Asymmetric Effects of Volatility Risk on Stock Returns: Evidence from VIX and VIX Futures

Xi Fu* Matteo Sandri Mark B. Shackleton

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Abstract

First, to separate different market conditions, this study focuses on how VIX spot (VIX), VIX futures (VXF), and their basis ($VIX - VXF$) perform different roles in asset pricing. Secondly, this study decomposes the VIX index into two parts, volatility calculated from out-of-the-money call options and volatility calculated from out-of-the-money put options. The analysis shows that out-of-the-money put options capture more useful information in predicting future stock returns.

Keywords: VIX index, VIX futures, VIX futures basis, volatility risk, asymmetric effect

JEL Classifications: G12

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* Corresponding author. Xi Fu is in Department of Accounting and Finance, Lancaster University Management School, Lancaster University, Lancaster, LA1 4YX, United Kingdom, Tel: +44(0)1524593628, Fax: +44(0)1524847321, Email: x.fu3@lancaster.ac.uk.

Matteo Sandri is in Department of Accounting and Finance, Lancaster University Management School, Lancaster University, Lancaster, United Kingdom.

Mark B. Shackleton is a Professor in Department of Accounting and Finance, Lancaster University Management School, Lancaster University, Lancaster, United Kingdom.

1. Introduction

Since the introduction of the Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966), the market risk premium, defined as the compensation required by investors to bear market risk, has been investigated. In addition to the market risk premium, various empirical studies (Bakshi and Kapadia, 2003; Arisoy, Salih and Akdeniz, 2007; Mo and Wu, 2007; Carr and Wu, 2009; Bollerslev, Tauchen and Zhou, 2009; Bollerslev, Gibson and Zhou, 2011) document the existence of a premium for bearing volatility risk; this supports the hypothesis that volatility is another important pricing factor in equity markets. Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) show that the aggregate volatility risk (measured by changes in volatility indices) is important in explaining the cross-section of returns: stocks that fall less as volatility rises have low average returns because they provide protection against downward movements in financial markets.[1]

Additionally, many empirical studies also reveal that the influence of market risk is not symmetric. For instance, Ang, Chen and Xing (2006) show the existence of a downside risk premium (approximately 6% per annum), where stocks with higher market covariance during recession periods provide higher average returns compared to those that exhibit lower covariance with the market.[2] Given that market risk has an asymmetric effect on equity returns, it is interesting to ask whether the influence of volatility risk on equity returns is also asymmetric. By using delta-hedged option portfolios, Bakshi and Kapadia (2003) provide evidence in support of an overall negative volatility risk premium. These empirical results also reveal time-variation of the volatility risk premium (i.e. the underperformance of delta-hedged strategies is greater during times of high volatility). DeLisle, Doran and Peterson (2011) use innovations in the VIX index to measure volatility risk and focus on its asymmetric effect. To be more specific, their study shows that sensitivity to VIX innovations is negatively related to stock returns when volatility is expected to increase, but it is unrelated when volatility is expected to decrease. Based on the ICAPM (Merton, 1973), Campbell (1993 and 1996) and Chen (2003) argue that an increment in aggregate volatility can be interpreted as a worsening of the investment opportunity set. More recently, Farago and Tedongap (2015) claim that investors' disappointment aversion is relevant to asset pricing theory, conjecturing that a worsening opportunity set may result either from a decrease in the market index or from an increase in the volatility index. Empirical results in their study show that these undesirable changes (decreases in market and increases in volatility indices) motivate significant premiums in the cross-section of stock returns. In order to understand the asymmetric effect due to market or volatility risks, it is important to distinguish between different cases: positive or negative market returns, and increments or reductions in the aggregate volatility, especially by using forward-looking measures of volatility.

This study first concentrates on the unconditional relationship between an asset's return and its sensitivity to volatility risk through a quintile portfolio level analysis. This study uses the VIX index itself to construct a volatility factor, i.e. innovations in the squared VIX index. In addition, this study introduces VIX index futures into asset pricing models. Thus, this study uses innovations in squares of the VIX index or VIX futures to measure changes in the volatility risk, and further tests the unconditional relationship between portfolio returns and sensitivity to volatility risk factors.

This study also focuses on the asymmetric effect of volatility risk. In order to do so, the empirical analysis follows the method used in DeLisle, Doran and Peterson (2011) and defines a dummy variable to distinguish different situations. To contribute beyond previous studies, this study defines a dummy variable based on the VIX futures *basis* (i.e. the difference between the VIX spot and VIX futures) instead of daily changes in VIX index. Daily innovations in the VIX index reflect how it changes from its level on the previous trading day. However, the VIX futures basis reflects how the spot VIX index deviates from its risk-neutral market expectation; the VIX futures basis captures more relevant ex-ante information and is better at predicting future trends in volatility than time series models. To test whether volatility risk plays the same role in explaining asset returns under different scenarios, this study investigates the relationship between an asset's returns and sensitivity to volatility risk in each market scenario.

Furthermore, this study also decomposes the aggregate volatility index into two components, volatility calculated either from out-of-the-money call options only or from out-of-the-money puts. The innovations in squares of volatility terms are used as separate volatility factors in the analysis. Such a decomposition enables us to test for an asymmetric effect of volatility risk from using ex-ante information, and to highlight whether investors treat information captured by different kinds of options in different ways.

This study contributes to previous literature in several areas. First, this study introduces VIX futures into asset pricing models. Previous literature (Ang, Hodrick, Xing and Zhang, 2006; DeLisle, Doran and Peterson, 2011; Chang, Christoffersen and Jacobs, 2013) uses the VIX index to construct a proxy for volatility risk.[3] However, the new VIX index is a model-free aggregate implied volatility index, and is a spot index. In order to replicate the VIX index, investors need to trade out-of-the-money options. However, such a replication is costly. Instead, VIX futures are tradable in derivative markets, and they reflect the market expectation of this volatility index at a future date. Few studies have used VIX futures in asset pricing and they only focus on theoretical pricing, the existence of a term structure, or causality between VIX spot and VIX futures.[4] Trading on the VIX futures provides investors with an expectation of the VIX index itself at a future expiration; so movements in the square of VIX futures reflect changes in market expectations of variance (i.e. implied volatility squared) at expiration. Rather than changes in the squared VIX spot index, introducing factors constructed from VIX futures into asset pricing models is expected to help to improve a model's ability to forecast returns through a volatility premium. Such an analysis also highlights the importance of VIX futures in asset pricing.

Secondly, this study contributes to the use of risk-neutral volatility measures in empirical tests of volatility risk premium. Historical data shows a negative relationship between the market and the volatility index. An increase in the market index is often accompanied by a decrease in the volatility index, while a downward movement of the market frequently comes together with a sharp increase in the volatility index. Additionally, such a relationship is time-varying, and is stronger during periods of financial turmoil (Campbell, Forbes, Koedijk and Kofman, 2008). In light of this, Jackwerth and Vilkov (2014) find the existence of a negative risk premium on the index-to-volatility correlation.[5] Thus, in addition to the market risk premium, volatility or variance risk premiums are commonly tested empirically.

Thirdly, this study takes an asymmetric effect of volatility risk into consideration. Whereas small increments in the market index and consequent reductions in the volatility index are consistent with investors' expectations, decreases in the market or increases in the volatility indices are perceived as shocks with negative news for investors. Separating these different cases through dummy variables enables us to analyze the role of volatility risk in asset pricing under different scenarios. Furthermore, the way to separate different scenarios used in this study is new compared to previous papers. In DeLisle, Doran and Peterson (2011), dummy variables are defined based on innovations in the VIX spot (they define dummy variables based on a lagged variable). This study separates different scenarios based on the sign of the VIX futures basis, which is an ex-ante measure. Such a definition captures information about ex-ante market conditions. Then this study investigates the effect of volatility risk in different situations.

Fourthly, this study decomposes the VIX index and distinguishes two different components of aggregate volatility. Volatility calculated by using out-of-the-money call options captures information conditional on increases in price of the underlying asset, while volatility calculated by using out-of-the-money put options captures information conditional on decreases in price of the underlying asset. By using these two components to construct separate volatility factors, this study investigates the asymmetric effect of volatility risk using ex-ante information. Such an analysis also sheds light on whether investors treat information captured by out-of-the-money call and put options, i.e. up and down market conditions, differently. If investors think one kind of option is more informative or more influential than the other, they can seek higher premiums by constructing trading strategies based on this kind of option alone. Thus, empirical results in this study give investors an indication of how to improve their trading strategies and capture premiums from their portfolios.

The rest of this study is organized as follows. Section 2 discusses details of data and methodology. Results for portfolio level analysis using VIX spot and VIX futures are presented in section 3. Section 4 documents results obtained by using two components of aggregate volatility (i.e. volatility terms calculated by using out-of-the-money call or put options). Finally, section 5 concludes.

2. Data and Methodology

2.1 Data Resources

This study focuses on the effect of aggregate volatility risk factors on individual stock returns in the US markets. Daily individual stock returns for ordinary common shares (share codes of 10, 11 and 12) are downloaded from CRSP.[6] When forming volatility factors, this study uses the VIX spot (VIX) and VIX futures (VXF), which are obtained from the CBOE official website.[7] Furthermore, in order to decompose the aggregate volatility index, this study uses data for options written on the S&P500 index (SPX), which are available from OptionMetrics. Our analysis also needs other factors, such as the market excess return (MKT), the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD). Data for these factors are all available from Kenneth French's data library.[8]

2.2 Data Description

The first part of this study separates different market scenarios based on a dummy variable defined from the VIX futures basis (i.e. periods with positive or negative VIX futures basis). The VIX futures basis is defined as the difference between VIX spot (VIX) and VIX futures (VXF). The VXF started trading on the CBOE in March 26th, 2004, however, only after October 2005, did VIX futures contracts expiring in each calendar month appear. So the sample period used in the first part of our analysis runs from October 2005 until December 2014. Figure 1 plots levels of VIX , VXF , SPX and MKT during the period from March 26th, 2004 to December 31st, 2014.[9]

[Insert Figure 1 here]

In Panel A of Figure 1, it is clear that VIX and VXF are very close, and they increase or decrease together.[10] There is a negative relationship between SPX and VIX or VXF . When the SPX increases, VIX and VXF decrease, and vice versa. This phenomenon is even stronger during the financial crisis: for instance, from the beginning of September 2008 to the end of October 2008, the SPX decreased dramatically from 1277.58 to 968.75, while the VIX (VXF) increased from 0.2199 (0.2208) to 0.5989 (0.5457). Then, in Panel B, it is clear that both VIX and VXF are good forward-looking proxies for measuring aggregate volatility of the market.[11] Levels of VIX and VXF are higher when the market becomes more volatile.

[Insert Table 1 here]

In addition, it can be easily seen that the VIX spot is less stable than its futures, VXF . The minimum value for VIX (0.0989) is slightly smaller than the minimum value for VXF (0.0995), while the maximum value for VIX (0.8086) is much larger than the maximum value for VXF (0.6795). The range of VIX is wider than that of VXF .[12] Correlations in Panel B of

Table 1 indicate that VIX and VXF are highly correlated (with the correlation of 0.9846). There is a negative relationship between the market excess returns and the aggregate volatility risk.

By using ex-ante information, the second part of this study investigates whether volatility risk has an asymmetric effect. This part also answers whether call or put options capture different information concerning future market conditions. This part replicates the VIX index and decomposes it into two components, i.e. volatility calculated from out-of-the-money call options (VXC) or volatility calculated from out-of-the-money put options (VXP).[13] In the second part, the sample period covers the period from January 1996 to September 2014.[14]

[Insert Figure 2 here]

In Panel A and Panel B of Figure 2, VXC and VXP have similar trends to VIX. VXC and VXP are both negatively related to SPX (they are both risk neutral parts of the aggregate volatility).[15] Panel C of Table 1 presents summary statistics of VIX, VXC and VXP. It is clear that VXP is always higher than VXC. Then, in Panel D, both VXC and VXP are highly correlated with VIX (with correlation of 0.9611 and 0.9840, respectively). Meanwhile, VXC and VXP are both negatively correlated with the market.

2.3 Methodology

In order to investigate the relationship between asset returns and sensitivities to aggregate volatility risk, this study uses a quintile portfolio level analysis among individual stock returns. Such an analysis enables us to test whether stocks with more negative correlations between returns and volatility changes outperform those with less negative correlations.

