Asymmetric Volatility and the Cross-Section of Returns: Is Implied Market Volatility a Risk Factor?

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ABSTRACT

Several versions of the Intertemporal Capital Asset Pricing Model predict that changes in aggregate volatility are priced into the cross-section of stock returns. Literature confirms this prediction and suggests that it is a risk factor. However, prior studies do not test whether asymmetric volatility affects if firm sensitivity to innovations in aggregate volatility is related to risk, or is just a characteristic uniformly affecting all firms. We find that sensitivity to VIX innovations affects returns when volatility is rising, but not when it is falling. When VIX rises this sensitivity is a priced risk factor, but when it falls there is a positive impact on all stocks irrespective of VIX loadings.
Introduction

Merton’s (1973) Intertemporal Capital Asset Pricing Model (ICAPM) implies that the cross-section of stock returns should be affected by systematic volatility. Using a time-varying model, Chen (2003) demonstrates that changes in the expectation of future market volatility are a source of risk. Verifying this prediction, Ang, Hodrick, Xing, and Zhang (2006) find that sensitivities to changes in implied market volatility have a cross-sectional effect on firm-level returns. While Ang et al. show that the cross-sectional pricing of sensitivity to innovations in implied market volatility is robust, it remains unclear if this sensitivity is a risk factor, or merely a firm characteristic where there is a premium related to volatility risk just for being a stock. In particular, Ang et al. do not account for the asymmetric return responses to positive and negative changes in expected systematic volatility, as found by Dennis, Mayhew, and Stivers (2006). Thus, the cross-sectional relation between sensitivity to market volatility innovations and firm returns may not yet be fully understood. We extend prior studies by more fully documenting this relation and testing for the presence of risk versus firm characteristics following procedures developed by Daniel and Titman (1997), while allowing for asymmetric volatility responses. We find that the asymmetric volatility phenomenon is an important element in the return process and that firm sensitivity to innovations in implied market volatility is a priced risk factor when implied market volatility rises, but not necessarily when it falls.

Identification of priced risk factors is at the core of asset pricing literature. However, the identification of risks versus characteristics has proven to be a daunting task. The debate about risk factors versus characteristics is important because it addresses the risk-return relation of securities. Investors should be compensated for assuming higher systematic risk, but characteristics are diversifiable and therefore should not be priced. In an efficient market,
loadings on risk factors should explain the cross-sectional variation in returns, and not characteristics.

The ratio of book-to-market equity (B/M), size, and market beta are firm traits at the center of the risk versus characteristic debate. Fama and French (1993) parse some characteristics commonly used to explain stock returns and find that B/M proxies for common risk factors. Davis, Fama, and French (2000) reach a similar conclusion, whereas Daniel and Titman (1997) and Daniel, Titman, and Wei (2001), instead, find that B/M is a characteristic. Lakonishok, Shleifer, and Vishney (1994) argue that the return premium for the B/M factor is too high for it to be a measure of systematic risk. The size premium has also not been definitively identified as a risk or characteristic. In fact, the formal tests on size performed by Daniel and Titman and Davis, Fama, and French find evidence that supports both risk-based and characteristic-based pricing processes. Additionally, there is little support for market beta as a measure of risk. Fama and French (1992, 1993) and Daniel and Titman find that there is a premium over the risk-free rate for being a stock, but the covariance of a stock’s return with the market is irrelevant.

Another aspect of the returns process that has been examined, but is also subject to individual interpretation, is the sensitivity of stock returns to aggregate volatility. Through their variations of Merton’s (1973) ICAPM, Campbell (1993, 1996) and Chen (2003) demonstrate that investors can interpret a market volatility increase as a decrease in their set of investment opportunities. Chen’s model shows that a decrease in expectation of future market volatility allows investors to decrease precautionary savings and increase consumption. Conversely, an increase in expected future market volatility produces a decrease in consumption and an increase in precautionary savings, resulting in price declines. Thus, risk-averse investors should hedge
against changes in future volatility by acquiring stocks that are positively correlated with aggregate volatility innovations. Investors choose the stocks that are positively correlated with changes in market volatility because market returns and market volatility are negatively correlated. Bakshi and Kapadia (2003) note that due to the negative correlation between returns and volatility, stocks that load heavily on market volatility provide insurance against downward market movements. The demand for such stocks drives up their prices contemporaneously, and thus lowers their future returns. This reasoning suggests that the pricing of sensitivity to market volatility is risk-based.¹

Prompted by these implications that exposure to market volatility changes can result in cross-sectional differences in returns, Ang, Hodrick, Xing, and Zhang (2006) investigate if sensitivity to systematic volatility is cross-sectionally priced. They employ the VIX index and a factor portfolio that mimics innovations in the VIX index. They first difference the VIX index since, as Chen points out, investors react to the changes in expected market volatility, as well as to avoid any serial correlation in the index.² Ang et al. obtain loadings on changes in VIX, henceforth denoted ΔVIX, sort the stocks into quintile portfolios monthly based on their loadings, and examine the portfolio returns in the following month.

