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

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Abstract

To capture volatility risk, we use factors from VIX, VIX futures, and their basis. We find that portfolios with lower (higher) factor loadings on the market and volatility risk from in-sample time-series regressions, have persistent out-of-sample lower (higher) factor loadings. More importantly, by separating cases based on the sign of volatility changes, this study documents the existence of an asymmetric effect due to volatility shocks on asset returns. When volatility is shocked positively, there is a significantly negative relationship between factors associated with uncertainty and asset returns. Furthermore, after incorporating this asymmetric effect, volatility factors have significant risk premia in Fama-MacBeth cross-sectional regressions.

Keywords: VIX index, VIX index future, volatility risk, asymmetric effect

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1. Introduction

The Capital Asset Pricing Model (CAPM) (Sharpe, 1964; and Lintner, 1965) assumes a simple linear relationship between an asset's expected returns and its risk synthesized by a covariance measure: the beta. Focusing on the first two moments of assets' returns, this beta is the only pricing factor and it reflects the relationship between an asset's return and the market. However, empirical studies provide evidence that the CAPM cannot adequately explain time-series and cross-sectional properties of asset returns.[1] Whether or not other factors affect expected returns remains an open question.[2]

Furthermore, the CAPM is based on the assumption that future market conditions are the same as those from the past. In particular, it assumes that volatility is constant. However, historical data are not able to reflect the current and future expectations if economic conditions change. 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 in options can reflect market expectations on future conditions. Given that several previous papers 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), very recently we have seen a surge of

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[1] Returns that cannot be explained by the CAPM are known as pricing anomalies. For example, the Monday effect (Cho, Linton and Whang, 2007), the P/E effect (Basu, 1977), the size effect (Banz, 1981), the B/M effect (Rosenberg, Reid and Lanstein, 1985), the momentum effect (Jegadeesh and Titman, 1993), the negative relationship between abnormal capital investments and stock returns (Titman, Wei and Xie, 2004), the significant relationship between the idiosyncratic risk and asset returns (Goyal and Santa-Clara, 2003; Ang, Hodrick, Xing and Zhang, 2006; Malkiel and Xu, 2006; Bali and Cakici, 2008; Fu, 2009).

[2] For example, Fama and French (1993) document that factors constructed on the basis of size and book-to-market ratio (SMB and HML, respectively) can help to improve the performance of asset pricing model. 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. Carhart (1997) find that the factor measured the momentum effect can explain stock returns. Furthermore, Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) find supportive evidence that the factor formed based on the change in volatility is significant in explaining equity returns.

interest in the literature which try to incorporate option-implied information in asset pricing models. For instance, Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) both document that the aggregate volatility (which is measured by change in VXO or VIX index) is important in explaining the cross-section of stock returns.[3]

Several empirical studies document the existence of a premium for bearing volatility risk, supporting the hypothesis that this may be an important additional pricing factor in equity markets. For instance, by investigating delta-hedged positions, Bakshi and Kapadia (2003) provide evidence which is supportive of a negative market volatility risk premium. Arisoy, Salih, and Akdeniz (2007) use zero-beta at-the-money straddle returns on the S&P500 index to capture volatility risk. Empirical results in their study show that volatility risk helps in explaining the size and book-to-market anomalies. By investigating three countries (the US, the UK, and Japan), Mo and Wu (2007) find that investors are willing to forgo positive premia in order to avoid increases in volatility. Carr and Wu (2009) use the difference between realized and implied variance to quantify the variance risk premium, and they find that the average variance risk premium is strongly negative for the S&P 500, the S&P 100, and the DJIA. Bollerslev, Tauchen and Zhou (2009) use the difference between model-free implied and realized variance to estimate the volatility risk premium and show that such a difference helps to explain the variation of quarterly stock market returns.[4] Using the same definition, Bollerslev, Gibson and Zhou (2011) also document that the volatility risk premium is relevant in predicting the return on the S&P500 index. Ammann and Buesser (2013) follow the same approach in order to investigate the importance of the variance risk premium in foreign exchange markets (EUR/USD, GBP/USD, USD/JPY and EUR/GBP).

[3] The VXO index is introduced in 1993 based on trading of S&P 100 (OEX) options. Then, on September 22nd, 2003, the CBOE revises the method for volatility index calculation (i.e. the VIX index). The VIX index is based on the S&P 500 (SPX) options. Both the VXO index and the VIX index reflect the expected volatility of 30-day period.

[4] Here, model-free implied volatility/variance refers to the volatility/variance calculated by using data (e.g. strike prices) on a range of options without depending on an option pricing model.

From these empirical studies, we can see that volatility risk could be an important pricing factor in equity markets.

Furthermore, the only pricing factor considered in the CAPM setup (i.e. the beta) is assumed to be constant and not dependent by upward or downward movements of the market portfolio. In contrast, some studies reveal that the influence of the market's realization is not symmetric. Ang, Chen and Xing (2006), for instance, show a downside risk premium of approximately 6% per annum, finding that, over the period from July 1963 to December 2001, stocks that covary strongly with the market during market declines have higher average returns compared with those exhibiting low covariance with the market.[5] Given that the market risk has an asymmetric effect on equity returns, it is noteworthy to ask whether the influence of volatility risk on equity returns is also asymmetric. Delisle, Doran and Peterson (2011) use the innovation in VIX index to measure volatility risk and focus on the asymmetric effect of the volatility risk. To be more specific, their study documents that sensitivity to VIX innovations is negatively related to returns when volatility is increasing, but is unrelated when it is decreasing. In the light of this, Farago and Tedongap (2012) claim that investors' disappointment aversion is relevant to asset pricing theory, conjecturing that this disappointment aversion results not only from a decrease in the market proxy but also an increase in the volatility index. Empirical results in their study show that undesirable changes (decrease in market and increase in volatility indices) motivate significant premia in the cross-section of stock returns. In order to understand the asymmetric effect due to market and volatility risks, it is important to distinguish between different cases: positive or negative market returns, and increment or reduction in the volatility index. However, we cannot use past data as a proxy for ex ante expectations. Thus, it needs to be clarified that the analysis of

[5] The measure of downside risk used in this study is introduced by Bawa and Lindenberg (1977).

the asymmetric effect focus on ex post realizations and do not help the investigation of asset return predictions.

Based on the prior literature, this study concentrates on two main research questions. First, to capture volatility risk and test whether volatility conveyed by options predicts equity returns, this study introduces VIX index (hereafter, VIX) and VIX index futures (hereafter, VIX futures) into asset pricing models. Second, by defining a dummy variable which reflects whether the volatility realisation is positive or negative, we focus on ex post analysis of two different scenarios: upward and downward movements of the market volatility. In addition, this study uses Fama-MacBeth cross-sectional regressions to test if the volatility risk premium is significant across portfolios. We consider the possibility that the ex post volatility realization could be asymmetric by including dummy variables in these cross-sectional regressions.

This study contributes to previous literature in the following areas. First, we introduce VIX and VIX futures into asset pricing models. Few studies have used VIX futures in asset pricing and those only focus on either the theoretical pricing or the existence of a term structure.[6] Trading on VIX futures can provide investors with an expectation of VIX itself at expiration; so the movements in VIX futures (the first difference of VIX future), can reflect changes in market expectations of volatility at expiration, while the difference between VIX and VIX future (i.e. basis) can reflect deviations of VIX from its expected path. Such shocks are unexpected by investors. Thus, introducing these factors into asset pricing models could help to improve the models' ability to represent the real market.

Secondly, we contribute to using risk-neutral volatility measures in empirical tests on volatility risk premia. Historical data reflects a negative relationship between the market and volatility indices. An increase in the market index often comes together with a decrease in the

[6] 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.

volatility index, while a downward movement of the market frequently comes together with a sharp increase in the volatility index. Additionally, such relationship is time-varying, and it is stronger during periods of financial turmoil; as highlighted by Campbell, Forbes, Koedijk and Kofman (2008) [7], an increased correlation between the market index and market volatility during crisis indicates deterioration in the benefits from assets' diversification. In light of this, Jackwerth and Vilkov (2013) prove the existence of a significant risk premium based on index-volatility correlation. They also provide an interpretation of the asset-volatility correlation premium which may be viewed as compensation for a fear of increasing volatility. In other words, Jackwerth and Vilkov (2013) argue that the investors are willing to pay a premium for the correlation between the market and the volatility indices. In addition, trading of options enables us to find a proxy for risk-neutral volatility. Thus, in addition to the market risk premium, volatility or variance risk premia are more commonly-tested in empirical tests than correlation risk premium.

Thirdly, our study takes an asymmetric effect of the volatility risk into consideration. In fact, 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 and negative news for investors. Separating these different cases through dummy variables enable us to analyze the role of volatility risk in asset pricing in these different scenarios. To this end, conducting an ex post analysis, we provide evidence of a significant negative relationship between volatility risk and asset returns during periods with positive volatility changes.

[7] Campbell, Forbes, Koedijk, and Kofman (2008) also point out that the reduction in diversification benefits is a result of the fat tailedness of financial asset return distributions.

The rest of this study is organized as follows. Section 2 discusses details of data and methodology. Results on time-series regressions and Fama-MacBeth cross-sectional regressions are presented in Section 3. Finally, section 4 concludes this study.

2. Data and Methodology

2.1 Data

This study focuses on the effect of volatility risk factors on individual stock returns. Daily stock returns are downloaded from CRSP. When forming volatility factors, this study uses the VIX and its futures, which are obtained from the CBOE website. Our models also include other factors, such as market excess return, SMB and HML.[8] These factors are available in Kenneth French's data library.[9]

VIX futures started trading on the CBOE in March 26th, 2004. So the sample period for our analysis with the VIX futures included starts from April 1st, 2004 and ends on December 31st, 2012. For the analysis focusing on the VIX, the sample period is extended, i.e. from January, 1996 to December, 2012.

2.2 Methodology

In order to investigate the relationship between individual stock returns and volatility factors constructed in this study, we implement the following procedure.

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[8] Market excess return is the difference between the 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 and the one-month Treasury bill rate (from Ibbotson Associates). SMB and HML have been discussed in footnote 2.

[9] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more details.

2.2.1 In-Sample and Out-of-Sample Time-Series Regressions

First, at the end of each calendar month, we run in-sample regression models by using daily data within that month. The models are as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{m,t} - r_{f,t}) \tag{1}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{VF} VF_t \tag{2}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{m,t} - r_{f,t}) + \beta_i^{VF} VF_t \tag{3}$$

where $r_{i,t}$ stands for daily returns on each individual asset, $r_{m,t}$ is return of the market, and $r_{f,t}$ is the risk-free rate. VF, which indicates the proxies used as volatility factors, can be defined in four different ways: ΔVX (change in VIX futures), ΔVIX (change in VIX), $VIX - VX$ (the difference between VIX and its futures, i.e. basis), and $log(VIX) - log(VX)$ (the difference between log VIX and log VIX futures).[10] With regards to the VIX futures, we use the settlement price of the future contract with shortest time-to-maturity (always contracts which expire over the next month) as VX in above models.[11]

After obtaining coefficient estimations in above in-sample regression models, we form quintile portfolios at the end of each month based on the beta coefficients.[12] Then, after

[10] VIX index futures reflect the expectation of VIX index at expiration. ΔVX is the daily change in VIX index futures. So, ΔVX can reflect the daily change in expectation of market index volatility during the 30-day period after expiration. If $\Delta VX > 0$, the settlement price of VIX index futures increases compared to the previous trading day, and vice versa. VIX index measures market index volatility at 30-day horizon. ΔVIX is the daily change in VIX index. Thus, ΔVIX measures the daily change in the market index volatility on each trading day. So, VIX index and it futures reflect 30-day volatility for different periods. If $\Delta VIX > 0$, the VIX index increases compared to the previous trading day, and vice versa. $VIX - VX$ measures the difference between VIX index and its futures on each day. So, $VIX - VX$ can reflect the deviation of VIX index from the market expectation. $log(VIX) - log(VX)$ measures difference between log VIX index and log VIX index future on each day, and it is more closed to normal distribution than $VIX - VX$. Thus, using $log(VIX) - log(VX)$ rather than $VIX - VX$ should improve the performance of the regression model.

[11] From the dataset, we find that, only after October 2005, CBOE has VIX index future contracts expiring in each month.

[12] In order to form portfolios, we use three weighting schemes. First, we allocate the equal number of stocks into each portfolio and the weights of all stocks are the same. If the number of stocks in one portfolio is N, the weight of each stock within the portfolio should be equal to $\frac{1}{N}$. Second, we still allocate the equal number of stocks into each portfolio, and we use value-weighted scheme within each portfolio. Thus, stocks with large market capitalization have high weights, while stocks with small market capitalization have low weights. Third,

the quintile portfolio formation, we run out-of-sample regressions by using the following one-month daily returns on quintile portfolios:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) \tag{4}$$

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{VF} VF_t \tag{5}$$

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) + \beta_p^{VF} VF_t \tag{6}$$

where $r_{p,t}$ stands for daily returns on each quintile portfolio. Based on the results from out-of-sample regression models, we can get results on whether the significance of coefficients on market and volatility risk for the "5-1" arbitrage portfolio persists during out-of-sample periods.