To test whether there is an asymmetric effect of volatility risk on asset returns, this study uses two different methods. First, this study separates different market conditions by defining a dummy variable and analyzes the relationship under two different situations. Secondly, this study decomposes VIX into two parts and uses forward-looking information to capture future market conditions. Then, this study examines whether the asymmetric effect of volatility risk exists if ex-ante information is used. Details about methodologies are discussed in following subsections.

2.3.1 Volatility Factor Construction

First, it should be highlighted that this study focuses on market-based pricing factors. That is, this study concentrates on pricing factors constructed at aggregate level, and uses pricing factors which are common for all individual assets in the market rather than firm-specific factors.

From existing literature, in addition to systematic market risk captured by beta, coskewness (or systematic skewness) is also an important pricing factor in asset pricing (Kraus and Litzenberger, 1976; Scott and Horvath, 1980; Sears and Wei, 1985 and 1988; Fang and Lai, 1997; Harvey and Siddique, 2000). Coskewness refers to how an individual asset's return co-moves with the second moment of the market return.[16] By using historical data, previous papers calculate ex-post estimates of systematic market risk and coskewness risk, and document that coskewness helps to explain asset returns.

Rather than using historical data, recent studies use option-implied information to measure the risk-neutral expected second moment of the market return, and further calculate coskewness for individual stocks. In empirical studies, due to potential non-stationarity issue, the first difference of the volatility index, instead of the level of the volatility index, is commonly used to measure the volatility risk.[17] For example, in order to measure the second moment of market returns, Ang, Hodrick, Xing and Zhang (2006) use daily innovations in the old volatility index (VXO), and Chang, Christoffersen and Jacobs (2013) use daily changes in the VIX index (the replacement for VXO). Rather than using change in aggregate volatility, this study uses changes in aggregate variance (i.e. changes in the square of volatility).

The first part of this study separates different market scenarios by defining a dummy variable and investigates the asymmetric effect of aggregate volatility risk. This part uses $\Delta\left(VIX^{2}\right)$ and $\Delta\left(VXF^{2}\right)$ as factors that capture variance changes.[18] Then, the second part of this study uses forward-looking information to check an asymmetric effect, and concentrates on whether out-of-the-money call or put options capture different information about future return prediction. This study decomposes the VIX index into two parts and then uses innovations in each variance term (i.e. $\Delta\left(VXC^{2}\right)$ and $\Delta\left(VXP^{2}\right)$) as risk factors. The construction of $\Delta\left(VXC^{2}\right)$ and $\Delta\left(VXP^{2}\right)$ and the relationship between VXC, VXP and VIX are discussed in subsection 2.3.4 in detail.

2.3.2 Quintile Portfolio Level Analysis

In order to test if there is a significant relationship between an asset's return and its sensitivity to volatility factors, this study uses a quintile portfolio level analysis for individual stocks. To be more specific, this study first estimates the following time-series regressions using daily data for each individual stock i:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VF} VF_t + \varepsilon_{i,t} \tag{1}$$

$$VF \in \left[\Delta\left(VIX^{2}\right), \Delta\left(VXF^{2}\right), \Delta\left(VXC^{2}\right), \Delta\left(VXP^{2}\right)\right]$$

where $r_{i,t}$ stands for daily returns on each individual stock, $r_{f,t}$ is the daily risk-free rate, MKT denotes daily market excess returns, and VF is one of the volatility risk factors (i.e. $\Delta\left(VIX^{2}\right)$, $\Delta\left(VXF^{2}\right)$, $\Delta\left(VXC^{2}\right)$ or $\Delta\left(VXP^{2}\right)$).[19]

Since the first part of this study compares VIX to VXF, the volatility factors (VF_t) are defined in different ways: $\Delta\left(VIX^{2}\right)$ (daily changes in square of VIX spot), and $\Delta\left(VXF^{2}\right)$ (daily changes in square of VIX futures). Since the final settlement date of VIX futures contracts is normally the third Wednesday in each month, the period used for the above regression model (equation (1)) starts from the next trading day with data available for the VIX future contracts expiring two months later and ends on the final settlement date of the corresponding VIX futures contract (i.e. around 40 observations for each time-series regression). For example, the third Wednesday in January 2008 is January 16th, 2008, and the third Wednesday in March 2008 is March 19th, 2008. To run a regression model during the period from January 2008 to March 2008, daily settlement prices of VIX futures contracts expiring in March 2008 are used. Such contracts started trading from January 17th, 2008. In order to form quintile portfolios in March 2008, the empirical analysis uses the data of VIX futures contracts expiring in March 2008, during the period from January 17th, 2008 to March 19th, 2008.

The second part of our analysis distinguishes information captured by out-of-the-money call and put options. Two components of VIX squared, $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$, are used to represent VF, the volatility factor. To be consistent with the first part of this study, the second part estimates equation (1) at a firm level and at the end of each calendar month by using previous 2-month daily data. Then, to avoid data overlaps for time-series regressions in different calendar months, this part also uses previous 1-month daily data for regression model presented in equation (1) at the end of each month.

After estimating equation (1) and obtaining beta coefficients on MKT and VF (β_i^{MKT} and β_i^{VF}) for each individual stock, among all stocks available, equally-weighted or value-weighted quintile portfolios are formed based on β_i^{VF}.[20] Portfolio 1 consists of the 20% of stocks with the lowest β_i^{VF}, while portfolio 5 consists of the 20% of stocks with the highest β_i^{VF}; that is, stocks in portfolio 1 have the lowest sensitivity to aggregate volatility risk, while stocks in portfolio 5 have the highest sensitivity. The “5-1” long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The first part of this study assumes that investors hold portfolios for 10-day, 20-day and 30-day horizons after construction, and calculates the return on each portfolio during these holding periods.[21] The second part of this study calculates portfolio returns in the following one calendar month. The empirical analysis calculates whether the "5-1" long-short portfolio has a significant non-zero mean return or Jensen's alpha with respect to the market-factor model, the Fama-French three-factor model, or the Carhart four-factor model (i.e. risk-adjusted return after controlling for MKT, SMB, HML and UMD).[22] If the "5-1" long-short portfolio has a significant and negative mean return, overall asset sensitivity to volatility factors is negatively related to returns.

However, if the realization of MKT or VF is close to zero, it is difficult to find significant non-zero average returns on any portfolio. Thus, by distinguishing periods with different market conditions, it is possible to detect statistically significant mean returns on the "5-1" long-short portfolio. Also, such an analysis sheds light on whether volatility risk plays different roles under different market conditions.

2.3.3 Asymmetric Quintile Portfolio Level Analysis

By using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ to capture volatility risk, although previous models (equation (1)) detail relationships between asset returns and sensitivities to volatility factors, these models ignore asymmetric effects of volatility risk. Financial markets may react differently to positive or negative volatility shocks, thus, this study incorporates an asymmetric effect of volatility risk.

In order to separate different cases, this study follows the method used in DeLisle, Doran and Peterson (2011) and includes dummy variables into the time-series regression model. DeLisle, Doran and Peterson (2011) define dummy variables based on daily innovations in

VIX. However, ΔVIX is a lagged variable and it reflects how aggregate volatility changes from its level on the previous trading day. It does not capture expectations in aggregate volatility. So instead of using the innovation in VIX index or VIX futures, this study uses the difference between VIX and VXF (i.e. the VIX futures basis), $VIX - VXF$.[23] Both VIX and VXF are forward looking and capture information about aggregate volatility levels in the near future but VXF represents an expectation as to the level of volatility at future expiry.

[Insert Figure 3 here]

If VIX is lower than VXF (i.e. a negative futures basis), it indicates that the current aggregate volatility index is below what is expected by the market in the future. Risk-averse investors would prefer such conditions since they present less risk. For example, as shown in Panel A of Figure 3, during the period from March 22nd 2007 to May 16th 2007, the SPX increased from 1434.54 to 1514.14. During this period, in 28 out of 39 trading days, VXF was higher than VIX. If VIX is higher than VXF (i.e. positive futures basis), it means that the current aggregate volatility index is higher than its market expectation. In this case, the current period is relatively more volatile for investors compared to future prospects. In Panel B of Figure 3, it is clear that VIX was higher than VXF in 31 out of 44 trading days during the period from August 21st 2008 to October 22nd 2008. During this highly volatile period, SPX dropped sharply from 1277.72 to 896.78.

Thus, a negative futures basis captures attractiveness to investors, while a positive futures basis indicates bad current conditions. In this study, the dummy variable D_t is defined to be 1 if the futures basis is positive and 0 otherwise. The regression model incorporating an asymmetric effect is specified as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VF} VF_t + \beta_i^{D} D_t VF_t + \varepsilon_{i,t} \quad (2)$$

where VF is either $\Delta\left(VIX^{2}\right)$ or $\Delta\left(VXF^{2}\right)$. After running the regression shown in equation (2) by using previous approximately 40-day daily data points at the final settlement date in each month, quintile portfolios and "5-1" long-short portfolios are formed separately in two different situations ($D_t = 0$ and $D_t = 1$).[24] In other words, this study forms portfolios on β_i^{VF} when $D_t = 0$ (i.e. only considering information about the volatility risk during the period with negative VIX futures basis), whereas, this study forms portfolios on $\left(\beta_i^{VF} + \beta_i^{D}\right)$ when $D_t = 1$ (i.e. only considering information about volatility risk during period with positive VIX futures basis). Furthermore, for the "5-1" long-short portfolios, Jensen's alphas with respect to the market-factor model, the Fama-French three-factor model or the Carhart four-factor model are calculated to see whether, in different scenarios, the relationships between an asset's return and sensitivity to volatility factors are significant even after taking MKT, SMB, HML and UMD factors into consideration. This analysis enables us to verify whether the asymmetric effect of volatility risk on asset returns is determined by existing factors.

2.3.4 Decomposition of the VIX Index

The VIX index measures the market's expectation of 30-day aggregate volatility implied by both out-of-the-money call and put options of S&P500 index. Nevertheless, out-of-the-money call and put options reflect information captured by different parts of the option cross section.

[Insert Figure 4 here]

Figure 4 indicates that out-of-the-money put options capture information conditional on future stock prices being lower than stock index forward, while out-of-the-money call options capture information conditional on future stock prices being higher. This study separates different market conditions based on ex-ante information. Information contained in out-of-the-money put options reflects state prices from bad news conditions, while information contained in out-of-the-money call options reflects state prices from good news conditions. Decomposing VIX^2 into two parts (i.e. VXC^2 and VXP^2) enables us to test whether information captured by different options affects asset returns in different ways and to test the asymmetric effect of volatility risk using ex-ante information. If information captured by one kind of option is more important and relevant to asset returns, investors could improve their trading strategies by only incorporating such information and avoid bearing unnecessary risk. Details about the decomposition are presented as follows.

According to the VIX Whitepaper from CBOE's website[25], the "model-free" variance is calculated using the following formula:

$$\sigma_T^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{rT} Q(K_i,T) - \frac{1}{T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{3}$$

where T refers to time to expiration, $F_{0,T}$ is the forward index level derived from index option prices, K_0 is the first strike below the forward index level, K_i is the strike price of the ith out-of-the-money option, $Q(K_i,T)$ is the midpoint of the bid-ask spread for each out-of-the-money call or put option with strike price of K_i and time-to-expiry of T (i.e. $Q(K_i,T) = \min(C(K_i,T), P(K_i,T))$ where $C(K_i,T)$ is the midpoint of the bid-ask spread for out-of-the-money call option, and $P(K_i,T)$ is the midpoint of the bid-ask spread for out-of-the-money put option). This study decomposes σ_T^2 into $\sigma_{C,T}^2$ and $\sigma_{P,T}^2$, which separates information extracted from out-of-the-money call and put options, respectively. Variances $\sigma_{C,T}^2$ and $\sigma_{P,T}^2$ can be written as:

$$\sigma_{C,T}^2 = \frac{2}{T}\sum_i^{K_i \geq K_0} \frac{\Delta K_i}{K_i^2} e^{rT} C(K_i,T) - \frac{1}{2T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{4}$$

$$\sigma_{P,T}^2 = \frac{2}{T}\sum_i^{K_i \leq K_0} \frac{\Delta K_i}{K_i^2} e^{rT} P(K_i,T) - \frac{1}{2T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{5}$$

The variance $\sigma^2_{C,T}$ is calculated by using only out-of-the-money call options with time-to-expiration of T, and $\sigma^2_{P,T}$ is calculated by using only out-of-the-money put options with time-to-expiration of T. Then, VXC^2 and VXP^2 are linear interpolation of near-term (T_1) and next term (T_2) variances.

$$VXC^2 = \left\{ T_1 \sigma^2_{C,T_1} \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}} \right] + T_2 \sigma^2_{C,T_2} \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}} \right] \right\} \times \frac{N_{365}}{N_{30}} \tag{6}$$

$$VXP^2 = \left\{ T_1 \sigma^2_{P,T_1} \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}} \right] + T_2 \sigma^2_{P,T_2} \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}} \right] \right\} \times \frac{N_{365}}{N_{30}} \tag{7}$$

Hence, VXC^2 and VXP^2 sum up to VIX^2. After decomposing VIX into two components (VXC and VXP), this study constructs VF in equation (1) by using VXC or VXP (i.e. $\Delta\left(VXC^2\right)$ or $\Delta\left(VXP^2\right)$).

