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 novel dataset from the Chicago Board Options Exchange, we calculate the put-call ratio based on the VIX option volume initiated by buyers to open new positions. We show that the put-call ratio negatively predicts the subsequent changes in the VIX index. The predictability is stronger during periods of elevated VIX levels and for short-dated contracts. These results support 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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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 risk-neutral 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 (Ang, Hodrick, Xing and Zhang, 2006). Hence, trading options on the VIX allows traders to not only potentially take advantage of their volatility information, but also hedge their market volatility risk in a direct and effective way. Although a relatively new product, VIX options are considered the most successful new product launch in the history of the CBOE (Chung, Tsai, Wang, and Weng, 2011), with a trading volume of about 4.5 million contracts in the first three quarters of their existence.[2]

We investigate the information 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 other VIX-related instruments,[3] option trading volume could be informative about subsequent movements in the underlying VIX index. Customer trades in VIX options could be perceived as a signal by option market makers, who will adjust their bid and ask quotes accordingly.

Using a novel dataset from the CBOE, we calculate the put-call ratio for VIX options

[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 (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).

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based on the trading 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 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 economic and financial factors on both investor expectations about the future and their VIX 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 predictive ability of the put-call ratio for the value of the underlying VIX 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 VIX changes out-of-sample.

It is possible that the negative relation between the put-call ratio and the subsequent changes in the VIX index is a consequence of investors' tendency to trade based on the expected mean reversion in the VIX index. That is, when the VIX rises to an unusually high level, traders may buy VIX puts, anticipating that the VIX will revert to the mean (e.g, Banerji, 2020). Similarly, when the VIX drops significantly below its average level, traders may sell puts and/or buy calls on the VIX, anticipating an upward reversal in the VIX. We do find evidence of stronger mean reversion in the VIX after large VIX changes. However, we show that the put-call ratio negatively predicts the subsequent changes in the VIX even after controlling for the VIX mean reversion tendency.

The interpretation of our results in terms of information-based trading in the VIX option

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market is corroborated by additional tests. We test the role of option volume during high versus low uncertainty periods, as well as in different stages of the business cycle. We also analyze VIX 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). These additional tests show that the predictive ability of the VIX put-call ratio for the future values of the VIX is more prevalent in times of high uncertainty, when information about future volatility is more valuable. We also find that the predictive ability of the put-call ratio for the underlying VIX is stronger for options 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 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 a higher value 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 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 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

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and attribute the findings to informed trading in options. 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 buying of stock index put options predicts higher subsequent market returns at the weekly horizon, 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 the literature examining informed trading in index options. While previous research provides evidence of informed trading in stock index options (Kaeck, van Kervel, and Seeger, 2017; Ahn, Kang, and Ryu, 2008), we investigate 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 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 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.

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 can also be predicted using the VIX options trading volume.

Our findings are useful for traders. We propose a trading strategy of selling VIX futures when the VIX put-call ratio is significantly above its mean and closing the position the next

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day. This strategy yields positive and statistically significant average excess returns and high annualized Sharpe ratios, especially in times of elevated VIX.

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. They classify the VIX option trades as either 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 the CBOE 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.

The paper proceeds as follows. Section 2 describes our data and introduces the main variables used in our analysis. Section 3 examines the relationships between the VIX put-call ratio and the subsequent changes in the VIX index. Section 4 briefly concludes the paper.

2. Data

We obtain the daily VIX option trading volume originated from non-market makers (i.e., end-users) from the CBOE's Open-Close database. Unlike the option call/put volume data that is publicly available, our dataset has several unique features. First, the daily aggregated volume is classified based on buying/selling and opening/closing criteria, and so is of four types: '*open-buy'* volume represents contracts purchased by an end-user to open a new option position, '*open-sell'* volume represents contracts sold by an end-user to open a new option position, '*close-buy'* volume refers to contracts purchased to close an existing short position, while

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'*close-sell'* volume denotes contracts sold to close an existing long position. Since investors trade options for different purposes, the signed option volume might be more informative than the regular non-signed option volume, which is publicly available. Second, the dataset also provides information on the remaining time to expiration of various option contracts, allowing us to consider options with different remaining times to expiration in our analysis.

The daily order flow of VIX options has also been used by Jacobs and Mai (2020). They construct measures of option net demand, by calculating all buy volume net of all sell volume, and show that the net demand of VIX options, especially puts, affects the VIX index. In our paper, instead of focusing on the aggregate net demand, we follow the method in Pan and Poteshman (2006) and use the '*open-buy'* option volume to construct the put-call volume ratio. We show that the put-call ratio can predict the subsequent changes in the VIX index. The put-call volume ratio is computed as:

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

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

Besides the VIX 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 constant maturity 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 on February 24, 2006 to March 17, 2021 and contains 3,789 daily observations.