Among the six time-series regression models listed above, Model (1), (2), (4) and (5) are univariate regression models, while Model (3) and (6) are multivariate regression models. Based on the results obtained from time series regressions, we compare the persistence of coefficients on market excess return and volatility factors. However, if the realization of the market excess return or the volatility factors is close to zero, it is difficult to find significant non-zero returns on the "5-1" arbitrage portfolio. Thus, if we can distinguish periods with positive and negative realizations of either market or volatility indices, it is possible to detect statistically significant returns (or even Jensen's alphas, i.e. risk-adjusted returns) on the arbitrage portfolio, by running the regressions for the quintiles' formation in each situation.

2.2.2 Asymmetric In-Sample and Out-of-Sample Time-Series Regression

Though previous models help us to learn the relationship between asset returns and volatility factors, these models ignore asymmetric effects of the volatility risk. Financial markets may react differently to positive or negative volatility shocks. Thus, this study incorporates an asymmetric effect of the volatility risk into models. In order to separate

we allocate different number of stocks in different portfolios, but we require that the total market capitalization of quintile portfolios should be the same. Then, within each portfolio, we still use value-weighted scheme.

different cases, we include dummy variables in our regression models. We set the dummy variable equal to 1 if the volatility factor (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$) is positive or zero, and equal to 0 if the volatility factor is negative.[13] Therefore, the model is specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{VF}} * D_t^{VF} + \beta_i^{MKT} * \left(R_{m,t} - R_{f,t}\right) + \beta_i^{VF} * VF_t + \beta_i^{D^{VF}} * D_t^{VF} * VF_t \quad (7)$$

After running the regression model shown in equation (7) by using one-month daily data at the end of each calendar month, we form quintile portfolios separately in two different situations ($D^{VF} = 1$ and $D^{VF} = 0$). In other words, when the volatility factor is positive or zero, we form quintile portfolios based on ($\beta_i^{VF} + \beta_i^{D^{VF}}$), whereas, when the volatility factor is negative, we form quintile portfolios based only on β_i^{VF}. Furthermore, we form "5-1" arbitrage portfolios, and calculate Jensen's alphas with respect to the CAPM or the Fama-French three-factor model for these arbitrage portfolios to see whether the relationship between asset returns and factor loadings to volatility factors is significant even after including market excess return, SMB and HML. This analysis enables us to verify whether the asymmetric effect of volatility risk on asset returns exists or not.

2.2.3 Fama-MacBeth Cross-Sectional Regression

In addition to time-series regressions, we also run Fama-MacBeth (1973) cross-sectional regressions to check whether investors are willing to pay risk premium or buy insurance for the volatility realization.

Before starting the cross-sectional regressions, we need to form portfolios to reduce idiosyncratic errors. We follow the method documented in Ang, Hodrick, Xing and Zhang (2006) for portfolio formation. We assume that the portfolios are rebalanced with monthly

[13] This study focuses on the asymmetric effect of the volatility risk, so we ignore the asymmetric effect of the market risk, which is confirmed in Ang, Chen, and Xing (2006).

frequency. Thus, at the end of each month, we first form five quintiles based on beta coefficients on market excess return (β_i^{MKT}) from the univariate regression:[14]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} * \left(R_{m,t} - R_{f,t}\right) \tag{8}$$

Then, within each market quintile, we form five quintile portfolios based on the beta coefficient associated with VF, β_i^{VF}:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} * \left(R_{m,t} - R_{f,t}\right) + \beta_i^{VF} * VF_t\ . \tag{9}$$

So, for Fama-MacBeth cross sectional regressions, there are 5×5 portfolios in total.

After forming 25 portfolios, we run the following regression by using daily data of each portfolio in the same one-month (the month for portfolio formation) to get factor loadings:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p^{MKT} * \left(R_{m,t} - R_{f,t}\right) + \beta_p^{VF} * VF_t \tag{10}$$

For each portfolio, we can get the intercept (α_p), the beta coefficient on market excess returns (β_p^{MKT}), and the beta coefficient on volatility factor (β_p^{VF}). That is, we have 25 β_p^{MKT} and 25 β_p^{VF}.

Then, we use these factor loadings in the second step of Fama-MacBeth cross-sectional regression. On each trading day within the following one-month period, we run the following regression by using data for 25 portfolios:

$$R_p - R_f = \alpha + \gamma^{MKT}\beta_p^{MKT} + \gamma^{VF}\beta_p^{VF} \tag{11}$$

where R_p is the daily return on each portfolio. We use the same β_p^{MKT} and β_p^{VF} in the following one-month to estimate γ^{MKT} and γ^{VF}. Since there are about 20 trading days within each month, after the cross-sectional regression, we can get about 20 γ_{mkt} and 20 γ_{VF} in each

[14] We use daily data within one month for regression models shown in equation (8) and (9).

calendar month. Finally, we use the t-test to check whether the risk premium on each volatility factor is significantly different from zero.

As we already mentioned earlier, this study also investigate whether the market and volatility risk premia are asymmetric. In order to consider different situations, we define four dummy variables (D_{+}^{MKT}, D_{-}^{MKT}, D_{+}^{VF}, and D_{-}^{VF}).[15]

$$R_p - R_f = \alpha + \gamma_{\pm}^{MKT} D_{\pm}^{MKT} \beta_p^{MKT} + \gamma_{\pm}^{VF} D_{\pm}^{VF} \beta_p^{VF} \tag{12}$$

The model above helps to separate different scenarios: upward or downward movements of the market portfolio, and positive or negative shocks of the volatility factor. So the model enables us to analyze whether the market and volatility risk premia differ by the direction of market. This model augments the cross-sectional regression to allow for the fact that the realized market and realized volatility risk premia can be negative over specific periods.

2.2.4 Discussion about the Methodology

As mentioned above, without including dummy variables in regression models, it is arduous to detect a significant difference between returns on extreme portfolios. Given that the data used in our analysis are downloaded with daily frequency, the average market or volatility realizations are expected to be close to zero (this is later confirmed in Panel A of Table 1). If the average market or volatility realization is close to zero, no matter how factor loadings change across different quintiles, returns on different quintiles are all similar. In contrast, by separating different market or volatility realizations, it is possible to find significant results. In other words, the inclusion of dummy variables to isolate different market or volatility realizations enables us to investigate the asymmetric effect of volatility shocks. However, the shortcoming of this methodology is due to the fact that we cannot

[15] We follow the method documented in Pettengill, Sundaram and Mathur (1995) and Hung, Shackleton and Xu (2004) to define dummy variables. We define that D_{+}^{MKT} is equal to 1 if the market excess return is positive or zero, otherwise 0; D_{-}^{MKT} is equal to 1 if the market excess return is negative, otherwise 0; D_{+}^{VF} is equal to 1 if volatility risk factor (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$) is positive or zero, otherwise 0; D_{-}^{VF} is equal to 1 if volatility risk factor (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$) is negative, otherwise 0.

predict future movements of both market and volatility indices. So, this kind of model can perform well in ex-post analysis, but it cannot help in predicting ex-ante asset return.

The results about in-sample and out-of-sample time-series regressions, and Fama-MacBeth cross-sectional regressions are presented and discussed in the next section.

3. Results

Before presenting the results for time-series and cross-sectional regressions, we first show some descriptive statistics.

3.1 Descriptive Statistics

First, we plot daily data of the VIX future, the VIX, and the S&P500 index during the period from April 1st, 2004 to December 31st, 2012 in Figure 1.

[Insert Figure 1 here]

It is clear that when the S&P500 index increases, VIX and VIX future 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 S&P500 index decreases dramatically (from about 1280 to 970), while VIX future (VIX) increases from 22% (22%) to 60% (80%).

[Insert Table 1 here]

Looking at the pairwise correlations in Panel B of Table 1, we find that the correlation between VIX futures and S&P500 index is -0.6257 and the correlation between VIX and S&P500 indices is -0.6036. Thus, we can confirm that VIX and its futures are both highly negatively correlated with S&P500 index. When the market index increases, the volatility index often decreases, so investors care less about volatility risk. In contrast, when the market index falls, the volatility index frequently increases because investors care more about downward returns related to the volatility risk. Thus, investigating the volatility risk premium is an important issue for investors.

Before starting the time-series and cross-sectional analysis, in order to make sure that our models are not mis-specified, we test whether variables used in our analysis are stationary or not. From the results for the augmented Dickey-Fuller unit root test (with the null hypothesis that the tested process has a unit root) presented in Panel C of Table 1, we find that the VIX future or the VIX are not stationary at 1% significance level (with p-values of 0.0717 and 0.0373, respectively). However, the first difference of VIX future or VIX is stationary (with a p-value smaller than 10^{-4}). [16] Thus, both VIX future and VIX are integrated. So, in later analysis, we use the first difference of VIX future or VIX rather than the level as the volatility factor. We also test whether the difference between VIX and VIX futures and the difference between log VIX and log VIX future are stationary or not. The results in last two rows in Panel C of Table 1 indicate that both differences have no unit root. So, all four factors (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$) used in our study are stationary.

In next sub-section, we present the results for in-sample and out-of-sample time series regressions.

3.2 Results for Time-Series Regressions

Table 2 to 6 present results for portfolio level analysis about in-sample and out-of-sample time series regressions. We form quintile portfolios based on the coefficients obtained from in-sample regressions. Quintile portfolio 1 consists of stocks with the lowest corresponding coefficient, and quintile portfolio 5 consists of stocks with the highest

[16] For ADF unit root test, in order to find the proper lag length, we use Schwarz info criterion with allowing for maximum lags of 24. For ADF unit root test, if Augmented Dickey-Fuller test statistic is smaller than critical values, it means that there is no unit root. If there is a unit root in a process, we will test whether the first difference is stationary or not. If the first difference of a variable is stationary, it means that the process is I(1) process.

corresponding coefficient. In addition, we form the "5-1" zero-investment portfolio by holding portfolio 5 and shorting portfolio 1.

3.2.1 Results for Univariate Regressions

First, we investigate the effect of each factor separately through univariate regressions. Table 2 reports the corresponding results.[17]

[Insert Table 2 here]

Looking at Panel A of Table 2, we cannot find any significantly non-zero monthly returns for the "5-1" arbitrage portfolio if we form quintile portfolios based on β_i^{MKT} . However, the out-of-sample regression's results show a persistent effect of market beta on asset returns. That is, the market beta (β_p^{MKT}) increases from quintile portfolio 1 to quintile portfolio 5 in out-of-sample period. The market beta on the arbitrage portfolio is statistically significant even at 1% significance level (1.1038 with a p-value smaller than 10^{-4}). This confirms the persistence of the market beta on asset returns.

Panel B to Panel E of Table 2 show results for in-sample and out-of-sample regression analysis by using volatility factors (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$). If we form quintile portfolios based on loadings of volatility factors, all these four panels reveal that $\bar{\beta}_p^{\Delta VX}$, $\bar{\beta}_p^{\Delta VIX}$, $\bar{\beta}_p^{VV}$, and $\bar{\beta}_p^{logVV}$ all increase from quintile portfolio 1 to quintile portfolio 5 in out-of-sample period. The beta coefficients on volatility factors for arbitrage portfolios are all statistically significant at a 1% significance level. Thus, these panels show that the effects of volatility factors on asset returns are persistent during an out-of-sample period.

So, from in-sample and out-of-sample univariate regressions, we find that the effect of market beta or betas associated with volatility factors on asset returns persists. In other words, portfolios with low (high) market beta or betas on volatility factors during in-sample

[17] Here, we only present the results for value-weighted portfolios because of the space limitation. Resutls for portfolios constructed by using other weighting scheme is available upon request.

regressions also have low (high) market beta or betas on volatility factor in out-of-sample regressions.

3.2.2 Results for Multivariate Regressions

In this section, we compare whether the persistence of the effect of market beta is stronger than the persistence of effect of volatility factors. Rather than using univariate regression models, we test our hypothesis through the use of multivariate regression models by including market excess return and each of the volatility proxies (ΔVX, ΔVIX, $VIX - VX$, or $logVIX - logVX$), one at a time, as explanatory variables. The corresponding results are shown in Table 3 to 6.

[Insert Table 3 to Table 6 here]

In these four tables, quintile portfolios from column 2 to column 8 are formed based on beta coefficients on market excess return, and quintile portfolios in column 9 to column 15 are formed based on beta coefficients on each volatility factor (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$, respectively).