3. Results for Portfolio Level Analysis Using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$

The results obtained by using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ are presented in this section in detail. First of all, this section shows results for portfolio level analysis obtained by using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ without incorporating an asymmetric effect. Then, this section incorporates the asymmetric effect into empirical analysis by including a dummy variable and checks whether volatility risk plays a significant role in explaining asset returns in different market conditions.

3.1 Results for Portfolio Level Analysis Using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$

First of all, results for quintile portfolio level analysis by using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ without incorporating asymmetric effects are presented. This subsection first estimates equation (1) on the final settlement date in each calendar month by using previous two-month daily data on each individual stock.[26] Then, quintile portfolios are constructed based on the beta coefficients of volatility factors (i.e. β_i^{VF}). The "5-1" long-short portfolio is formed by holding a long position in quintile portfolio 5 and a short position in quintile portfolio 1. The corresponding results obtained when using $\Delta\left(VIX^2\right)$ are found in Table 2.

[Insert Table 2 here]

Panel A and Panel B of Table 2 present results for equally-weighted portfolios and value-weighted portfolios, respectively. In these two panels, no matter what holding period horizon is used after portfolio formation, there is no significant relationship between an asset's sensitivity to $\Delta\left(VIX^2\right)$ and its return.

[Insert Table 3 here]

As well as using $\Delta\left(VIX^2\right)$, our analysis uses $\Delta\left(VXF^2\right)$ as the volatility factor. The results are shown in Table 3. Two panels of Table 3 show that there is no significant relationship between an asset's sensitivity to $\Delta\left(VXF^2\right)$ and its return.

The insignificant relationship between an asset's sensitivity to volatility factors and its return could be due to the fact that the sample period of this study is from October 2005 to December 2014. The sample period is relatively short but it covers the recent financial crisis, where asset markets were relatively volatile and dynamic. Insignificant relationships between quintile portfolio returns and sensitivity to $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ may be due to crash factors.

3.2 Results for Asymmetric Portfolio Level Analysis Using $\Delta\left(VIX^2\right)$

Without separating market scenarios, the previous subsection does not detect any significant relationship between an asset's sensitivity to volatility risk and its return. So, this subsection includes a dummy variable in the time-series regression model to separate different market conditions (see equation (2)).[27] Such an analysis enables us to investigate the asymmetric effect of the volatility risk. First, this subsection focuses on the asymmetric effect of $\Delta\left(VIX^2\right)$; the corresponding results are presented in Table 4.

[Insert Table 4 here]

The results show the asymmetric effect of aggregate volatility risk reflected by $\Delta\left(VIX^2\right)$. From Panel A and Panel C, investors do not earn premiums from the "5-1" long-short portfolio if they only take into account the information during the periods with negative futures basis (i.e. $D_t = 0$). From Panel B and Panel D of Table 4, it is shown that, if investors construct their trading strategies based on information during the period with positive futures basis, they lose money by holding a long position in portfolios with the highest beta on $\Delta\left(VIX^2\right)$ and short selling portfolios with the lowest beta on $\Delta\left(VIX^2\right)$ for different investment horizons. If investors construct an equally-weighted "5-1" long-short portfolio and hold the portfolio for the following 10 trading days, Jensen's alpha with respect to the Carhart four-factor model (controlling for MKT, SMB, HML or UMD) is -0.22% (with a p-value of 0.0256). If investors hold the "5-1" long-short portfolio for a longer period, 30 trading-day, the risk-adjusted return with respect to Carhart four-factor model becomes -0.39% (with a p-value of 0.0544). For the value-weighted "5-1" long-short portfolio, the risk-adjusted return with respect to Carhart four-factor model is -0.71% (with a p-value of 0.0360) for a 20 trading-day period, and is -0.96% (with a p-value of 0.0093) for a 30 trading-day period.

The asymmetric effect of the volatility risk constructed by using VIX is also documented in DeLisle, Doran and Peterson (2011); findings in this subsection are consistent with their paper.

3.3 Results for Asymmetric Portfolio Level Analysis Using $\Delta\left(VXF^2\right)$

After confirming the existence of the asymmetric effect of volatility risk by using VIX, this subsection investigates whether the traded derivative, VIX index futures (VXF), plays a similar role in separating the asymmetric effect of the volatility risk. Instead of using $\Delta\left(VIX^2\right)$, this subsection uses $\Delta\left(VXF^2\right)$ as a proxy for the volatility risk in the portfolio level analysis with the asymmetric effect incorporated. Table 5 shows corresponding results.

[Insert Table 5 here]

In Panels A and C of Table 5, when only taking into consideration the information during the period with negative futures basis, there is no significant relationship between a stock's sensitivity to $\Delta\left(VXF^2\right)$ and quintile portfolio return. However, from Panels B and D, it is easy to find that, under the assumption of a 30-day holding period, there is a significant and negative relationship between an asset's sensitivity to $\Delta\left(VXF^2\right)$ and its return considering the information during the period with positive futures basis. For example, under the assumption of a 30 trading-day holding period after portfolio formation, for the equally-weighted "5-1" long-short portfolio, the risk-adjusted mean return with respect to Carhart four-factor model is -0.35% (with a p-value of 0.0637); for the value-weighted "5-1" long-short portfolio, the risk-adjusted mean return with respect to Carhart four-factor model is -0.85% (with a p-values of 0.0461).

Thus, the asymmetric effect of the volatility risk still exists if $\Delta\left(VXF^2\right)$ is used to measure volatility risk. When only considering information about volatility risk in the period with positive futures basis (i.e. fearful markets), there is a negative relationship between an asset's return and its sensitivity to $\Delta\left(VXF^2\right)$. However, such a relationship is insignificant when only considering information about volatility risk in the period with negative futures basis (i.e. calm markets).

3.4 Discussions for Asymmetric Portfolio Analysis Using $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$

From the above analysis, it is obvious that sensitivity to $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ is significantly and negatively correlated with quintile portfolio return when incorporating an asymmetric effect of the volatility risk into the empirical analysis (Panels B and D in Tables 4 and 5). During periods with positive futures basis, the market is relatively more volatile, and the return on the market portfolio is negative. If individual stock returns are highly correlated with volatility during such periods, investors will take into consideration the correlation between stock returns and volatility risk, and returns on these stocks will be lower over a short horizon. However, if stock returns are correlated with the volatility risk in clam markets, investors in the market will ignore such correlations and future stock returns will not be affected.

Furthermore, profits from holding a long position in portfolio 1 and a short position in portfolio 5 constructed based on $\left(\beta_i^{\Delta\left(VXF^2\right)} + \beta_i^D\right)$ when $D_t = 1$ (around 0.35% for equally-weighted portfolio and around 0.85% for value-weighted portfolio for a 30-day holding period) are comparable with those obtained from holding a long position in portfolio 1 and a short position in portfolio 5 based on $\left(\beta_i^{\Delta\left(VIX^2\right)} + \beta_i^D\right)$ when $D_t = 1$ (around 0.40% for equally-weighted portfolio and around 0.95% for value-weighted portfolio for a 30-day holding period). The asymmetric effect found from using $\Delta\left(VXF^2\right)$ is also significant. So, from the comparison, this study confirms the importance of VXF in stock pricing and returns.

4. Results for Portfolio Level Analysis Using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$

The full VIX index contains information captured by both out-of-the-money call and put options. This section separates information captured by each kind of options (i.e. decomposes VIX^2 into VXC^2 and VXP^2) and investigates the asymmetric effect of volatility risk ($\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$) by using ex-ante information.

4.1 Results for Quintile Portfolio Level Analysis

At the end of each calendar month, this subsection regresses an individual asset's return on market excess return (MKT) and volatility risk factors ($\Delta\left(VIX^2\right)$, $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$) by using previous 2-month daily data (shown in equation (1)) during the period from January 1996 to August 2014.[28] Then, this subsection constructs quintile portfolios based on factor loadings of volatility risk factors ($\beta_i^{\Delta\left(VIX^2\right)}$, $\beta_i^{\Delta\left(VXC^2\right)}$ and $\beta_i^{\Delta\left(VXP^2\right)}$) in the following calendar month and uses a quintile portfolio level analysis to clarify the relationship between an asset's sensitivity to volatility risk factors and its return.

[*Insert Table 6 here*]

From column 1 to column 4 of Table 6, it is obvious that, by using $\Delta\left(VIX^2\right)$ as a proxy for aggregate volatility risk, there is a significant and negative relationship between quintile portfolio returns and sensitivity to volatility risk. After controlling for MKT , SMB , HML and UMD, the average return on equally-weighted "5-1" long-short portfolio is -0.37% (with a p-value of 0.0345).

The remaining eight columns of Table 6 give us indications of the negative drivers between an asset's return and its sensitivity to volatility risk. From columns 5 to 8, if $\Delta\left(VXC^2\right)$

is used as a proxy for aggregate volatility risk, there is no evidence that the "5-1" long-short portfolio has significant and non-zero mean return.

However, if quintile portfolios are formed based on factor loading on $\Delta\left(VXP^2\right)$, there is a significant and negative relationship between an asset's return and its sensitivity to $\Delta\left(VXP^2\right)$. To be more specific, by using the equally-weighted scheme, the mean return on the "5-1" long-short portfolio is -0.23% per month (with a p-value of 0.0796). After controlling for commonly-used pricing factors, Jensen's alpha with respect to the Carhart four-factor model is -0.37% per month (with a p-value of 0.0087) for equally-weighted "5-1" long-short portfolio, and it is -0.58% per month (with a p-value of 0.0739) for value-weighted "5-1" long-short portfolio.

In order to construct quintile portfolios, prior analysis uses previous 2-month daily data for time-series regressions. Thus, there is some data overlap for time-series regressions in different calendar months. In order to avoid this issue, this subsection next uses previous 1-month daily data for regression model presented in equation (1).[29]

[*Insert Table 7 here*]

Table 7 documents similar results to those shown in Table 6. If $\Delta\left(VIX^2\right)$ is used to measure the volatility risk, after controlling for common-used pricing factors, there is a significant and negative relationship between an asset's return and its sensitivity to $\Delta\left(VIX^2\right)$ (column 1 to column 4). The Jensen's alpha with respect to Carhart four-factor model is -0.37% (with a p-value of 0.0480) for equally-weighted "5-1" long-short portfolio.

The results obtained by using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ in Table 7 confirm that out-of-the-money put options drive the negative relationship between an asset's return and its sensitivity to volatility risk. To be more specific, if $\Delta\left(VXC^2\right)$ is used to measure volatility risk, there is no significant mean return or risk-adjust return on "5-1" long-short portfolios (columns 5 to 8).

Nevertheless, if $\Delta\left(VXP^2\right)$ is used to measure volatility risk, the average return on equally-weighted "5-1" long-short portfolio is -0.31% (with a p-value of 0.0544). After controlling for MKT, SMB, HML or UMD, greater significance and more negative premiums are obtained from the equally-weighted "5-1" long-short portfolio (-0.34% with a p-value of 0.0263 for Jensen's alpha with respect to the market-factor model, -0.37% with a p-value of 0.0237 for Jensen's alpha with respect to the Fama-French three-factor model, and -0.44% with a p-value of 0.0102 with respect to the Carhart four-factor model). By switching to a value-weighted scheme, the average return and Jensen's alpha on the "5-1" long-short portfolio become more negative. The average return without controlling factors on the value-weighted "5-1" long-short portfolio is -0.72% per month (with a p-value of 0.0173). Controlling for common-used pricing factors makes the Jensen's alphas more negative. For example, the risk-adjusted return with respect to Carhart four-factor model on the "5-1" long-short portfolio is -1.00% per month (with a p-value of 0.0020).

