The Information Content of the VIX Options Trading Volume

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Abstract

This paper investigates the predictive content of the VIX options trading volume for the future dynamics of the underlying VIX index. Using a unique dataset from the Chicago Board Options Exchange, we calculate put-call ratios based on the VIX option volume initiated by buyers to open new positions. We show that put-call ratios negatively predict the subsequent values of the VIX index. The predictability is stronger during periods of elevated VIX levels, during recessions, on days preceding important macroeconomic announcements, and for short-dated contracts. Overall, the results are consistent with the hypothesis that informed traders use the VIX option market as a venue for their trading.

Keywords: VIX options; put-call ratio; information; volatility

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This paper investigates the predictive content of the VIX options trading volume for the future dynamics of the underlying VIX index. Using a unique dataset from the Chicago Board Options Exchange, we calculate put-call ratios based on the VIX option volume initiated by buyers to open new positions. We show that put-call ratios negatively predict the subsequent values of the VIX index. The predictability is stronger during periods of elevated VIX levels, during recessions, on days preceding important macroeconomic announcements, and for short-dated contracts. Overall, the results are consistent with the hypothesis that informed traders use the VIX option market as a venue for their trading.

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1. Introduction

The information flow between options and the market of the underlying asset has received extensive attention in the past decades. So far, the focus of previous research has mainly been concentrated on either stock options or stock index options and their underlying markets, and the results obtained are mixed.[1] The current paper studies a market that has not been examined as much in this context, namely the market of options on the Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX). The VIX reflects the expected volatility of the S&P 500 index over the following 30 calendar days and is a key measure of the expected systematic risk in the economy. Hence, trading options on the VIX allows informed traders to not only potentially take advantage of their volatility information, but also hedge in a direct and effective way their market volatility risk. In fact, although a relatively new product, VIX options are considered the most successful new product launch in the history of the Chicago Board Options Exchange (Chung, Tsai, Wang, and Weng, 2011), with a trading volume of about 4.5 million contracts in the first 3 quarters of their existence.[2]

We investigate the informational content of the CBOE VIX options trading volume on the future dynamics of the underlying VIX index. If informed traders use VIX options due to either the higher leverage and/or lower transaction costs relative to the underlying market,[3] option trading volume could be informative about subsequent movements in the underlying index. For instance, the purchase of calls or the sale of puts (the purchase of puts or the sale of calls) could be perceived as a positive (negative) signal by market makers, who will then adjust their bid and ask quotes accordingly.

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[1] There is some evidence that the stock option market leads in price discovery (Kumar, Sarin and Shastri, 1992; Manaster and Rendleman, 1982; Fleming, Ostdiek, and Whaley, 1996; Diltz and Kim, 1996; Bhattacharya, 1987, Cremers and Weinbaum, 2010; Atilgan, Bali, and Demirtas, 2015; Chan, Ge, and Lin, 2015), but also opposing evidence (Stephan and Whaley, 1990), or evidence that the option market does not contain significant information which is not incorporated yet in the underlying stock market (Chakravarty, Gulen, and Mayhew, 2004; Muravyev, Pearson, and Broussard, 2013).

[2] VIX options were introduced by the CBOE in February 2006.

[3] In line with Black (1975) and Easley, O'Hara and Srinivas (1998).

Using a unique dataset from the CBOE, we calculate the put-call ratio from VIX options based on the option volume initiated by buyers to open new positions. We show that the put-call ratio is a strong predictor of the subsequent changes in the VIX. The results are economically significant. One unit increase in the put-call ratio leads to a decrease of 0.57 in the VIX the following day. Furthermore, the negative effect of the put-call ratio on the value of the underlying VIX is not followed by a subsequent reversal. That is, our results do not seem to be a manifestation of temporary price pressure, but are rather consistent with the hypothesis that informed traders use the VIX option market as a venue for their trading.

One can argue that our results could be the artefact of the simultaneous impact of standard macro/financial factors on both investor expectations about the future and their option trading decisions, and also on the underlying VIX index. To control for such a potential impact, we include in our predictive regression the change in the term spread, the change in the credit spread, the change in the T-bill yield, and the lagged S&P 500 return. The predictability of the put-call ratio on the value of the underlying index the following day remains in both OLS and VAR estimations. Furthermore, we also show that the put-call ratio has a significant predictive ability for the subsequent changes in the VIX out-of-sample.

The interpretation of our results in terms of information-based trading in the VIX option market is corroborated by some additional tests. First, we test the role of option volume during high versus low uncertainty periods, as well as in different stages of the business cycle. Second, we investigate whether our findings are different during periods preceding important macroeconomic announcements, including the Consumer Price Index, the Gross Domestic Product, the unemployment rate, and the Federal Open Market Committee (FOMC) announcements. Previous research shows that informed investors are likely to exploit their informational advantage before releases of fundamental information.[4] Third, we analyze VIX

[4] For example, Amin and Lee (1997) find that a greater proportion of long (or short) positions are initiated in the

options with different remaining time to expiration, as they provide different degrees of leverage. When choosing their trading venue, informed investors prefer the leverage offered by the option market relative to the spot market (Black, 1975).

The additional tests show that the predictive ability of the put-call ratio on the future values of the VIX is more prevalent in times of high uncertainty, when information about future volatility is more valuable. Moreover, we find that the predictive ability of the put-call ratio on the subsequent values of the underlying VIX holds during both recessions and expansionary periods, as well as in periods preceding important macroeconomic announcements and at other times. However, the predictability is stronger during preannouncement periods, which is consistent with the informed trading explanation of the results. Finally, we find that the predictive ability of the put-call ratio for the subsequent values of the VIX is the strongest for option categories providing higher leverage, such as the short-maturity contracts.

We also show that the put-call volume ratio can predict the subsequent changes in the stress level in financial markets, which is useful for anticipating the future developments in the real economy. Compared to implied volatility that reflects expectations of stock return volatility and is not strongly related to the developments in the real economy (Beetsma and Giuliodori, 2012), higher financial stress can have a strong dampening effect on real economy. We find that higher values of the put-call ratio of VIX options predicts a decline in the financial market stress in the U.S. The VIX put-call ratio does not seem to have significant predictive ability for the financial market stress in other advanced economies or in emerging markets.

Options trading activity has been shown to predict future underlying asset prices for stock options and stock index options. One strand of literature attributes this predictability to

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option market immediately before good (or bad) earnings news on the underlying stock. Cao, Chen, and Griffin (2003) show that in a sample of firms experiencing takeover announcements, higher pre-announcement volume on call options is predictive of higher takeover premiums. Hendershott, Livdan, and Schürhoff (2015) show that institutional trading predicts macroeconomic news, indicating that sophisticated traders have information about the macroeconomy.

nonpublic information held by option traders. For instance, Pan and Poteshman (2006) show that put-call ratios calculated from new buyer-initiated volume of stock options negatively predict individual stock returns for up to two weeks ahead. Roll, Schwartz and Subrahmanyam (2010) show that the options/stock volume ratio during pre-earnings announcement periods predicts the post-earnings announcement returns. Similarly, Johnson and So (2012) find that the options/stock volume ratio predicts the underlying stock returns over a one week horizon and attribute the findings to option informed trading. Another strand of literature attributes this predictability to option-based risk protection strategies used by investors. Chordia, Kurov, Muravyev, and Subrahmanyam (2021) show that net put buying of stock index options predicts higher subsequent market returns at the weekly horizon, and particularly during times of elevated uncertainty. That is, investors buy put options as insurance during periods of increased uncertainty, so higher put buy volume signals higher market risk premia.

We contribute to this literature by investigating the informational role of trading activity in the VIX option market, which is a relatively new market. Having a better understanding of trading based on volatility information is needed, since volatility is a key input for option pricing and for risk management. We show that the put-call ratio of VIX options negatively predicts the underlying VIX on the following day. Our findings are in line with the first strand of the literature mentioned above and are consistent with the hypothesis of informed traders using the VIX option market as a venue for information-based trading.

In a study related to our paper, Tsai, Chiu, and Wang (2015) estimate a vector autoregression of VIX returns and signed VIX option volumes using five-minute data. They find no evidence that the difference between buyer- and seller-initiated volume of VIX options predicts VIX returns. Their empirical methodology relies on classifying VIX option trades as buyer- or seller-initiated using the Lee and Ready (1991) algorithm. This algorithm attempts to identify the aggressive side in each trade. However, O'Hara (2015) shows that sophisticated traders rarely use aggressive orders (buy at the offer or sell at the bid). We do not need to use trade classification algorithms because we use so-called "open-close" data for VIX options, which directly measures customer buy and sell volumes for position-opening and position-closing trades. Our results show that the VIX option trading volume does contain information about future changes in the VIX.