On the **left** panels of these four tables (column 2 to 8), we find that, with in-sample regressions, portfolios with low market betas also have low betas on volatility factors. In out-of-sample regressions, no matter which weighting scheme is used for portfolio formation, beta coefficients on market excess return increase monotonically from quintile portfolios with low average market beta (portfolio 1) to quintile portfolios with high average market beta (portfolio 5). Meanwhile, $\bar{\beta}_p^{MKT}$ on the arbitrage portfolios is significant in each panel of all four tables. However, beta coefficients on volatility factors ($\bar{\beta}_p^{\Delta VX}$, $\bar{\beta}_p^{\Delta VIX}$, $\bar{\beta}_p^{VV}$, and $\bar{\beta}_p^{logVV}$) regarding to the arbitrage portfolios are not always statistically significant during out-of-sample regressions. In table 3, none of three panels has significant $\bar{\beta}_p^{\Delta VX}$ on the arbitrage portfolio. The insignificant $\bar{\beta}_p^{VF}$ on the arbitrage portfolio can also be found in Panel C of Table 4, Table 5, and Table 6.

On the **right** panels of these same four tables, we show the findings regarding the effects of the volatility risk on asset returns. In all four tables, with in-sample regressions, portfolios exhibiting low betas on volatility factors also have low market betas. Analyzing these four tables we extract stylized facts. First, there is no monotonic pattern in beta coefficients on market excess returns or volatility factors in all three panels of Table 3. Then, in Table 4, in Panel A, we find that the arbitrage portfolio has statistically significant $\bar{\beta}_p^{MKT}$ and $\bar{\beta}_p^{\Delta VIX}$ even though there is no monotonic pattern. Meanwhile, in Panel B, $\bar{\beta}_p^{MKT}$ on the "5-1" arbitrage portfolio is marginally significant under 10% significance level; this can show the weak persistence of market and volatility betas. In Table 5, we find some interesting results: $\bar{\beta}_p^{MKT}$ and $\bar{\beta}_p^{VV}$ of the arbitrage portfolio are statistically significant in Panel A, B and C of Table 5 even though we can only find a monotonic pattern in $\bar{\beta}_p^{VV}$ in Panel C. Similar results are found in Table 6 where all $\bar{\beta}_p^{MKT}$ and $\bar{\beta}_p^{logVV}$ on the arbitrage portfolios are statistically significant.

The results obtained by using ΔVIX in Table 4 are comparable to the results documented in previous studies. In the right part of Panel B in Table 4, beta coefficients on ΔVIX from in-sample regressions increase monotonically from -1.0013 for quintile portfolio 1 to 1.0990 for quintile portfolio 5. From out-of-sample regressions, we can find that beta coefficients on ΔVIX increase from quintile 1 (-0.0093) to quintile 5 (0.0186) with exception of quintile 3. Similar patterns can be found in Ang, Hodrick, Xing and Zhang (2006); from Table 1 in Ang, Hodrick, Xing and Zhang (2006), beta coefficients on ΔVXO from in-sample regressions increase from -2.09 for quintile portfolio 1 to 2.18 for quintile portfolio 5. For out-of-sample regressions, beta coefficients on ΔVXO still increase from quintile portfolio 1 to quintile portfolio 5. However, the range is narrower, only from -0.033 to 0.018.

Comparable results are also documented in Chang, Christoffersen and Jacobs (2013); Panel A of Table 1 in their paper show that, with in-sample time-series regressions, beta coefficients on change in volatility increase monotonically from -1.30 for quintile portfolio 1 to 1.40 for quintile portfolio 5.

From in-sample and out-of-sample univariate regressions, we find that the persistence of the effect of market beta on asset returns is stronger than that of the effect of betas on volatility factors on asset returns. However, the inclusion of volatility factors in the regression model slightly improves the performance of the model (R-square).[18] So it is useful to include volatility factors in addition to market excess return in the regression model. Then, in multivariate time-series regressions, we can find that both market and volatility risks have persistent beta coefficients. Furthermore, the persistence effect of the beta on market risk seems to be stronger compared to the beta on the volatility risk. However, our analysis shows the importance of the volatility risk in asset pricing.

In the next sub-section, we focus on the asymmetric effect of volatility risk.

3.3 Results for Asymmetric Time-Series Regressions

3.3.1 Results for Four Factors during the Period from Apr 2004 to Dec 2012

As we mentioned in section 2.2.2, the models used in section 3.1 and 3.2 assume that the effects of market risk and volatility risk are symmetric. However, empirical studies highlight the existence about asymmetric effect of the market risk (Ang, Chen and Xing, 2006) and the volatility risk (Farago and Tedongap, 2012). In the light of this, models

[18] For in-sample regressions, among all univariate regression models, the model including the market excess return has the highest R-square (0.2292). This means that the traditional CAPM can explain 22.92% variation of the equity returns. In addition, if we include the volatility risk factor (ΔVX, and ΔVIX) in the time-series regression model, the R-square can be improved a little (0.2305 and 0.2313, respectively). Furthermore, for out-of-sample regressions, all multi-variate regression models outperform the univariate regression models in explaining variation of portfolio returns. The R-square for univariate regression model including market excess return is 0.7808, while the R-square for multivariate regression model including both market excess return and change in VIX future is 0.8799.

incorporating an asymmetric effect may therefore be more precise. In order to investigate the asymmetric effect, we define a dummy variable which is equal to 1 if the volatility factor (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$) is larger than or equal to zero, and equal to 0 if the volatility factor is smaller than zero. Then, we include this dummy variable into the regression (as shown in eq. (7)) and form quintile portfolios in two different situations ($D^{VF} = 0$ and $D^{VF} = 1$). The results on Jensen's alpha with respect to the CAPM and the Fama-French three-factor model are provided in Table 7 to 10.

[Insert Table 7 here]

Table 7 presents results for portfolio analysis about Jensen's alpha when we form quintile portfolios in two different situations separated on the basis of ΔVX. When ΔVX is negative, we do not find any significant Jensen's alpha on the "5-1" arbitrage portfolio no matter which weighting scheme is used for quintile portfolio formation. Conversely, the results are different for portfolios formed when ΔVX is positive. In this case, we find significantly negative Jensen's alpha with respect to the CAPM (significant at 5% significance level) in Panel B and Panel C of Table 7 (-0.0273% per day with p-value of 0.0435 and -0.0246% per day with p-value of 0.0318). Thus, the results show weak evidence that, when there is a positive change in VIX future, portfolios with low exposure to the volatility risk (measured by ΔVX) outperform those with high exposure to the volatility risk.

[Insert Table 8 here]

Differently, we obtain the results in Table 8 replacing ΔVX with ΔVIX as proxy for the volatility risk. The five columns on the left present results obtained during the period when there is a negative change in the VIX. There is no evidence that we are able to obtain statistically significant returns on the "5-1" arbitrage portfolio when the VIX decreases. Conversely, if quintile portfolios are formed when the VIX increases, we find statistically significant and negative alphas with respect to the Fama-French three-factor model on the arbitrage portfolio (-0.0162% per day with p-value of 0.0523 in Panel A, -0.0365% with p-value of 0.0125 in Panel B, and -0.0291% per day with p-value of 0.0161 in Panel C).[19] This means that investors can generate significant positive excess returns by selling the portfolio with high exposure to the volatility risk (portfolio 5) and holding the portfolio with low exposure to the volatility risk (portfolio 1).

[Insert Table 9 & Table 10 here]

Table 9 and Table 10 use $VIX - VX$ and $log(VIX) - log(VX)$ to measure the volatility risk, respectively. The results show that only when we form quintile portfolios during periods in which the VIX is higher than its future (i.e. positive basis), we find marginally significant negative alpha with respect to Fama-French three-factor model (around -0.023% per day in Panel B of Table 9 and 10. Thus, investors expect that portfolios with lower exposure to the volatility risk earn higher returns when VIX remains higher than its expectation.

From the analysis of the asymmetric effect of the volatility risk, investors treat negative and positive volatility realizations differently. When the volatility factor is negative, none of the four volatility proxies (ΔVX, ΔVIX, $VIX - VX$, and $log(VIX) - log(VX)$) presents significant relationship with the quintile portfolio returns. However, when the volatility factor is positive, all four volatility factors are significantly negatively related to quintile portfolio returns even after controlling for market excess returns, SMB and HML. That is, when we register positive volatility shocks, all four volatility factors generate significant and negative risk-adjusted returns on arbitrage portfolios.

In addition, the use of ΔVIX as indicator for volatility shocks allows to better (compared to ΔVX, $VIX - VX$, or $log(VIX) - log(VX)$) highlight the importance of

[19] Even though we can find significant alpha on the arbitrage portfolio after controlling for size and book-to-market ratio (Fama-French three-factor model), we cannot find significant alpha on the arbitrage portfolio with respect to the CAPM. This can be due to the high variation of the alpha with respect to the CAPM.

considering the asymmetric effect of volatility on equity returns. Accordingly, in the next sub-section, we only focus on the asymmetric effect generated by the ΔVIX and test the robustness of our results by extending the sample period.

3.3.2 Results for ΔVIX during the Period from Jan 1996 to Dec 2012

In this sub-section, only ΔVIX is used as a proxy for the volatility risk, and the sample period is extended to the period from January, 1996 to December, 2012. Furthermore, the period for portfolio formation is extended from one month to two or three months. The results are documented in Table 11 to Table 13.

[Insert Table 11 here]

Quintile portfolios in Table 11 are formed by coefficients obtained from time-series regressions using one-month daily data. The results show that, when the VIX decreases, we cannot find any significant relationship between the volatility risk and quintile portfolio returns. However, when the VIX increases, we can find significant results. In Panel A, we observe a significantly negative Jensen's alpha with respect to both the CAPM and the Fama-French three-factor model (-0.0172% per day with p-value of 0.0153 and -0.0150% per day with p-value of 0.0344, respectively). Then, in Panel B and C, we can find a significantly negative Jensen's alpha with respect to the Fama-French three-factor model (-0.0253% per day with p-value of 0.0251, and -0.0241% per day with p-value of 0.0115, respectively). Thus, results in Table 11 are still consistent with the results obtained in previous sub-section even extending the sample period.

[Insert Table 12 here]

Subsequently, we try to use more data in time series regressions for portfolio formation. Table 12 show results obtained when we use two months' daily data for portfolio formation. From these results, we can only find two significant alphas on the "5-1" arbitrage portfolio: both cases are found when the VIX increases. The first one is the significantly negative alpha with respect to the CAPM in Panel A (-0.0126% per day with p-value of 0.0770), and the second one is the significantly negative alpha with respect to the Fama-French three-factor model in Panel C (-0.0196% per day with p-value of 0.0299).

[Insert Table 13 here]

In case we use three months' daily data in time series regressions for portfolio formation, we get the results documented in Table 13. The only significant coefficient on the arbitrage portfolio is the CAPM Jensen's alpha in Panel A (-0.0125% per day with respect to 0.0678).

Thus, from the results in this sub-section, we find that, if we use one month's daily data in time-series regression for portfolio formation, quintile portfolio returns are negatively correlated with ΔVIX only when the VIX increases. If we extend the in-sample period to two or three months, the results are weaker. However, we can still find evidence on the asymmetric effect of the volatility risk on asset returns.

In brief, results of asymmetric time-series regressions mainly show that, among all four volatility factors (ΔVX, ΔVIX, $VIX - VX$, or $log(VIX) - log(VX)$), ΔVIX is the most powerful to highlight the importance of the asymmetric effect due to the volatility risk. Volatility risk only matters when its change is positive (i.e. the VIX future increases, the VIX increases, or the VIX is higher than its expectation). The results about ΔVIX are robust even if we extend the sample period to January 1996 or we increase the period for portfolio formation to two months or three months.

From Figure 1 and Panel B of Table 1, we find a negative correlation between volatility index (the VIX) and market index (S&P 500 Index). Thus, decreases in the market index often come together with increases in the volatility index. From Ang, Chen, and Xing (2006) and Farago and Tedongap (2012) document the asymmetric effect of the market risk and the volatility risk, respectively. Stocks that have a strong relationship with the market index during crashes have higher average returns. In addition, investors are willing to buy insurance for an undesirable increase in volatility index. Thus, results about the asymmetric effect of volatility factors in this section are somewhat consistent with findings in previous studies. This research confirms a significant negative relationship between the volatility risk and asset returns during the period with increasing volatility index. Investors expect that the market index will increase. Meanwhile, the volatility index will decrease correspondingly unless it is below its mean. So, increases in market index and decreases in volatility index are consistent with investors' expectations. However, a decrease in market index and an increase in volatility index are not expected by investors. Investors treat them as shocks. Thus, it is reasonable that volatility factors used in this study are negatively related to asset returns only during the period with positive volatility factors.

3.4 Results for Fama-MacBeth Cross-Sectional Regressions

Even though results from time-series regressions reflect the negative relationship between quintile portfolio returns and volatility factors, we still need to use Fama-MacBeth cross-sectional regressions in order to confirm whether investors are willing to pay significant risk premia to protect their investment for volatility risk, i.e. accept a lower return.