In summary, there is a significant and negative relationship between quintile portfolio return and sensitivity to volatility risk factors constructed from VIX. However, if separating the information captured by out-of-the-money call and put options, the negative relationship between quintile portfolio return and sensitivity to volatility risk becomes more statistically significant when using out-of-the-money put options only (i.e. $\Delta\left(VXP^2\right)$). When using $\Delta\left(VXC^2\right)$ to measure the volatility risk, there is no significant and negative relationship between portfolio return and sensitivity to volatility risk.[30]

4.2 Discussions for Asymmetric Portfolio Analysis Using Ex-Ante Information

As discussed in section 3, there is no evidence of a negative relationship between an asset's return and its sensitivity to volatility risk during the period from October 2005 to December 2014. This could be due to the fact that the market is under stress during the relatively short sample period used in section 3. In subsection 4.1, the sample period is longer, from January 1996 to September 2014. During this period, this study provides evidence on the negative relationship between an asset's return and its sensitivity to aggregate volatility risk when using $\Delta\left(VIX^2\right)$ as a proxy.

The comparison between results obtained by using $\Delta\left(VXC^2\right)$ and those results obtained from $\Delta\left(VXP^2\right)$ indicates that out-of-the-money put options capture more relevant information about future asset returns. Different results obtained from using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ also reflect the asymmetric effect of aggregate volatility risk. Out-of-the-money put options capture information about the potential future market with downward movements in market index and upward movements in aggregate volatility, while out-of-the-money call options capture information about the potential future market with upward movements in market index and downward movements in aggregate volatility. Thus, information captured by put options represents negative shocks for investors, while information captured by call options is consistent with investors' positive news. Results discussed in subsection 4.1 provide evidence of this asymmetric effect of aggregate volatility risk obtained by using forward-looking information. Holding a long position in portfolio 1 and a short position in portfolio 5 constructed on put options brings more statistically significant and higher premiums than the strategy using the VIX index does.

Furthermore, if investors use previous 1-month daily data for portfolio construction rather than use previous 2-month daily data, the average return and Jensen's alphas on arbitrage portfolios are more statistically significant. This indicates that more immediate data capture relevant information about future market conditions.

5. Conclusions

From the analysis presented previously, during the period from October 2005 to December 2014, it is difficult to find any unconditional significant relationship between an asset's sensitivity to volatility risk and its return by using innovations in square of VIX index or VIX futures ($\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$) as a proxy for the volatility risk. This could be due to the fact that the sample period covers the recent financial crisis; during the sample period, asset markets were more stressed. Furthermore, the average return on the market portfolio and the average volatility change are close to zero. So, it is difficult to detect an unconditional relationship between an asset's sensitivity to volatility risk and its return.

However, this study tests whether volatility risk plays different roles in different market conditions. This study uses a dummy variable defined on the VIX futures basis to distinguish different expectations. The empirical results provide evidence supporting the asymmetric effect of volatility risk on asset returns. When only taking into consideration the information during the period with positive VIX futures basis (i.e. period with VIX spot higher than VIX futures), stocks with higher sensitivities to volatility risk have significantly lower returns than those with lower sensitivities to volatility risk. That is, an asset's return is significantly and negatively related to its sensitivity to volatility risk measured by $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ but only if quintile portfolios are formed on information during periods with positive VIX futures basis.

Finally, this study decomposes the VIX index into two components. One component is the volatility calculated from out-of-the-money call options (VXC), and the other component is the volatility calculated from out-of-the-money put options (VXP). Such a decomposition enables us to test if information captured by one type of option is more important to investors in verifying the existence of the asymmetric effect by using ex-ante information. Such an analysis reveals that the asymmetric negative relationship between an asset's sensitivity to volatility risk and its return is more significant when using $\Delta\left(VXP^2\right)$. Information captured by out-of-the-money put options is the main driver of the negative relationship between asset return and sensitivity to aggregate volatility risk. Put options contain more useful information about negative news in future market conditions. Such findings are expected to give indications to investors about how to design their trading strategies to capture premiums.

Reference

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. Review of Financial Studies, 19, 1191-1239.

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. Journal of Finance, 61, 259-299.

Arisoy, Y. E., Salih, A., & Akdeniz, L. (2007). Is volatility risk priced in the securities market? Evidence from S&P 500 index options. Journal of Futures Markets, 27, 617-642.

Bakshi, G., & Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. Review of Financial Studies, 16, 527-566.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies, 16, 101-143.

Bawa, V. S., & Lindenberg, E. B. (1977). Capital market equilibrium in a mean-lower partial moment framework. Journal of Financial Economics, 5, 189-200.

Blair, B. J., Poon, S., & Taylor, S. J. (2001). Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns. Journal of Econometrics, 105, 5-26.

Bollerslev, T., Gibson, M., & Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. Journal of Econometrics, 160, 235-245.

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premium. Review of Financial Studies, 22, 4463-4492.

Campbell, J. Y. (1993). Intertemporal asset pricing without consumption data. American Economic Review, 83, 487-512.

Campbell, J. Y. (1996). Understanding risk and return. Journal of Political Economy, 104, 298-345.

Campbell, R. A. J., Forbes, C. S., Koedijk, K. G., & Kofman, P. (2008). Increasing correlations or just fat tails? Journal of Empirical Finance, 15, 287-309.

Carr, P., & Wu, L. (2009). Variance risk premiums. Review of Financial Studies, 22, 1311-1341.

Chang, B. Y., Christoffersen, P., & Jacobs, K. (2013). Market skewness risk and the cross-section of stock returns. Journal of Financial Economics, 107, 46-68.

Chen, J. (2003). Intertemporal CAPM and the cross-section of stock returns. Paper presented at the 29th Annual Meeting of European Finance Association, Berlin, Germany.

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

DeLisle, R. J., Doran, J. S., & Peterson, D. R. (2011). Asymmetric pricing of implied systematic volatility in the cross-section of expected returns. Journal of Futures Markets, 31, 34-54.

Fang, H., & Lai, T. Y. (1997). Co-kurtosis and capital asset pricing. Financial Review, 32, 293-307.

Farago, A., & Tedongap, R. (2015). Downside risks and the cross-section of asset returns. Working Paper.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. Journal of Finance, 55, 1263-1295.

Huskaj, B., & Nossman, M. (2012). A term structure model for VIX futures. Journal of Futures Markets, 33, 421-442.

Jackwerth, J. C., & Vilkov, G. (2014). Asymmetric volatility risk: Evidence from option markets. Working Paper.

Karagiannis, S. (2014). An investigation of the lead-lag relationship between the VIX index and the VIX futures on the S&P500. Journal of Science, Innovation and New Technology, 1, 43-56.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. Journal of Finance, 31, 1085-1100.

Lin, Y. (2007). Pricing futures: Evidence from integrated physical and risk neutral probability measures. Journal of Futures Markets, 27, 1175-1217.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics, 47, 13-37.

Lu, Z., & Zhu, Y. (2009). Volatility components: The term structure dynamics of VIX futures. Journal of Futures Markets, 30, 230-256.

Merton, R. C. (1973). An intertemporal asset pricing model. Econometrica, 41, 867-887.

Mo, H., & Wu, L. (2007). International capital asset pricing: Evidence from options. Journal of Empirical Finance, 14, 465-498.

Mossin, J. (1966). Equilibrium in a capital asset market. Econometrica, 34, 768-783.

Muzzioli, S. (2011). The skew pattern of implied volatility in the DAX index options market. Frontiers in Finance and Economics, 8, 43-68.

Poon, S., & Granger, C. (2005). Practical issues in forecasting volatility. Financial Analysis Journal, 61, 45-56.

Scott, R. C., & Horvath, P. A. (1980). On the direction of preference for moments of higher order than the variance. Journal of Finance, 35, 915-919.

Sears, S., & Wei, K.C. J. (1985). Asset pricing, higher moments and the market risk premium: A note. Journal of Finance, 40, 1251-1253.

Sears, S., & Wei, K.C. J. (1988). The structure of skewness preferences in asset pricing models with higher moments: An empirical test. Financial Review, 23, 25-38.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19, 425-442.

Shu, J., & Zhang, J. E. (2012). Causality in the VIX futures market. Journal of Futures Markets, 32, 24-46.

Taylor, S. J., Yadav, P. K., & Zhang, Y. (2010). The information content of implied volatilities and model-free volatility expectations: Evidence from options written on individual stocks. Journal of Banking and Finance, 34, 871-881.

Zhang, J. E., and Zhu, Y. (2006). VIX futures. Journal of Futures Markets, 26, 521-531.

[1] In the previous literature, historical data are used to calculate the aggregate volatility. However, if economic conditions change, historical data no longer reflect the current and future expectations. Since it is known that option prices incorporate market expectations, the introduction of forward-looking information into asset pricing models becomes extremely valuable. In fact, information, such as volatility, incorporated into options reflects market expectations of future conditions. Given that several previous studies provide supportive evidence that option-implied information outperforms historical in volatility prediction (Christensen and Prabhala, 1998; Blair, Poon and Taylor, 2001; Poon and Granger, 2005; Taylor, Yadav and Zhang, 2010; and Muzzioli, 2011), using a volatility index constructed from using option data is expected to incorporate more information about aggregate volatility.

[2] The measure of downside risk used in Ang, Chen and Xing (2006) was originally introduced by Bawa and Lindenberg (1977).

[3] Here, the VIX index refers to both old VXO index and new VIX index. The old VXO index is CBOE S&P100 Volatility Index, and is an average of the Black-Scholes implied volatilities on eight near-the-money S&P100 options at the two nearest maturities. The new VIX index is CBOE S&P500 Volatility Index, and is a weighted sum of a broader range of strike prices on out-of-the-money S&P500 options at the two nearest maturities.

[4] For example, Lin (2007), Zhang and Zhu (2006) focus on the pricing of the VIX index future. Huskaj and Nossman (2012) and Lu and Zhu (2009) both investigate the term structure of VIX index future. Shu and Zhang (2012) and Karagiannis (2014) look at the causal relationship between the VIX index and its futures.

[5] Jackwerth and Vilkov (2014) estimate the implied index-to-volatility correlation from the out-of-the-money option on S&P500 index and VIX index. By comparing the implied correlation with its realized counterpart, they find a significantly negative and time-varying risk premium on the correlation risk.

[6] Following DeLisle, Doran and Peterson (2011), this study only keeps stocks with CRSP share codes 10, 11 and 12 in the sample.

[7] This study converts the VIX index and VIX futures from percentage to decimal numbers, i.e. 20% = 0.20. In later equations, volatility terms, VIX , VXF , VXC and VXP , are all decimal numbers too not percentage numbers.

[8] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more details. MKT is the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t , good shares and price data at the beginning of t , and good return data for t minus the one-month Treasury bill rate (from Ibbotson

Associates). SMB (Small-Minus-Big) is the average return on the three small portfolios minus the average return on the three big portfolios. HML (High-Minus-Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. UMD (Winners-Minus-Losers) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolio.

[9] March 26th, 2004 is the first trading day with VIX future data available, while December 31st, 2014 is the last trading day of the sample period. In order to draw the figure and get the summary statistics, for VIX index futures, Figure 1 and Table 1 use the settlement price of future contracts with near-term expiration.

[10] The lead-lag relationship between spot and futures markets is an important topic. However, this study is not looking at the causal relationship between VIX spot and VIX futures.

[11] Panel B of Figure 1 plots the market factor (MKT) together with VIX and VXF . This study also calculates the daily simple returns and logarithmic returns on the S&P500 index. The data indicates that daily simple returns and logarithmic returns on the S&P500 index are highly correlated with MKT (with correlations of 0.9917 and 0.9918, respectively). This study concentrates on market-based pricing factors. So, rather than using the return on S&P500 index, this study uses the market excess return provided by French's online data library.

[12] The descriptive statistics of different variables presented in Table 1 are all calculated at daily frequency. For example, the mean of daily market excess returns is 0.04% (Panel A of Table 1), which translates to around 13.64% p.a. using continuous compounding.

[13] Details about the decomposition are discussed in section 2.3.4.

