From these figures we can roughly infer that there is informed trading in the Chinese index options market, and VPIN might have great efficiency in capturing it.

<Insert Figure 3>

<Insert Figure 4>

3.Option informed trading and future index volatility: calendar-time regressions using VPIN and Volatility Demand

In this part, we test the impact of the informed trading in the options market on future index volatilities. Specially, we compare the relative performance of two volume-based measurement of the informed trading in the options market, namely the VPIN metric and the Volatility Demand (D^{σ}), in predicting the future volatility risks in the stock market. And because of the relative scale of the Volatility Demand and other variables, all the regression data used in this part are standardized.

3.1 Daily VPIN and Volatility Demand in forecasting RV

We firstly investigate the information in VPIN and the Volatility Demand of the SSE 50 ETF options for future realized volatility of the SSE 50 index through the predictive regression model:

$$RV_t = \beta_0 + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5} + \varepsilon_t \qquad (8)$$

$$RV_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5}$$

$$+\varepsilon_t \tag{9}$$

$$RV_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5}$$

$$+\varepsilon_t \tag{10}$$

Where equation (8) is the benchmark model of the realized volatility. RV_t is the realized volatility of the index calculated by the quadratic sum of the 1-minute index return for the SSE 50 index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market and the last value of the day is selected as the daily VPIN for day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. And j is selected to be 1 to 5.

Table 1 presents the regression results, from which we can see that VPIN in lag 1, 4 and 5 is positively significant in 1% level in forecasting future volatility after controlling five lag terms of the realized volatility itself. Among them, the fourth order lag VPIN has the largest impact with the highest coefficient of 0.2195 and the largest R-squared value of 0.4731, indicating that VPIN has a relative long term predictive power for future volatility. Most importantly, the VPIN component is significant after controlling 5 lag terms of RV, and compared to the benchmark model (the autoregressive model of RV itself), the add of VPIN has improved the R-squared value by approximately 5% percent, which indicates that VPIN does have incremental information for future short term volatility. This is a key point of the debate on the validity of VPIN. ELO does not do the regression work about the predictive ability of VPIN for future return volatility, while Anderson and Bondarenko does and find it invalid when control the lagged volatility, but they adjust the VPIN to 1-mitute series not volume-time and use the absolute 1-min return as the volatility measure. On the contrary, the Volatility Demand fails to forecast the future volatility risk, since none of the five lags of D^{σ} show any significance. And all the R-squared values in panel A are larger than the corresponding ones in panel B, confirming that VPIN has a stronger explanatory power for future index volatility than D^{σ}.

<Insert Table 1>

3.2 Daily VPIN and Volatility Demand in forecasting Jump and BPV of realized volatility

Then, we further decompose the realized volatility (RV) into continuous (BPV) and discontinuous (Jump) parts and test the predictability of VPIN and volatility demand for these two parts respectively.

Table 2 and 3 display the predictability of VPIN and volatility demand for future Jump and BPV of the RV. The volatility demand still predicts neither the Jump nor the BPV component of future index volatility. While VPIN has a significant positive forecasting power for both the jump and the BPV. And VPIN component has improved the R-squared value of both jump- and BPV-benchmark models, confirming its incremental information content for future market volatility. And comparing the coefficients and significance of VPIN for jumps and BPV, we can see that actually VPIN has a stronger and longer lasting forecasting power for the jump component than that for BPV, and the greatest predictability of VPIN comes from VPIN_{t-5}, indicating that VPIN has a very great risk warning power for sharp increases of future market risks with a long leading lag. In the empirical, the jump component has typically been found to be largely unpredictable, which is in line with the relative R-squared value of the Jump- and BPV- models (the R^2 of the BPV model has an average of 0.65 while the R^2 of the Jump model is only about 0.2), but our results show that VPIN metric has greatly improves the forecast of the jump component. Comparing panels A and B in table 2, we can see that VPIN has improved the R-squared value by around 10% to 40% percent.

<Insert Table 2>

<Insert Table 3>

3.3 Daily VPIN and Volatility Demand in forecasting implied volatility

While realized volatility is a kind of historical volatility, we further investigate the predictive ability of VPIN and volatility demand for the implied volatility of the stock market. We use the China Volatility Index (IVX) as the proxy and replace the RV in the previous regressions with it.

Table 4 shows the regression results. As expected, VPIN can positively forecast the future IVX, however, the volatility demand is negatively correlated with the next period IVX. The negative coefficient of D^{σ} is a little bit confusing and we think that might be related to the noises of the data series. More important, the first and fifth lag of IVX in the IVX-benchmark model are significant but when VPIN is included, the fifth lag of IVX loses its significance. And when IVX itself only has a 1-day ahead predictive power, VPIN shows a long-term forecasting power for future IVX up to five days, which means that VPIN an IVX may have some information overlapping, but VPIN has incremental information for future IVX and can capture the dynamics of the implied volatility even earlier than itself.

<Insert Table 4>

4. Option informed trading and future index volatility: volume-time regressions using VPIN and the role of 2015 melt down

In this part, we further investigate the predictive power of VPIN for future volatilities of the stock market in its original volume-time pattern during the whole sample period and the 2015 melt down, in order to deeply examine the characteristics of VPIN and also test the robustness of its forecasting performance. And in this part, all the data are adjusted to the volume-time of VPIN.

4.1 Volume-time VPIN in forecasting RV

Here table 5 shows the predictive regression results of the VPIN for RV during the whole sample period and the 2015 melt down. During the full sample, all five lags of VPIN are positively significant at 1% level, while during the crisis, only the first three lags of VPIN can positively predict the future RV and their significance is lower than their full sample counterparts. This is reasonable that during the 2015 melt down when the market is highly volatile, it is surely more difficult to forecast the future volatility conditions or have inside information about it, and even the second lag of RV itself loses the significant forecasting power.