Before the cross-sectional regressions, to reduce idiosyncratic errors, we need to form portfolios. At the end of each month, we run the regression models presented in equation (8) and (9). We divide individual stocks into five quintiles based on β_i^{MKT} obtained from equation (8). Then, within each market quintile, we form quintile portfolios on β_i^{VF} obtained from equation (9). So, for our cross-sectional regressions, we have $5 \times 5 = 25$ portfolios in total.

First, we run Fama-MacBeth cross-sectional regressions by using 25 portfolio returns without distinguishing whether market excess returns are positive or negative, and volatility factors are positive or negative. The corresponding results are documented in Table 14.

[Insert Table 14 here]

In all eight columns, we cannot find any supportive evidence that investors are willing to pay premia or buy insurance for either market risk or volatility risk. This could be due to the fact that the risk premium on each pricing factor (i.e. gamma) is calculated at daily frequency. The variation of the risk premium on each pricing factor should be quite high. Thus, the high variation in the risk premium leads to insignificant risk premium on different pricing factors.

In addition, we investigate whether the market risk premium or volatility risk premium are asymmetric by using the cross-sectional regression model presented in equation (12) after defining four dummy variables (D_{+}^{MKT}, D_{-}^{MKT}, D_{+}^{VF}, and D_{-}^{VF}). The results on the asymmetric cross-sectional regression are presented in Table 15.

[Insert Table 15 here]

In all eight columns in this table, we find that the market risk premium in both bear markets and bull markets are quite persistent no matter which volatility factor is used in the regression models or which weighting scheme is used for portfolio formation. In bull markets, the market risk premium is between 0.43% and 0.46% per day, and is significant at the 1% significance level. In bear markets, the market risk premium is around -0.53% per day and also significant at the 1% significance level. If we look at the volatility risk premium, we can find significant risk premium on almost all four risk premium at 1% significance level except for γ_{+}^{VIX-VX} obtained by using value-weighted scheme. To be more specific, the risk premium on ΔVX when ΔVX is positive is 0.3025% per day if we use equal-weighted scheme and 0.3206% per day if we use value-weighted scheme. The risk premium on ΔVX when ΔVX is negative is around -0.26% per day. If ΔVIX is used as the volatility factor, $\gamma_{+}^{\Delta VIX}$ is higher than 0.49% per day while $\gamma_{-}^{\Delta VIX}$ is -0.4295% if we form equal-weighted portfolios and -0.4650% if we form value-weighted portfolios. Then, if we use the difference between the VIX and the VIX future as the volatility factor, the risk premium on $VIX - VX$ is significant when $VIX - VX$ is negative (around -0.30% if VIX is lower than VIX future). If we use $logVIX - logVX$ rather than $VIX - VX$ as the volatility factor, $\gamma_{+}^{logVIX-logVX}$ is higher than 0.32% per day and $\gamma_{-}^{logVIX-logVX}$ is lower than -0.12% per day.

Concluding, when we incorporate the asymmetric effect into our analysis, the risk premium on market excess return and volatility factors are significant.

4. Conclusions

Coefficients obtained from in-sample and out-of-sample time-series regressions show that portfolios with lower (higher) coefficients on market or volatility risk during in-sample period also have lower (higher) coefficients in out-of-sample period. Furthermore, the persistence of a market beta effect on asset returns is stronger than that of betas on volatility factors. Moreover, including a volatility factor in the regression model improves the performance of the model even though we cannot detect significant univariate relationship between volatility and portfolio returns.

However, using distinguished negative or positive volatility through a dummy variable, we find that investors treat negative and positive volatility realizations differently. When this volatility realization is negative, there is no significant difference among quintile portfolio returns. Conversely, when the volatility realization is positive, all volatility factors are significantly negative related to quintile portfolio returns (even after controlling for market excess returns, SMB and HML). So, our study provides supportive evidence that the effect of the volatility risk on asset returns is asymmetric and influential at times of market stress.

To conclude, if we incorporate this asymmetric effect into our analysis, the results for Fama-MacBeth cross-sectional regressions reveal that the risk premia on market return and volatility realization are significant.

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Appendix

Figure 1: VIX Index Future (VX), VIX Index (VIX), and S&P500 Index (April 1st, 2004 to December 31st, 2012)

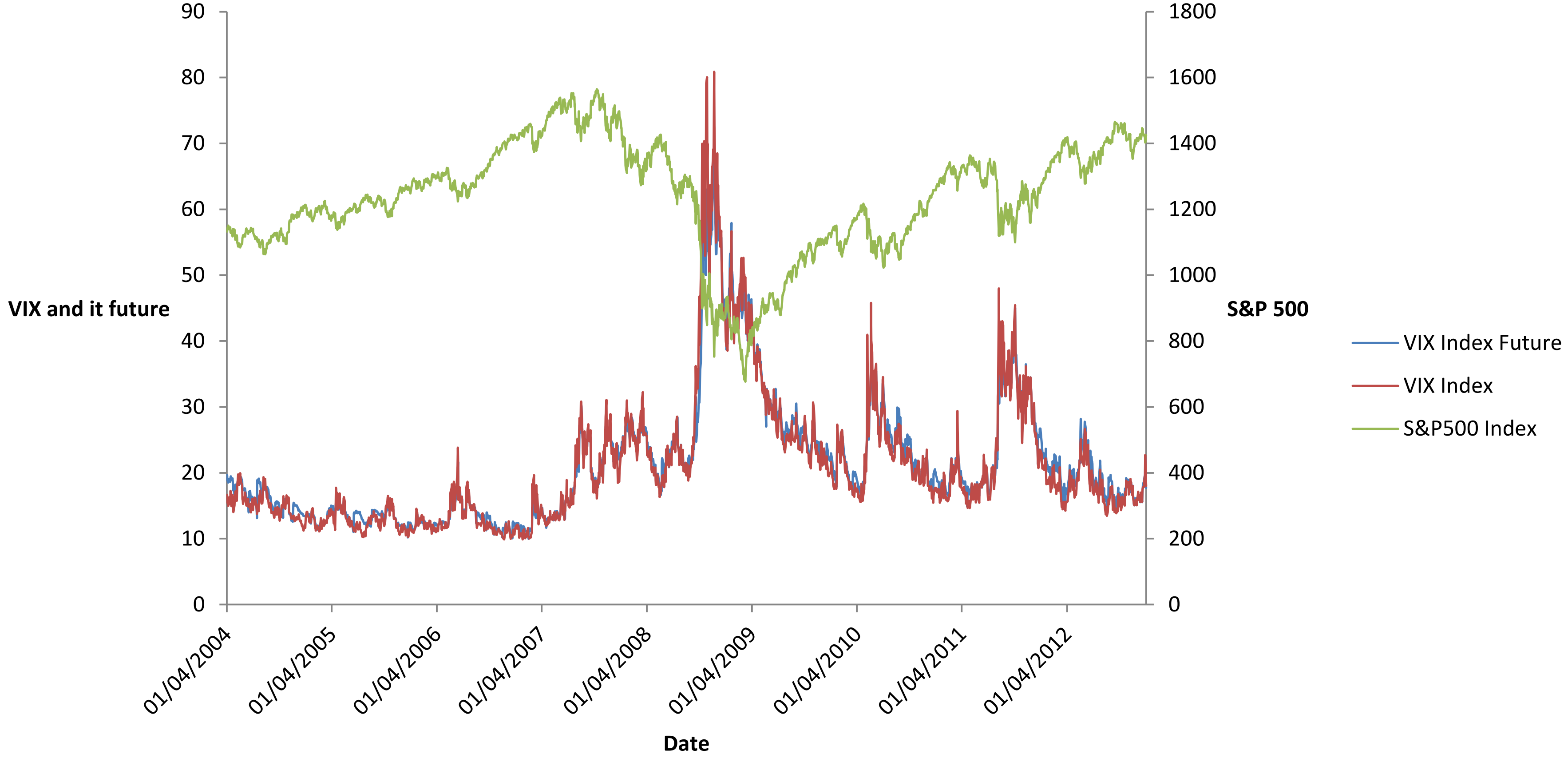

Table 1: Descriptive Statistics

In our analysis, we calculate daily changes for VIX index future (VX) and VIX index (VIX).

Panel A: Summary Statistics

	VX	VIX	ΔVX	ΔVIX	$VIX - VX$	$log(VIX) - log(VX)$	r_m
Mean	21.3154	20.9471	-0.0009	0.0006	-0.3683	-0.0294	0.0002
Std	9.4873	10.3202	1.3773	1.9386	1.9607	0.0701	0.0135
Min	9.9540	9.8900	-13.0200	-17.3600	-4.9700	-0.2788	-0.0896
Max	67.9500	80.8600	10.2400	16.5400	23.3100	0.3571	0.1135

Panel B: Correlation Table

	VX	VIX	ΔVX	ΔVIX	$VIX - VX$	$log(VIX) - log(VX)$	$S\&P500$	$\Delta S\&P500$	$r_{S\&P500}$	r_m
VX	1									
VIX	**0.9839**	1								
ΔVX	0.0728	0.0964	1							
ΔVIX	0.0430	0.0938	**0.8088**	1						
$VIX - VX$	0.3401	**0.5027**	0.1554	0.2858	1					
$log(VIX) - log(VX)$	0.2894	0.4325	0.1049	0.2432	**0.8763**	1				
$S\&P500$	**-0.6257**	**-0.6036**	-0.0110	-0.0131	-0.1495	-0.1149	1			
$\Delta S\&P500$	-0.0900	-0.1309	**-0.7262**	**-0.8306**	-0.2539	-0.2404	0.0461	1		
$r_{S\&P500}$	-0.0805	-0.1197	**-0.7371**	**-0.8397**	-0.2408	-0.2164	0.0385	**0.9809**	1	
r_m	-0.0782	-0.1189	**-0.7348**	**-0.8385**	-0.2475	-0.2232	0.0350	**0.9797**	**0.9972**	1

Panel C: Unit Root Tests

	Augmented Dickey-Fuller test statistic	p-value
VX	-2.7140	0.0717
VIX	-2.9769	0.0373
ΔVX	-39.5390	0.0000
ΔVIX	-28.9845	0.0000
$VIX - VX$	-9.2935	0.0000
$log(VIX) - log(VX)$	-11.1879	0.0000

Table 2: Quintile Portfolios Formed on the Coefficient from Uni-Variate Regressions from April 2004 to December 2012

First, we run regression model (1) and (2) for each individual stock by using the previous one-month daily data. Then, we form value-weighted quintile portfolios based on beta coefficient. Portfolio 1 consists of stocks with the lowest beta coefficient, while portfolio 5 consists of stocks with the highest beta coefficient. After portfolio formation, we conduct out-of-sample time-series regression (model (4) and (5)) for next one-month quintile portfolio daily returns by using the following regression model. The "return" column reports compounded returns of quintile portfolios during the post one-month period.