[14] The regression model in equation (1) is estimated until the end of August 2014. Then, quintile portfolios are constructed by using monthly return in September 2014.

[15] Due to the existence of volatility risk premium, there is a bias when using risk-neutral volatility.

[16] For example, according to Kraus and Litzenberger (1976), the relation between returns and risk is given by:

$$E[r_i] - r_f = b_1\beta_i + b_2\gamma_i$$

where r_i is the return on the ith asset, $\beta_i = \sigma_{im}/\sigma_m^2$ is the market beta or systematic standard deviation of the ith asset, $\gamma_i = m_{imm}/m_m^3$ is the market gamma or systematic skewness of the ith asset (σ_m and m_m are the standard deviation and the cube root of third moment, respectively). Factor loading b_1 can be interpreted as the risk premium on beta, and b_2 can be interpreted as the risk premium on gamma.

[17] Panel E of Table 1 present results for Augmented Dickey-Fuller unit root tests for both levels of each volatility index (VIX , VXF , VXC and VXP) and changes in variance terms ($\Delta(VIX^2)$, $\Delta(VXF^2)$, $\Delta(VXC^2)$ and

$\Delta\left(VXP^2\right)$). The results indicate that, by using first differences in variance terms to measure the volatility risk, the autocorrelation in variables of interest could be controlled.

[18] The VIX index measures market index volatility at 30-day horizon. $\Delta\left(VIX^2\right)$ is the daily change in the square of VIX . Thus, $\Delta\left(VIX^2\right)$ measures the daily change in the aggregate variance on each trading day. If $\Delta\left(VIX^2\right) > 0$, aggregate variance increases compared to the closing level on the previous trading day, and vice versa. For VIX index futures, this study uses the settlement price of the futures contract. VXF reflects the expectation of VIX at expiration. $\Delta\left(VXF^2\right)$ is the daily change in the square of VXF . So, $\Delta\left(VXF^2\right)$ reflects the daily change in expectation of aggregate variance during the 30-day period after expiration. If $\Delta\left(VXF^2\right) > 0$, the settlement price of VXF increases compared to the previous trading day, and vice versa.

[19] In addition to two explanatory variables in equation (1) (i.e. MKT and VF), SMB , HML, or other factors could be included. However, this study principally uses forward looking information about volatility not historical regressors. So, only MKT and VF are included in one regression model.

[20] For equally-weighted portfolios, the weight for each constituent is determined by the total number of stocks included in the portfolio, while for value-weighted portfolios, the weight of each constituent depends on the market capitalization of stocks in the portfolio.

[21] It is known that VIX reflects the market's expectation of stock market volatility over the next 30 day period. VIX is calculated by using near-term and next-term options with maturities longer than 7 days. Here, “10-day”, “20-day”, and “30-day” refer to trading days, and correspond to 2-week, 4-week, and 6-week periods. So lengths of holding periods used in this study are consistent with predictive periods indicated by options used for VIX calculations.

[22] In empirical analysis of this study, p-values reported in Table 2 to 7 are calculated after controlling for autocorrelation (i.e. adjusted by using the Newey-West method).

[23] As highlighted in CBOE official website, VIX futures are contracts on forward 30-day “model-free” implied volatilities. The price of a VIX futures contract can be lower, equal to or higher than VIX index, depending on whether the market expects volatility to be lower, equal to or higher in the 30-day forward period covered by the VIX futures contract than in the 30-day spot period covered by VIX index. The VIX index is a volatility forecast, not an asset. Hence, it is very expensive for investors to create a position equivalent to one in VIX futures by buying a portfolio of options to replicate VIX index and holding the position to futures expiration date while

financing the transaction. In this study, a positive VIX futures basis refers to "backwardation", while a negative VIX futures basis refers to "contango". Within the sample, there are more observations of "contago". However, "backwardation" reflects highly volatile periods. For example, in the most volatile 2% trading days during the period from March 26th, 2004 to December 31st, 2014, 92.59% of observations refers to "backwardation", while only 7.41% of them refers to "contango".

[24] Small fraction of observations are omitted because the dummy variable does not change value.

[25] Available from: https://www.cboe.com/micro/vix/vixwhite.pdf.

[26] When using $\Delta\left(VIX^2\right)$ in equation (1), the average adjusted R-square of the regression model among all individual stocks is 20.53%. Among all individual stocks, 7.75% of them have significant non-zero intercept at a 10% significance level. When switching to use $\Delta\left(VXF^2\right)$ in equation (1), the average adjusted R-square is 20.45%. The percentage of individual stocks with significant non-zero intercept is 7.69%.

[27] When using $\Delta\left(VIX^2\right)$ in equation (2), the average adjusted R-square of the regression model among all individual stocks is 20.17%. After incorporating the asymmetric effect of volatility risk, at a 10% significance level, 7.27% of individual stocks have significant non-zero intercept, and 8.85% of individual stocks have significant factor loading on the dummy variable, i.e. β_i^D. When using $\Delta\left(VXF^2\right)$ in equation (2), similar results are obtained. The adjusted R-square of the regression model is 20.11%. 7.24% of individual stocks have significant non-zero intercept, and 9.06% have significant β_i^D. A significant intercept indicates the failure of the asset pricing model. Although incorporating the asymmetric effect does not increase the adjusted R-square of the model (compared with the results discussed in footnote 26), it does decrease cases with significant intercept.

[28] When using $\Delta\left(VIX^2\right)$ in equation (1), the average R-square of the regression model among all individual stocks is 14.10%. Using $\Delta\left(VXC^2\right)$ or $\Delta\left(VXP^2\right)$ in equation (1) gives the average R-square of 14.10% and 14.07%, respectively.

[29] When using previous 1-month daily returns to estimate equation (1), the average R-squares are almost the same. When using $\Delta\left(VIX^2\right)$, the R-square is 14.15%. When using $\Delta\left(VXC^2\right)$, the R-square is 14.24%. When using $\Delta\left(VXP^2\right)$, the R-square is 14.17%.

[30] This study follows the method documented in VIX Whitepaper from CBOE for VIX replication. To obtain the results presented in this subsection, this study uses equations (4) and (7) to construct $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$

rather than using the method with interpolation across strike prices documented by Bakshi, Kapadia, and Madan (2003). This study also calculates $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ by using the method with interpolation. The results are different to what we find in this subsection. Thus, results presented here are sensitive to the method used for volatility factor calculation.

Figure 1: VIX Index (*VIX*), VIX Index Futures (*VXF*), S&P500 Index (*SPX*), and Market Excess Returns (*MKT*)

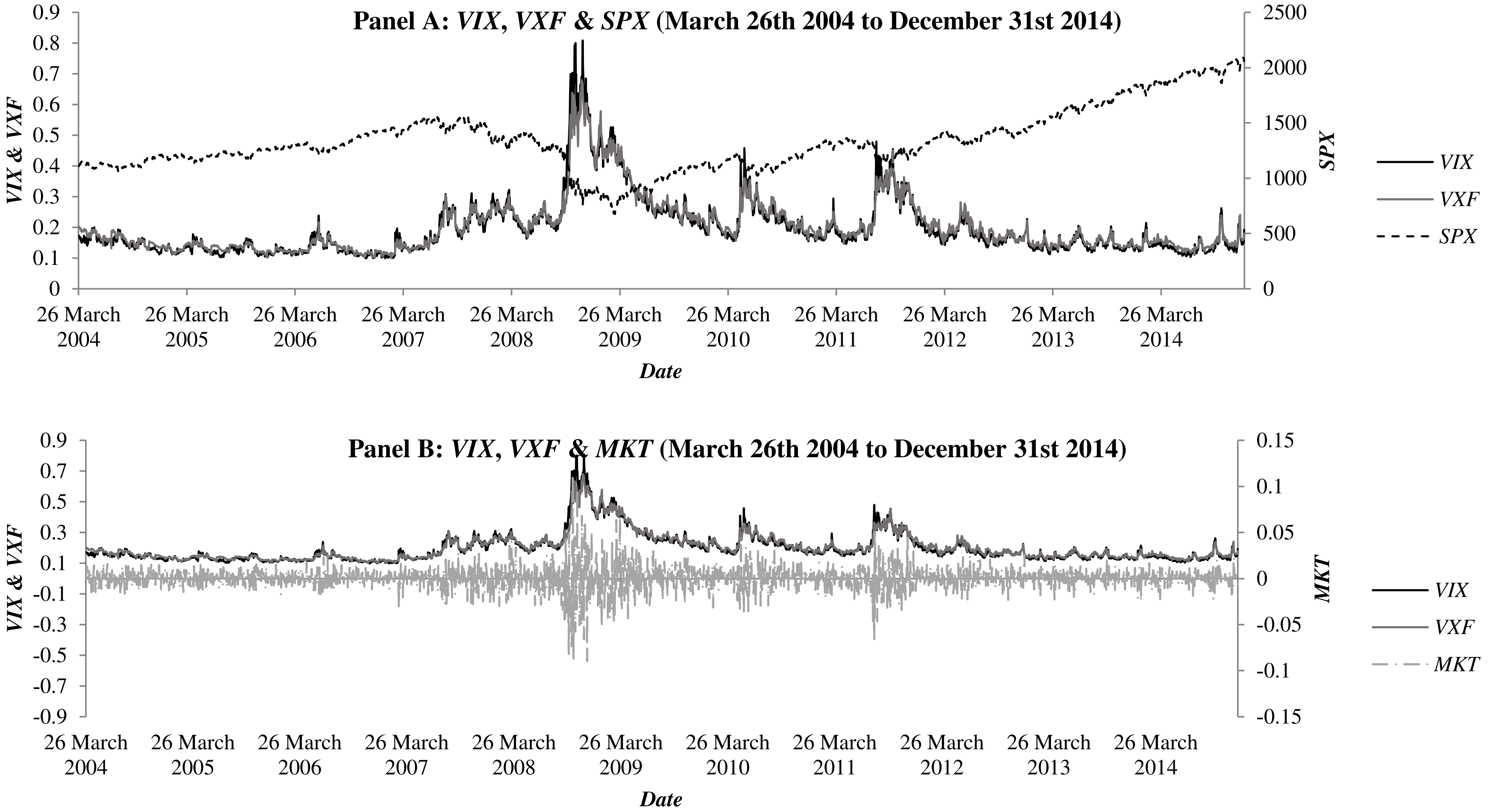


Figure 2: VIX Index (*VIX*), Call VIX Index (*VXC*), Put VIX Index (*VXP*), S&P500 Index (*SPX*), and Market Excess Returns (*MKT*)