Our paper also contributes to the large literature on the dynamics of uncertainty. Fernandez-Perez, Frijns, and Tourani-Rad (2017) show that the VIX decreases after FOMC announcements, due to the resolution of market uncertainty. Gu, Kurov, and Wolfe (2018) further show that only FOMC announcements accompanied by the release of the Summary of Economic Projections are followed by VIX declines. Some studies document a significant decrease in implied volatility at the release time of macroeconomics announcements (Ederington and Lee, 1996; Chan and Gray, 2018). Our study shows that changes in the VIX are not only affected by economic news, but can also be predicted using the trading volume from the VIX options.

2. Data

The daily VIX option trading volume data are obtained from the CBOE and has several unique features, unlike the option call/put volume data that is publicly available. First, the daily aggregated volume is classified based on buying/selling and opening/closing criteria, and so is of four types: '*open-buys*' represents contracts purchased by a buyer to open a new option position, '*open-sells*' represents contracts sold by a seller to open a new position, '*close-buys*' represents contract purchased by a buyer to close an existing short position, and '*close-sells*' represents contract sold by a seller to close an existing long position. Since investors can place different positions for different purposes, the signed volume helps us extract useful information from option volume. Second, besides option volume, the data also contain the remaining time to expiration of various option contracts. This characteristic allows us to consider option contracts with various remaining times to expiration in our analysis.

Following Pan and Poteshman (2006), we use the '*open-buy'* option volume to construct the put-call ratio as:

$$PC_t = \frac{Put_t}{Call_t + Put_t}, \tag{1}$$

where Put_t ($Call_t$) denotes the trading volume of VIX put (call) options initiated by a buyer to open a new position.

Besides option volume data, we use the S&P 500 index return, the VIX and three other macroeconomic variables, namely the short-term interest rate, the term spread, and the credit spread, in our analysis. The macroeconomic variables are downloaded from the FRED database of the Federal Reserve Bank of St. Louis. Following Chordia, Kurov, Muravyev, and Subrahmanyam (2021), we use the three-month U.S. Treasury bill yield as a proxy for the short-term interest rate. The term spread is computed as the difference between the 10-year and the three-month Treasury yields. The credit spread is calculated as the difference between the Moody's BAA and AAA corporate bond yields. Figure 1 plots the put-call ratio and the VIX during our sample period, which extends from the inception of the VIX options trading in February 2006 to March 2021.

[Insert Figure 1 Here]

Table 1 reports the summary statistics for the put-call ratio and for the main macroeconomic variables included in our analysis. Each variable contains 3,789 daily observations. The average put-call ratio is 0.309. That is, the call volume initiated by a buyer to open a new position is about twice as large on average as the put volume initiated by a buyer to open a new position. Over our sample period, the VIX change has a mean (median) value of 0.002 (-0.090), while the S&P 500 return has a daily average (median) value of 0.03% (0.07%). The average values for the three-month T-bill rate change, the term-spread change, and the credit-spread change are -0.131 bps, 0.077 bps, and -0.001 bps, respectively. Panel B shows that the put-call ratio is generally not highly correlated with the other variables. It is weakly positively correlated with the change in the credit spread. That is, when the credit spread increases and investors demand a higher compensation against the potential risk of insolvency, more puts seem to be bought, relative to calls. As expected, the S&P 500 return and the VIX change are highly negatively correlated.

[Insert Table 1 Here]

3. Results

3.1. Baseline Regressions

Pan and Poteshman (2006) show that the put-call ratio from the position-opening buy volume of stock options can predict individual stock returns. Also, Chordia, Kurov, Muravyev, and Subrahmanyam (2021) document that the order imbalance of index put options can predict future aggregate stock returns. Following the literature, we also investigate the information content of the put-call ratio, but we focus on a different market, namely the market of VIX options. We calculate the put-call ratio based on the expression in (1). As a first step, we estimate the folowing regression:

$$X_t = a_0 + \sum_{j=1}^{2} a_{1j} PC_{t-j} + \sum_{j=1}^{2} a_{2j} dVIX_{t-j} + \sum_{j=1}^{2} a_{3j} Return_{t-j} + \sum_{j=1}^{2} a_{4j} dTbill_{t-j} + \sum_{j=1}^{2} a_{5j} dTerm_{t-j} + \sum_{j=1}^{2} a_{6j} dCredit_{t-j} + e_t, \quad (2)$$

where X_t is the dependent variable and denotes either the change in the VIX ($dVIX_t$), the S&P 500 index return ($Return_t$), the change in the 3-month T-bill yield ($dTbill_t$), the change in the term spread ($dTerm_t$), or the change in the credit spread ($dCredit_t$). PC denotes the put-call ratio constructed from VIX options. The optimal number of lags is determined by the Schwarz information criterion.

The estimates reported in Table 2 reveal that the put-call ratio is a strong predictor of the next-day change in the VIX. A one-unit increase in the put-call ratio leads to a decrease in the VIX by 0.57% and the effect is significant at the 5% significance level. The negative impact of the VIX put-call ratio on the subsequent changes in the underlying VIX index indicates that informed investors seem to use the VIX option market as a venue for information-based trading.[5] However, the VIX put-call ratio fails to predict the subsequent stock returns or the future changes in the T-bill yield, the term spread, and the credit spread.

[Insert Table 2 Here]

3.2. Vector Autoregression Results

It is possible that past returns and macroeconomic conditions have an impact on the speculative and hedging needs of investors, and so they could also affect options trading. Due to the possible existence of bi-directional causality, we estimate the following vector autoregressive (VAR) model:

$$\boldsymbol{X_t} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_j}\, \boldsymbol{X_{t-j}} + \boldsymbol{e_t}, \tag{3}$$

where $\boldsymbol{X_t}$ is a vector of six variables ($dVIX, PC, Return, dTbill, dTerm,$ and $dCredit$) defined above. All variables are measured at the daily frequency. The vector of intercepts is $\boldsymbol{a_0}$, while $\boldsymbol{a_j}$ is the vector of coefficients of the explanatory variables for lag j. The number of lags in the VAR model is selected using the Schwarz criterion.

Figure 2 plots the accumulated impulse response functions (IRF) of $dVIX$ and the S&P 500 return to one standard-deviation innovation in the put-call ratio, for up to 10 days ahead. The impulse response functions are obtained by estimating the VAR model in equation (3) and using the following Cholesky ordering: $dVIX$, PC, $Return$, $dTbill$, $dTerm$ and $dCredit$.[6] We observe that the put-call ratio has a significant negative and permanent effect on the

[5] In the next sub-section, we show that this effect is not reversed, so our results are not a manifestation of temporary price pressure.
[6] Generalized (order invariant) impulse responses are similar.

subsequent changes in the VIX index, as both the accumulated response and the corresponding error bands are below zero. The impact of the put-call ratio on the subsequent changes in the VIX index is economically meaningful. A one standard deviation shock to the put-call ratio leads to a 0.21 decrease in the VIX over the next 10 trading days. The VIX changes associated with option volume are not subsequently reversed. This finding suggests that the VIX put-call ratio does not simply reflect sentiment of uninformed traders. Instead, option volume contains relevant information that is incorporated into VIX with one-day delay.

Panel B of Figure 2 plots the accumulated response of the S&P 500 index returns to one standard deviation innovation in the VIX put-call volume ratio. One standard deviation increase in the put-call volume ratio leads to an increase of about 0.07% in the S&P 500 return over the next 10 trading days. However, this effect is insignificant at the 5% significance level.

[Insert Figure 2 Here]

3.3. Results for High and Low Uncertainty Periods

In this subsection, we examine whether the predictive ability of the VIX put-call ratio on the future values of the VIX depends on market conditions. Previous research shows that option volume has greater predictive ability on underlying asset prices when uncertainty is high (Chordia, Kurov, Muravyev, and Subrahmanyam, 2021). To investigate this issue, we estimate the following VAR model which distinguishes between periods of high and low uncertainty:

$$\tilde{\boldsymbol{X}}_{\boldsymbol{t}} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_{1j}}\, \boldsymbol{X_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, H_{VIX_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-j} H_{VIX_{t-j}} + \boldsymbol{e_t}, \quad (4)$$

where $\tilde{\boldsymbol{X}}_{\boldsymbol{t}}$ is a vector that includes the VIX put-call ratio (PC), the change in the VIX index ($dVIX$), the S&P 500 index return ($Return$), the change in the 3-month T-bill yield ($dTbill$), the change in the term spread ($dTerm$), and the change in the credit spread ($dCredit$). In addition to these variables, $\tilde{\boldsymbol{X}}_{\boldsymbol{t}}$ includes an interaction term between the VIX put-call ratio and a dummy variable (H_{VIX_t}) for high uncertainty periods. This dummy variable is equal to one on days when the VIX is above it median value, and zero otherwise. The model also contains the lagged value of the high-VIX dummy as an exogenous variable.