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[Insert Figure 1 Here]

Table 1 reports the summary statistics for the VIX put-call ratio, the S&P 500 index return, the changes in VIX, and the three macroeconomic variables mentioned above. 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 following regression:

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

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 statistically significant at the 5% 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.[4] 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

[4] In the next subsection, we show that this effect is not reversed, so our results are not a manifestation of temporary price pressure.

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$\boldsymbol{a_0}$, 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 $dCredit$.[5] We observe that the put-call ratio has a significant negative and permanent effect on the 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 a 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 not statistically significant at the 5% 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

[5] Generalized (order invariant) impulse responses are similar.

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(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:

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

where $\widetilde{\boldsymbol{X}}_{\boldsymbol{t}}$ 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, $\widetilde{\boldsymbol{X}}_{\boldsymbol{t}}$ 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 its 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

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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:

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

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.[6] 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 index

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

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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 S&P 500 index 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 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.[7] In this subsection, we examine whether the predictability we find depends on the business cycle. We use the following VAR model:

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

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 $PC_{t-1}NBER_{t-1}$ and $PC_{t-1}(1 - NBER_{t-1})$ in the regression having $dVIX_t$ as the dependent variable are both negative and statistically significant at the 5% level. That is, a higher put-call ratio leads to a decrease in the VIX during both economic expansions and recessions. 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]

[7] 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.

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3.5. 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, O'Hara, and Srinivas (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.[8] We report the estimated coefficients of the lagged put-call ratio in Table 6. 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 6 Here]

3.6. 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 section, we implement an out-of-sample test to investigate whether the put-call ratio has

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[8] 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.

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incremental predictive ability for the subsequent $dVIX$, relative to the prevailing mean benchmark. 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:

$$\widehat{dVIX}_{m+1} = \hat{a}_{0,m} + \sum_{j=0}^{1} \hat{a}_{1j,m}\, PC_{m-j} + \sum_{j=0}^{1} \hat{a}_{2j,m}\, H_{VIX_{m-j}} + \sum_{j=0}^{1} \hat{a}_{3j,m}\, PC_{m-j} H_{VIX_{m-j}} + \sum_{j=0}^{1} \hat{a}_{4j,m}\, dVIX_{m-j} \tag{7}$$

In the equation above, m refers to the number of observations included in our estimation window, while $\hat{a}_{0,m}$, $\hat{a}_{1j,m}$, $\hat{a}_{2j,m}$, $\hat{a}_{3j,m}$ and $\hat{a}_{4j,m}$ are the coefficient estimates obtained from estimating a regression with the same variables as in equation (7) using data for an in-sample period. We select various starting points for our out-of-sample period (2009, 2010, 2011, and 2012, 2013), 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.

$$R^2_{OS} = 1 - \frac{\sum_{k=q_0+1}^{q}\left(dVIX_{m+k} - \widehat{dVIX}_{m+k}\right)^2}{\sum_{k=q_0+1}^{q}\left(dVIX_{m+k} - \overline{dVIX}_{m+k}\right)^2} \tag{8}$$

$\overline{dVIX}_{m+k}$ 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 that 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 calculate the Clark and West (2007) out-of-sample MSPE-adjusted statistic.

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.

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This is because the more complex model introduces noise into its forecasts by including useless parameters. Clark and West (2007) propose a simple "MSPE-adjusted" statistic that adjusts for this bias and can be used to test the predictive accuracy of nested models. They show that this statistic is approximately standard normal and recommend using the one-tailed standard normal critical values.[9] Our results reported in Table 7 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.

[Insert Table 7 Here]

3.7. Trading on the Expected VIX Mean Reversion

The VIX index is known to have a strong mean reversion tendency, which is apparent in Panel B of Figure 1. When the VIX spikes, traders may buy VIX puts, expecting that the VIX will decline (e.g., Banerji, 2020). Similarly, when the VIX is lower than average, traders may sell VIX puts and/or buy VIX calls, anticipating that the VIX will revert to its mean. Thus, one might argue that the negative relation we find between the put-call ratio of VIX options and the subsequent changes in the VIX index could be a consequence of investors trading on the expected VIX mean reversion. To test this potential alternative explanation of our results, we estimate the regression in equation (9) below. The lags of $dVIX$ help us control for the VIX mean reversion tendency. We would expect the mean reversion tendency to be stronger after large changes in the VIX. Therefore, we also interact the lagged VIX changes with a dummy variable ${H_{DVIX}}_t$ equal to one when $dVIX$ is in its top or bottom deciles, and zero otherwise.