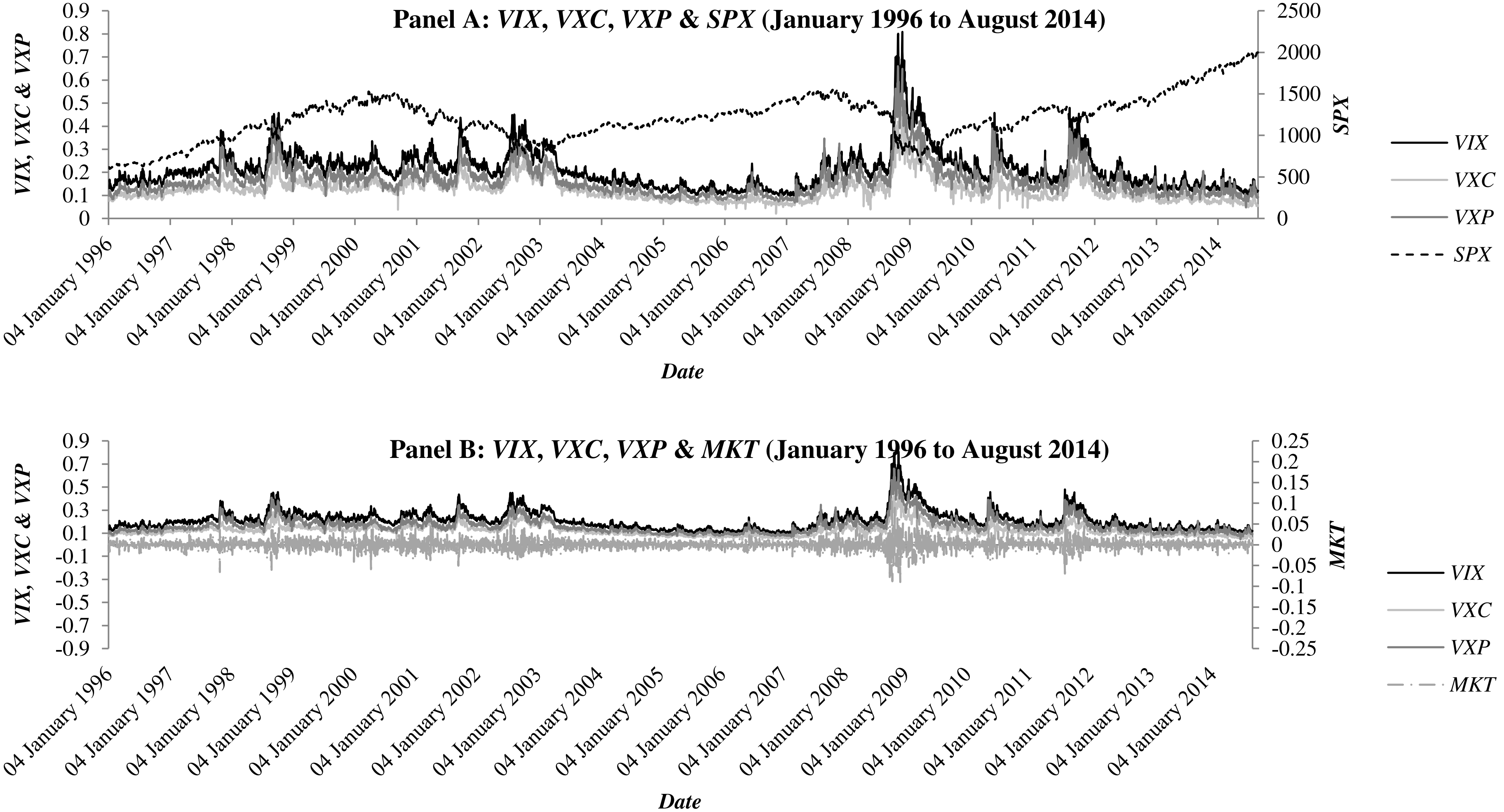
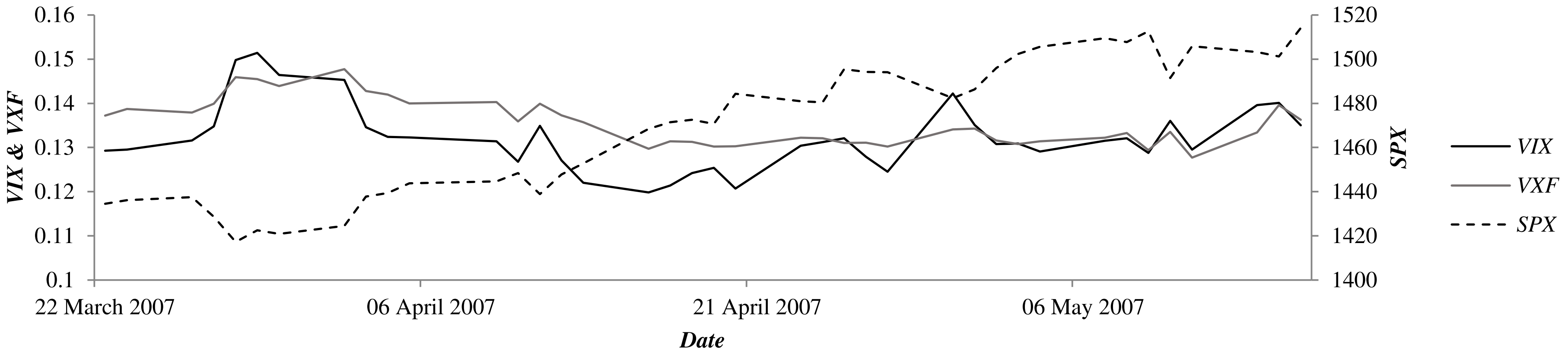


Figure 3: Relationship between VIX Futures Basis and S&P500 Index (*SPX*)

Panel A: *VIX*, *VXF* & *SPX* (March 22nd 2007 to May 16th 2007)



Panel B: *VIX*, *VXF* & *SPX* (August 21st 2008 to October 22nd 2008)

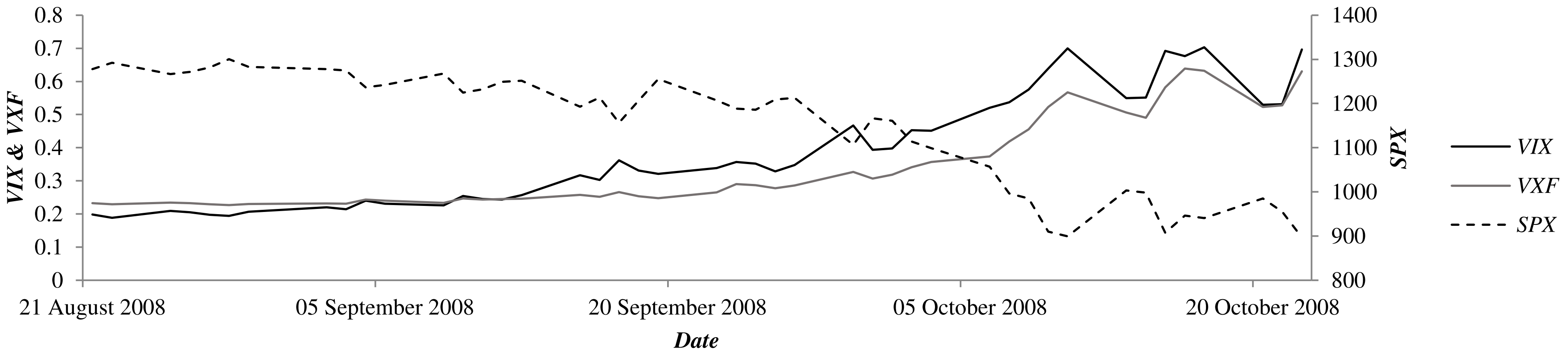


Figure 4: Prices of Out-of-Money Options $Q(K,T)$ and Implied Volatilities on October 22nd 2008 (31 Day-to-Maturity)

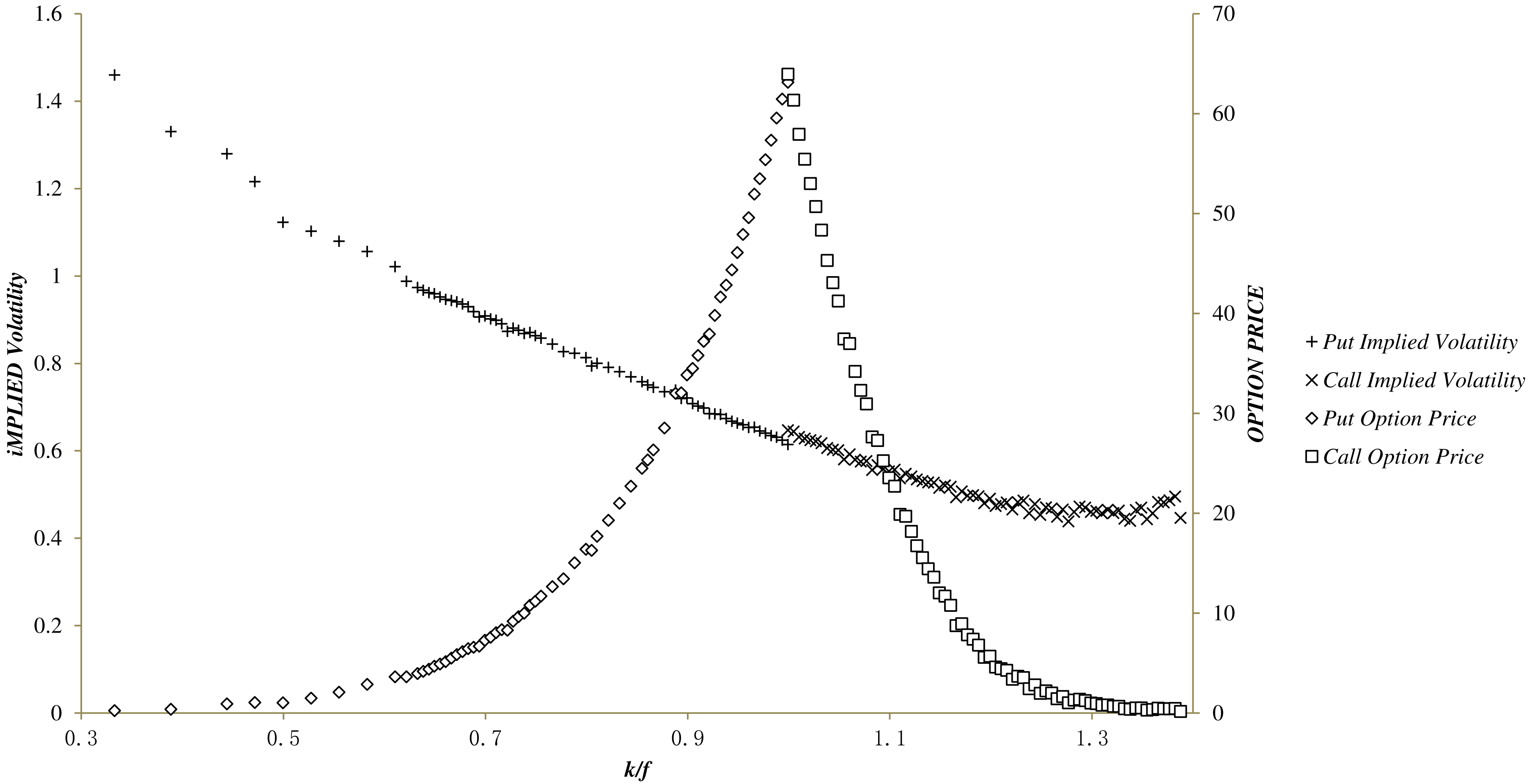


Table 1: Descriptive Statistics

Panel A: Summary Statistics during the Period from March 26th 2004 to December 31st 2014						
	SPX	MKT $(Daily)$	VIX	$\Delta\left(VIX^2\right)$	VXF	$\Delta\left(VXF^2\right)$
Mean	1336.5	0.0004	0.1969	0.0000	0.2012	-0.0000
Median	1294.0	0.0009	0.1660	-0.0002	0.1727	-0.0002
Standard Deviation	274.4	0.0126	0.0971	0.0155	0.0894	0.0098
Minimum	676.5	-0.0895	0.0989	-0.2140	0.0995	-0.1472
Maximum	2090.6	0.1135	0.8086	0.2030	0.6795	0.1186

Panel B: Pairwise Correlations during the Period from March 26th 2004 to December 31st 2014						
	SPX	MKT	VIX	$\Delta\left(VIX^2\right)$	VXF	$\Delta\left(VXF^2\right)$
SPX	1					
MKT	0.0329	1				
VIX	-0.5367	-0.1222	1			
$\Delta\left(VIX^2\right)$	-0.0080	-0.7528	0.0841	1		
VXF	-0.5550	-0.0812	0.9846	0.0390	1	
$\Delta\left(VXF^2\right)$	-0.0069	-0.6768	0.0888	0.8173	0.0660	1

Panel C: Summary Statistics during the Period from January 1996 to August 2014								
	SPX	MKT $(Daily)$	VIX	$\Delta\left(VIX^2\right)$	VXC	$\Delta\left(VXC^2\right)$	VXP	$\Delta\left(VXP^2\right)$
Mean	1206.3	0.0003	0.2131	0.0000	0.1252	-0.0000	0.1646	-0.0000
Median	1204.5	0.0008	0.1984	-0.0002	0.1180	-0.0000	0.1502	-0.0001
Standard Deviation	274.3	0.0125	0.0845	0.0130	0.0506	0.0065	0.0686	0.0099
Minimum	598.5	-0.0895	0.0989	-0.2140	0.0209	-0.1018	0.0486	-0.1357
Maximum	2003.4	0.1135	0.8086	0.2030	0.4635	0.1159	0.6600	0.1507