	In-Sample		Out-of-Sample		
Panel A: Portfolios formed by $\bar{\beta}_i^{MKT}$					
	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$
1	0.0008	-0.1485	0.0049	0.0001	0.4636
2	0.0004	0.4491	0.0060	0.0001	0.6762
3	0.0003	0.8607	0.0065	0.0001	0.9083
4	0.0002	1.2818	0.0078	0.0000	1.1746
5	0.0002	2.0378	0.0076	0.0000	1.5674
5-1			0.0027	-0.0002	1.1038***
pval			(0.6760)	(0.3317)	(0.0000)
Panel B: Portfolios formed by $\bar{\beta}_i^{\Delta VX}$					
	$\bar{\alpha}_i$	$\bar{\beta}_i^{\Delta VX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{\Delta VX}$
1	0.0008	-1.9034	0.0071	0.0003	-1.1785
2	0.0005	-1.1113	0.0077	0.0003	-0.9099
3	0.0005	-0.6948	0.0064	0.0003	-0.7525
4	0.0005	-0.3036	0.0057	0.0003	-0.6076
5	0.0009	0.3237	0.0055	0.0003	-0.5271
5-1			-0.0016	0.0000	0.6515***
pval			(0.7928)	(0.9186)	(0.0000)
Panel C: Portfolios formed by $\bar{\beta}_i^{\Delta VIX}$					
	$\bar{\alpha}_i$	$\bar{\beta}_i^{\Delta VIX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{\Delta VIX}$
1	0.0006	-1.4604	0.0081	0.0003	-1.0145
2	0.0004	-0.8773	0.0068	0.0002	-0.7678
3	0.0004	-0.5636	0.0063	0.0002	-0.6035
4	0.0004	-0.2621	0.0054	0.0002	-0.4716
5	0.0009	0.2052	0.0055	0.0003	-0.3632
5-1			-0.0027	0.0000	0.6513***
pval			(0.6638)	(0.9922)	(0.0000)
Panel D: Portfolios formed by $\bar{\beta}_i^{VV}$					
	$\bar{\alpha}_i$	$\bar{\beta}_i^{VV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{VV}$
1	-0.0036	-1.1913	0.0085	-0.0001	-0.4797
2	-0.0011	-0.5910	0.0072	-0.0001	-0.3794
3	0.0002	-0.3040	0.0069	-0.0001	-0.3322
4	0.0014	-0.0402	0.0053	-0.0001	-0.3021
5	0.0043	0.4318	0.0058	-0.0001	-0.3140
5-1			-0.0027	0.0000	0.1657***
pval			(0.5268)	(0.9557)	(0.0000)
Panel E: Portfolios formed by $\bar{\beta}_i^{logVV}$					
	$\bar{\alpha}_i$	$\bar{\beta}_i^{logVV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{logVV}$
1	-0.0038	-0.2520	0.0082	-0.0003	-0.1106
2	-0.0012	-0.1286	0.0067	-0.0003	-0.0869
3	0.0001	-0.0697	0.0065	-0.0002	-0.0761
4	0.0013	-0.0155	0.0060	-0.0001	-0.0675
5	0.0041	0.0808	0.0058	-0.0002	-0.0690
5-1			-0.0025	0.0001	0.0416***
pval			(0.5457)	(0.6417)	(0.0000)

Table 3: Results for Time-Series Regressions with ΔVX Included from April 2004 to December 2012

First, we run the following regression for each individual stock by using the previous one-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{m,t} - r_{f,t}) + \beta_i^{\Delta VX} \Delta VX_t$$

where ΔVX_t represents daily change in VIX future. Then, we form quintile portfolios based on β_i^{MKT} (Column 2 to 8) or $\beta_i^{\Delta VX}$ (Column 9 to 15). Portfolio 1 consists of stocks with the lowest β_i^{MKT} or $\beta_i^{\Delta VX}$, while portfolio 5 consists of stocks with the highest β_i^{MKT} or $\beta_i^{\Delta VX}$. After portfolio formation, we conduct out-of-sample time-series regression for next one-month quintile portfolio daily returns by using the following regression model:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) + \beta_p^{\Delta VX} \Delta VX_t$$

The "return" column reports compounded returns of quintile portfolios during the post one-month period.

	Portfolios Sorted on β_i^{MKT}							Portfolios Sorted on $\beta_i^{\Delta VX}$						
	In-Sample			Out-of-Sample				In-Sample			Out-of-Sample			
	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{\Delta VX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{\Delta VX}$	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{\Delta VX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{\Delta VX}$
Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios														
1	0.0008	-0.8227	-1.0516	0.0104	0.0004	0.3350	-0.0522	0.0006	-0.0193	-1.7553	0.0129	0.0003	0.9179	-0.0441
2	0.0001	0.3153	-0.2375	0.0092	0.0002	0.5719	-0.0162	0.0000	0.6178	-0.4262	0.0096	0.0002	0.8396	-0.0291
3	0.0000	0.8250	-0.0592	0.0097	0.0002	0.8800	-0.0190	0.0000	0.7292	-0.0239	0.0086	0.0002	0.7360	-0.0188
4	-0.0001	1.3453	0.1736	0.0104	0.0001	1.1041	-0.0283	0.0000	1.0436	0.3673	0.0086	0.0001	0.8346	-0.0158
5	0.0001	2.6090	1.0105	0.0111	0.0001	1.3579	-0.0430	0.0004	1.9007	1.6740	0.0121	0.0002	0.9209	-0.0508
5-1				0.0007	-0.0003***	1.0229***	0.0092				-0.0008	-0.0001	0.0030	-0.0067
pval				(0.9016)	(0.0092)	(0.0000)	(0.6769)				(0.6986)	(0.4094)	(0.8776)	(0.6988)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0009	-0.3846	-0.9139	0.0065	0.0001	0.6325	-0.0152	0.0007	0.4779	-1.2758	0.0081	0.0002	1.1780	0.0140
2	0.0004	0.3539	-0.3474	0.0082	0.0002	0.7165	-0.0070	0.0003	0.7429	-0.4165	0.0077	0.0001	0.9628	-0.0229
3	0.0003	0.8250	-0.0887	0.0073	0.0001	0.9162	-0.0055	0.0002	0.8981	-0.0227	0.0067	0.0001	0.9029	-0.0195
4	0.0002	1.3307	0.1564	0.0070	0.0001	1.1402	-0.0115	0.0002	1.1661	0.3599	0.0064	0.0001	0.9605	0.0006
5	0.0003	2.2607	0.6654	0.0066	-0.0001	1.4559	-0.0347	0.0005	1.7975	1.1825	0.0050	0.0000	1.1258	-0.0044
5-1				0.0001	-0.0002	0.8234***	-0.0195				-0.0031	-0.0002	-0.0522	-0.0184
pval				(0.9849)	(0.2036)	(0.0000)	(0.5727)				(0.3495)	(0.2789)	(0.1157)	(0.5217)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0006	0.0661	-0.5533	0.0063	0.0001	0.6792	-0.0011	0.0005	0.5700	-0.9932	0.0086	0.0002	1.1124	0.0032
2	0.0003	0.6137	-0.1781	0.0072	0.0001	0.8135	-0.0062	0.0003	0.7769	-0.3021	0.0071	0.0001	0.9341	-0.0204
3	0.0002	0.9225	-0.0240	0.0065	0.0001	0.9420	-0.0104	0.0003	0.8877	-0.0158	0.0051	0.0000	0.8886	-0.0187
4	0.0002	1.2690	0.1419	0.0064	0.0001	1.1110	-0.0043	0.0002	1.0906	0.2725	0.0072	0.0001	0.9315	-0.0141
5	0.0003	2.0700	0.5577	0.0059	-0.0001	1.3968	-0.0217	0.0004	1.6245	0.9722	0.0046	0.0000	1.0829	0.0061
5-1				-0.0004	-0.0002	0.7175***	-0.0206				-0.0040	-0.0002	-0.0295	0.0029
pval				(0.9372)	(0.1807)	(0.0000)	(0.4984)				(0.1540)	(0.1541)	(0.2767)	(0.9036)

Table 4: Results for Time-Series Regressions with ΔVIX Included from April 2004 to December 2012

First, we run the following regression for each individual stock by using the previous one-month daily data:

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

where ΔVIX_t represents daily change in VIX index. Then, we form quintile portfolios based on β_i^{MKT} (Column 2 to 8) or $\beta_i^{\Delta VIX}$ (Column 9 to 15). Portfolio 1 consists of stocks with the lowest β_i^{MKT} or $\beta_i^{\Delta VIX}$, while portfolio 5 consists of stocks with the highest β_i^{MKT} or $\beta_i^{\Delta VIX}$. After portfolio formation, we conduct out-of-sample time-series regression for next one-month quintile portfolio daily returns by using the following regression model:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) + \beta_p^{\Delta VIX}\Delta VIX_t$$

The "return" column reports compounded returns of quintile portfolios during the post one-month period.

	Portfolios Sorted on $\beta_{i,MKT}$							Portfolios Sorted on $\beta_{i,\Delta VIX}$						
	In-Sample			Out-of-Sample				In-Sample			Out-of-Sample			
	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{\Delta VIX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{\Delta VIX}$	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{\Delta VIX}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{\Delta VIX}$
Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios														
1	0.0007	-1.0579	-1.0128	0.0118	0.0004	0.4187	0.0141	0.0004	-0.4512	-1.4391	0.0139	0.0003	0.9438	0.0237
2	0.0001	0.2870	-0.2027	0.0090	0.0002	0.6118	0.0127	0.0000	0.5316	-0.3232	0.0091	0.0001	0.8528	0.0157
3	0.0000	0.8522	-0.0120	0.0093	0.0001	0.9099	0.0225	0.0000	0.7662	0.0162	0.0084	0.0001	0.7765	0.0222
4	-0.0001	1.4486	0.2410	0.0099	0.0001	1.1471	0.0388	0.0000	1.2129	0.3632	0.0088	0.0001	0.8932	0.0288
5	0.0001	2.9791	1.1328	0.0110	0.0000	1.3859	0.0469	0.0005	2.4495	1.5293	0.0116	0.0002	1.0070	0.0447
5-1				-0.0008	-0.0005***	0.9672***	0.0327*				-0.0023	-0.0002**	0.0632***	0.0211*
pval				(0.8740)	(0.0001)	(0.0000)	(0.0598)				(0.1976)	(0.0200)	(0.0008)	(0.0741)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0008	-0.5183	-0.8404	0.0070	0.0002	0.6599	-0.0255	0.0007	0.1788	-1.0013	0.0084	0.0002	1.1349	-0.0093
2	0.0004	0.3202	-0.3024	0.0065	0.0001	0.7467	-0.0088	0.0003	0.6484	-0.3151	0.0068	0.0001	0.9506	-0.0070
3	0.0002	0.8513	-0.0592	0.0070	0.0001	0.9222	-0.0112	0.0002	0.9160	0.0121	0.0068	0.0001	0.8893	-0.0121
4	0.0001	1.4318	0.1879	0.0073	0.0001	1.1543	0.0044	0.0002	1.3322	0.3548	0.0056	0.0000	0.9958	0.0087
5	0.0003	2.5355	0.7367	0.0074	-0.0001	1.5009	0.0286	0.0006	2.2661	1.0990	0.0060	0.0000	1.2012	0.0186
5-1				0.0004	-0.0003*	0.8410***	0.0540**				-0.0023	-0.0002	0.0663*	0.0279
pval				(0.9493)	(0.0695)	(0.0000)	(0.0475)				(0.4963)	(0.2055)	(0.0864)	(0.2943)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0006	-0.0871	-0.5541	0.0055	0.0001	0.6886	-0.0155	0.0005	0.3071	-0.8165	0.0085	0.0002	1.0835	-0.0075
2	0.0003	0.5575	-0.1815	0.0067	0.0001	0.8189	-0.0032	0.0003	0.6856	-0.2520	0.0064	0.0001	0.9259	-0.0129
3	0.0002	0.9144	-0.0282	0.0070	0.0001	0.9322	-0.0167	0.0002	0.8787	-0.0153	0.0064	0.0001	0.8790	-0.0115
4	0.0002	1.3138	0.1446	0.0069	0.0001	1.1021	-0.0017	0.0002	1.1667	0.2300	0.0060	0.0000	0.9459	0.0011
5	0.0003	2.2549	0.5970	0.0062	-0.0001	1.4094	0.0201	0.0004	1.9247	0.8292	0.0055	0.0000	1.1242	0.0135
5-1				0.0007	-0.0002	0.7208***	0.0356				-0.0030	-0.0002	0.0408	0.0210
pval				(0.8833)	(0.1415)	(0.0000)	(0.1000)				(0.3098)	(0.1688)	(0.1834)	(0.3193)

Table 5: Results for Time-Series Regressions with $(VIX - VX)$ Included from April 2004 to December 2012

First, we run the following regression for each individual stock by using the previous one-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{m,t} - r_{f,t}) + \beta_i^{VV}(VIX_t - VX_t)$$

Then, we form quintile portfolios based on β_i^{MKT} (Column 2 to 8) or β_i^{VV} (Column 9 to 15). Portfolio 1 consists of stocks with the lowest β_i^{MKT} or β_i^{VV}, while portfolio 5 consists of stocks with the highest β_i^{MKT} or β_i^{VV}. After portfolio formation, we conduct out-of-sample time-series regression for next one-month quintile portfolio daily returns by using the following regression model:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) + \beta_p^{VV}(VIX_t - VX_t)$$

The "return" column reports compounded returns of quintile portfolios during the post one-month period.