The VAR coefficient estimates are reported in Table 3. The predictive ability of the put-call ratio on the subsequent changes in the VIX index and market returns seems to be statistically significant only in periods of high uncertainty, namely periods with elevated VIX levels. That is, when uncertainty is high, the effect of the VIX put-call volume ratio on the future values of the VIX index is significant and negative (-0.921), while its impact on the subsequent S&P 500 index return is significant and positive (0.575). The impact of the put-call ratio on the two aforementioned variables becomes insignificant in times of low uncertainty.

[Insert Table 3 Here]

Figure 3 represents graphically the accumulated impulse response functions of $dVIX$ and $Return$ to one standard deviation shock in the VIX put-call ratio, for up to 10 days ahead. The IRFs are obtained when estimating the VAR model in (4) using Cholesky decomposition. Overall, the put-call ratio has a significant negative and permanent impact on the subsequent changes in the VIX index and a positive and permanent impact on the subsequent stock return. These effects are economically meaningful, and are clearly stronger in times of elevated uncertainty. When the VIX is below its sample median (i.e., periods of low uncertainty), a one-standard deviation increase in the put-call ratio results in a 0.16 decrease in $dVIX$ and a 0.09% increase in $Return$ over the next 10 trading days. These effects are significantly stronger, almost double, in times of elevated uncertainty (i.e., when the VIX index is above its sample median).

[Insert Figure 3 Here]

As a robustness check, we also investigate whether the predictive ability of the put-call ratio on the subsequent changes in the VIX index holds when using a Markov-switching model to determine market regimes, instead of imposing these regimes exogenously. We estimate the following model:

$$X_t = a_{0,s_t} + a_{1,s_t}PC_{t-1} + a_{2,s_t}PC_{t-2} + \sum_{j=1}^{2} a_{3j}dVIX_{t-j} + \sum_{j=1}^{2} a_{4j}Return_{t-j} + \sum_{j=1}^{2} a_{5j}dTbill_{t-j} + \sum_{j=1}^{2} a_{6j}dTerm_{t-j} + \sum_{j=1}^{2} a_{7j}dCredit_{t-j} + e_t, \tag{5}$$

where X_t denotes the change in the VIX index or the daily S&P 500 return, $e_t \sim N(0, \sigma_{s_t}^2)$ is the error term, and the unobserved state variable s_t = {1, 2} follows a Markov process with transition probabilities $p_{11} = P(s_t = 1|s_{t-1} = 1)$ and $p_{22} = P(s_t = 2|s_{t-1} = 2)$.

Panel A of Table 4 reports the estimation results with the change in the VIX used as the dependent variable.[7] State 2 has a standard deviation of the model errors about four times as high as that of state 1 and positive and significant estimate of the intercept. Hence, we interpret state 1(2) as a low- (high-) variance state. Expected durations of these states are about 23 days and 8 days, respectively. The put-call ratio has a significant predictive ability for the subsequent changes in the VIX index in both states, but the effect is much stronger and happens sooner in the high-variance state. This finding is consistent with the VAR results in Table 3.

[Insert Table 4 Here]

Panel B of Table 4 reports the estimated results for predicting the daily S&P 500 return (X_t) using a similar Markov-switching model. As seen in the panel, State 1 is associated with positive average returns and low volatility, whereas State 2 has negative mean returns and high volatility. Therefore, State 1 (2) can be interpreted as a low- (high-) variance state. Similar to the VAR results in Table 3, the put-call ratio significantly predicts future returns only during volatile times.

3.4. Vector Autoregression Results for Economic Recessions and Expansions

Investor attitudes tend to fluctuate between fear and confidence. These fluctuations tend to follow the business cycle (e.g., Garcia, 2013). Therefore, during an economic weakening, the

[7] We do not tabulate the coefficient estimates of the common regressors to save space. These estimates ae available upon request.

VIX tends to rise, revealing a greater level of fear and financial stress among market participants. The opposite usually occurs when the economy strengthens. The VIX index tends to decrease then, as investor confidence is growing.[8] In this subsection, we examine whether the predictability we find depends on the business cycle. We use the following VAR model:

$$\boldsymbol{\widetilde{X}_t} = \boldsymbol{a_0} + \sum_{\boldsymbol{j=1}}^{\boldsymbol{2}} \boldsymbol{a_{1j}}\ \boldsymbol{X_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, PC_{t-j}NBER_{t-j} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-j}\left(1 - NBER_{t-j}\right) + \sum_{j=1}^{2} \boldsymbol{a_{4j}}\, NBER_{t-j} + \boldsymbol{e_t}, \tag{6}$$

where the dummy variable $NBER_t$ is equal to one during NBER recessions and to zero otherwise. The results are summarized in Table 5. The coefficients corresponding to PC_{t-1} and $PC_{t-1}NBER_{t-1}$ in the regression having as dependent variable $dVIX_t$ are both negative and significant at the 5% significance level. That is, a higher put-call ratio leads to a decrease in the subsequent $dVIX$ during both expansionary and recession periods. These results are consistent with the hypothesis of information-based trading in the VIX option market, during both good and bad economic times.

[Insert Table 5 Here]

3.5. Vector Autoregression Results for Days before Macroeconomic Announcements

We interpret the predictive ability of the VIX put-call ratio on the underlying VIX index as evidence of informed trading in the VIX option market. Prior literature finds that informed investors are likely to take advantage of their informational advantage before the release of important fundamental information (Amin and Lee, 1997; Cao, Chen and Griffin, 2005).[9] To investigate further our hypothesis of information-based trading in the VIX option market, we

[8] We do not argue that increasing VIX levels are indicative of recessions. Instead, we simply observe that recessions are usually accompanied by higher levels of the VIX.

[9] Some studies document a significant decrease in implied volatility at the release time of macroeconomic and monetary policy announcements (Ederington and Lee, 1996; Nikkinen and Sahlström, 2004; Carr and Wu, 2006; Chen and Clements, 2007; Fernandez-Perez, Frijns, and Tourani-Rad, 2017; Vähämaa and Äijö, 2011).

distinguish between days preceding important macroeconomic announcements and other trading days. We estimate the following VAR model:

$$\tilde{\boldsymbol{X}}_{\boldsymbol{t}} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_{1j}}\ \boldsymbol{X_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, PC_{t-j}ECON_{t-j} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-j}\left(1 - ECON_{t-j}\right) + \boldsymbol{e_t}, \quad (7)$$

Where $\boldsymbol{X_t}$ is a vector that includes the VIX put-call ratio (PC), the change in the VIX ($dVIX$), the S&P 500 index return ($Return$), the change in the 3-month T-bill yield ($dTbill$), the change in the term spread ($dTerm$), and the change in the credit spread ($dCredit$). In addition to these variables, $\tilde{\boldsymbol{X}}_{\mathbf{t}}$ is a vector that also includes two interaction terms: $PC_t * ECON_t$ and $PC_t * (1 - ECON_t)$. The dummy variable $ECON_t$ is equal to one on days preceding important macroeconomic announcements including the Consumer Price Index (CPI), the Gross Domestic Product (GDP), the unemployment rate, and the FOMC announcements. Otherwise, $ECON_t$ is equal to zero. If we find a stronger predictive ability of the VIX put-call ratio for the underlying VIX during preannouncement periods relative to other days, we would interpret this as additional evidence in favor of our informed trading hypothesis.

Table 6 summarizes the estimated coefficients of the interaction terms $PC_{t-1}ECON_{t-1}$ and $PC_{t-1}(1 - ECON_{t-1})$. The table reveals that the put-call ratio is a significant predictor of the future values of the VIX during both preannouncement days and other days (i.e., days not preceding the CPI, GDP, unemployment rate and FOMC announcements). However, the predictive ability is stronger during preannouncement periods, as the coefficient of PC_{t-1} on days preceding important macroeconomic announcements is more than three times as large as the corresponding coefficient during other days. Furthermore, not only does a higher put-call volume ratio predict a decrease in the VIX the following day, but it also has a positive impact on the subsequent stock market return, during both preannouncement days and regular trading days.[10]

[10] By regular days we mean days not preceding announcements including the Consumer Price Index (CPI), the Gross Domestic Product (GDP), the unemployment rate, or the FOMC announcements.