Panel D: Pairwise Correlations during the Period from January 1996 to August 2014								
	SPX	*MKT* (*Daily*)	*VIX*	$\Delta\left(VIX^2\right)$	*VXC*	$\Delta\left(VXC^2\right)$	*VXP*	$\Delta\left(VXP^2\right)$
SPX	1							
MKT	0.0234	1						
VIX	-0.3845	-0.1249	1					
$\Delta\left(VIX^2\right)$	-0.0107	-0.7267	0.0886	1				
VXC	-0.4217	-0.1199	0.9611	0.0768	1			
$\Delta\left(VXC^2\right)$	-0.0067	-0.4613	0.0554	0.6006	0.1463	1		
VXP	-0.3483	-0.1266	0.9840	0.0924	0.9116	0.0209	1	
$\Delta\left(VXP^2\right)$	-0.0090	-0.6215	0.0730	0.8522	0.0261	0.2706	0.1139	1

Panel E: Augmented Dickey-Fuller Unit Root Tests (H_0: there is a unit root in time series data)		
	p-value	*T-statistic*
Sample Period: March 26th 2004 to December 31st 2014		
VIX	0.0128	-3.3518
VXF	0.0326	-3.0269
$\Delta\left(VIX^2\right)$	0.0000	-18.3054
$\Delta\left(VXF^2\right)$	0.0000	-32.8952
Sample Period: January 1996 to August 2014		
VIX	0.0001	-4.7915
VXC	0.0001	-4.6040
VXP	0.0000	-4.8263
$\Delta\left(VIX^2\right)$	0.0000	-23.9694
$\Delta\left(VXC^2\right)$	0.0000	-38.1739
$\Delta\left(VXP^2\right)$	0.0000	-15.4873

Table 2: Results for Quintile Portfolio Level Analysis by Using $\Delta\left(VIX^2\right)$

The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VIX^2\right)} \Delta\left(VIX^2\right)_t$$

Equally-weighted and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta\left(VIX^2\right)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VIX^2\right)}$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VIX^2\right)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the holding period (10-day, 20-day, and 30-day) after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0122	0.0053	0.0064	0.0063	0.0153	0.0070	0.0073	0.0074	0.0281	0.0101	0.0121	0.0145
2	0.0089	0.0025	0.0032	0.0031	0.0106	0.0030	0.0033	0.0034	0.0204	0.0048	0.0062	0.0073
3	0.0080	0.0016	0.0024	0.0023	0.0107	0.0032	0.0034	0.0035	0.0191	0.0037	0.0050	0.0060
4	0.0092	0.0023	0.0031	0.0031	0.0113	0.0032	0.0035	0.0036	0.0204	0.0039	0.0055	0.0068
5	0.0129	0.0051	0.0062	0.0061	0.0145	0.0057	0.0061	0.0062	0.0268	0.0080	0.0103	0.0126
5-1	0.0007	-0.0001	-0.0002	-0.0002	-0.0007	-0.0013	-0.0012	-0.0012	-0.0013	-0.0021	-0.0018	-0.0019
p-value	(0.5259)	(0.8689)	(0.8734)	(0.8622)	(0.7143)	(0.4539)	(0.5090)	(0.5129)	(0.5239)	(0.2784)	(0.3829)	(0.3621)

Panel B: Results for Value-Weighted Quintile Portfolios

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0058	-0.0010	-0.0004	-0.0004	0.0068	-0.0016	-0.0015	-0.0015	0.0160	-0.0002	0.0001	0.0005
2	0.0047	-0.0007	-0.0007	-0.0007	0.0067	-0.0003	-0.0003	-0.0004	0.0127	-0.0001	-0.0002	-0.0003
3	0.0062	0.0007	0.0006	0.0006	0.0076	0.0011	0.0011	0.0011	0.0136	0.0011	0.0010	0.0011
4	0.0081	0.0019	0.0018	0.0018	0.0084	0.0011	0.0013	0.0013	0.0150	0.0006	0.0008	0.0013
5	0.0087	0.0006	0.0009	0.0009	0.0072	-0.0016	-0.0011	-0.0010	0.0161	-0.0006	0.0002	0.0014
5-1	0.0030	0.0016	0.0013	0.0013	0.0004	-0.0000	0.0004	0.0005	0.0001	-0.0004	0.0001	0.0009
p-value	(0.3777)	(0.5499)	(0.6147)	(0.6152)	(0.9137)	(0.9959)	(0.9154)	(0.8948)	(0.9718)	(0.9184)	(0.9776)	(0.8266)

Table 3: Results for Quintile Portfolio Level Analysis by Using $\Delta\left(VXF^2\right)$

The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VXF^2\right)} \Delta\left(VXF^2\right)_t$$

Equally-weighted and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta\left(VXF^2\right)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VXF^2\right)}$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VXF^2\right)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the holding period (10-day, 20-day, and 30-day) after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0130	0.0056	0.0067	0.0065	0.0149	0.0064	0.0068	0.0070	0.0270	0.0085	0.0106	0.0129
2	0.0093	0.0025	0.0033	0.0032	0.0110	0.0032	0.0035	0.0035	0.0205	0.0045	0.0061	0.0072
3	0.0083	0.0020	0.0027	0.0026	0.0107	0.0032	0.0034	0.0035	0.0196	0.0046	0.0059	0.0068
4	0.0088	0.0022	0.0030	0.0030	0.0104	0.0025	0.0028	0.0029	0.0201	0.0039	0.0054	0.0067
5	0.0119	0.0046	0.0057	0.0056	0.0154	0.0067	0.0071	0.0073	0.0278	0.0091	0.0111	0.0138
5-1	-0.0010	-0.0009	-0.0010	-0.0009	0.0004	0.0003	0.0003	0.0003	0.0009	0.0005	0.0006	0.0009
p-value	(0.5670)	(0.6041)	(0.5605)	(0.5576)	(0.8209)	(0.8827)	(0.8865)	(0.8716)	(0.7096)	(0.8067)	(0.7978)	(0.6584)

Panel B: Results for Value-Weighted Quintile Portfolios

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0076	0.0002	0.0006	0.0006	0.0069	-0.0016	-0.0015	-0.0015	0.0149	-0.0017	-0.0012	-0.0008
2	0.0062	0.0003	0.0003	0.0003	0.0068	-0.0003	-0.0002	-0.0002	0.0131	0.0001	-0.0001	-0.0002
3	0.0060	0.0006	0.0004	0.0004	0.0069	0.0003	0.0003	0.0003	0.0131	0.0009	0.0008	0.0008
4	0.0057	0.0001	0.0001	0.0001	0.0066	-0.0004	-0.0005	-0.0005	0.0136	-0.0000	0.0000	0.0002
5	0.0084	0.0009	0.0013	0.0012	0.0092	0.0006	0.0008	0.0009	0.0187	0.0006	0.0014	0.0032
5-1	0.0008	0.0006	0.0006	0.0007	0.0023	0.0022	0.0023	0.0024	0.0038	0.0024	0.0026	0.0040
p-value	(0.7628)	(0.8009)	(0.8072)	(0.7915)	(0.6080)	(0.6209)	(0.6075)	(0.5546)	(0.5309)	(0.6670)	(0.6250)	(0.3949)

Table 4: Results for Asymmetric Quintile Portfolio Level Analysis by Using $\Delta\left(VIX^2\right)$

The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VIX^2)} \Delta\left(VIX^2\right)_t + \beta_i^D D_t \Delta\left(VIX^2\right)_t$$

where D_t=1 if VIX future basis is positive and zero otherwise. Then, equally-weighted and value-weighted quintile portfolios are constructed in two different situations, D_t=0 and D_t=1. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VIX^2)}$ or $\left(\beta_i^{\Delta(VIX^2)} + \beta_i^D\right)$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VIX^2)}$ or $\left(\beta_i^{\Delta(VIX^2)} + \beta_i^D\right)$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the holding period (10-day, 20-day, and 30-day) after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios Formed When D_t=0

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0084	0.0040	0.0055	0.0056	0.0118	0.0051	0.0057	0.0062	0.0226	0.0081	0.0098	0.0123
2	0.0059	0.0017	0.0027	0.0029	0.0082	0.0019	0.0023	0.0026	0.0172	0.0043	0.0056	0.0067
3	0.0053	0.0013	0.0023	0.0024	0.0083	0.0022	0.0027	0.0029	0.0159	0.0037	0.0049	0.0059
4	0.0062	0.0020	0.0030	0.0032	0.0089	0.0025	0.0030	0.0032	0.0166	0.0033	0.0047	0.0062
5	0.0086	0.0040	0.0053	0.0055	0.0116	0.0047	0.0054	0.0059	0.0220	0.0068	0.0086	0.0117
5-1	0.0002	-0.0000	-0.0001	-0.0001	-0.0001	-0.0004	-0.0003	-0.0003	-0.0006	-0.0013	-0.0012	-0.0006
p-value	(0.8615)	(0.9808)	(0.9200)	(0.9333)	(0.9525)	(0.8436)	(0.8959)	(0.8991)	(0.8396)	(0.6409)	(0.6720)	(0.8438)

Panel B: Results for Equally-weighted Quintile Portfolios Formed When D_t=1

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0098	0.0055	0.0069	0.0071	0.0134	0.0066	0.0073	0.0078	0.0252	0.0104	0.0120	0.0148
2	0.0060	0.0020	0.0029	0.0030	0.0088	0.0026	0.0030	0.0033	0.0171	0.0045	0.0058	0.0069
3	0.0050	0.0010	0.0019	0.0020	0.0069	0.0009	0.0012	0.0015	0.0147	0.0024	0.0036	0.0045
4	0.0056	0.0014	0.0025	0.0026	0.0085	0.0020	0.0026	0.0029	0.0159	0.0026	0.0040	0.0055
5	0.0079	0.0032	0.0047	0.0049	0.0112	0.0041	0.0048	0.0053	0.0213	0.0063	0.0082	0.0110
5-1	-0.0019*	-0.0022**	-0.0022**	-0.0022**	-0.0022	-0.0025*	-0.0025	-0.0025	-0.0038**	-0.0041**	-0.0038**	-0.0039*
p-value	(0.0776)	(0.0191)	(0.0187)	(0.0256)	(0.1601)	(0.0958)	(0.1099)	(0.1158)	(0.0348)	(0.0254)	(0.0430)	(0.0544)

(Continued)

Panel C: Results for Value-Weighted Quintile Portfolios Formed When D_t =0												
	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0031	-0.0013	-0.0009	-0.0008	0.0049	-0.0020	-0.0019	-0.0017	0.0126	-0.0017	-0.0015	-0.0006
2	0.0038	-0.0000	-0.0000	-0.0000	0.0056	-0.0002	-0.0001	-0.0001	0.0122	0.0012	0.0011	0.0011
3	0.0044	0.0010	0.0009	0.0008	0.0065	0.0010	0.0010	0.0009	0.0118	0.0016	0.0015	0.0014
4	0.0045	0.0008	0.0008	0.0008	0.0062	0.0004	0.0005	0.0005	0.0112	0.0000	0.0002	0.0006
5	0.0032	-0.0012	-0.0008	-0.0008	0.0049	-0.0019	-0.0017	-0.0017	0.0099	-0.0036	-0.0031	-0.0021
5-1	0.0001	0.0001	0.0001	0.0000	-0.0000	0.0001	0.0002	-0.0000	-0.0027	-0.0018	-0.0016	-0.0015
p-value	(0.9527)	(0.9572)	(0.9546)	(0.9987)	(0.9969)	(0.9822)	(0.9453)	(0.9986)	(0.5349)	(0.6889)	(0.7348)	(0.7404)
Panel D: Results for Value-Weighted Quintile Portfolios Formed When D_t =1												
	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0054	0.0010	0.0016	0.0015	0.0085	0.0016	0.0018	0.0016	0.0176	0.0044	0.0045	0.0052
2	0.0034	-0.0003	-0.0003	-0.0003	0.0065	0.0007	0.0007	0.0007	0.0118	0.0009	0.0008	0.0007
3	0.0042	0.0007	0.0006	0.0006	0.0062	0.0008	0.0008	0.0007	0.0109	0.0006	0.0005	0.0004
4	0.0048	0.0009	0.0009	0.0009	0.0053	-0.0005	-0.0005	-0.0004	0.0104	-0.0010	-0.0009	-0.0004
5	0.0022	-0.0024	-0.0018	-0.0018	0.0008	-0.0061	-0.0058	-0.0054	0.0071	-0.0071	-0.0065	-0.0045
5-1	-0.0032	-0.0034	-0.0034	-0.0033	-0.0076**	-0.0077**	-0.0075*	-0.0071**	-0.0105**	-0.0115***	-0.0110***	-0.0096***
p-value	(0.1806)	(0.1600)	(0.1284)	(0.1365)	(0.0469)	(0.0418)	(0.0505)	(0.0360)	(0.0148)	(0.0042)	(0.0067)	(0.0093)