The quintile portfolios show a monotonic decrease in future value-weighted returns as the loadings increase, and the difference in the returns of the extreme quintile portfolios are significantly different from each other. In concordance with the predictions of Merton (1973), Campbell (1993, 1996), and Chen (2003), these empirical findings indicate that there is a

¹ However, studies of the time-series relation between market volatility and market returns by French, Schwert, and Stambaugh (1987), Campbell and Hentschel (1992), Glosten, Jagannathan, and Runkle (1993), and Wu (2001) are ambiguous about if market volatility is a priced risk factor in the cross-section of stock returns.
² Ang et al. find that their results are robust to measuring volatility innovations in an AR(1) model of VIX, as well as a model using an optimal number of autoregressive lags as specified by the Bayesian Information Criteria (BIC).
negative premium associated with the sensitivity to innovations in market volatility. Investors appear to pay more for securities that do well when volatility risk increases; thus, the high-loading firms have lower future returns than the low-loading firms. Ang et al. conclude that the sensitivity to innovations in implied market volatility is a priced risk factor after showing the results are robust to matching firm returns from one of the Fama and French (1993) 25 size and B/M portfolio returns and after controlling for liquidity, volume, and momentum.

Ang et al. provide preliminary evidence that aggregate volatility sensitivity is cross-sectionally priced; however, their tests are incomplete for three reasons. First, they present incomplete results about whether the pricing of sensitivity is actually risk-based or characteristic-based. All reported zero-cost portfolio returns have both means and Fama and French (1993) three-factor alphas that are significantly different from zero, which suggests a risk-based pricing kernel. But if expected market volatility is a priced risk factor and the sole explanation for returns of portfolios differing only in loadings, then the incorporation of volatility innovations as an additional explanatory variable into an augmented factor model should produce alphas indistinguishable from zero. While Ang et al.’s focus is not on this issue, the implications of their findings lead us to test a broader, more robust specification.

Second, more powerful tests can be made by grouping stocks into portfolios of like characteristics prior to examining the sensitivities to volatility changes. The portfolios formed in Ang et al. are not initially size and B/M characteristic-balanced, possibly confounding tests of a risk versus characteristic pricing process. Additionally, alphas from the size and B/M matching analysis performed by Ang et al. are unreported, so it is not clear if loadings matter after controlling for the Fama and French factors.
Third, and most important, the model used by Ang et al. to obtain loadings on volatility changes assumes a symmetric relation between returns and innovations in implied market volatility. Significant literature, however, shows there is an asymmetric volatility phenomenon where positive returns are associated with smaller changes in implied volatilities than negative returns of the same magnitude. Specifically, Dennis, Mayhew, and Stivers (2006) examine the relation between stock returns and $\Delta VIX$ allowing for stock returns to react asymmetrically to volatility shocks. Their goal is to determine if the asymmetric volatility phenomenon stems from systematic or idiosyncratic effects. While not directly testing for a risk-return relation, they find that firm-level returns have a much stronger relation with changes in market-level implied volatility than with innovations in implied idiosyncratic volatility. Their findings suggest that the asymmetric volatility phenomenon at the firm level is very much related to systematic effects. The relation to systematic effects means that sensitivities to VIX innovations may be cross-sectionally priced with different relations for upward and downward innovations; firm-level returns should react differently in magnitude to a positive innovation in VIX than to a negative innovation in VIX.

Consequently, the specification used by Ang et al. may only capture a mean loading that is not sensitive to the state of $\Delta VIX$. This can be an important omission, since the degree of asymmetry of the loading can place a stock into an incorrect quintile ranking if the asymmetry is ignored. The asymmetric volatility phenomenon may be why Ang et al. find that the average turnover in their monthly quintile portfolios is above 70%; the mean-reversion property of VIX suggests that a period of upward movements will be followed by downward movements and

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3 See Bekaert and Wu (2000) and Wu (2001) for asymmetric volatility models and literature review.
4 Adrian and Rosenberg (2008) employ an asymmetric volatility model to examine short- and long-run effects of market volatility on the cross-section of stock returns, but use historic volatility rather than the VIX index.
stocks with asymmetric relations to changes in VIX may migrate to different portfolios depending on the degree of asymmetric relations. Ang et al. find that the longer their formation window, the smaller the spread in pre-formation loadings on $\Delta$VIX. Ignoring the asymmetric relation could cause this outcome because as more observations enter the window, the more equal are the number of positive and negative innovations in VIX. Thus, the loadings on VIX changes would move toward an average of loadings on positive innovations and loadings on negative innovations.