<Insert Table 5>

4.2 Volume-time VPIN in forecasting Jump and BPV of realized volatility

Then the forecasting power of VPIN for the continuous (BPV) and discontinuous (Jump) part of RV is further explored in volume-time and under different sample periods. Table 6 and 7 present the regression results. During the whole sample period, VPIN has a significant positive predictive ability for both Jump and BPV, while during the stock crash in 2015, the result of BPV becomes insignificant, but VPIN can still positively predict the next period Jump variation of the realized volatility with the coefficient of 0.1820 at 10% significant level. These results mean that even during the crisis time, the extreme movement of index volatility can be captured by the VPIN metric in advance, which reconfirms that index options VPIN is a very good risk warning proxy for the index market.

<Insert Table 6>

<Insert Table 7>

4.3 Volume-time VPIN in forecasting IVX

Then we also explore the forecasting performance of the volume-time VPIN for future implied volatility of the index. Consistent with the RV results, VPIN has a significantly positive predictive power for future IVX, but during the 2015 melt down, the significance and early warning ability drops, reflecting the influence of the noises and uncertainty of the market.

<Insert Table 8>

In summary, the volume-time result confirms the great forecasting ability of VPIN for future index uncertainty. VPIN can serve as an early warning indicator for future increases of market volatility that the higher the VPIN the higher the future realized and implied volatility of the underlying index market. And under the highly volatile market conditions such as the 2015 stock crash, the predictive power of VPIN for future risks still holds, but both magnitudes and statistical significance of regression coefficients decrease, indicating that the high volatile market condition can make the volatility informed trading more difficult.

5. Robustness

In this part, we test the robustness of our results from several perspectives.

Firstly, we think that the measure of return volatility might have impact on the result, so we replace the realized volatility in the calendar time regression with the measure used in Ni, Pan and Poteshman (2008) which is calculated as the difference of the intraday high and low price divided by the closing price of the stock index. From table 9 we can see that the volatility demand remains insignificant, as for VPIN, although its significance drops, it remains positively correlated with 1 day ahead volatility at 10% significance level, confirming its validity.

<Insert Table 9>

Secondly, Ni, Pan and Poteshman (2008) uses the daily data to calculated volatility demand, so the price variable used in the D^{σ} (equation 4) measure is the closing price of each option contract, and we follow this in our previous analysis. Nevertheless, we have the intraday high frequency data of the options, so we also replace the closing price in the formula with the volume weighted average price of the day for each contract, to capture more detailed and accurate price information. The results show that the volatility demand based on the weighted average price is still insignificant for future volatility, neither its jump nor continuous component[3].

Lastly, we replace the volatility demand and VPIN with their first difference in the regression, and the results are consistent with the level version. Volatility demand still show no impact on future volatility, and the difference of VPIN remains significantly positive with a little decline in significance[4].

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[3] The results are not displayed for space reason, but it can be provided if in need.
[4] The results are not displayed for space reason, but it can be provided if in need.

Therefore, our results are robust from many aspects.

5. Conclusion

In this paper, we use the volume-synchronized probability of informed trading (VPIN) metric to investigate the volatility informed trading in the Chinese index options market. We explore the informed trading in forecasting future realized volatility and implied volatility, and specially, we compare i) the information content of VPIN with another volume-based measurement of the option informed trading (the Volatility Demand proposed by Ni, Pan and Poteshman, 2008); ii) the forecasting performance of VPIN during the whole sample period and the 2015 stock crash in China. And we decompose the realized volatility into its jump and continuous components in our analysis.

We have several important findings. First, we document the existence of volatility informed trading in the Chinese stock index market, since VPIN metric has significantly positive forecasting power for future realized volatility of the index, and for its jump components and continuous components as well. It should be noted that VPIN is significant after controlling for five lagged terms of RV itself, so it is proved to have incremental information for future volatility. Second, the VPIN metric also has positive impacts on future implied volatilities. Third, the relative performance of VPIN and volatility demand suggests that the choose of measurement for the option informed trading counts in this issue.

Moreover, the volume-time regression of VPIN further confirms the positive forecasting power of VPIN for future realized volatilities and implied volatilities, and during the melt down in 2015, the forecasting power still holds, indicating that VPIN can early warn the volatility risk in the stock market even when the uncertainty of the market peaks. But the magnitudes of regression coefficients, the statistical significance and the lasting time of the forecasting power of VIPIN all decrease during the crisis, in line with the common belief that the high volatile market condition can make the informed trading harder.

All in all, we document that there is volatility information trading in the Chinese index option market, and the VPIN metric is a very good proxy to measure it. It efficiently captures volatility information trading in the options market and has a valid and stable early warning power for increases of future volatility in the underlying market, even when the market is highly volatile. Thus, it is a valuable indicator in risk management for both investors and financial regulators to consider.