$$dVIX = a_0 + \sum_{j=1}^{2} a_{0j}\, {H_{DVIX}}_{t-j} + \sum_{j=1}^{2} a_{1j}\; dVIX_{t-j} + \sum_{j=1}^{2} a_{2j}\, dVIX_{t-j}{H_{DVIX}}_{t-j} + \sum_{j=1}^{2} a_{3j}\, PC_{t-j} + \sum_{j=1}^{2} a_{4j} Return_{t-j} + \sum_{j=1}^{2} a_{5j} dTbill_{t-j} + \sum_{j=1}^{2} a_{6j} dTerm_{t-j} + \sum_{j=1}^{2} a_{7j} dCredit_{t-j} + e_t, \tag{9}$$

[9] Examples of studies using the MSPE-adjusted statistic include Rapach, Strauss and Zhou (2010) and Rapach, Ringgenberg and Zhou (2016).

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where PC denotes the VIX put-call volume ratio, and $dVIX$ is the change in the VIX. As controls, we include the return of the S&P 500 index ($Return$), 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 results in Column (1) of Table 8 show that the ability of the put-call ratio to predict the subsequent changes in the VIX holds after controlling for the VIX mean reversion tendency. The results in Column (2) of Table 8 are based on the estimation of a regression similar to the one in equation (2), where we distinguish between positive and negative changes in the VIX. We find a stronger mean reversion tendency after positive rather than negative changes in the VIX. However, the coefficient estimates of the lags of the put-call ratio are similar to the corresponding estimates in Table 2 and in Column (1) of Table 8.

[Insert Table 8 Here]

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

In this subsection, we examine 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 conditions. 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, and 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) of the U.S. Department of the Treasury. The FSI is a daily measure of the stress in global financial markets, calculated at the end of each U.S. trading day (Monin, 2019). Zero values of the index indicate normal level of stress, while positive (negative) values reveal a level of stress above (below) average. We estimate the regression in

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equation (2) where the dependent variable X_t is 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, showing that the trading volume in the VIX option market can predict the subsequent changes in financial stress. The sum of the coefficients 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]

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 into 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 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, and the funding market may 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-

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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 into 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.

3.9. Trading Strategy

Are our main findings useful for traders? In this section, we propose a trading strategy of selling VIX futures when the put-call ratio is significantly above its mean and closing the position the next day. We first normalize the historical put-call ratio using different expanding windows. The first normalization is done using the first 600 observations in the sample period. On trading day 600, if the VIX put-call ratio is 0.75 (1.00, or 1.25) standard deviations above the mean (i.e., the corresponding z-score is larger than 0.75 (1.00, or 1.25)), we establish a short position in VIX futures.[10] Otherwise, we do not trade.[11] The short futures position is closed the next

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[10] We use daily closing prices of the nearby VIX futures contracts. Because these contracts become relatively illiquid shortly before expiration, we use the next-to-maturity contracts when their daily trading volumes exceed those of the nearby contracts. Futures returns are adjusted for contract rollovers.

[11] We also considered a trading strategy that includes buying VIX futures when the VIX put-call ratio is significantly below its mean. However, this strategy has lower mean excess returns and annualized Sharpe ratios than the strategy that involves only short VIX futures positions. VIX futures are known to have negative average returns (e.g., Whaley, 2013).

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day. This process is then rolled forward to day 601, where the normalization of the put-call ratio is done using 601 observations, and the process is repeated for other expanding windows.

The average excess return of our trading strategy is reported in Table 10. The trading strategy yields a positive and significant excess return on average, and this excess return is visibly higher during times of elevated VIX for two of the three thresholds used. Furthermore, the corresponding annualized Sharpe ratios are greater during high VIX periods, relative to periods of low VIX. This is consistent with our previous results showing that the put-call ratio predicts VIX changes only in high-VIX periods.

[Insert Table 10 Here]

4. Conclusion

This paper examines 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 buyer-initiated volume of VIX options can predict future changes in the VIX. Our findings are consistent with the hypothesis of informed traders using the VIX option market as a venue for their trading. The predictive ability of the put-call ratio on the subsequent changes in the VIX index is stronger during periods of elevated volatility, that is, in times when information about future volatility is more valuable. This predictive ability holds during both recessions and expansionary periods and is the strongest for option categories providing higher leverage, such as the short-maturity contracts. Our results are not a consequence of temporary price pressure and remain significant after controlling for the expected mean reversion in the VIX.