[Insert Table 6 Here]

3.6. Vector Autoregression Results for Options with Different Leverage

In addition to using VIX options, investors can speculate on the short-term movements of the VIX using other instruments tied to the VIX, including VIX futures and VIX exchange-traded funds (ETFs). According to Black (1975) and Easley et al. (1998), the leverage of an option is an important factor determining whether informed investors choose to trade in the option market. To investigate whether the information content of the VIX put-call ratio varies with different levels of leverage, we consider options with various remaining time to expiration. Short-dated options are known to offer considerably higher leverage than long-dated options. Thus, we construct put-call ratios from option contracts with different remaining time to expiration and re-estimate the VAR model in equation (3) for different ranges of time to expiration.[11] We report the estimated coefficients of the lagged put-call ratio in Table 7. When moving from top to bottom of the table, the options are of decreasing leverage. We observe that the predictive ability of the put-call ratio for the underlying VIX is stronger for options with shorter time to expiration, particularly for options with less than 30 days to expiration. Overall, the results support the argument that informed investors prefer option contracts that offer higher leverage.

[Insert Table 7 Here]

3.7. Out-of-Sample Forecasting Results

Our results so far show that the VIX put-call volume ratio is a significant predictor of future changes in the VIX. Prior literature shows that predictive regressions with good in-sample performance can have little forecasting power out-of-sample (Welch and Goyal, 2008). In this

[11] In our sample period, most VIX option volume is decreasing with remaining time to expiration. Specifically, 45.5% of option volume is in the under 30 days subset; about 31.9% of option volume is in the 30-59 days subset; about 12.7% of option volume is in the 60-89 days subset; about 5.8% of option volume is in the 90-119 subset; about 4.1% of option volume is in the above 119 days subset.

section, we implement an out-of-sample test to investigate if the put-call ratio has incremental predictive ability for the subsequent $dVIX$, relative to the prevailing mean benchmarks. More precisely, we determine the out-of-sample forecasts of $dVIX$ using an expanding estimation window, similar to Rapach, Strauss, and Zhou (2010). Our predictive model is:

$$\widehat{dVIX}_{m+1} = \hat{a}_{0,m} + \sum_{j=0}^{1} \hat{a}_{1j,m}\, PC_{m-j} + \sum_{j=0}^{1} \hat{a}_{2j,m}\, H_{VIX_{m-j}} + \sum_{j=0}^{1} \hat{a}_{3j,m}\, PC_{m-j} H_{VIX_{m-j}} \quad (8)$$

In the equation above, m refers to the number of observations included in our estimation window, while $\hat{a}_{0,m}$, $\hat{a}_{1j,m}$, $\hat{a}_{2j,m}$ and $\hat{a}_{3j,m}$are the coefficient estimates obtained from estimating equation (4) using data for an in-sample period. We select various starting points for our out-of-sample period (2008, 2009, 2010, 2011 and 2012), to ensure that our results remain robust. Then, we compute the out-of-sample R^2 statistics, denoted by R^2_{OS}, as the proportional reduction in the mean square prediction error (MSPE) of our predictive regression, relative to the mean benchmark forecast.

$$R^2_{OS} = 1 - \frac{\sum_{k=q_0+1}^{q} \left(dVIX_{m+k} - \widehat{dVIX}_{m+k}\right)^2}{\sum_{k=q_0+1}^{q} \left(dVIX_{m+k} - \overline{dVIX}_{m+k}\right)^2} \quad (9)$$

$\overline{dVIX}_{m+k}$ denotes the historical average of the change in the VIX before period $m + k$. q_0 and q denote the number of observations in our in-sample period and the overall sample periods, respectively. If the calculated R^2_{OS} is positive, it means our predictor outperforms the prevailing mean benchmark. To formally test the null hypothesis that $R^2_{OS} \leq 0$ (the alternative hypothesis: $R^2_{OS} > 0$), we use the Clark and West (2007) out-of-sample MSPE-adjusted statistic.[12] The results reported in Table 8 show that the null hypothesis of no predictability is rejected at the 5% significance level. That is, the put-call ratio has a strong predictive ability for the VIX both in- and out-of-sample.

[12] Clark and West (2007) show that when one compares forecasting accuracy of a simple model with that of a more complex model that nests the simple model, the MSPE of the more complex model is expected to be larger than the MSPE of the simple model under the null. This happens because the larger model introduces noise into its forecasts by adding useless parameters. Clark and West (2007) propose a simple "MSPE-adjusted" statistic that adjust for this bias and can be used to test the predictive accuracy of nested models. Examples of studies using the MSPE-adjusted statistic include Rapach, Strauss and Zhou (2010) and Rapach, Ringgenberg and Zhou (2016).

[Insert Table 8 Here]

3.8. VIX Put-Call Ratio and Indicators of Financial Stress

In this subsection, we investigate whether the put-call ratio contains information about variables that can predict subsequent developments in the real economy. Cochrane (2007) suggests that predictive regressions for asset returns are more economically convincing if the predictors are associated with future macroeconomic condition. We test whether the put-call ratio can predict subsequent changes in the level of stress in financial markets, as higher financial stress can dampen the economic activity (Hakkio and Keeton, 2009; Cardarelli, Elekdag, Lall, 2011). Financial market stress has been shown in the literature to have a strong effect on the real economy for up to a few months ahead, in a variety of countries (Islami and Kurz-Kim, 2014).

We proxy the financial market stress by the Financial Stress Index (FSI) provided by the Office of Financial Research (OFR), which is a daily measure of the stress in global financial markets, calculated at the end of each U.S. trading day (Monin, 2019).[13] Zero values of the index indicate normal level of stress, while positive (negative) values reveal a level of stress above (below) average. We re-run the regression in (2) where the dependent variable X_t denotes the change in the OFR Financial Stress Index (ΔFSI_t). The estimated coefficients of the lagged put-call volume ratio are reported in Panel A of Table 9. The coefficient of the first lag of the put-call ratio is negative and significant at the 5% level, revealing that the trading volume in the VIX option market can predict the subsequent level of financial stress in the market. The sum of the coefficient of the two lags of the put-call ratio in Panel A of Table 9 is also negative and statistically significant.

[Insert Table 9 Here]

[13] The FSI data is available at https://www.financialresearch.gov/financial-stress-index/.

We perform a similar analysis for the components of the OFR Financial Stress Index. The FSI is calculated based on 33 financial market variables that capture various features of financial stress and are classified in five main categories: credit, equity valuation, funding, safe assets, and volatility. The *credit* category includes measures of credit spread, while the *equity valuation* category includes stock valuations of various stock market indexes. The variables within the *funding* category generally measure how easily financial institutions can fund their activities, while those variables within the *safe assets* category include valuation measures of assets that are considered stores of value. The last category entitled *volatility* includes measures of realized and implied volatility from the currency, credit, equity, and commodity markets. These categories are carefully chosen, as during times of high market stress, credit spreads widen revealing higher default risk, stock prices tend to fall, the funding market might freeze due to the high level of counterparty risk. Also, volatility tends to be high in times of high financial stress, and investors tend to migrate towards safer assets.

We estimate the regression in equation (2) where the dependent variable X_t denotes the change in one of the FSI component indexes (credit, equity valuation, funding, safe assets, and volatility). The estimated coefficients of the lagged put-call volume ratio are reported in Panel B of Table 9. The only coefficient that is significant individually is the one corresponding to the *equity valuation* category. Its negative value indicates that a higher level of the VIX put-call ratio can predict lower subsequent stock market valuations. The sums of the coefficient of the two lags of the put-call ratio are also negative and statistically significant for the components of the FSI measuring changes in credit conditions and volatility in financial markets, indicating that the put-call ratio of VIX options contains information about financial market conditions more broadly.

The 33 financial market variables used to construct the FSI are also grouped in regions based on the location of the market they represent. The Office of Financial Research provides three stress market indicators in this respect: for the United States, for other advanced economies, and for emerging markets. We estimate the regression in equation (2) where the dependent variable X_t denotes the change in one of the regional financial stress indicators. We report the estimated coefficients of the lagged put-call volume ratio in Panel C of Table 9. The results show that the trading volume in the VIX option market significantly predicts the subsequent level of financial stress only in the United States.

4. Conclusion

This paper investigates the informational content of trading volume in the CBOE VIX options with respect to future changes in the underlying VIX. Our results provide evidence that the put-call ratio calculated from buy volume of VIX options can predict future changes in the underlying VIX without subsequent reversal. The results are consistent with the hypothesis of informed traders using the VIX option market as a venue for their trading. Our findings are stronger during periods of elevated VIX levels and during days preceding important macroeconomic announcements. In addition, the informed trading in the VIX options market seems to be more prevalent for options providing high leverage, such as out-of-the-money and short-dated contracts.

We find that the put-call volume ratio can predict the subsequent changes in the VIX, but also other measures of financial market stress, such as the global and the U.S. specific financial stress indicators provided by the Office of Financial Research. However, the put-call ratio has no significant predictive power for the financial stress levels in other advanced economies or in emerging markets.