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Table 1

The predictability of options VPIN and Volatility Demand (D^{σ}) for future realized volatility (Daily)

Panel A: The predictability of options VPIN for future realized volatility

j	Const.	$VPIN_{t-j}$	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	R^2
	0.0012		**0.3767*** **	**0.3078*** **	-0.0422	0.0814	0.0556	0.4401
1	0.0017	**0.1359** **	**0.3184*** **	**0.2780*** **	-0.0317	0.0806	0.0589	0.4533
2	0.0005	-0.0727	**0.3893*** **	**0.3342*** **	-0.0300	0.0756	0.0541	0.4438
3	0.0017	0.0410	**0.3804*** **	**0.2994*** **	-0.0582	0.0749	0.0588	0.4413
4	0.0046	**0.2195*** **	**0.3667*** **	**0.3331*** **	-0.0846	0.0006	0.0280	0.4731
5	0.0038	**0.1777*** **	**0.3279*** **	**0.3161*** **	-0.0060	0.0390	-0.0136	0.4607

Panel B: The predictability of Volatility Demand (D^{σ}) for future realized volatility

j	Const.	D^{σ}_{t-j}	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	R^2
1	0.0012	-0.0125	**0.3770*** **	**0.3081*** **	-0.0427	0.0813	0.0559	0.4403
2	0.0012	0.0197	**0.3772*** **	**0.3072*** **	-0.0426	0.0820	0.0555	0.4405
3	0.0012	0.0306	**0.3757*** **	**0.3089*** **	-0.0429	0.0807	0.0566	0.4411
4	0.0012	0.0021	**0.3766*** **	**0.3078*** **	-0.0421	0.0814	0.0556	0.4401
5	0.0011	-0.0457	**0.3769*** **	**0.3102*** **	-0.0417	0.0792	0.0562	0.4422

Note: Panel A and B present the predictive regression results of the model (1): $RV_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5} + \varepsilon_t$, and model (2): $RV_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5} + \varepsilon_t$. Where RV_t is the realized volatility of the index calculated by the quadratic sum of the index return for the SSE 50 index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market on day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 2

The predictability of options VPIN and Volatility Demand (D^{σ}) for the discontinuous part (Jump) of future realized volatility (Daily)

Panel A: The predictability of options VPIN for Jumps

j	Const.	$VPIN_{t-j}$	J_{t-1}	J_{t-2}	J_{t-3}	J_{t-4}	J_{t-5}	R^2
	0.0019		0.0714	**0.4809*** **	-0.0958	**-0.1898*** **	**0.1236** **	0.2063
1	0.0023	**0.1598*** **	0.0323	**0.4431*** **	-0.1034	**-0.1992*** **	**0.1156***	0.2277
2	0.0021	0.0279	0.0665	**0.4746*** **	-0.1001	**-0.1920*** **	**0.1210***	0.2069
3	0.0032	**0.1058***	0.0671	**0.4645*** **	**-0.1175***	**-0.2109*** **	**0.1140***	0.2154
4	0.0058	**0.2716*** **	0.0391	**0.4760*** **	**-0.1217***	**-0.2587*** **	0.0624	0.2661
5	0.0064	**0.3338*** **	-0.0292	**0.4600*** **	-0.0511	**-0.2613*** **	0.0168	0.2932

Panel B: The predictability of Volatility Demand (D^{σ}) for Jumps

j	Const.	D^{σ}_{t-j}	J_{t-1}	J_{t-2}	J_{t-3}	J_{t-4}	J_{t-5}	R^2
1	0.0019	0.0017	0.0714	**0.4809*** **	-0.0958	**-0.1898*** **	**0.1236** **	0.2063
2	0.0019	0.0197	0.0713	**0.4810*** **	-0.0962	**-0.1900*** **	**0.1239** **	0.2067
3	0.0019	0.0223	0.0709	**0.4808*** **	-0.0955	**-0.1902*** **	**0.1234** **	0.2068
4	0.0019	0.0089	0.0711	**0.4808*** **	-0.0957	**-0.1898*** **	**0.1234** **	0.2064
5	0.0018	-0.0145	0.0716	**0.4813*** **	-0.0956	**-0.1898*** **	**0.1036** **	0.2065

Note: Panel A and B present the predictive regression results of the model (3): $J_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 J_{t-1} + \theta_2 J_{t-2} + \theta_3 J_{t-3} + \theta_4 J_{t-4} + \theta_5 J_{t-5} + \varepsilon_t$, and model (4): $J_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 J_{t-1} + \theta_2 J_{t-2} + \theta_3 J_{t-3} + \theta_4 J_{t-4} + \theta_5 J_{t-5} + \varepsilon_t$. Where J_t is the discontinuous part of realized volatility of the index return for the SSE 50 index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market on day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 3
The predictability of options VPIN and Volatility Demand (D^{σ}) for the continuous part (BPV) of future realized volatility (Daily)

Panel A: The predictability of options VPIN for BPV

j	Const.	$VPIN_{t-j}$	BPV_{t-1}	BPV_{t-2}	BPV_{t-3}	BPV_{t-4}	BPV_{t-5}	R^2
	0.0012		**0.6765*** **	**-0.2023*** **	**0.2386*** **	**0.3625*** **	**-0.2213*** **	0.6550
1	0.0017	**0.1197*** **	**0.5975*** **	**-0.2036*** **	**0.2291*** **	**0.3713*** **	**-0.2046*** **	0.6643
2	0.0013	-0.0005	**0.6767*** **	**-0.2021*** **	**0.2386*** **	**0.3625*** **	**-0.2214*** **	0.6550
3	0.0008	-0.0304	**0.6780*** **	**-0.1971*** **	**0.2515*** **	**0.3649*** **	**-0.2244*** **	0.6556
4	0.0017	0.0320	**0.6775*** **	**-0.2038*** **	**0.2344*** **	**0.3478*** **	**-0.2220*** **	0.6556
5	0.0013	0.0009	**0.6765*** **	**-0.2023*** **	**0.2385*** **	**0.3624*** **	**-0.2217*** **	0.6550