Our analysis is useful for traders. Based on our findings, we propose a trading strategy of selling VIX futures when the VIX put-call ratio is significantly above the mean and closing the position the next day. This simple strategy yields positive average excess returns, which

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are higher in periods of elevated VIX. The performance of the trading strategy supports the economic significance of our findings. Our paper also shows that besides predicting the future changes in the VIX, the VIX put-call ratio can also predict 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 emerging markets. These results may be useful to regulators and policy makers.

Data Availability Statement

The data used in this study are available from Genesis Financial Technologies, the Chicago Board Options Exchange (CBOE), the FRED database of the Federal Reserve Bank of St. Louis, and the Office of Financial Research (OFR). Restrictions apply to the availability of the VIX futures data and the CBOE 'open-close' trading volume data for VIX options. These datasets can be acquired from Genesis Financial Technologies and the CBOE, respectively, by paying subscription fees. Daily data for the S&P 500 index, the VIX, interest rates, and the NBER recession indicator variable are freely available on the FRED website at https://fred.stlouisfed.org/. The data for the OFR Financial Stress Index and its components are freely available at https://www.financialresearch.gov/financial-stress-index/.

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Data Citation

[dataset] Daily data for buy and sell trading volumes for position-opening and position-closing trades for VIX options; February 24, 2006-March 17, 2021; not publicly available; data can be obtained from the CBOE; https://datashop.cboe.com/cboe-open-close-volume-summary.

[dataset] Daily data for nearby VIX futures; February 24, 2006-March 17, 2021; not publicly available; data can be obtained from Genesis Financial Technologies on payment of a data service fee; https://www.tradenavigator.com/.

[dataset] Daily data for the S&P 500 index, the VIX, interest rates, and the NBER recession indicator variable; February 24, 2006-March 17, 2021; FRED database of the Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/.

[dataset] Daily data for the OFR Financial Stress Index and its components; February 24, 2006-March 17, 2021; Office of Financial Research; https://www.financialresearch.gov/financial-stress-index/.

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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. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 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**	

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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. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 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

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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. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 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)

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Table 4. Markov-Switching Model Results

This table reports the estimated results for the following Markov-switching model: $X_t = a_{0,s_t} + \sum_{j=1}^{2} a_{1j,s_t} PC_{t-j} + \sum_{j=1}^{2} a_{3j} dVIX_{t-j} + \sum_{j=1}^{2} a_{4j} Return_{t-j} + \sum_{j=1}^{2} a_{5j} dTbill_{t-j} + \sum_{j=1}^{2} a_{6j} dTerm_{t-j} + \sum_{j=1}^{2} a_{7j} dCredit_{t-j} + e_t$, 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. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 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		

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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, $\widetilde{\boldsymbol{X}}_{\mathbf{t}}$ 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. Bold text indicates statistical significance at the 5% level. Standard errors are shown in parentheses. The sample period is from February 24, 2006 to March 17, 2021 and contains 3,789 observations.

	$dVIX_t$	$Return_t$	$dTbill_t$	$dTerm_t$	$dCredit_t$
$PC_{t-1}NBER_{t-1}$	**-1.729**	0.576	1.308	-0.886	1.064
	(0.501)	(0.320)	(1.206)	(2.079)	(1.113)
$PC_{t-2}NBER_{t-2}$	-0.012	-0.355	-2.677	1.543	2.634
	(0.502)	(0.320)	(1.206)	(2.080)	(1.113)
Sum of coef. of $PC_{t-j}NBER_{t-j}$	-1.717	0.221	-1.369	0.657	3.697
	(1.069)	(0.680)	(2.866)	(4.456)	(2.905)
$PC_{t-1}(1 - NBER_{t-1})$	**-0.389**	0.175	-0.278	1.650	0.329
	(0.198)	(0.127)	(0.479)	(0.824)	(0.441)
$PC_{t-2}(1 - NBER_{t-2})$	-0.238	0.093	-0.167	-0.182	-0.243
	(0.199)	(0.127)	(0.478)	(0.825)	(0.441)
Sum of coef. of $PC_{t-j}\left(1 - NBER_{t-j}\right)$	**-0.628**	**0.268**	-0.445	1.468	0.086
	(0.190)	**(0.111)**	(0.307)	(0.807)	(0.364)

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Table 6. 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. Bold text indicates statistical significance at the 5% level. Standard errors are shown in parentheses. The sample period is from February 24, 2006 to March 17, 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)

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Table 7. Out-of-Sample Forecasting Results

The table reports the proportional reduction in the mean square forecast error (R_{OS}^2) calculated as described in equation (9). We test the null hypothesis that $R_{OS}^2 \leq 0$, against the alternative hypothesis that $R_{OS}^2 > 0$. The statistical significance is determined using the Clark and West (2007) out-of-sample MSPE-adjusted statistic. The sample period covered is from February 24, 2006 to March 17, 2021. *** denotes statistical significance at the 1% level.