References

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

Atilgan, Y., Bali, T., & Demirtas, O. (2015). Implied Volatility Spreads and Expected Market Returns. *Journal of Business and Economic Statistics*, 33, 87-101.

Beetsma, R., & Giuliodori, M. (2012). The changing macroeconomic response to stock market volatility shocks. *Journal of Macroeconomics*, 34, 281–293.

Beltratti, A., & Morana, C. (2006). Breaks and persistency: macroeconomic causes of stock market volatility. *Journal of Econometrics*, 131, 151–177.

Bhattacharya, M. (1987). Price changes of related securities: The case of call options and stocks. *Journal of Financial and Quantitative Analysis*, 22, 1-15.

Black, F. (1975). Fact and Fantasy in the Use of Options. *Financial Analysts Journal* 31, 36–41, 61–72.

Chan, K., Ge, L., & Lin, T.C. (2015). Informational Content of Options Trading on Acquirer Announcement Return. *Journal of Financial and Quantitative Analysis*, 50, 1057-1082.

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

Cardarelli, R., Elekdag, S., & Lall, S. (2011). Financial stress and economic contractions. *Journal of Financial Stability*, 7, 78–97.

Carr, P., & Wu, L. (2006). A tale of two indices. *Journal of Derivatives*, 13, 13-29.

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

Chan, K. F., & Gray, P. (2018). Volatility jumps and macroeconomic news announcements. *Journal of Futures Markets*, 38, 881-897.

Chen, E., & Clements, A., (2007). S&P 500 implied volatility and monetary policy announcements. *Finance Research Letters*, 4, 227-232.

Chordia, T., Kurov, A., Muravyev, D., & Subrahmanyam, A. (2021). Index option trading activity and market returns. *Management Science*, 67, 1758-1778.

Chung, S. L., Tsai, W. C., Wang, Y. H., & Weng, P. S. (2011). The information content of the S&P 500 index and VIX options on the dynamics of the S&P 500 index. *Journal of Futures Markets*, 31, 1170-1201.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics,* 138, 291-311.

Cremers, M., & Weinbaum, D. (2010). Deviations from Put-Call Parity and Stock Return Predictability. *Journal of Financial and Quantitative Analysis*, 45, 335-367.

Cochrane, J. H., (2007). Financial markets and the real economy. In: Mehra, R., Prescott, E. C. (eds.), Handbook of the Equity Premium, Elsevier: Amsterdam, pp. 237–330.

Diltz, J. D., & Kim, S. (1996). The relationship between stock and option price changes. *Financial Review*, 31, 499-519.

Easley, D., M. O'Hara, & Srinivas, P. (1998). Option volume and stock prices: Evidence on where informed traders trade. *Journal of Finance,* 53, 431–465.

Ederington, L. H., & Lee, J. H., (1996). The creation and resolution of market uncertainty: The impact of information releases on implied volatility. *Journal of Financial and Quantitative Analysis*, 31, 513-539.

Fernandez-Perez, A., Frijns, B., & Tourani-Rad, A., (2017). When no news is good news – The decrease in investor fear after the FOMC announcement. *Journal of Empirical Finance*, 41, 187-199.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 16, 353-387.

Garcia, D., (2013). Sentiment during recessions. *Journal of Finance*, 68, 1267-1300.

Gu, C., Kurov, A., & Wolfe, M. H. (2018). Relief rallies after FOMC announcements as a resolution of uncertainty. *Journal of Empirical Finance,* 49, 1-18

Hakkio, C. S., & Keeton, W. R. (2009). Financial stress: what is it, how can it be measured, and why does it matter? *Economic Review*, Federal Reserve Bank of Kansas City, 5–50.

Islami, M., & Kurz-Kim, J. R. (2014). A single composite financial stress indicator and its real impact in the Euro area. *International Journal of Finance and Economics*, 19, 204-211.

Hendershott, T., Livdan, D., & Schürhoff, N. (2015). Are institutions informed about news? *Journal of Financial Economics*, 117, 249-287.

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

Kumar, R., Sarin, A., & Shastri, K. (1992). The Behavior of Option Price around Large Block Transactions in the Underlying security, *Journal of Finance*, 47, 879-889.

Lee, C., & Ready, M. (1991). Inferring trade direction from intraday data. *Journal of Finance*, 46, 733-747.

Manaster, S., & Rendleman, R. (1982). Option Prices as Predictors of Equilibrium Stock Prices. *Journal of Finance*, 37, 1043-1057.

Monin, P. J. (2019). The OFR financial stress index. *Risks*, 7, 25.

Muravyev, D., Pearson, N. D., & Broussard, J. P. (2013). Is there price discovery in equity options? *Journal of Financial Economics,* 107, 259-283.

Nikkinen, J., & Sahlström, P., (2004). Impact of the federal open market committee's meetings and scheduled macroeconomic news on stock market uncertainty. *International Review of Financial Analysis*, 13, 1-12.

O'Hara, M., (2015). High frequency market microstructure. *Journal of Financial Economics*, 116, 257-270.

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

Rapach, D. E., Ringgenberg, M. C., & Zhou, G., (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121, 46-68.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: combination forecasts and links to the real economy. *Review of Financial Studies,* 23, 821-862.

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

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

Tsai, W.-C., Chiu, Y.-T. & Wang, Y.-H. (2015). The information content of trading activity and quote changes: Evidence from VIX options. *Journal of Futures Markets*, 35, 715-37.

Vähämaa, S., & Äijö, J., (2011). The Fed's policy decision and implied volatility. *Journal of Futures Markets*, 31, 995-1009.

Welch, I., & Goyal. A. (2008). A Comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies,* 21, 1455–1508.

Table 1. Descriptive Statistics

Panel A reports the summary statistics for the put-call ratio (PC_t), the VIX change ($dVIX_t$), the S&P 500 index return ($Return_t$), the 3-month T-bill yield change ($dTbill_t$), the term spread change ($dTerm_t$), and the credit spread change ($dCredit_t$). Changes in the three interest rate variables are in basis points. Panel B reports the Pearson correlation coefficients among the variables. The put-call ratio is constructed from the trading volume of VIX options initiated by a buyer to open a new position. The bold text indicates statistical significance at the 5% significance level. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	PC	$dVIX$	$Return$	$dTbill$	$dTerm$	$dCredit$
Panel A. Summary Statistics						
Mean	0.309	0.002	0.030	-0.131	0.077	-0.001
Median	0.283	-0.090	0.072	0.000	0.000	0.000
Std. Dev.	0.183	2.014	1.281	4.878	8.355	4.669
Panel B. Correlation						
$dVIX$	-0.022					
$Return$	0.014	**-0.825**				
$dTbill$	-0.022	**-0.096**	**0.124**			
$dTerm$	0.012	**-0.159**	**0.200**	**-0.468**		
$dCredit$	**0.031**	**0.094**	**-0.113**	-0.013	**-0.034**	

Table 2. Regressions of VIX changes, S&P 500 Returns and Macroeconomic Indicators on Lagged VIX option Put-Call Ratio

This table reports the estimated results for the following regression: $X_t = a_0 + \sum_{j=1}^{2} a_{1j} PC_{t-j} + \sum_{j=1}^{2} a_{2j} dVIX_{t-j} + \sum_{j=1}^{2} a_{3j} Return_{t-j} + \sum_{j=1}^{2} a_{4j} dTbill_{t-j} + \sum_{j=1}^{2} a_{5j} dTerm_{t-j} + \sum_{j=1}^{2} a_{6j} dCredit_{t-j} + e_t$, where X_t is the dependent variable and is either the change in the VIX ($dVIX_t$), the S&P 500 return ($Return_t$), the change in the 3-month T-bill yield ($dTbill_t$), the change in the term spread ($dTerm_t$), or the change in the credit spread ($dCredit_t$). The regressions are estimated using OLS with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix. All variables are measured at the daily frequency. Standard errors are shown in parentheses. The bold text indicates statistical significance at the 5% significance level. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
$Intercept$	**0.241**	-0.045	0.065	-0.371	-0.178
	(0.068)	(0.041)	(0.175)	(0.307)	(0.141)
PC_{t-1}	**-0.571**	0.218	-0.116	1.334	0.477
	(0.185)	(0.113)	0.408）	(0.762)	(0.345)
PC_{t-2}	-0.214	0.027	-0.529	0.051	0.177
	(0.185)	(0.122)	(0.377)	(0.781)	(0.400)
$dVIX_{t-1}$	**-0.131**	0.033	0.033	0.252	-0.350
	(0.066)	(0.044)	(0129)	(0.239)	(0.316)
$dVIX_{t-2}$	-0.021	-0.001	0.021	-0.194	-0.164
	(0.064)	(0.041)	(0.081)	(0.215)	(0.112)
$Return_{t-1}$	0.091	-0.095	0.186	0.227	-0.703
	(0.095)	(0.057)	(0.205)	(0.364)	(0.493)
$Return_{t-2}$	0.060	-0.018	0.114	-0.308	-0.224
	(0.080)	(0.055)	(0.126)	(0.319)	(0.123)
$dTbill_{t-1}$	-0.013	-0.003	**0.185**	**-0.357**	-0.004
	(0.014)	(0.007)	**(0.053)**	**(0.085)**	(0.020)
$dTbill_{t-2}$	0.008	-0.007	-0.149	0.041	-0.022
	(0.011)	(0.008)	(0.095)	(0.096)	(0.021)
$dTerm_{t-1}$	-0.007	0.005	-0.025	**-0.190**	-0.014
	(0.006)	(0.003)	(0.016)	**(0.079)**	(0.016)
$dTerm_{t-2}$	-0.007	0.005	0.009	-0.074	0.005
	(0.007)	(0.004)	(0.015)	(0.050)	(0.015)
$dCredit_{t-1}$	-0.028	0.022	0.007	0.021	**-0.344**
	(0.021)	(0.015)	(0.025)	(0.038)	**(0.084)**
$dCredit_{t-2}$	0.003	-0.016	-0.011	-0.053	0.011
	(0.015)	(0.010)	(0.019)	(0.044)	(0.058)
$Adj.R^2$	4.63	3.73	5.71	4.78	12.50