Panel B: The predictability of Volatility Demand (D^{σ}) for BPV

j	Const.	D^{σ}_{t-j}	BPV_{t-1}	BPV_{t-2}	BPV_{t-3}	BPV_{t-4}	BPV_{t-5}	R^2
1	0.0012	-0.0243	**0.6772*** **	**-0.2020*** **	**0.2368*** **	**0.3633*** **	**-0.2211*** **	0.6556
2	0.0013	0.0444	**0.6795*** **	**-0.2056*** **	**0.2387*** **	**0.3650*** **	**-0.2236*** **	0.6569
3	0.0013	0.0099	**0.6754*** **	**-0.2011*** **	**0.2374*** **	**0.3630*** **	**-0.2208*** **	0.6551
4	0.0012	-0.0043	**0.6767*** **	**-0.2020*** **	**0.2380*** **	**0.3630*** **	**-0.2216*** **	0.6550
5	0.0011	-0.0396	**0.6768*** **	**-0.2018*** **	**0.2406*** **	**0.3582*** **	**-0.2187*** **	0.6565

Note: Panel A and B present the predictive regression results of the model (5): $BPV_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 BPV_{t-1} + \theta_2 BPV_{t-2} + \theta_3 BPV_{t-3} + \theta_4 BPV_{t-4} + \theta_5 BPV_{t-5} + \varepsilon_t$, and model (6): $BPV_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 BPV_{t-1} + \theta_2 BPV_{t-2} + \theta_3 BPV_{t-3} + \theta_4 BPV_{t-4} + \theta_5 BPV_{t-5} + \varepsilon_t$. Where BPV_t is the continuous part of realized volatility of the index return for the SSE 50 index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market on day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 4

The predictability of options VPIN and Volatility Demand (D^{σ}) for future IVX (Daily)

Panel A: The predictability of options VPIN for future IVX

j	Const.	$VPIN_{t-j}$	IVX_{t-1}	IVX_{t-2}	IVX_{t-3}	IVX_{t-4}	IVX_{t-5}	R^2
	0.0042		**1.0086*** **	-0.0940	0.0196	0.1220	**-0.1141***	0.9079
1	0.0053	**0.1053*** **	**0.9168*** **	-0.0749	0.0567	0.0938	-0.0876	0.9171
2	0.0044	0.0038	**0.9969*** **	-0.0929	0.0208	0.1263	**-0.1141***	0.9080
3	0.0039	-0.0135	**1.0098*** **	-0.0823	0.0185	0.1207	0.1188	0.9081
4	0.0049	0.0337	**1.1011*** **	-0.0996	-0.0087	0.1233	-0.0986	0.9088
5	0.0052	**0.0503** **	**0.9933*** **	-0.0744	0.0109	0.0772	-0.0884	0.9098

Panel B: The predictability of Volatility Demand (D^{σ}) for future IVIX

j	Const.	D^{σ}_{t-j}	IVX_{t-1}	IVX_{t-2}	IVX_{t-3}	IVX_{t-4}	IVX_{t-5}	R^2
1	0.0042	**-0.0386** **	**1.0109*** **	-0.0861	0.0129	0.1212	-0.1187	0.9094
2	0.0042	-0.0173	**1.0016*** **	-0.0859	0.0225	0.1194	-0.1165	0.9082
3	0.0042	0.0037	**1.0092*** **	-0.0931	0.0180	0.1213	-0.1130	0.9079
4	0.0042	0.0244	**1.0068*** **	-0.0881	0.0254	0.1104	-0.1112	0.9085
5	0.0042	0.0113	**1.0082*** **	-0.0937	0.0199	0.1223	-0.1145	0.9079

Note: Panel A and B present the predictive regression results of the model (7): $IVX_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 IVX_{t-1} + \theta_2 IVX_{t-2} + \theta_3 IVX_{t-3} + \theta_4 IVX_{t-4} + \theta_5 IVX_{t-5} + \varepsilon_t$, and model (8): $IVX_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 IVX_{t-1} + \theta_2 IVX_{t-2} + \theta_3 IVX_{t-3} + \theta_4 IVX_{t-4} + \theta_5 IVX_{t-5} + \varepsilon_t$. Where IVX_t is the China volatility index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market on day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 5

The predictability of options VPIN for future realized volatility during the whole sample period and the 2015 melt down (Volume-time)

Panel A: Full sample result (from February 2015 to March 2016)

j	Const.	$VPIN_{\tau-j}$	$RV_{\tau-1}$	$RV_{\tau-2}$	$RV_{\tau-3}$	$RV_{\tau-4}$	$RV_{\tau-5}$	R^2
1	-0.0019	**0.3340*** **	**1.0061*** **	**0.0582*** **	**-0.0662*** **	-0.0077	-0.0033	0.9833
2	-0.0023	**0.3433*** **	**1.0064*** **	**0.0582*** **	**-0.0664*** **	-0.0076	-0.0036	0.9833
3	-0.0020	**0.3356*** **	**1.0064*** **	**0.0586*** **	**-0.0664*** **	-0.0079	-0.0037	0.9833
4	-0.0012	**0.3187*** **	**1.0065*** **	**0.0586*** **	**-0.0660*** **	-0.0079	-0.0039	0.9833
5	-0.0007	**0.3050*** **	**1.0066*** **	**0.0585*** **	**-0.0661*** **	-0.0075	-0.0042	0.9833

Panel B: During the 2015 melt down (from June 2015 to August 2015)

j	Const.	$VPIN_{\tau-j}$	$RV_{\tau-1}$	$RV_{\tau-2}$	$RV_{\tau-3}$	$RV_{\tau-4}$	$RV_{\tau-5}$	R^2
1	-0.0157	**0.2939** **	**1.0142*** **	0.0434	**-0.0568** **	-0.0286	0.0160	0.9838
2	-0.0126	**0.2728** **	**1.0145*** **	0.0435	**-0.0569** **	-0.0287	0.0160	0.9838
3	-0.0093	**0.2505* **	**1.0147*** **	0.0436	**-0.0568** **	-0.0288	0.0159	0.9838
4	-0.0026	0.2054	**1.0150*** **	0.0436	**-0.0567** **	-0.0287	0.0159	0.9838
5	-0.0024	0.2041	**1.0151*** **	0.0436	**-0.0567** **	-0.0286	0.0157	0.9838