In-Sample Period	R_{OS}^2 (%)	MSPE-adjusted Statistic
2006.2-2008.12	2.20	3.30***
2006.2-2009.12	1.82	2.74***
2006.2-2010.12	2.08	2.62***
2006.2-2011.12	2.35	2.59***
2006.2-2012.12	2.41	2.32***

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Table 8. Controlling for the VIX Mean Reversion

Column (1) reports the estimated results of the following model:

$dVIX = a_0 + \sum_{j=1}^{2} a_{0j}\, H_{DVIX_{t-j}} + \sum_{j=1}^{2} a_{1j}\ dVIX_{t-j} + \sum_{j=1}^{2} a_{2j}\, dVIX_{t-j}H_{DVIX_{t-j}} + \sum_{j=1}^{2} a_{3j}\, PC_{t-j} + \sum_{j=1}^{2} a_{4j} Return_{t-j} + \sum_{j=1}^{2} a_{5j} dTbill_{t-j} + \sum_{j=1}^{2} a_{6j} dTerm_{t-j} + \sum_{j=1}^{2} a_{7j} dCredit_{t-j} + e_t$, where PC denotes the VIX put-call ratio, while $dVIX$ is the change in the VIX. H_{DVIX} is a dummy variable taking values of one when $dVIX$ is in its bottom or top decile, and values of zero otherwise. The model also includes the return of the S&P 500 index ($Return$), 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 results in Column (2) are based on the estimation of the following model:

$dVIX = a_0 + \sum_{j=1}^{2} a_{1j}\ POS\_dVIX_{t-j} + \sum_{j=1}^{2} a_{2j}\, NEG\_dVIX_{t-j} + \sum_{j=1}^{2} a_{3j}\, PC_{t-j} + \sum_{j=1}^{2} a_{4j} Return_{t-j} + \sum_{j=1}^{2} a_{5j} dTbill_{t-j} + \sum_{j=1}^{2} a_{6j} dTerm_{t-j} + \sum_{j=1}^{2} a_{7j} dCredit_{t-j} + e_t$, where $POS\_dVIX = max(0,\ dVIX)$ and $NEG\_dVIX = min(0,\ dVIX)$. The regressions are estimated using OLS with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix. All the variables are measured at the daily frequency. The standard errors are shown in parentheses. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 2021 and contains 3,789 observations.

	(1)	(2)
PC_{t-1}	**-0.479 (0.186)**	**-0.513 (0.187)**
PC_{t-2}	-0.138 (0.186)	-0.182 (0.187)
Sum of Coefficients of PC_{t-j}	**-0.617 (0.222)**	**-0.695 (0.201)**
$dVIX_{t-1}$	0.020 (0.057)	
$dVIX_{t-2}$	0.031 (0.057)	
$dVIX_{t-1}H_{DVIX_{t-1}}$	**-0.166 (0.053)**	
$dVIX_{t-2}H_{DVIX_{t-2}}$	-0.064 (0.057)	
POS_DVIX_{t-1}		**-0.202 (0.033)**
POS_DVIX_{t-2}		0.049 (0.034)
NEG_DVIX_{t-1}		-0.008 (0.041)
NEG_DVIX_{t-2}		**-0.094 (0.038)**

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Table 9. Regressions for Changes in the Financial Stress Index 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 (for the United States, Other Advanced Economies, and for 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. Bold text indicates statistical significance at the 5% level. The sample period is from February 24, 2006 to March 17, 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)	

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Table 10. Trading Strategy

The table reports the average excess return of a trading strategy based on the VIX put-call ratio. We first normalize the historical put-call ratio by using expanding windows. The first normalization is done at day 600 for 600 observations. On day 600, if the normalized put-call ratio (z-score) is above 0.75 (1.00, or 1.25), we sell the VIX futures. Otherwise, we do not trade. The short futures position is closed the next day. This process is then rolled forward for day 601, and the normalization is done for 601 observations, etc. The out-of-sample period is from July 17, 2008 (day 601) to March 17, 2021 (day 3789), for a total of 3190 trading days. Excess return is the return of VIX future in excess of the daily risk-free rate. The *t*-statistics shown are for the mean excess returns. Bold text indicates statistical significance at the 5% level. Annualized Sharpe ratio is the Sharpe ratio per trade multiplied by the square root of the average number of trades per year. The Low/High VIX periods are determined based on the median value of the VIX.