	Portfolios Sorted on $\beta_{i,MKT}$							Portfolios Sorted on $\beta_{i,VV}$						
	In-Sample			Out-of-Sample				In-Sample			Out-of-Sample			
	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{VV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{VV}$	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{VV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{VV}$
Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios														
1	-0.0001	-0.5208	-0.3135	0.0103	0.0006	0.2435	-0.0649	-0.0051	0.6338	-1.1509	0.0132	0.0005	0.8943	-0.0643
2	0.0002	0.3863	-0.0989	0.0093	0.0004	0.5564	-0.0413	-0.0011	0.7611	-0.2701	0.0090	0.0003	0.8195	-0.0322
3	0.0002	0.8463	-0.0402	0.0098	0.0003	0.8794	-0.0224	0.0002	0.7307	-0.0135	0.0080	0.0003	0.7281	-0.0137
4	0.0002	1.2974	0.0364	0.0104	0.0002	1.1380	-0.0061	0.0014	0.9193	0.2349	0.0091	0.0003	0.8536	-0.0103
5	0.0011	2.3038	0.2570	0.0108	0.0002	1.4750	-0.0077	0.0062	1.2681	1.0405	0.0124	0.0003	0.9969	-0.0219
5-1				0.0005	-0.0004**	1.2315***	0.0572***				-0.0009	-0.0001	0.1026***	0.0424***
pval				(0.9365)	(0.0460)	(0.0000)	(0.0005)				(0.6476)	(0.3415)	(0.0000)	(0.0015)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0002	-0.2003	-0.2793	0.0067	0.0003	0.4837	-0.0531	-0.0032	0.9277	-0.8304	0.0093	0.0002	1.1202	-0.0246
2	0.0003	0.4233	-0.1108	0.0059	0.0002	0.6786	-0.0169	-0.0008	0.8863	-0.2660	0.0071	0.0001	0.9514	-0.0271
3	0.0002	0.8457	-0.0333	0.0068	0.0001	0.9097	0.0008	0.0004	0.9061	-0.0117	0.0061	0.0001	0.9013	-0.0022
4	0.0004	1.2818	0.0474	0.0077	0.0000	1.1610	0.0115	0.0017	1.0365	0.2325	0.0051	0.0001	0.9899	0.0092
5	0.0008	2.0705	0.1868	0.0065	-0.0001	1.5489	-0.0004	0.0044	1.3728	0.7455	0.0063	0.0000	1.1799	0.0198
5-1				-0.0002	-0.0004	1.0652***	0.0527**				-0.0030	-0.0002	0.0597*	0.0444**
pval				(0.9692)	(0.1060)	(0.0000)	(0.0444)				(0.2657)	(0.4198)	(0.0566)	(0.0494)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0002	0.2153	-0.1562	0.0052	0.0002	0.6043	-0.0243	-0.0026	0.9141	-0.6587	0.0085	0.0001	1.0660	-0.0268
2	0.0002	0.6672	-0.0606	0.0080	0.0002	0.8017	-0.0113	-0.0006	0.8794	-0.1878	0.0069	0.0001	0.9247	-0.0192
3	0.0002	0.9359	-0.0157	0.0060	0.0001	0.9474	-0.0006	0.0003	0.9012	0.0020	0.0064	0.0001	0.8902	-0.0023
4	0.0004	1.2334	0.0454	0.0062	0.0001	1.1289	0.0110	0.0012	0.9990	0.1858	0.0048	0.0001	0.9658	0.0073
5	0.0008	1.9166	0.1587	0.0068	-0.0001	1.4815	0.0017	0.0035	1.2863	0.6206	0.0060	0.0000	1.1251	0.0174
5-1				0.0016	-0.0003	0.8772***	0.0260				-0.0026	-0.0001	0.0591**	0.0442**
pval				(0.7677)	(0.2296)	(0.0000)	(0.2456)				(0.2916)	(0.5551)	(0.0389)	(0.0276)

Table 6: Results for Time-Series Regressions with $(logVIX - logVX)$ Included from April 2004 to December 2012

First, we run the following regression for each individual stock by using the previous one-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{m,t} - r_{f,t}) + \beta_i^{logVV}[log(VIX_t) - log(VX_t)]$$

Then, we form quintile portfolios based on β_i^{MKT} (Column 2 to 8) or β_i^{logVV} (Column 9 to 15). Portfolio 1 consists of stocks with the lowest β_i^{MKT} or β_i^{logVV}, while portfolio 5 consists of stocks with the highest β_i^{MKT} or β_i^{logVV}. After portfolio formation, we conduct out-of-sample time-series regression for next one-month quintile portfolio daily returns by using the following regression model:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT}(r_{m,t} - r_{f,t}) + \beta_p^{logVV}[log(VIX_t) - log(VX_t)]$$

The "return" column reports compounded returns of quintile portfolios during the post one-month period.

	Portfolios Sorted on $\beta_{i,MKT}$							Portfolios Sorted on $\beta_{i,logVV}$						
	In-Sample			Out-of-Sample				In-Sample			Out-of-Sample			
	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{logVV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{logVV}$	$\bar{\alpha}_i$	$\bar{\beta}_i^{MKT}$	$\bar{\beta}_i^{logVV}$	return	$\bar{\alpha}_p$	$\bar{\beta}_p^{MKT}$	$\bar{\beta}_p^{logVV}$
Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios														
1	-0.0002	-0.5204	-0.0615	0.0102	0.0005	0.2441	-0.0137	-0.0052	0.6307	-0.2301	0.0128	0.0004	0.8956	-0.0124
2	0.0002	0.3866	-0.0207	0.0092	0.0004	0.5567	-0.0091	-0.0011	0.7594	-0.0544	0.0089	0.0003	0.8195	-0.0069
3	0.0001	0.8467	-0.0078	0.0098	0.0003	0.8798	-0.0044	0.0002	0.7300	-0.0029	0.0082	0.0003	0.7299	-0.0028
4	0.0002	1.2975	0.0076	0.0105	0.0002	1.1380	0.0003	0.0014	0.9217	0.0477	0.0091	0.0003	0.8521	-0.0021
5	0.0011	2.3033	0.0532	0.0109	0.0002	1.4746	0.0005	0.0062	1.2719	0.2105	0.0126	0.0004	0.9961	-0.0023
5-1				0.0007	-0.0004*	1.2306***	0.0142***				-0.0002	0.0000	0.1005***	0.0101***
pval				(0.9130)	(0.0816)	(0.0000)	(0.0020)				(0.9234)	(0.8214)	(0.0000)	(0.0033)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0001	-0.2005	-0.0532	0.0065	0.0002	0.4872	-0.0102	-0.0033	0.9238	-0.1656	0.0092	0.0002	1.1216	-0.0044
2	0.0003	0.4245	-0.0213	0.0058	0.0002	0.6799	-0.0045	-0.0008	0.8858	-0.0535	0.0068	0.0000	0.9534	-0.0052
3	0.0002	0.8467	-0.0050	0.0069	0.0001	0.9086	0.0002	0.0004	0.9063	-0.0024	0.0061	0.0001	0.9044	0.0006
4	0.0004	1.2813	0.0105	0.0076	0.0000	1.1602	0.0043	0.0017	1.0397	0.0471	0.0055	0.0001	0.9863	0.0005
5	0.0008	2.0679	0.0354	0.0067	-0.0001	1.5476	0.0001	0.0044	1.3714	0.1514	0.0061	0.0001	1.1787	0.0054
5-1				0.0002	-0.0003	1.0605***	0.0103*				-0.0030	-0.0001	0.0571*	0.0097**
pval				(0.9705)	(0.1863)	(0.0000)	(0.0991)				(0.2686)	(0.6528)	(0.0597)	(0.0283)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios														
1	0.0002	0.2155	-0.0307	0.0052	0.0001	0.6044	-0.0058	-0.0027	0.9126	-0.1302	0.0083	0.0001	1.0670	-0.0048
2	0.0002	0.6673	-0.0117	0.0080	0.0002	0.8027	-0.0025	-0.0006	0.8839	-0.0372	0.0065	0.0000	0.9270	-0.0035
3	0.0002	0.9357	-0.0015	0.0059	0.0000	0.9480	0.0004	0.0003	0.8946	0.0004	0.0068	0.0001	0.8887	-0.0011
4	0.0003	1.2329	0.0092	0.0063	0.0001	1.1274	0.0035	0.0012	1.0016	0.0371	0.0048	0.0001	0.9635	0.0012
5	0.0008	1.9153	0.0313	0.0068	-0.0001	1.4807	0.0012	0.0035	1.2879	0.1247	0.0062	0.0001	1.1253	0.0051
5-1				0.0016	-0.0002	0.8763***	0.0070				-0.0021	0.0000	0.0584**	0.0099**
pval				(0.7779)	(0.3325)	(0.0000)	(0.1677)				(0.3902)	(0.9258)	(0.0381)	(0.0123)

Table 7: Quintile Portfolios Formed on the Coefficient on Change in VIX Futures from April 2004 to December 2012

First, we run the following regression model for each individual stock by using the previous one-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{\Delta VX}} * D_t^{\Delta VX} + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{\Delta VX} * \Delta VX_t + \beta_i^{D^{\Delta VX}} * D_t^{\Delta VX} * \Delta VX_t$$

Where $D^{\Delta VX}$ is equal to 1 if ΔVX is larger than or equal to zero, and equal to 0 if ΔVX is smaller than zero. In left five columns, we form quintile portfolios when ΔVX is negative. Portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta VX}$, while portfolio 5 consists of stocks with the highest $\beta_i^{\Delta VX}$. In right five columns, we form quintile portfolios when ΔVX is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{\Delta VX} + \beta_i^{D^{\Delta VX}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{\Delta VX} + \beta_i^{D^{\Delta VX}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios									
$D^{\Delta VX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0322%**	(0.0350)	0.0385%**	(0.0117)	1	0.0256%	(0.1171)	0.0338%**	(0.0313)
2	0.0163%*	(0.0664)	0.0179%**	(0.0255)	2	0.0186%**	(0.0365)	0.0226%***	(0.0038)
3	0.0136%*	(0.0508)	0.0159%**	(0.0113)	3	0.0127%*	(0.0740)	0.0156%**	(0.0138)
4	0.0102%	(0.2514)	0.0169%**	(0.0212)	4	0.0142%*	(0.0955)	0.0208%***	(0.0032)
5	0.0219%	(0.1862)	0.0375%**	(0.0102)	5	0.0231%	(0.1367)	0.0340%**	(0.0169)
5-1	-0.0103%	(0.2067)	-0.0010%	(0.9027)	5-1	-0.0025%	(0.7653)	0.0002%	(0.9839)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0055%	(0.5456)	0.0068%	(0.4690)	1	0.0189%*	(0.0685)	0.0188%*	(0.0885)
2	0.0049%	(0.1947)	0.0004%	(0.9131)	2	0.0133%***	(0.0042)	0.0122%***	(0.0055)
3	0.0034%	(0.4184)	0.0047%	(0.1738)	3	0.0072%**	(0.0282)	0.0056%*	(0.0703)
4	0.0104%**	(0.0315)	0.0144%***	(0.0037)	4	0.0023%	(0.5635)	0.0046%	(0.2531)
5	0.0041%	(0.6211)	0.0246%**	(0.0101)	5	-0.0084%	(0.3026)	0.0074%	(0.4433)
5-1	-0.0014%	(0.9192)	0.0178%	(0.2086)	5-1	-0.0273%**	(0.0435)	-0.0114%	(0.4090)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0070%	(0.3690)	0.0056%	(0.4461)	1	0.0197%**	(0.0153)	0.0185%**	(0.0236)
2	0.0044%	(0.2671)	-0.0007%	(0.8684)	2	0.0082%*	(0.0876)	0.0087%*	(0.0822)
3	0.0037%	(0.3258)	0.0032%	(0.3362)	3	0.0077%**	(0.0497)	0.0057%	(0.1299)
4	0.0088%	(0.1034)	0.0102%**	(0.0224)	4	0.0017%	(0.6609)	0.0044%	(0.2544)
5	0.0089%	(0.1778)	0.0256%***	(0.0034)	5	-0.0050%	(0.4483)	0.0066%	(0.3807)
5-1	0.0020%	(0.8665)	0.0199%	(0.1140)	5-1	-0.0246%**	(0.0318)	-0.0119%	(0.3115)

Table 8: Quintile Portfolios Formed on the Coefficient on Change in VIX Index from April 2004 to December 2012

First, we run the following regression model for each individual stock by using the previous one-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{\Delta VIX} * \Delta VIX_t + \beta_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} * \Delta VIX_t$$