Note: Panel A and B present the predictive regression results of the model: $RV_\tau = \beta_0 + \beta_j VPIN_{\tau-j} + \theta_1 RV_{\tau-1} + \theta_2 RV_{\tau-2} + \theta_3 RV_{\tau-3} + \theta_4 RV_{\tau-4} + \theta_5 RV_{\tau-5} + \varepsilon_\tau$ during the whole sample period (from February 2015 to March 2016) and the 2015 melt down (from June 2015 to August 2015), respectively. Where RV_τ is the realized volatility of the index calculated by the quadratic sum of the index return for the SSE 50 index of the during the volume-time period τ, $VPIN_{\tau-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market during the volume-time period $\tau - j$. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 6

The predictability of options VPIN for the discontinues (Jump) part of the future realized volatility during the whole sample period and the 2015 melt down (Volume-time)

Panel A: Full sample result (from February 2015 to March 2016)

j	Const.	$VPIN_{\tau-j}$	$J_{\tau-1}$	$J_{\tau-2}$	$J_{\tau-3}$	$J_{\tau-4}$	$J_{\tau-5}$	R^2
1	-0.0015	**0.1567****	**0.8476*****	**0.1661*****	**-0.0326*****	0.0056	-0.0102	0.9538
2	-0.0020	**0.1660****	**0.8477*****	**0.1661*****	**-0.0327*****	0.0056	-0.0103	0.9538
3	-0.0020	**0.1656****	**0.8477*****	**0.1663*****	**-0.0327*****	0.0055	-0.0104	0.9538
4	-0.0015	**0.1561****	**0.8477*****	**0.1663*****	**-0.0325*****	0.0055	-0.0105	0.9538
5	-0.0012	**0.1497****	**0.8477*****	**0.1662*****	**-0.0325*****	0.0057	-0.0106	0.9538

Panel B: During the 2015 melt down (from June 2015 to August 2015)

j	Const.	$VPIN_{\tau-j}$	$J_{\tau-1}$	$J_{\tau-2}$	$J_{\tau-3}$	$J_{\tau-4}$	$J_{\tau-5}$	R^2
1	-0.0128	**0.1820***	**0.7585*****	**0.2139*****	0.0297	0.0026	**-0.0325***	0.9429
2	-0.0111	0.1719	**0.7587*****	**0.2140*****	0.0296	0.0025	**-0.0325***	0.9429
3	-0.0099	0.1647	**0.7588*****	**0.2141*****	0.0297	0.0025	**-0.0326***	0.9429
4	-0.0054	0.1376	**0.7590*****	**0.2142*****	0.0298	0.0026	**-0.0326***	0.9429
5	-0.0053	0.1368	**0.7591*****	**0.2141*****	0.0298	0.0026	**-0.0326***	0.9429

Note: Panel A and B present the predictive regression results of the model: $J_\tau = \beta_0 + \beta_j VPIN_{\tau-j} + \theta_1 J_{\tau-1} + \theta_2 J_{\tau-2} + \theta_3 J_{\tau-3} + \theta_4 J_{\tau-4} + \theta_5 J_{\tau-5} + \varepsilon_\tau$ during the whole sample period (from February 2015 to March 2016) and the 2015 melt down (from June 2015 to August 2015), respectively.. Where J_τ is the discontinuous part of realized volatility of the index return for the SSE 50 index during the volume-time period τ, $VPIN_{\tau-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market of the volume-time period $\tau - j$. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 7

The predictability of options VPIN for the continues (BPV) part of the future realized volatility during the whole sample period and the 2015 melt down (Volume-time)

Panel A: Full sample result (from February 2015 to March 2016)

j	Const.	$VPIN_{\tau-j}$	$BPV_{\tau-1}$	$BPV_{\tau-2}$	$BPV_{\tau-3}$	$BPV_{\tau-4}$	$BPV_{\tau-5}$	R^2
1	-0.0006	**0.0963*** **	**1.3698*** **	**-0.4101*** **	**0.0443*** **	-0.0061	-0.0027	0.9960
2	-0.0004	**0.0915*** **	**1.3699*** **	**-0.4100*** **	**0.0443*** **	-0.0062	-0.0028	0.9960
3	-0.0002	**0.0858*** **	**1.3701*** **	**-0.4100*** **	**0.0445*** **	-0.0062	-0.0030	0.9960
4	-0.0000	**0.0808*** **	**1.3602*** **	**-0.4100*** **	**0.0445*** **	-0.0060	-0.0032	0.9960
5	-0.0004	**0.0714*** **	**1.3703*** **	**-0.4100*** **	**0.0445*** **	-0.0058	-0.0033	0.9960

Panel B: During the 2015 melt down (from June 2015 to August 2015)

j	Const.	$VPIN_{\tau-j}$	$BPV_{\tau-1}$	$BPV_{\tau-2}$	$BPV_{\tau-3}$	$BPV_{\tau-4}$	$BPV_{\tau-5}$	R^2
1	-0.0044	0.0879	**1.4644*** **	**-0.6209*** **	**0.1903*** **	**-0.1123*** **	**0.0739*** **	0.9953
2	-0.0027	0.0758	**1.4647*** **	**-0.6209*** **	**0.1905*** **	**-0.1125*** **	**0.0739*** **	0.9953
3	-0.0009	0.0633	**1.4649*** **	**-0.6210*** **	**0.1905*** **	**-0.1124*** **	**0.0738*** **	0.9953
4	-0.0002	0.0554	**1.4650*** **	**-0.6211*** **	**0.1905*** **	**-0.1123*** **	**0.0737*** **	0.9953
5	-0.0006	0.0529	**1.4651*** **	**-0.6211*** **	**0.1905*** **	**-0.1123*** **	**0.0737*** **	0.9953