Table 3. Vector Autoregression Results
for VAR with interaction terms for high VIX periods

The results reported in this table are based on the estimation of the following vector autoregressive model: $\widetilde{\boldsymbol{X}}_{\mathbf{t}} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_{1j}}\, \boldsymbol{X_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, H_{VIX_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-j} H_{VIX_{t-j}} + \boldsymbol{e_t}$, where $\boldsymbol{X_t}$ is a vector of several variables $(PC, dVIX, Return, dTbill, dTerm, dCredit)$, while e_t is a vector of random disturbances. PC denotes the put-call ratio, $dVIX$ is the change in the VIX, $Return$ is the return of the S&P 500 index, $dTbill$ is the change in the 3-month T-bill yield, $dTerm$ is the change in the term spread, while $dCredit$ is the change in the credit spread. In addition to these variables, $\widetilde{\boldsymbol{X}}_{\boldsymbol{t}}$ includes an interaction term between the VIX put-call ratio and a dummy variable (H_{VIX_t}) that indicates high uncertainty periods. This dummy variable is equal to one during days when the VIX is above its median value, and zero otherwise. The following Cholesky ordering is used: $dVIX$, PC, $PC \times High_{VIX}$, $Return$, $dTbill$, $dTerm$ and $dCredit$. All variables are measured at the daily frequency. Standard errors are shown in parentheses. The bold text indicates statistical significance at the 5% significance level. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
PC_{t-1}	0.024	-0.083	-0.342	1.747	0.375
	(0.282)	(0.180)	(0.680)	(1.171)	(0.627)
PC_{t-2}	0.013	-0.032	0.117	-0.687	-0.025
	(0.281)	(0.180)	(0.678)	(1.168)	(0.626)
Sum of coef. of PC_{t-j}	0.037	-0.115	-0.225	1.060	0.350
	(0.181)	(0.111)	(0.311)	(1.055)	(0.552)
$PC_{t-1}H_{VIX_{t-1}}$	**-0.921**	**0.575**	0.871	-0.821	0.158
	(0.378)	**(0.241)**	(0.910)	(1.567)	(0.840)
$PC_{t-2}H_{VIX_{t-2}}$	-0.233	0.116	-0.758	1.277	0.338
	(0.377)	(0.241)	(0.909)	(1.567)	(0.839)
Sum of coef. of $PC_{t-j}H_{VIX_{t-J}}$	**-1.154**	**0.691**	0.113	0.456	0.496
	(0.436)	**(0.275)**	(1.097)	(1.956)	(1.078)

Table 4. Markov-Switching Model Results

This table reports the estimated results for the following Markov-switching model: $X_t = a_{0,s_t} + a_{1,s_t}PC_{t-1} + a_{2,s_t}PC_{t-2} + \sum_{j=1}^{2} a_{3j}dVIX_{t-j} + \sum_{j=1}^{2} a_{4j}Return_{t-j} + \sum_{j=1}^{2} a_{5j}dTbill_{t-j} + \sum_{j=1}^{2} a_{6j}dTerm_{t-j} + \sum_{j=1}^{2} a_{7j}dCredit_{t-j} + e_t$, where X_t is the change in the VIX index in Panel A and the S&P 500 return in Panel B. Independent variables include the lags of the change in the VIX index ($dVIX$), the put-call ratio (PC), the S&P 500 return ($Return$), the change in the 3-month T-bill yield ($dTbill$), the change in the term spread ($dTerm$), and the change in the credit spread ($dCredit$). The error term $e_t \sim N(0, \sigma_{s_t}^2)$, and the unobserved state variable s_t = {1, 2} follows a Markov process with fixed transition probabilities: $p_{11} = P(s_t = 1 | s_{t-1} = 1)$, $p_{22} = P(s_t = 2 | s_{t-1} = 2)$. The z-statistics are based on Huber-White robust standard errors. The bold text indicates statistical significance at the 5% significance level. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

		Estimate	z-statistics	p-value
Panel A. $X_t = dVIX_t$				
State 1 (Low Variance)	Intercept	-0.013	-0.335	0.737
	PC_{t-1}	-0.163	-1.516	0.130
	PC_{t-2}	**-0.218**	**-2.122**	**0.034**
	σ_1	**0.818**	**4.934**	**0.000**
State 2 (High Variance)	Intercept	**1.369**	**4.441**	**0.000**
	PC_{t-1}	**-2.289**	**-3.667**	**0.000**
	PC_{t-2}	-0.542	-0.827	0.408
	σ_2	**3.562**	**17.160**	**0.000**
Expected Duration	State 1	22.930		
	State 2	8.182		
Panel B. $X_t = Return_t$				
State 1 (Low Variance)	Intercept	0.041	1.293	0.196
	PC_{t-1}	0.150	1.780	0.072
	PC_{t-2}	0.134	1.451	0.147
	σ_1	**0.647**	**10.261**	**0.000**
State 2 (High Variance)	Intercept	**-0.535**	**-3.046**	**0.002**
	PC_{t-1}	**0.837**	**2.203**	**0.028**
	PC_{t-2}	0.061	0.137	0.891
	σ_2	**2.143**	**10.871**	**0.000**
Expected Duration	State 1	47.384		
	State 2	17.881		

Table 5. Vector Autoregression Results
for VAR with interaction terms for NBER recessions

The results reported in this table are based on the estimation of the following vector autoregressive model: $\widetilde{\boldsymbol{X}}_{\mathbf{t}} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_{1j}}\ \boldsymbol{X_{t-j}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, PC_{t-j}NBER_{t-j} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-j}\left(1 - NBER_{t-j}\right) + \sum_{j=1}^{2} \boldsymbol{a_{4j}}\ NBER_{t-j} + \boldsymbol{e_t}$, where $\boldsymbol{X_t}$ is a vector of several variables ($dVIX,\ PC,\ Return,\ dTbill,\ dTerm,\ dCredit$), while e_t is a vector of random disturbances. PC denotes the put-call ratio, $dVIX$ is the change in the VIX, $Return$ is the return of the S&P 500 index, $dTbill$ is the change in the 3-month T-bill yield, $dTerm$ is the change in the term spread, while $dCredit$ is the change in the credit spread. In addition to these variables, $\widetilde{\boldsymbol{X}}_{\mathbf{t}}$ is a vector that also includes two interaction terms: $PC_t * NBER_t$ and $PC_t * (1 - NBER_t)$. $NBER_t$ is a dummy variable equal to one during NBER recession periods, and zero otherwise. The following Cholesky ordering is used: $dVIX$, $PC * NBER$, $PC * (1 - NBER)$, $Return$, $dTbill$, $dTerm$ and $dCredit$. All variables are measured at the daily frequency. The bold text indicates statistical significance at the 5% significance level. Standard errors are shown in parentheses. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
$PC_{t-1}NBER_{t-1}$	**-1.151**	0.499	1.155	1.214	0.726
	(0.405)	(0.259)	(0.975)	(1.680)	(0.900)
$PC_{t-2}NBER_{t-2}$	-0.012	-0.022	-1.093	-1.115	1.190
	(0.406)	(0.259)	(0.976)	(1.682)	(0.901)
Sum of coef. of $PC_{t-j}NBER_{t-j}$	-1.162	0.477	0.062	0.099	1.916
	(0.692)	(0.439)	(2.049)	(3.046)	(1.747)
$PC_{t-1}(1 - NBER_{t-1})$	**-0.446**	0.186	-0.251	1.210	0.367
	(0.210)	(0.134)	(0.504)	(0.868)	(0.465)
$PC_{t-2}(1 - NBER_{t-2})$	-0.282	0.076	-0.217	0.188	-0.117
	(0.210)	(0.134)	(0.504)	(0.869)	(0.465)
Sum of coef. of $\left(1 - PC_{t-j}NBER_{t-j}\right)$	**-0.728**	**0.262**	-0.470	1.398	0.250
	(0.182)	**(0.112)**	(0.357)	(0.864)	(0.370)