	Number of Trades	Mean Excess Return	*t*-statistic	Annualized Sharpe Ratio
Panel A: Threshold 0.75σ				
Total	799	**0.6459**	**3.31**	0.9291
Low VIX periods	204	0.3589	1.28	0.3610
High VIX periods	595	**0.7444**	**3.05**	0.8564
Panel B: Threshold 1.00σ				
Total	603	**0.6357**	**2.76**	0.7759
Low VIX periods	132	0.1549	0.39	0.1108
High VIX periods	471	**0.7704**	**2.82**	0.7922
Panel C: Threshold 1.25σ				
Total	444	**0.6986**	**2.64**	0.7409
Low VIX periods	96	0.6798	1.86	0.5239
High VIX periods	348	**0.7038**	**2.18**	0.6123

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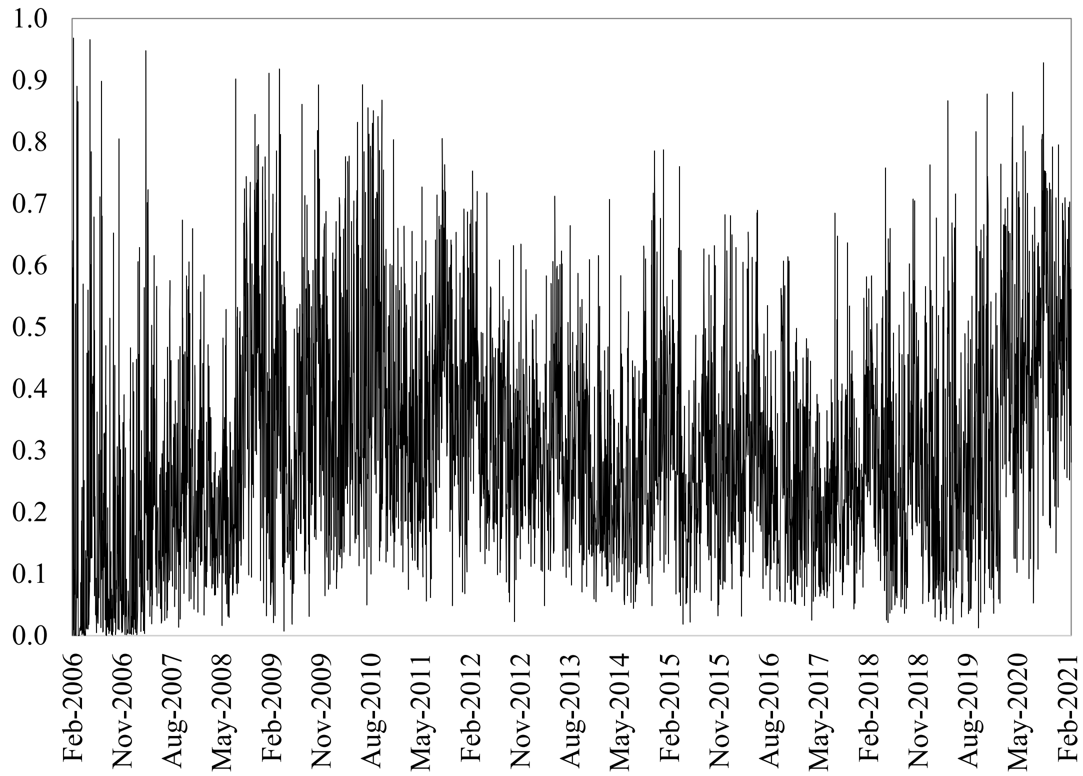
Figure 1. The Put-Call Ratio and the VIX Index

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 24, 2006 to March 17, 2021.