Note: Panel A and B present the predictive regression results of the model: $BPV_{\tau} = \beta_0 + \beta_j VPIN_{\tau-j} + \theta_1 BPV_{\tau-1} + \theta_2 BPV_{\tau-2} + \theta_3 BPV_{\tau-3} + \theta_4 BPV_{\tau-4} + \theta_5 BPV_{\tau-5} + \varepsilon_{\tau}$, during the whole sample period (from February 2015 to March 2016) and the 2015 melt down (from June 2015 to August 2015), respectively.. Where BPV_{τ} is the continuous part of realized volatility of the index return for the SSE 50 index during the volume-time period τ, $VPIN_{\tau-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market of the volume-time period τ. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 8

The predictability of options VPIN for future IVX during the whole sample period and the 2015 melt down (Volume-time)

Panel A: Full sample result (from February 2015 to March 2016)

j	Const.	$VPIN_{\tau-j}$	$IVX_{\tau-1}$	$IVX_{\tau-2}$	$IVX_{\tau-3}$	$IVX_{\tau-4}$	$IVX_{\tau-5}$	R^2
1	0.0004	**0.0041*** **	**0.8158*** **	**0.1268*** **	**0.0232* **	**0.0206* **	0.0118	0.9987
2	0.0004	**0.0038*** **	**0.8160*** **	**0.1269*** **	**0.0231* **	**0.0206* **	0.0118	0.9987
3	0.0004	**0.0037*** **	**0.8161*** **	**0.1269*** **	**0.0231* **	**0.0205* **	0.0118	0.9987
4	0.0004	**0.0036*** **	**0.8161*** **	**0.1270*** **	**0.0232* **	**0.0205* **	0.0117	0.9987
5	0.0004	**0.0034*** **	**0.8162*** **	**0.1270*** **	**0.0232* **	**0.0205* **	0.0116	0.9987

Panel B: During the 2015 melt down (from June 2015 to August 2015)

j	Const.	$VPIN_{\tau-j}$	$IVX_{\tau-1}$	$IVX_{\tau-2}$	$IVX_{\tau-3}$	$IVX_{\tau-4}$	$IVX_{\tau-5}$	R^2
1	**0.0012* **	**0.0052** **	**0.7401*** **	**0.1785*** **	**0.1302*** **	**-0.0428* **	-0.0104	0.9952
2	**0.0011* **	**0.0043* **	**0.7407*** **	**0.1785*** **	**0.1304*** **	**-0.0428* **	-0.0107	0.9952
3	**0.0011* **	**0.0040* **	**0.7411*** **	**0.1786*** **	**0.1302*** **	**-0.0428* **	-0.0109	0.9952
4	0.0010	0.0031	**0.7414*** **	**0.1789*** **	**0.1303*** **	**-0.0429* **	-0.0109	0.9952
5	0.0010	0.0030	**0.7416*** **	**0.1788*** **	**0.1304*** **	**-0.0429* **	-0.0111	0.9952

Note: Panel A and B present the predictive regression results of the model: $IVX_\tau = \beta_0 + \beta_j VPIN_{\tau-j} + \theta_1 IVX_{\tau-1} + \theta_2 IVX_{\tau-2} + \theta_3 IVX_{\tau-3} + \theta_4 IVX_{\tau-4} + \theta_5 IVX_{\tau-5} + \varepsilon_\tau$ during the whole sample period (from February 2015 to March 2016) and the 2015 melt down (from June 2015 to August 2015), respectively. Where IVX_τ is the China volatility index during the volume-time period τ, $VPIN_{\tau-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market during the volume-time period $\tau - j$. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

Table 9
The predictability of options VPIN and Volatility Demand (D^{σ}) for future *OneDayRV* (Daily)

Panel A: The predictability of options VPIN for future *OneDayRV*

j	Const.	$VPIN_{t-j}$	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	R^2
	0.0024		**0.4023***	0.0986	0.1039	**0.1212***	0.0291	0.3784
1	0.0033	**0.1164***	**0.3433*****	0.0676	0.1082	0.1303	0.0171	0.3856
2	0.0026	0.0142	**0.4008*****	0.0918	0.1001	0.1217	0.0298	0.3785
3	0.0029	0.0326	**0.4019*****	0.0955	0.0885	0.1127	0.0310	0.3789
4	0.0032	0.0444	**0.4011*****	0.0988	0.1002	0.1006	0.0187	0.3794
5	0.0031	0.0412	**0.4005*****	0.0969	0.1034	0.1170	0.0062	0.3794

Panel B: The predictability of Volatility Demand (D^{σ}) for future *OneDayRV*

j	Const.	D^{σ}_{t-j}	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	R^2
1	0.0024	0.0002	**0.4023*****	0.0986	0.1039	**0.1212***	0.0291	0.3784
2	0.0025	0.0237	**0.4023*****	0.0993	0.1034	**0.1209***	0.0288	0.3789
3	0.0026	0.0451	**0.4006*****	0.0992	0.1054	**0.1204***	0.0286	0.3804
4	0.0024	-0.0010	**0.4024*****	0.0986	0.1039	**0.1211***	0.0291	0.3784
5	0.0024	-0.0261	**0.4023*****	0.1005	0.1042	**0.1207***	0.0282	0.3791

Note: Panel A and B present the predictive regression results of the model (1): $RV_t = \beta_0 + \beta_j VPIN_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5} + \varepsilon_t$, and model (2): $RV_t = \beta_0 + \beta_j D^{\sigma}_{t-j} + \theta_1 RV_{t-1} + \theta_2 RV_{t-2} + \theta_3 RV_{t-3} + \theta_4 RV_{t-4} + \theta_5 RV_{t-5} + \varepsilon_t$. Where RV_t is the *OneDayRV* (Ni, Pan and Poteshman, 2008) calculated as the difference of the intraday high and low price divided by the closing price of the stock index on day t, $VPIN_{t-j}$ is the Volume-Synchronized Probability of Informed Trading of the SSE 50 ETF options market on day t-j, and D^{σ}_{t-j} is the demand for volatility in the options market on day t-j. *,** and *** indicate significance at 10%, 5% and 1% levels, respectively and R^2 is the R-squared value of the model.