Table 6. Vector Autoregression Results
for VAR with interaction terms for days before macroeconomic announcements

The results reported in this table are based on the estimation of the following vector autoregressive model: $\boldsymbol{\widetilde{X}_t} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_{1j}}\ \boldsymbol{X_{t-1}} + \sum_{j=1}^{2} \boldsymbol{a_{2j}}\, PC_{t-1}ECON_{t-1} + \sum_{j=1}^{2} \boldsymbol{a_{3j}}\, PC_{t-1}(1 - ECON_{t-1}) + \boldsymbol{e_t}$, where $\boldsymbol{X_t}$ is a vector of several variables ($dVIX,\ PC,\ Return,\ dTbill,\ dTerm,\ dCredit$), while e_t is a vector of random disturbances. PC denotes the put-call ratio, $dVIX$ is the change in the VIX, $Return$ is the return of the S&P 500 index, $dTbill$ is the change in the 3-month T-bill yield, $dTerm$ is the change in the term spread, while $dCredit$ is the change in the credit spread. In addition to these variables, $\boldsymbol{\widetilde{X}_t}$ is a vector that also includes two interaction terms: $PC_t * ECON_t$ and $PC_t * (1 - ECON_t)$. $ECON_t$ is a dummy variable equal to one on days preceding important macroeconomic and monetary announcements such as the Consumer Price Index (CPI), the unemployment rate, the Gross Domestic Product (GDP), and FOMC statements, and zero otherwise. The following Cholesky ordering is used: $dVIX$, $PC * ECON$, $PC * (1 - ECON)$, $Return$, $dTbill$, $dTerm$, and $dCredit$. All variables are measured at the daily frequency. The bold text indicates statistical significance at the 5% significance level. Standard errors are shown in parentheses. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
$PC_{t-1}ECON_{t-1}$	**-1.814**	**0.342**	**0.451**	-1.104	1.067
	(0.284)	**(0.028)**	**(0.182)**	(0.687)	(1.182)
$PC_{t-2}ECON_{t-2}$	**0.646**	**0.256**	-0.335	-0.208	-1.713
	(0.286)	**(0.028)**	(0.183)	(0.691)	(1.189)
$PC_{t-1}(1 - ECON_{t-1})$	**-0.488**	**0.198**	0.187	0.033	1.401
	(0.187)	**(0.018)**	(0.120)	(0.452)	(0.778)
$PC_{t-2}(1 - ECON_{t-2})$	-0.339	**0.174**	0.080	-0.572	0.315
	(0.187)	**(0.018)**	(0.120)	(0.452)	(0.778)

Table 7. Vector Autoregression Results
using put-call ratio for options with different remaining time to expiration

The results reported in this table are based on the estimation of the following vector autoregressive model: $\boldsymbol{X_t} = \boldsymbol{a_0} + \sum_{j=1}^{2} \boldsymbol{a_j} \boldsymbol{X_{t-j}} + \boldsymbol{e_t}$, where $\boldsymbol{X_t}$ is a vector of several variables (PC, $dVIX$, $Return$, $dTbill$, $dTerm$, $dCredit$), while $\boldsymbol{e_t}$ is a vector of random disturbances. PC denotes the put-call ratio, $dVIX$ is the change in the VIX, $Return$ is the return of the S&P 500 index, $dTbill$ is the change in the 3-month T-bill yield, $dTerm$ is the change in the term spread, while $dCredit$ is the change in the credit spread. All variables are measured at the daily frequency. The table reports the coefficient of PC_{t-1} when the VAR model is estimated for option categories having various remaining time to expiration. The bold text indicates statistical significance at the 5% significance level. Standard errors are shown in parentheses. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

Coefficient of PC_{t-1}	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
Under 30 Days	**-0.424**	0.017	-0.295	0.291	-0.016
	(0.147)	(0.099)	(0.296)	(0.651)	(0.339)
30-59 Days	**-0.356**	0.096	-0.326	0.101	0.629
	(0.146)	(0.096)	(0.320)	(0.649)	(0.383)
60-89 Days	-0.224	0.038	-0.340	0.872	0.398
	(0.132)	(0.084)	(0.323)	(0.537)	(0.305)
90-119 Days	0.035	0.051	-0.341	0.425	0.167
	(0.147)	(0.092)	(0.286)	(0.528)	(0.264)
Over 119 Days	0.109	-0.071	-0.129	-0.159	-0.043
	(0.145)	(0.090)	(0.309)	(0.525)	(0.242)

Table 8. Out-of-Sample Forecasting Results

The table reports the proportional reduction in the mean square forecast error (R^2_{OS}) calculated as described in equation (9). We test the null hypothesis that $R^2_{OS} \leq 0$, against the alternative hypothesis that $R^2_{OS} > 0$. The statistical significance is determined using the Clark and West (2007) out-of-sample MSPE-adjusted statistic. The sample period covered is from February 2006 to March 2021. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In-Sample Period	R^2_{OS} (%)	MSPE-adjusted Stat.
2006.2-2008.1	1.86	3.18***
2006.2-2009.1	1.82	3.00***
2006.2-2010.1	1.90	2.74***
2006.2-2011.1	2.05	2.59***
2006.2-2012.1	2.37	2.42***

Table 9. Regressions of Financial Distress Indicators and its Components on Lagged VIX option Put-Call Ratio

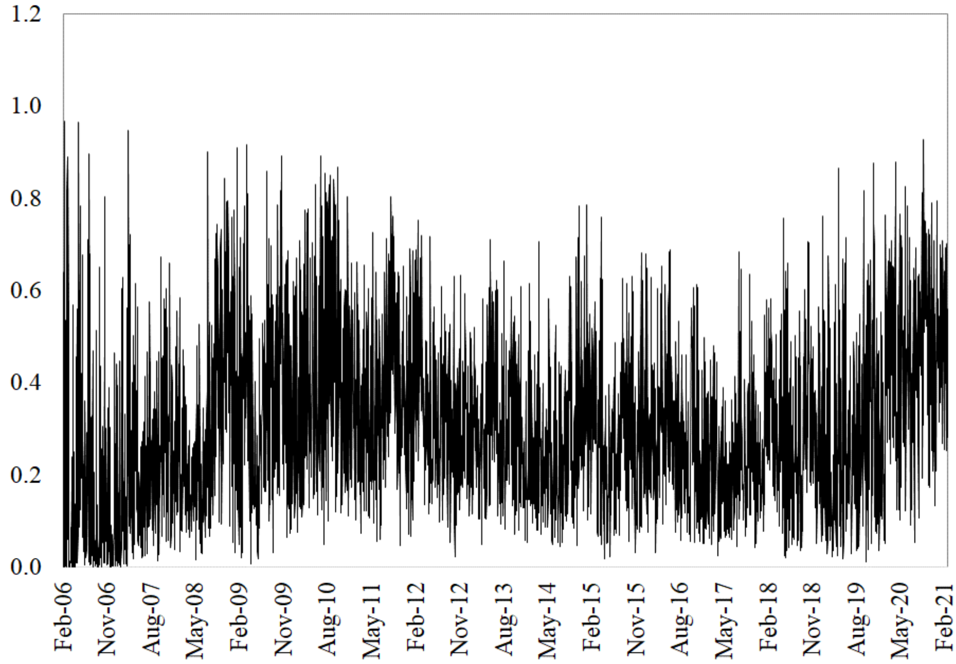
This table reports the estimated results for the following regression: $X_t = a_0 + \sum_{j=1}^{2} a_{1j} PC_{t-j} + \sum_{j=1}^{2} a_{2j} dVIX_{t-j} + \sum_{j=1}^{2} a_{3j} Return_{t-j} + \sum_{j=1}^{2} a_{4j} dTbill_{t-j} + \sum_{j=1}^{2} a_{5j} dTerm_{t-j} + \sum_{j=1}^{2} a_{6j} dCredit_{t-j} + e_t$, where X_t is the dependent variable and is either the change in the Office of Financial Research (OFR) Financial Stress Index (ΔFSI_t), the change in one of the FSI component indexes ($\Delta Credit_t$, $\Delta Equity\_Valuation_t$, $\Delta Funding_t$, $\Delta Safe\_Assets_t$, $\Delta Volatility_t$), or the change in one of the regional FSI ($United\ States$, $Other\ Advanced\ Economies$, $Emerging\ Markets$). The regressions are estimated using OLS with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix. All variables are measured at the daily frequency. Standard errors are shown in parentheses. The bold text indicates statistical significance at the 5% significance level. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