Where $D^{\Delta VIX}$ is equal to 1 if ΔVIX is larger than or equal to zero, and equal to 0 if ΔVIX is smaller than zero. In left five columns, we form quintile portfolios when ΔVX is negative. Portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta VIX}$, while portfolio 5 consists of stocks with the highest $\beta_i^{\Delta VIX}$. In right five columns, we form quintile portfolios when ΔVIX is positive. Portfolio 1 consists of stocks with the lowest ($\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}}$), while portfolio 5 consists of stocks with the highest ($\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}}$). Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0243%	(0.1045)	0.0321%**	(0.0226)	1	0.0309%*	(0.0607)	0.0429%***	(0.0053)
2	0.0156%*	(0.0676)	0.0196%***	(0.0083)	2	0.0189%**	(0.0405)	0.0243%***	(0.0038)
3	0.0157%**	(0.0338)	0.0177%**	(0.0104)	3	0.0139%*	(0.0580)	0.0160%**	(0.0181)
4	0.0158%*	(0.0646)	0.0212%***	(0.0042)	4	0.0122%	(0.1371)	0.0167%**	(0.0144)
5	0.0228%	(0.1641)	0.0362%**	(0.0162)	5	0.0183%	(0.2275)	0.0268%*	(0.0548)
5-1	-0.0015%	(0.8242)	0.0041%	(0.5617)	5-1	-0.0126%	(0.1170)	-0.0162%*	(0.0523)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	-0.0026%	(0.7676)	0.0050%	(0.5830)	1	0.0116%	(0.2992)	0.0295%**	(0.0107)
2	-0.0006%	(0.8998)	0.0003%	(0.9336)	2	0.0091%*	(0.0644)	0.0122%***	(0.0096)
3	0.0130%***	(0.0023)	0.0110%***	(0.0063)	3	0.0068%*	(0.0711)	0.0064%*	(0.0882)
4	0.0119%***	(0.0079)	0.0125%***	(0.0046)	4	0.0074%	(0.1018)	0.0061%	(0.1146)
5	0.0091%	(0.3188)	0.0227%**	(0.0274)	5	-0.0016%	(0.8662)	-0.0070%	(0.4373)
5-1	0.0117%	(0.3624)	0.0177%	(0.1591)	5-1	-0.0132%	(0.4132)	-0.0365%**	(0.0125)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	-0.0018%	(0.8003)	0.0044%	(0.5347)	1	0.0129%	(0.1567)	0.0275%***	(0.0034)
2	-0.0003%	(0.9515)	-0.0006%	(0.8821)	2	0.0058%	(0.2603)	0.0054%	(0.2290)
3	0.0073%	(0.1043)	0.0074%	(0.1083)	3	0.0096%**	(0.0152)	0.0095%**	(0.0167)
4	0.0171%***	(0.0006)	0.0172%***	(0.0006)	4	0.0036%	(0.3361)	0.0038%	(0.2640)
5	0.0096%	(0.1393)	0.0155%**	(0.0181)	5	0.0009%	(0.9061)	-0.0017%	(0.8119)
5-1	0.0114%	(0.2956)	0.0111%	(0.3011)	5-1	-0.0120%	(0.3804)	-0.0291%**	(0.0161)

Table 9: Quintile Portfolios Formed on the Coefficient on Differences between VIX Index and VIX Index Future from April 2004 to December 2012

First, we run the following regression model for each individual stock by using the previous one-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{VV}} * D_t^{VV} + \beta_i^{MKT} * (R_m - R_f) + \beta_i^{VV} * (VIX_t - VX_t) + \beta_i^{D^{VV}} * D_t^{VV} * (VIX_t - VX_t)$$

Where D^{VV} is equal to 1 if $(VIX - VX)$ is larger than or equal to zero, and equal to 0 if $(VIX - VX)$ is smaller than zero. In left five columns, we form quintile portfolios when $(VIX - VX)$ is negative. Portfolio 1 consists of stocks with the lowest β_i^{VV}, while portfolio 5 consists of stocks with the highest β_i^{VV}. In right five columns, we form quintile portfolios when $(VIX - VX)$ is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{VV} + \beta_i^{D^{VV}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{VV} + \beta_i^{D^{VV}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios

$D^{VV} = 0$	CAPM α	p-value	FF α	p-value	$D^{VV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0218%	(0.1779)	0.0319%**	(0.0305)	1	0.0275%	(0.1045)	0.0405%***	(0.0071)
2	0.0136%	(0.1296)	0.0193%**	(0.0132)	2	0.0152%*	(0.0714)	0.0184%**	(0.0165)
3	0.0138%**	(0.0434)	0.0155%**	(0.0182)	3	0.0102%	(0.1351)	0.0123%*	(0.0719)
4	0.0163%*	(0.0507)	0.0210%***	(0.0029)	4	0.0156%*	(0.0500)	0.0172%**	(0.0211)
5	0.0287%*	(0.0707)	0.0389%***	(0.0090)	5	0.0279%**	(0.0469)	0.0328%**	(0.0169)
5-1	0.0069%	(0.3566)	0.0070%	(0.3001)	5-1	0.0004%	(0.9591)	-0.0077%	(0.3291)

Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios

$D^{VV} = 0$	CAPM α	p-value	FF α	p-value	$D^{VV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0110%	(0.1795)	0.0142%	(0.1155)	1	0.0087%	(0.4483)	0.0256%**	(0.0256)
2	0.0100%**	(0.0394)	0.0080%*	(0.0992)	2	0.0093%*	(0.0502)	0.0102%**	(0.0209)
3	0.0039%	(0.2641)	0.0033%	(0.3058)	3	0.0046%	(0.1856)	0.0039%	(0.2526)
4	0.0073%*	(0.0536)	0.0113%***	(0.0033)	4	-0.0003%	(0.9368)	0.0003%	(0.9443)
5	0.0084%	(0.3598)	0.0189%**	(0.0471)	5	0.0008%	(0.9239)	0.0021%	(0.7940)
5-1	-0.0026%	(0.8270)	0.0047%	(0.6943)	5-1	-0.0079%	(0.6315)	-0.0235%*	(0.0846)

Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios

$D^{VV} = 0$	CAPM α	p-value	FF α	p-value	$D^{VV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0103%	(0.1236)	0.0117%	(0.1245)	1	0.0081%	(0.3959)	0.0202%**	(0.0401)
2	0.0095%**	(0.0275)	0.0057%	(0.1655)	2	0.0119%**	(0.0217)	0.0123%**	(0.0111)
3	0.0009%	(0.8069)	0.0023%	(0.5112)	3	0.0056%	(0.1557)	0.0056%	(0.1312)
4	0.0055%	(0.1351)	0.0091%**	(0.0183)	4	0.0041%	(0.4234)	0.0050%	(0.2633)
5	0.0067%	(0.3620)	0.0157%**	(0.0422)	5	0.0028%	(0.7013)	0.0013%	(0.8546)
5-1	-0.0036%	(0.7353)	0.0039%	(0.7186)	5-1	-0.0053%	(0.7079)	-0.0190%	(0.1444)

Table 10: Quintile Portfolios Formed on the Coefficient on Differences between log VIX Index and log VIX Index Future from April 2004 to December 2012

First, we run the following regression model for each individual stock by using the previous one-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{logVV}} * D_t^{logVV} + \beta_i^{MKT} * \left(R_m - R_f\right) + \beta_i^{logVV} * [log(VIX_t) - log(VX_t)] + \beta_i^{D^{logVV}} * D_t^{logVV} * [log(VIX_t) - log(VX_t)]$$

Where D^{logVV} is equal to 1 if $(logVIX - logVX)$ is larger than or equal to zero, and equal to 0 if $(logVIX - logVX)$ is smaller than zero. In left five columns, we form quintile portfolios when $(logVIX - logVX)$ is negative. Portfolio 1 consists of stocks with the lowest β_i^{logVV}, while portfolio 5 consists of stocks with the highest β_i^{logVV}. In right five columns, we form quintile portfolios when $(logVIX - logVX)$ is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{logVV} + \beta_i^{D^{logVV}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{logVV} + \beta_i^{D^{logVV}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios

$D^{logVV} = 0$	CAPM α	p-value	FF α	p-value	$D^{logVV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0220%	(0.1815)	0.0327%**	(0.0269)	1	0.0293%*	(0.0868)	0.0420%***	(0.0063)
2	0.0120%	(0.1713)	0.0175%**	(0.0230)	2	0.0161%*	(0.0641)	0.0185%**	(0.0174)
3	0.0138%**	(0.0477)	0.0162%**	(0.0123)	3	0.0105%	(0.1564)	0.0130%*	(0.0563)
4	0.0173%**	(0.0402)	0.0223%***	(0.0019)	4	0.0170%**	(0.0398)	0.0188%**	(0.0139)
5	0.0291%*	(0.0627)	0.0381%***	(0.0099)	5	0.0268%*	(0.0542)	0.0318%**	(0.0170)
5-1	0.0070%	(0.3652)	0.0053%	(0.4044)	5-1	-0.0025%	(0.7613)	-0.0102%	(0.1833)

Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios

$D^{logVV} = 0$	CAPM α	p-value	FF α	p-value	$D^{logVV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0097%	(0.2256)	0.0151%	(0.1198)	1	0.0092%	(0.4026)	0.0272%**	(0.0189)
2	0.0063%	(0.1379)	0.0061%	(0.1602)	2	0.0068%	(0.1900)	0.0082%*	(0.0738)
3	0.0063%*	(0.0674)	0.0042%	(0.2064)	3	0.0053%	(0.1505)	0.0050%	(0.1746)
4	0.0090%**	(0.0174)	0.0125%***	(0.0025)	4	0.0016%	(0.6845)	0.0018%	(0.6245)
5	0.0090%	(0.3167)	0.0193%**	(0.0389)	5	0.0033%	(0.6925)	0.0035%	(0.6596)
5-1	-0.0007%	(0.9473)	0.0042%	(0.7240)	5-1	-0.0059%	(0.7102)	-0.0237%*	(0.0811)

Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios

$D^{logVV} = 0$	CAPM α	p-value	FF α	p-value	$D^{logVV} = 1$	CAPM α	p-value	FF α	p-value
1	0.0083%	(0.1844)	0.0119%	(0.1201)	1	0.0074%	(0.4296)	0.0204%**	(0.0366)
2	0.0077%*	(0.0771)	0.0047%	(0.2626)	2	0.0118%	(0.0196)**	0.0132%***	(0.0044)
3	0.0039%	(0.2593)	0.0032%	(0.3909)	3	0.0055%	(0.1740)	0.0050%	(0.2050)
4	0.0032%	(0.3862)	0.0067%*	(0.0813)	4	0.0042%	(0.3520)	0.0040%	(0.3341)
5	0.0096%	(0.1855)	0.0180%**	(0.0220)	5	0.0035%	(0.6256)	0.0018%	(0.7872)
5-1	0.0014%	(0.8932)	0.0061%	(0.5676)	5-1	-0.0039%	(0.7797)	-0.0187%	(0.1401)

Table 11: Quintile Portfolios Formed on the Coefficient on Change in VIX Index from Jan 1996 to Dec 2012

First, we run the following regression model for each individual stock by using the previous **one**-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{\Delta VIX} * \Delta VIX_t + \beta_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} * \Delta VIX_t$$

Where $D^{\Delta VIX}$ is equal to 1 if ΔVIX is larger than or equal to zero, and equal to 0 if ΔVIX is smaller than zero. In left five columns, we form quintile portfolios when ΔVX is negative. Portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta VIX}$, while portfolio 5 consists of stocks with the highest $\beta_i^{\Delta VIX}$. In right five columns, we form quintile portfolios when ΔVIX is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0728%***	(0.0000)	0.0714%***	(0.0000)	1	0.0798%***	(0.0000)	0.0797%***	(0.0000)
2	0.0353%***	(0.0001)	0.0330%***	(0.0000)	2	0.0387%***	(0.0000)	0.0346%***	(0.0000)
3	0.0309%***	(0.0000)	0.0265%***	(0.0000)	3	0.0296%***	(0.0000)	0.0245%***	(0.0000)
4	0.0341%***	(0.0001)	0.0296%***	(0.0000)	4	0.0302%***	(0.0002)	0.0270%***	(0.0000)
5	0.0680%***	(0.0001)	0.0701%***	(0.0000)	5	0.0626%***	(0.0001)	0.0647%***	(0.0000)
5-1	-0.0048%	(0.5185)	-0.0013%	(0.8424)	5-1	-0.0172%**	(0.0153)	-0.0150%**	(0.0344)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0026%	(0.7493)	0.0118%*	(0.0945)	1	0.0077%	(0.4058)	0.0234%***	(0.0081)
2	0.0081%**	(0.0278)	0.0136%***	(0.0009)	2	0.0082%*	(0.0635)	0.0119%***	(0.0021)
3	0.0125%***	(0.0012)	0.0089%**	(0.0114)	3	0.0099%**	(0.0118)	0.0122%***	(0.0007)
4	0.0074%**	(0.0386)	0.0025%	(0.5540)	4	0.0082%*	(0.0520)	0.0053%	(0.2133)
5	0.0007%	(0.9288)	0.0167%*	(0.0549)	5	-0.0037%	(0.6363)	-0.0019%	(0.8016)
5-1	-0.0019%	(0.8654)	0.0049%	(0.6511)	5-1	-0.0114%	(0.3469)	-0.0253%**	(0.0251)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0015%	(0.8007)	0.0116%**	(0.0419)	1	0.0093%	(0.1283)	0.0232%***	(0.0004)
2	0.0126%***	(0.0016)	0.0156%***	(0.0004)	2	0.0078%*	(0.0917)	0.0100%**	(0.0121)
3	0.0098%**	(0.0173)	0.0076%**	(0.0401)	3	0.0080%**	(0.0482)	0.0097%***	(0.0092)
4	0.0095%**	(0.0140)	0.0053%	(0.1995)	4	0.0110%***	(0.0080)	0.0098%**	(0.0294)
5	0.0023%	(0.6807)	0.0116%*	(0.0572)	5	-0.0004%	(0.9465)	-0.0009%	(0.8759)
5-1	0.0008%	(0.9268)	0.0000%	(0.9965)	5-1	-0.0097%	(0.3275)	-0.0241%**	(0.0115)