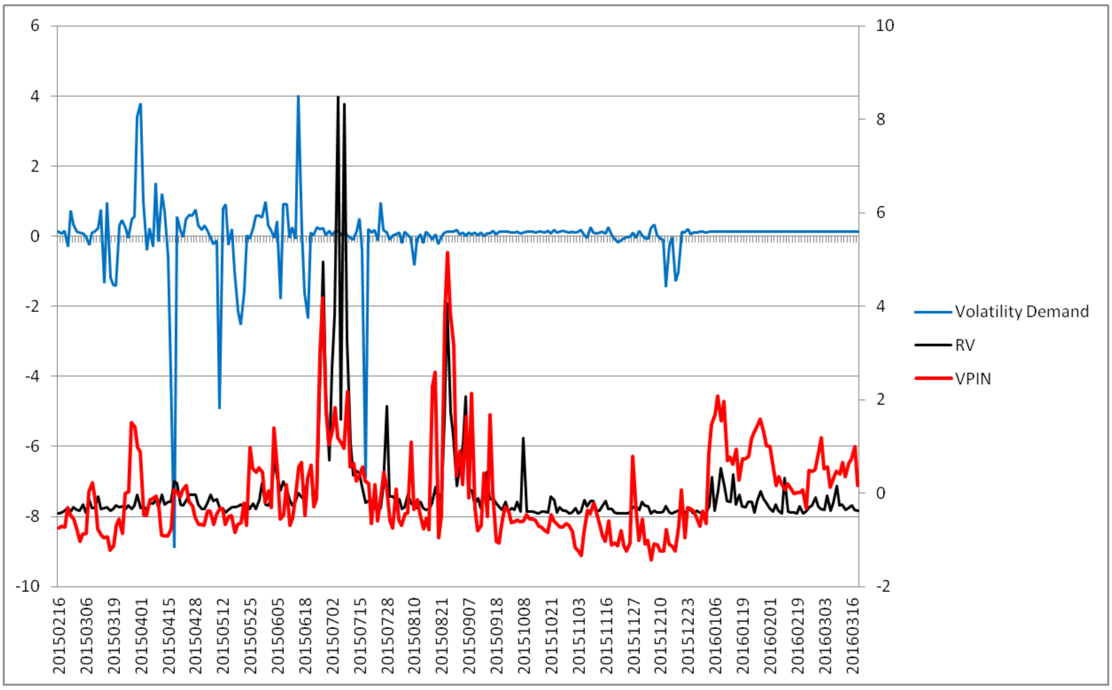

Figure 1

Daily time series of VPIN and Volatility Demand for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index

This figure plots the daily time series of VPIN and Volatility Demand for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index from 16th February, 2015 to 16th March, 2016. The volatility demand refers to the left axis while VPIN and RV refer to the right axis. The last VPIN of the day is selected as the daily VPIN value. The data series are all standardized.

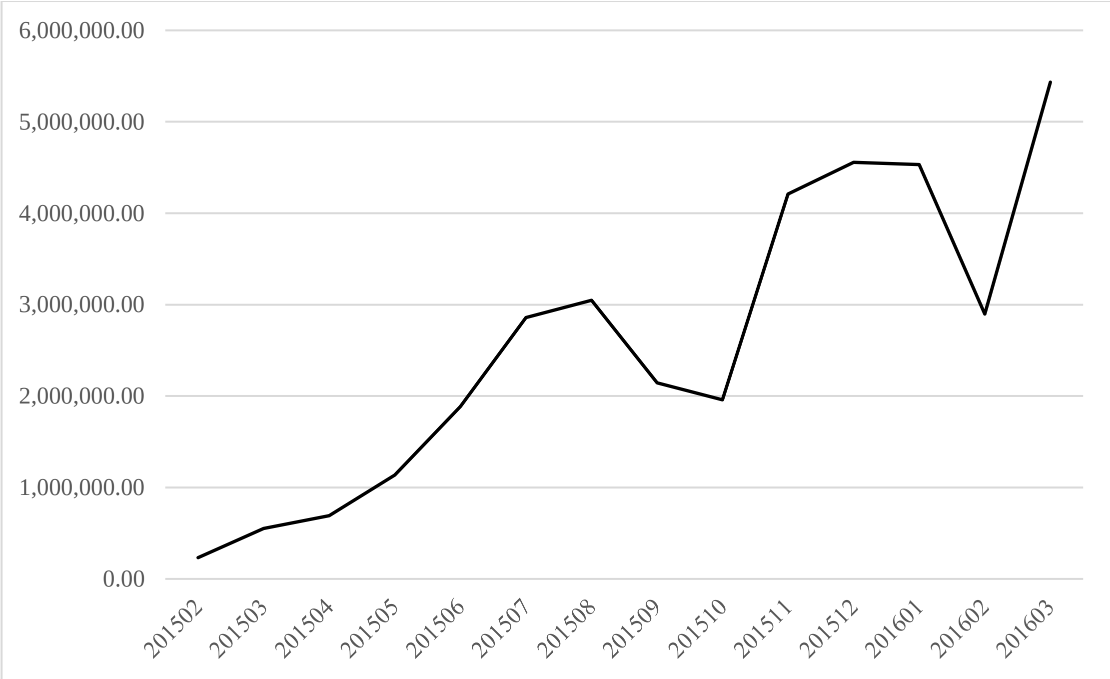

Figure 2

The monthly trading volume of the SSE 50 ETF options (from February, 2015 to March, 2016)