Panel A. The Put-Call Ratio



Panel B. The VIX Index

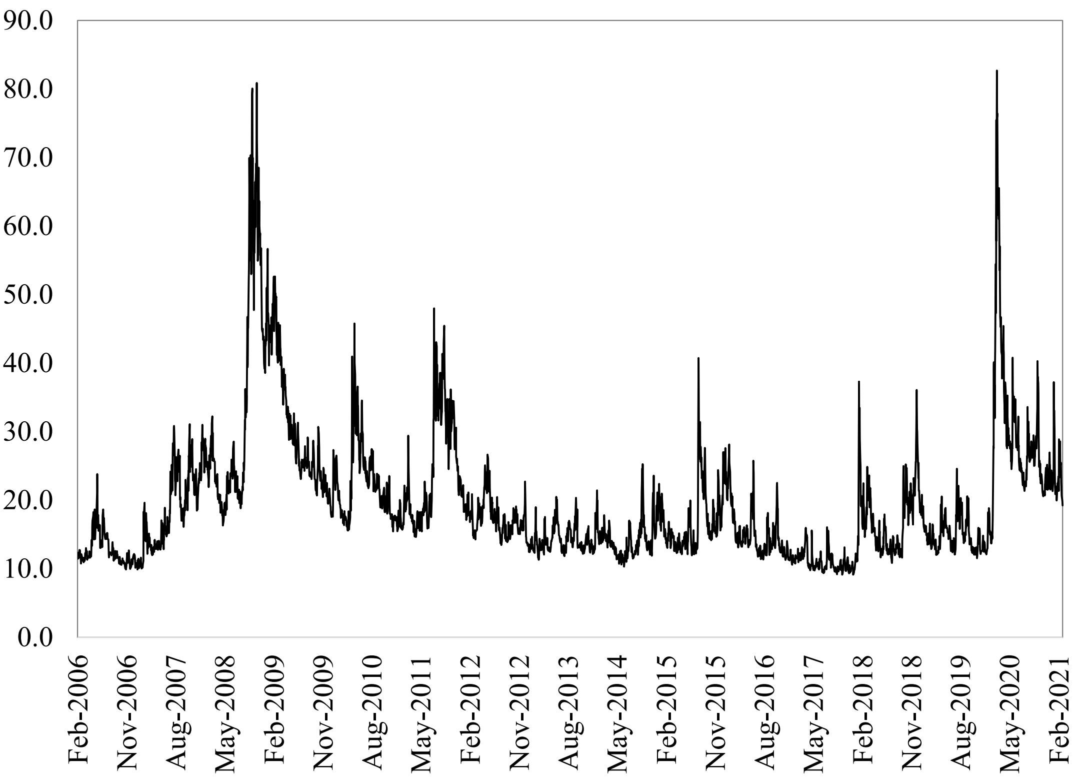


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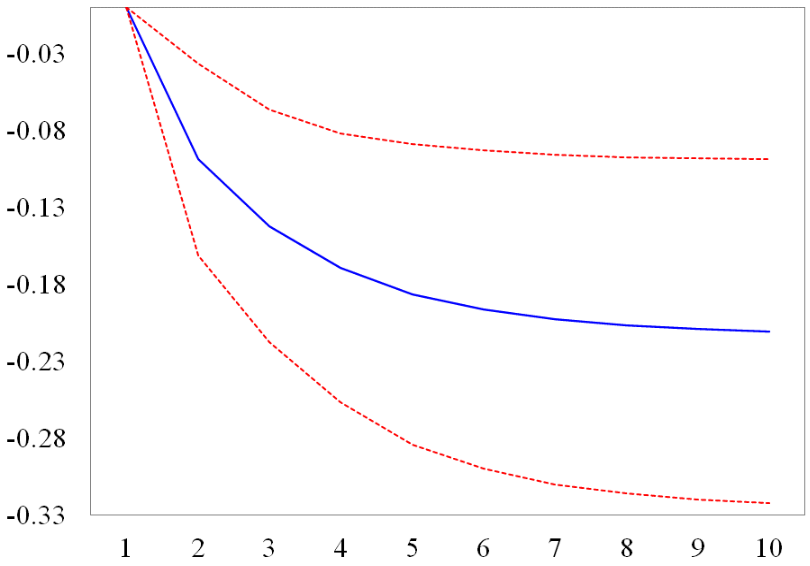
Figure 2. Impulse Response Functions

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 24, 2006 to March 17, 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