Table 5: Results for Asymmetric Quintile Portfolio Level Analysis by Using $\Delta\left(VXF^2\right)$

The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXF^2)} \Delta\left(VXF^2\right)_t + \beta_i^D D_t \Delta\left(VXF^2\right)_t$$

where D_t=1 if VIX future basis is positive and zero otherwise. Then, equally-weighted and value-weighted quintile portfolios are constructed in two different situations, D_t=0 and D_t=1. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VXF^2)}$ or $\left(\beta_i^{\Delta(VXF^2)} + \beta_i^D\right)$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VXF^2)}$ or $\left(\beta_i^{\Delta(VXF^2)} + \beta_i^D\right)$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the holding period (10-day, 20-day, and 30-day) after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios Formed When D_t=0

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0077	0.0032	0.0047	0.0049	0.0115	0.0046	0.0053	0.0058	0.0223	0.0076	0.0094	0.0119
2	0.0058	0.0016	0.0027	0.0028	0.0084	0.0021	0.0026	0.0028	0.0172	0.0044	0.0057	0.0067
3	0.0054	0.0014	0.0023	0.0024	0.0086	0.0026	0.0030	0.0032	0.0163	0.0040	0.0052	0.0060
4	0.0064	0.0023	0.0034	0.0035	0.0086	0.0023	0.0028	0.0030	0.0167	0.0036	0.0050	0.0065
5	0.0090	0.0045	0.0058	0.0059	0.0116	0.0047	0.0053	0.0059	0.0219	0.0067	0.0084	0.0116
5-1	0.0013	0.0013	0.0010	0.0010	0.0001	0.0000	0.0000	0.0001	-0.0004	-0.0008	-0.0010	-0.0003
p-value	(0.2522)	(0.2780)	(0.3776)	(0.3905)	(0.9548)	(0.9920)	(0.9872)	(0.9529)	(0.8632)	(0.6906)	(0.6421)	(0.8899)

Panel B: Results for Equally-weighted Quintile Portfolios Formed When D_t=1

	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0100	0.0056	0.0069	0.0071	0.0131	0.0064	0.0071	0.0075	0.0245	0.0100	0.0118	0.0145
2	0.0064	0.0023	0.0034	0.0035	0.0093	0.0030	0.0035	0.0038	0.0182	0.0053	0.0065	0.0077
3	0.0051	0.0011	0.0020	0.0021	0.0075	0.0014	0.0018	0.0020	0.0149	0.0027	0.0039	0.0048
4	0.0050	0.0008	0.0019	0.0020	0.0074	0.0009	0.0014	0.0017	0.0154	0.0020	0.0033	0.0048
5	0.0078	0.0033	0.0046	0.0048	0.0114	0.0044	0.0051	0.0057	0.0213	0.0062	0.0080	0.0110
5-1	-0.0022	-0.0023	-0.0023	-0.0023	-0.0017	-0.0020	-0.0020	-0.0019	-0.0033*	-0.0038**	-0.0038**	-0.0035*
p-value	(0.1690)	(0.1417)	(0.1480)	(0.1397)	(0.3297)	(0.2297)	(0.2387)	(0.2536)	(0.0866)	(0.0389)	(0.0444)	(0.0637)

(Continued)

Panel C: Results for Value-Weighted Quintile Portfolios Formed When D_t=0												
	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0025	-0.0020	-0.0015	-0.0013	0.0027	-0.0042	-0.0039	-0.0037	0.0115	-0.0021	-0.0016	-0.0008
2	0.0039	0.0001	0.0001	0.0001	0.0067	0.0010	0.0011	0.0011	0.0136	0.0028	0.0028	0.0028
3	0.0041	0.0007	0.0005	0.0005	0.0063	0.0010	0.0009	0.0009	0.0112	0.0010	0.0009	0.0008
4	0.0038	0.0001	0.0000	-0.0001	0.0052	-0.0007	-0.0008	-0.0009	0.0098	-0.0018	-0.0016	-0.0015
5	0.0044	0.0001	0.0006	0.0005	0.0049	-0.0018	-0.0017	-0.0016	0.0112	-0.0025	-0.0020	-0.0009
5-1	0.0019	0.0021	0.0021	0.0019	0.0022	0.0024	0.0022	0.0021	-0.0003	-0.0004	-0.0004	-0.0001
p-value	(0.4707)	(0.4480)	(0.4260)	(0.4615)	(0.5779)	(0.5539)	(0.5830)	(0.6197)	(0.9390)	(0.9305)	(0.9223)	(0.9726)
Panel D: Results for Value-Weighted Quintile Portfolios Formed When D_t=1												
	10-Day Holding Period				20-Day Holding Period				30-Day Holding Period			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0055	0.0012	0.0016	0.0016	0.0076	0.0010	0.0012	0.0011	0.0167	0.0040	0.0044	0.0049
2	0.0043	0.0005	0.0005	0.0005	0.0069	0.0010	0.0009	0.0009	0.0135	0.0026	0.0024	0.0022
3	0.0037	0.0003	0.0001	0.0001	0.0065	0.0011	0.0011	0.0011	0.0115	0.0013	0.0012	0.0012
4	0.0046	0.0008	0.0009	0.0009	0.0046	-0.0014	-0.0013	-0.0012	0.0097	-0.0020	-0.0019	-0.0015
5	0.0040	-0.0006	-0.0003	-0.0002	0.0031	-0.0039	-0.0036	-0.0033	0.0085	-0.0062	-0.0056	-0.0036
5-1	-0.0016	-0.0018	-0.0019	-0.0018	-0.0045	-0.0049	-0.0048	-0.0044	-0.0082	-0.0102**	-0.0100**	-0.0085**
p-value	(0.5336)	(0.4637)	(0.4500)	(0.4583)	(0.3119)	(0.2397)	(0.2495)	(0.2445)	(0.1209)	(0.0317)	(0.0345)	(0.0461)

Table 6: Results for Quintile Portfolio Level Analysis

The following time-series regression is estimated at the end of each calendar month by using previous 2-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VIX^2)} \Delta\left(VIX^2\right)_t$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXC^2)} \Delta\left(VXC^2\right)_t$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXP^2)} \Delta\left(VXP^2\right)_t$$

Equally-weighted and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the following 1-month after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios

	$\Delta\left(VIX^2\right)$				$\Delta\left(VXC^2\right)$				$\Delta\left(VXP^2\right)$			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0124	0.0028	0.0021	0.0052	0.0109	0.0013	0.0005	0.0031	0.0130	0.0034	0.0027	0.0056
2	0.0120	0.0039	0.0023	0.0037	0.0104	0.0022	0.0006	0.0018	0.0117	0.0034	0.0019	0.0034
3	0.0112	0.0036	0.0019	0.0028	0.0116	0.0039	0.0023	0.0032	0.0110	0.0034	0.0017	0.0025
4	0.0105	0.0023	0.0006	0.0015	0.0116	0.0034	0.0018	0.0029	0.0102	0.0019	0.0002	0.0013
5	0.0103	0.0003	-0.0006	0.0016	0.0119	0.0020	0.0012	0.0038	0.0107	0.0007	-0.0002	0.0020
5-1	-0.0021	-0.0025*	-0.0027*	-0.0037**	0.0009	0.0007	0.0007	0.0008	-0.0023*	-0.0026**	-0.0029**	-0.0037***
p-value	(0.1324)	(0.0853)	(0.0605)	(0.0345)	(0.3384)	(0.4910)	(0.5141)	(0.4663)	(0.0796)	(0.0414)	(0.0219)	(0.0087)

Panel B: Results for Value-weighted Quintile Portfolios

	$\Delta\left(VIX^2\right)$				$\Delta\left(VXC^2\right)$				$\Delta\left(VXP^2\right)$			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0073	-0.0016	-0.0018	-0.0002	0.0053	-0.0040	-0.0039	-0.0032	0.0078	-0.0016	-0.0011	0.0010
2	0.0081	0.0005	0.0005	0.0008	0.0083	0.0009	0.0009	0.0006	0.0092	0.0014	0.0011	0.0016
3	0.0085	0.0010	0.0008	0.0006	0.0075	0.0001	-0.0002	-0.0004	0.0084	0.0011	0.0008	0.0005
4	0.0075	-0.0005	-0.0007	-0.0009	0.0096	0.0016	0.0014	0.0016	0.0058	-0.0020	-0.0022	-0.0027
5	0.0046	-0.0053	-0.0050	-0.0050	0.0073	-0.0028	-0.0024	-0.0015	0.0048	-0.0049	-0.0046	-0.0048
5-1	-0.0027	-0.0038	-0.0033	-0.0048	0.0021	0.0012	0.0015	0.0017	-0.0030	-0.0033	-0.0035	-0.0058*
p-value	(0.4365)	(0.2961)	(0.3936)	(0.1876)	(0.4382)	(0.6422)	(0.5972)	(0.5162)	(0.3345)	(0.3312)	(0.2887)	(0.0739)

Table 7: Results for Quintile Portfolio Level Analysis

The following time-series regression is estimated at the end of each calendar month by using previous 1-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VIX^2)} \Delta(VIX^2)_t$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXC^2)} \Delta(VXC^2)_t$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXP^2)} \Delta(VXP^2)_t$$

Equally-weighted and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$, while portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this study calculates the return for each portfolio during the following 1-month after the portfolio formation.

Panel A: Results for Equally-weighted Quintile Portfolios

	$\Delta(VIX^2)$				$\Delta(VXC^2)$				$\Delta(VXP^2)$			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0132	0.0035	0.0026	0.0056	0.0111	0.0014	0.0005	0.0031	0.0130	0.0034	0.0026	0.0055
2	0.0115	0.0034	0.0018	0.0033	0.0108	0.0026	0.0010	0.0020	0.0123	0.0041	0.0027	0.0040
3	0.0108	0.0032	0.0014	0.0023	0.0117	0.0041	0.0025	0.0034	0.0113	0.0037	0.0020	0.0029
4	0.0106	0.0023	0.0007	0.0016	0.0116	0.0032	0.0016	0.0028	0.0102	0.0019	0.0002	0.0012
5	0.0108	0.0007	-0.0002	0.0019	0.0117	0.0017	0.0008	0.0035	0.0100	-0.0001	-0.0011	0.0011
5-1	-0.0024	-0.0028*	-0.0029*	-0.0037**	0.0006	0.0003	0.0003	0.0003	-0.0031*	-0.0034**	-0.0037**	-0.0044**
p-value	(0.1180)	(0.0620)	(0.0537)	(0.0480)	(0.6173)	(0.8323)	(0.7938)	(0.7767)	(0.0544)	(0.0263)	(0.0237)	(0.0102)

Panel B: Results for Value-weighted Quintile Portfolios

	$\Delta(VIX^2)$				$\Delta(VXC^2)$				$\Delta(VXP^2)$			
	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α	Return	MKT α	FF3F α	CH4F α
1	0.0082	-0.0010	-0.0008	0.0004	0.0051	-0.0044	-0.0042	-0.0041	0.0102	0.0008	0.0014	0.0031
2	0.0083	0.0007	0.0006	0.0009	0.0079	0.0004	0.0003	0.0002	0.0103	0.0027	0.0025	0.0030
3	0.0080	0.0007	0.0003	0.0002	0.0085	0.0012	0.0010	0.0008	0.0073	-0.0002	-0.0005	-0.0007
4	0.0079	-0.0003	-0.0005	-0.0009	0.0088	0.0006	0.0005	0.0006	0.0062	-0.0017	-0.0020	-0.0025
5	0.0055	-0.0046	-0.0044	-0.0040	0.0079	-0.0022	-0.0018	-0.0010	0.0030	-0.0068	-0.0067	-0.0068
5-1	-0.0027	-0.0036	-0.0036	-0.0044	0.0027	0.0022	0.0024	0.0032	-0.0072**	-0.0076**	-0.0081**	-0.0100***
p-value	(0.3678)	(0.2512)	(0.2436)	(0.1514)	(0.2315)	(0.3728)	(0.3317)	(0.1888)	(0.0173)	(0.0132)	(0.0118)	(0.0020)