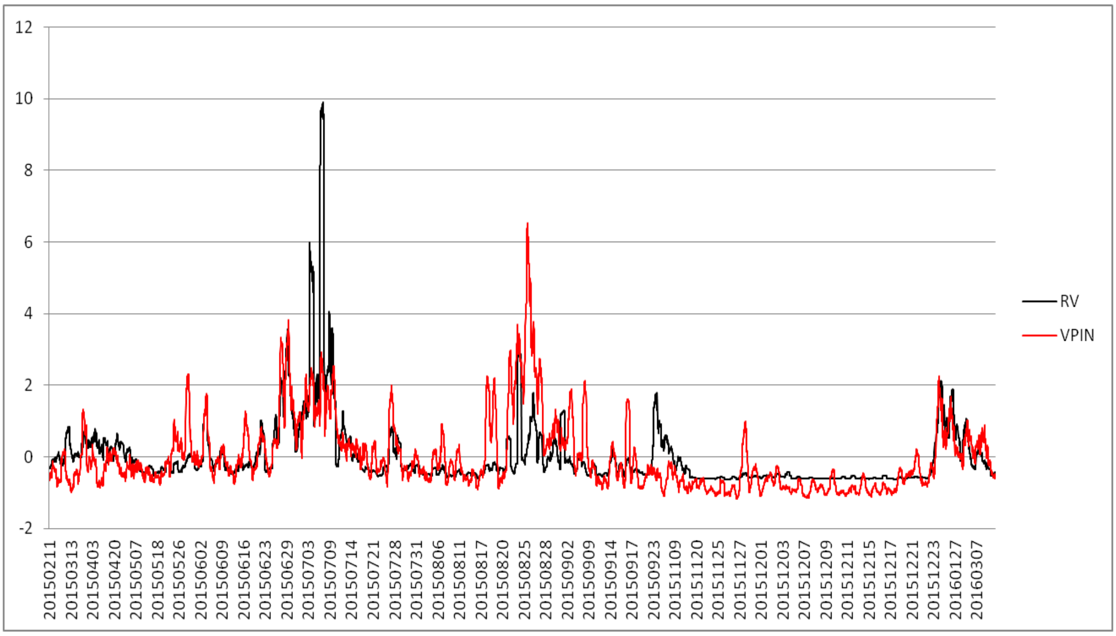

Figure 3

Volume-time series of VPIN for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index during the full sample (from February, 2015 to March, 2016)

This figure plots the volume-time series of VPIN for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index from February, 2015 to March, 2016. The data series are all standardized.

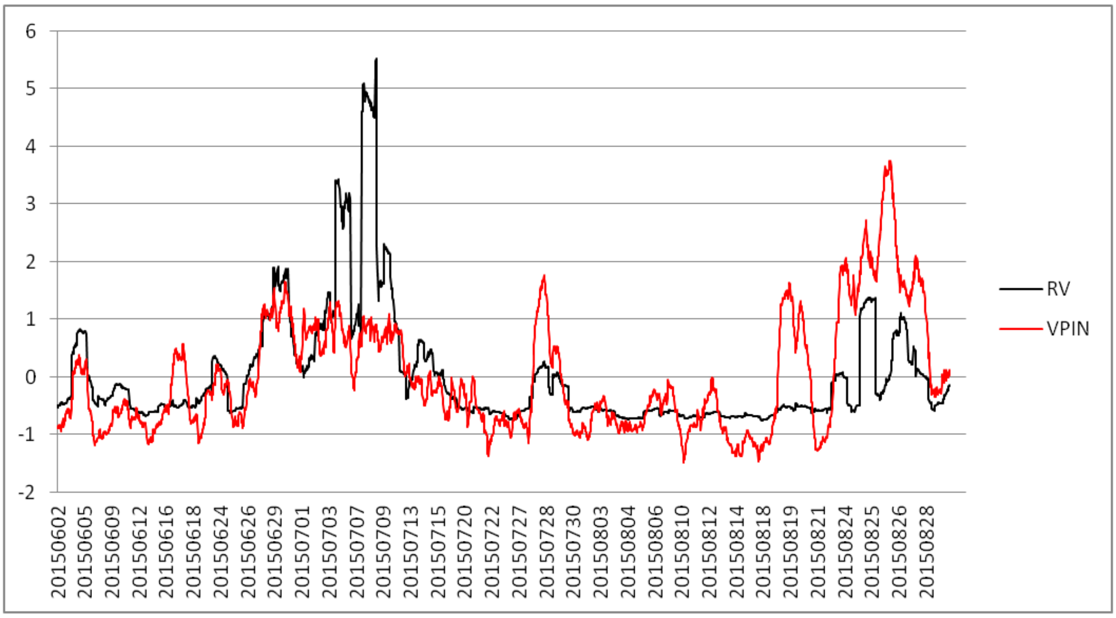

Figure 4

Volume-time series of VPIN for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index during the 2015 melt down (from June, 2015 to August, 2015)

This figure plots the volume-time series of VPIN for the SSE 50 ETF options and the realized volatility (RV) of the SSE 50 index from June, 2015 to August, 2015. The data series are all standardized.