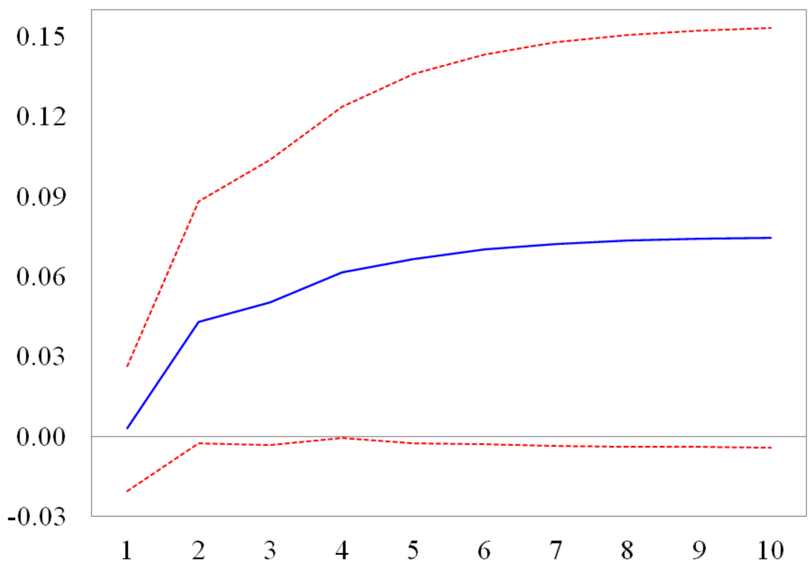


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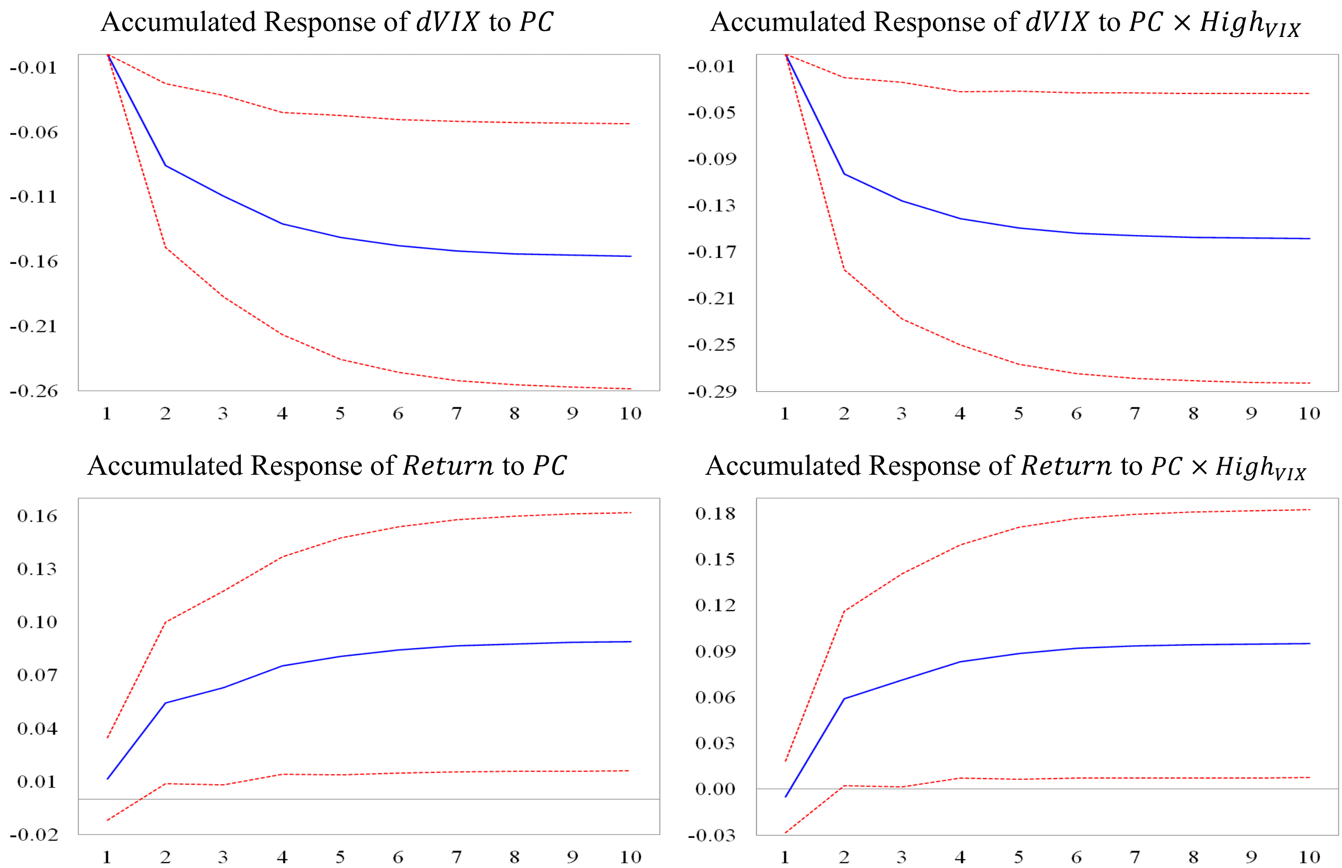
Figure 3. Impulse Response Functions
for VAR with interaction terms for high VIX periods

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 24, 2006 to March 17, 2021 and contains 3,789 observations.

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



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