Table 12: Quintile Portfolios Formed on the Coefficient on Change in VIX Index from Jan 1996 to Dec 2012

First, we run the following regression model for each individual stock by using the previous **two**-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{\Delta VIX} * \Delta VIX_t + \beta_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} * \Delta VIX_t$$

Where $D^{\Delta VIX}$ is equal to 1 if ΔVIX is larger than or equal to zero, and equal to 0 if ΔVIX is smaller than zero. In left five columns, we form quintile portfolios when ΔVX is negative. Portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta VIX}$, while portfolio 5 consists of stocks with the highest $\beta_i^{\Delta VIX}$. In right five columns, we form quintile portfolios when ΔVIX is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0729%***	(0.0000)	0.0715%***	(0.0000)	1	0.0772%***	(0.0000)	0.0763%***	(0.0000)
2	0.0359%***	(0.0001)	0.0316%***	(0.0000)	2	0.0404%***	(0.0000)	0.0352%***	(0.0000)
3	0.0306%***	(0.0000)	0.0268%***	(0.0000)	3	0.0300%***	(0.0000)	0.0252%***	(0.0000)
4	0.0341%***	(0.0001)	0.0304%***	(0.0000)	4	0.0301%***	(0.0002)	0.0274%***	(0.0000)
5	0.0690%***	(0.0001)	0.0715%***	(0.0000)	5	0.0646%***	(0.0001)	0.0677%***	(0.0000)
5-1	-0.0039%	(0.5668)	0.0000%	(0.9959)	5-1	-0.0126%*	(0.0770)	-0.0086%	(0.2110)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0080%	(0.3187)	0.0121%	(0.1022)	1	0.0117%	(0.2145)	0.0191%**	(0.0240)
2	0.0078%**	(0.0351)	0.0122%***	(0.0007)	2	0.0105%**	(0.0136)	0.0158%***	(0.0000)
3	0.0077%**	(0.0283)	0.0048%	(0.1671)	3	0.0067%*	(0.0725)	0.0078%**	(0.0461)
4	0.0080%*	(0.0502)	0.0101%**	(0.0255)	4	0.0029%	(0.4160)	0.0016%	(0.6944)
5	0.0085%	(0.3319)	0.0212%**	(0.0218)	5	-0.0058%	(0.5305)	0.0053%	(0.5161)
5-1	0.0005%	(0.9630)	0.0091%	(0.3966)	5-1	-0.0175%	(0.2041)	-0.0138%	(0.2265)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0084%	(0.1869)	0.0129%**	(0.0294)	1	0.0124%*	(0.0619)	0.0225%***	(0.0002)
2	0.0065%	(0.1039)	0.0108%**	(0.0197)	2	0.0107%**	(0.0173)	0.0114%**	(0.0114)
3	0.0096%**	(0.0132)	0.0076%**	(0.0319)	3	0.0085%**	(0.0319)	0.0091%**	(0.0206)
4	0.0099%**	(0.0126)	0.0076%**	(0.0379)	4	0.0077%**	(0.0470)	0.0061%	(0.1336)
5	0.0017%	(0.7792)	0.0129%**	(0.0489)	5	-0.0033%	(0.6461)	0.0029%	(0.6595)
5-1	-0.0067%	(0.4870)	0.0000%	(0.9985)	5-1	-0.0157%	(0.1602)	-0.0196%**	(0.0299)

Table 13: Quintile Portfolios Formed on the Coefficient on Change in VIX Index from Jan 1996 to Dec 2012

First, we run the following regression model for each individual stock by using the previous **three**-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{\Delta VIX} * \Delta VIX_t + \beta_i^{D^{\Delta VIX}} * D_t^{\Delta VIX} * \Delta VIX_t$$

Where $D^{\Delta VIX}$ is equal to 1 if ΔVIX is larger than or equal to zero, and equal to 0 if ΔVIX is smaller than zero. In left five columns, we form quintile portfolios when ΔVX is negative. Portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta VIX}$, while portfolio 5 consists of stocks with the highest $\beta_i^{\Delta VIX}$. In right five columns, we form quintile portfolios when ΔVIX is positive. Portfolio 1 consists of stocks with the lowest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$, while portfolio 5 consists of stocks with the highest $(\beta_i^{\Delta VIX} + \beta_i^{D^{\Delta VIX}})$. Then, we calculate Jensen's alphas with respect to the CAPM and Fama-French three-factor model for each quintile portfolio and the "5-1" arbitrage portfolio.

Panel A: Equal-Weighted across Portfolios and Equal-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0733%***	(0.0000)	0.0718%***	(0.0000)	1	0.0778%***	(0.0000)	0.0768%***	(0.0000)
2	0.0341%***	(0.0001)	0.0311%***	(0.0000)	2	0.0388%***	(0.0000)	0.0350%***	(0.0000)
3	0.0317%***	(0.0000)	0.0270%***	(0.0000)	3	0.0300%***	(0.0000)	0.0258%***	(0.0000)
4	0.0343%***	(0.0001)	0.0305%***	(0.0000)	4	0.0311%***	(0.0002)	0.0268%***	(0.0000)
5	0.0696%***	(0.0001)	0.0718%***	(0.0000)	5	0.0652%***	(0.0000)	0.0679%***	(0.0000)
5-1	-0.0037%	(0.6224)	0.0000%	(0.9957)	5-1	-0.0125%*	(0.0678)	-0.0089%	(0.1862)
Panel B: Equal-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0017%	(0.8333)	0.0135%**	(0.0492)	1	0.0076%	(0.4317)	0.0161%*	(0.0548)
2	0.0050%	(0.1867)	0.0085%**	(0.0204)	2	0.0019%	(0.6796)	0.0104%**	(0.0136)
3	0.0092%**	(0.0194)	0.0071%*	(0.0622)	3	0.0108%***	(0.0074)	0.0105%***	(0.0055)
4	0.0104%***	(0.0071)	0.0097%**	(0.0485)	4	0.0076%**	(0.0492)	0.0048%	(0.2246)
5	0.0067%	(0.4428)	0.0183%**	(0.0456)	5	-0.0033%	(0.6966)	0.0071%	(0.4117)
5-1	0.0050%	(0.6934)	0.0048%	(0.6800)	5-1	-0.0109%	(0.4105)	-0.0090%	(0.4318)
Panel C: Value-Weighted across Portfolios and Value-Weighted within Portfolios									
$D^{\Delta VIX} = 0$	CAPM α	p-value	FF α	p-value	$D^{\Delta VIX} = 1$	CAPM α	p-value	FF α	p-value
1	0.0025%	(0.7044)	0.0110%*	(0.0725)	1	0.0080%	(0.2718)	0.0201%***	(0.0020)
2	0.0077%**	(0.0322)	0.0112%***	(0.0033)	2	0.0057%	(0.1965)	0.0083%*	(0.0576)
3	0.0087%**	(0.0261)	0.0077%**	(0.0362)	3	0.0126%***	(0.0043)	0.0124%***	(0.0021)
4	0.0112%**	(0.0120)	0.0097%**	(0.0257)	4	0.0082%**	(0.0302)	0.0030%	(0.4738)
5	0.0051%	(0.4068)	0.0121%*	(0.0609)	5	0.0006%	(0.9233)	0.0078%	(0.2467)
5-1	0.0026%	(0.7977)	0.0011%	(0.9141)	5-1	-0.0074%	(0.5239)	-0.0123%	(0.2213)

Table 14: Results for Cross-Sectional Regressions

At the end of each month, we first form five quintiles based on the beta coefficient on market excess return (β_i^{MKT}) in the univariate regression using one-month daily data:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} * (R_{m,t} - R_{f,t})$$

Then, within each market quintile, I form five quintile portfolios based on the beta coefficient on volatility risk factor, VF, from the following model.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} * (R_{m,t} - R_{f,t}) + \beta_i^{VF} * VF_t$$

So there are 5×5 portfolios in total. After forming 25 portfolios, we run the following regression by using daily data of each portfolio in the same one-month to get the factor loadings:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p^{MKT} * (R_{m,t} - R_{f,t}) + \beta_p^{VF} * VF_t$$

For each portfolio, we can get the intercept, α_1, beta coefficient on market excess returns, β_{mkt}, and beta coefficient on volatility risk factor, β_{VF}. That is, we have 25 β_p^{MKT} and 25 β_p^{VF}. Then, we use these factor loadings in the second step of Fama-MacBeth cross-sectional regression. On each trading day, we run the following regression:

$$R_p - R_f = \alpha + \gamma^{MKT}\beta_p^{MKT} + \gamma^{VF}\beta_p^{VF}$$

where R_p is the daily return on each portfolio. I use the same β_p^{MKT} and β_p^{VF} in the following one-month to estimate γ^{MKT} and γ^{VF}. Since there are about 20 trading days in each month, we can get about 20 γ^{MKT} and 20 γ^{VF} in each month after the cross-sectional regression. Then, we can use t-test to check whether the risk premium on each volatility risk factor is significantly different from zero.

	Equal-Weighted				Value-Weighted			
	I	II	III	IV	I	II	III	IV
Intercept	0.0448%***	0.0453%***	0.0444%***	0.0450%***	0.0280%*	0.0285%*	0.0283%*	0.0283%*
	(0.0018)	(0.0015)	(0.0018)	(0.0015)	(0.0787)	(0.0742)	(0.0782)	(0.0797)
γ^{MKT}	0.0049%	0.0052%	0.0056%	0.0054%	0.0093%	0.0088%	0.0088%	0.0093%
	(0.7882)	(0.7750)	(0.7586)	(0.7669)	(0.6470)	(0.6667)	(0.6668)	(0.6492)
$\gamma^{\Delta VX}$	-0.0052%				-0.0109%			
	(0.7169)				(0.5226)			
$\gamma^{\Delta VIX}$		-0.0078%				-0.0173%		
		(0.7249)				(0.5037)		
γ^{VIX-VX}			0.0022%				-0.0021%	
			(0.8210)				(0.9015)	
$\gamma^{log(VIX)-log(VX)}$				0.0069%				0.0001%
				(0.8461)				(0.9982)

Table 15: Results for Cross-Sectional Regressions

For Table 15, the 1st step of Fama-MacBeth cross-sectional regression is the same as the procedure illustrated in Table 14. Then, in the 2nd step, to separate different situations (whether volatility risk factors are positive or negative), we define four dummy variables ($D_+^{MKT}, D_-^{MKT}, D_+^{VF}, and\, D_-^{VF}$).

$$R_p - R_f = \alpha + \gamma_\pm^{MKT} D_\pm^{MKT} \beta_p^{MKT} + \gamma_\pm^{VF} D_\pm^{VF} \beta_p^{VF}$$

I use the same β_p^{MKT} and β_p^{VF} in the following one-month to estimate $\gamma_\pm^{MKT}$ and $\gamma_\pm^{VF}$. Since there are about 20 trading days in each month, we can get about 20 $\gamma_\pm^{MKT}$ and 20 $\gamma_\pm^{VF}$ in each month after the cross-sectional regression. Then, we can use t-test to check whether the risk premium on each volatility risk factor is significantly different from zero.

	Equal-Weighted				Value-Weighted			
	I	II	III	IV	I	II	III	IV
Intercept	0.0379%***	0.0384%***	0.0375%***	0.0381%***	0.0211%	0.0216%	0.0214%	0.0214%
	(0.0081)	(0.0072)	(0.0083)	(0.0072)	(0.1848)	(0.1759)	(0.1830)	(0.1848)
γ_+^{MKT}	0.4353%***	0.4362%***	0.4366%***	0.4366%***	0.4561%***	0.4545%***	0.4583%***	0.4574%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_-^{MKT}	-0.5173%***	-0.5176%***	-0.5173%***	-0.5176%***	-0.5327%***	-0.5318%***	-0.5364%***	-0.5343%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\gamma_+^{\Delta VX}$	0.3025%***				0.3206%***			
	(0.0000)				(0.0000)			
$\gamma_-^{\Delta VX}$	-0.2538%***				-0.2787%***			
	(0.0000)				(0.0000)			
$\gamma_+^{\Delta VIX}$		0.4906%***				0.5118%***		
		(0.0000)				(0.0000)		
$\gamma_-^{\Delta VIX}$		-0.4295%***				-0.4650%***		
		(0.0000)				(0.0000)		
γ_+^{VIX-VX}			0.0721%***				0.0772%	
			(0.0075)				(0.1098)	
γ_-^{VIX-VX}			-0.0270%***				-0.0352%***	
			(0.0005)				(0.0047)	
$\gamma_+^{log(VIX)-log(VX)}$				0.3261%***				0.3419%**
				(0.0003)				(0.0302)
$\gamma_-^{log(VIX)-log(VX)}$				-0.1267%***				-0.1430%**
				(0.0002)				(0.0125)