	PC_{t-1}	PC_{t-2}	Sum of coef. of PC_{t-j}	$Adj.R^2$(%)
Panel A. Global FSI Changes				
ΔFSI_t	**-0.075**	-0.020	**-0.095**	6.41
	(0.030)	(0.028)	**(0.037)**	
Panel B. FSI's Five Components				
$\Delta Credit_t$	-0.010	-0.005	**-0.015**	12.62
	(0.005)	(0.005)	**(0.007)**	
$\Delta Equity\_Valuation_t$	**-0.013**	-0.004	**-0.017**	6.51
	(0.006)	(0.006)	**(0.007)**	
$\Delta Funding_t$	-0.018	0.005	-0.013	3.05
	(0.011)	(0.011)	(0.014)	
$\Delta Safe\_Assets_t$	-0.005	-0.001	-0.006	1.68
	(0.003)	(0.003)	(0.003)	
$\Delta Volatility_t$	-0.029	-0.015	**-0.044**	5.11
	(0.015)	(0.014)	**(0.018)**	
Panel C. Three Regional FSI Changes				
$United\ States$	**-0.046**	-0.011	**-0.057**	2.52
	(0.016)	(0.015)	**(0.021)**	
$Other\ Advanced\ Economies$	-0.022	-0.008	-0.030	14.59
	(0.015)	(0.013)	(0.016)	
$Emerging\ Markets$	-0.006	-0.001	-0.007	9.17
	(0.003)	(0.003)	(0.004)	

Figure 1. The Put-Call Ratio and the VIX Index

This figure plots the daily put-call ratio for VIX options in Panel A and the daily values of the VIX in Panel B, from February 2006 to March 2021.

Panel A. The Put-Call Ratio



Panel B. The VIX Index

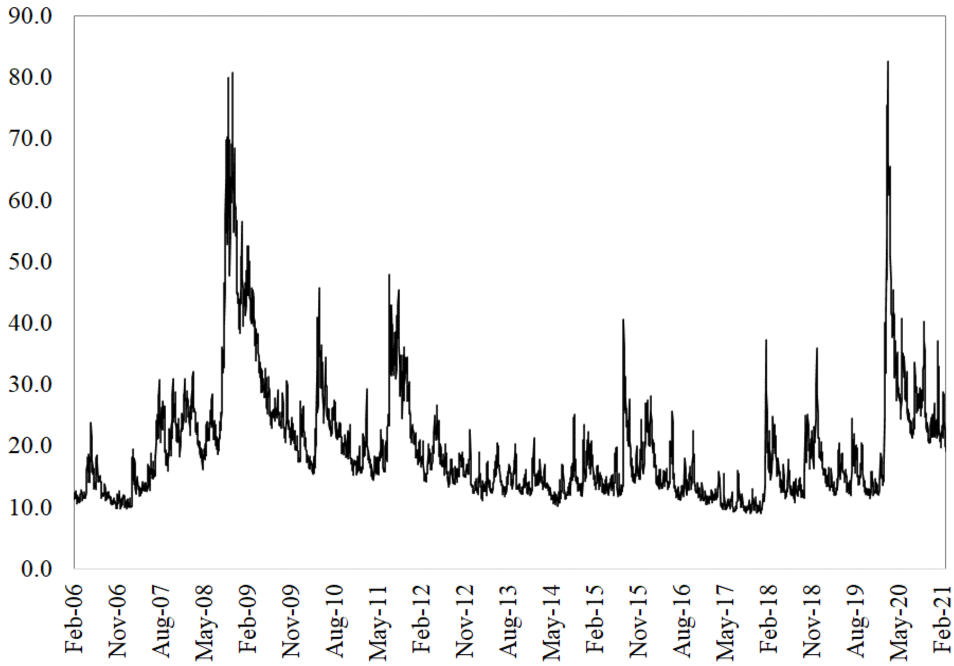
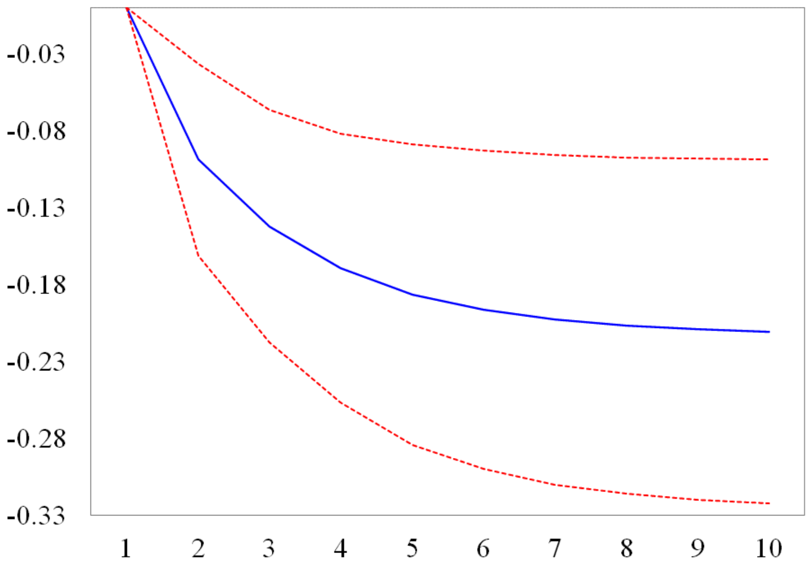


Figure 2. Impulse Response Functions

This figure plots the accumulated impulse response functions of $dVIX$ and $Return$ to one standard-deviation innovation in the put-call ratio, for up to 10 days ahead. The impulse response functions are obtained from the VAR model in equation (3) using Cholesky decomposition and the following ordering of variables: $dVIX$, PC, $Return$, $dTbill$, $dTerm$ and $dCredit$. PC denotes the put-call ratio, $dVIX$ is the change in the VIX index, $Return$ is the return of the S&P 500 index, $dTbill$ is the change in the 3-month T-bill yield, $dTerm$ is the change in the term spread, while $dCredit$ is the change in the credit spread. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.

Acculumated Response of $dVIX$ to PC



Acculumated Response of $Return$ to PC

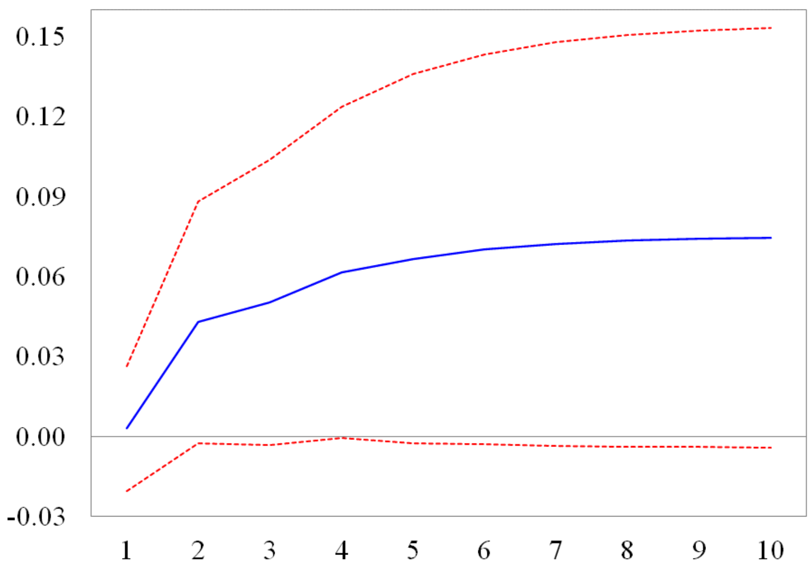


Figure 3. Impulse Response Functions
for VAR with interaction terms for high VIX periods

This figure plots the accumulated impulse response functions of $dVIX$ and $Return$ to one standard-deviation innovation in PC and to a one standard deviation shock in $PC \times High_{VIX}$, for up to 10 days ahead. The impulse response functions are obtained from the VAR model in equation (4) and the following ordering of variables: $dVIX$, PC, $PC \times High_{VIX}$, $Return$, $dTbill$, $dTerm$ and $dCredit$. $High_{VIX}$ is a dummy variable equal to one when the VIX is above its median level, and zero otherwise. The sample period is from February 2006 to March 2021 and contains 3,789 observations.

Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.