We build on the findings of Ang et al. (2006) and Dennis et al. (2006). We examine the effect of sensitivities to implied market volatility on portfolio returns by modeling the return process as a function of the innovations in the VIX index, allowing for asymmetric reaction to implied market volatility. Portfolios are formed by sorting the sample into nine size and B/M portfolio bins. We then use a Daniel and Titman (1997) approach to discern if the contemporaneous relation is risk or characteristic based. The stocks in each size and B/M bin are sorted according to their loadings on $\Delta$VIX and characteristic-balanced, zero-cost portfolios are created by buying stocks that load high on $\Delta$VIX and selling stocks that load low on $\Delta$VIX. The portfolios are considered characteristic-balanced since all stocks in a portfolio have the same size and B/M characteristics, and any contemporaneous differences in the returns in the long-short portfolios can be attributed to their different loadings on $\Delta$VIX. Therefore, if the mean returns of the zero-cost portfolios and alphas from the traditional three-factor model (without volatility innovations included) are significantly different from zero, and the alphas from the Fama and French (1993) three-factor model augmented with $\Delta$VIX are not significantly different from zero, then the risk-based process is accepted as the correct pricing model. If the characteristic model is correct, then mean returns for the zero-cost portfolios will be zero.
For each security we estimate two different loadings on monthly VIX innovations, conditional on whether the innovations are positive or negative. We apply the appropriate loading to a given future month conditional on whether that month has a positive or negative VIX innovation, and form five portfolios in that month based on ranked loadings. We examine portfolio returns in the same month and, thus, returns are examined in a contemporaneous setting with VIX innovations. Our framework is not intended to be predictive, but merely to illustrate the contemporaneous risk-return relation, where that relation is allowed to conditionally change depending on whether VIX increases or decreases.

Our analysis can be directly related to the risk-based hypotheses in Ang et al. (2006). They argue that the inverse relation between market volatility change loadings and the next period’s returns reflects investors paying a premium (resulting in lower expected returns) for stocks with high sensitivities to market volatility changes because they like stocks with relatively high payoffs when volatility increases. In our model this will lead to an increase in market volatility contemporaneously associating with high volatility loading stocks outperforming low volatility loading stocks. When VIX declines, however, our model suggests that low volatility loading stocks outperform high volatility loading stocks. Thus, our predicted risk-return relation will be conditional on whether VIX rises or falls. By analyzing markets when VIX increases separately from when it decreases, we are also able to explicitly incorporate asymmetric volatility effects.

For the size and B/M characteristic-balanced portfolios, when there are positive innovations in VIX, contemporaneous returns across the nine portfolios are negative, as
expected. They also have significantly negative three-factor alphas.\(^5\) When there are negative innovations in VIX, contemporaneous returns across the nine portfolios are strongly positive and three-factor alphas are significantly positive. These results suggest that VIX innovations affect returns and the relation differs depending on whether VIX increases or decreases.

For the characteristic-balanced zero-cost portfolio returns, when there are positive innovations in VIX, firms with high loadings on \(\Delta VIX\) significantly outperform those with low loadings. Three-factor alphas are significantly positive, while alphas for a three-factor model augmented with \(\Delta VIX\) are generally indistinguishable from zero. Since there are a few significant alphas, however, hints of some unexplained effects in the augmented model remain. Overall, these results tend to favor a risk-based explanation over a characteristic-based explanation; they are also consistent with the results in Ang et al. When there are negative innovations in VIX, firms with high loadings on \(\Delta VIX\) perform similarly to firms with low loadings. Three-factor and augmented three-factor alphas are indistinguishable from zero. For negative innovations in VIX, these results are not consistent with a risk story. Instead, as VIX falls there is a contemporaneous strong positive effect on stock returns that influences different stocks about the same. In other words, there is a premium just for being a stock. If a risk explanation existed when VIX declines, the low-loading portfolio should contemporaneously outperform the high-loading portfolio. Our above results are robust to liquidity, momentum, price, volume, and leverage. They are also robust to cross-sectional firm-level Fama and MacBeth (1973) regressions. Ultimately, our findings show that investors only care about loadings when there are increases in implied market volatility.

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\(^5\) As developed in the methodology section, in our three-factor model the traditional market factor is replaced by a market factor orthogonalized to changes in VIX.
Our primary focus is on \( \Delta \text{VIX} \) since the VIX index is used for many purposes in finance, is readily observable, and is a tradable asset. Also, Dennis et al.’s finding that innovations in the VIX index are significant in predicting future realized index volatility make \( \Delta \text{VIX} \) a useful and prudent proxy for changes in expected future market volatility. However, we repeat our analyses using Ang et al.’s factor mimicking portfolio, FVIX, as the proxy for changes in aggregate volatility in place of \( \Delta \text{VIX} \). Our results are generally similar as to when we use \( \Delta \text{VIX} \), with a small difference for the zero-cost portfolios when FVIX is negative. Then, unlike with \( \Delta \text{VIX} \), zero-cost low-loading portfolios significantly outperform high-loading portfolios and two of nine three-factor alphas are significantly different from zero. These results when FVIX is negative may suggest a minor role for a risk-based explanation, whereas there is none when \( \Delta \text{VIX} \) is negative.

The paper is developed in the following sections. Section I describes the data. Section II explains the methodology and models. Section III presents the empirical results for \( \Delta \text{VIX} \). Section IV provides robustness results using FVIX. Section V concludes the paper.

I. Data

The sample is from January 1986 through December 2007. Monthly VIX index levels are from the Chicago Board Options Exchange (CBOE) website, from which \( \Delta \text{VIX} \) is calculated. The VIX index represents the implied volatility of a synthetic, at-the-money option on the S&P

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6 We construct FVIX similar to Ang et al (2006).
The VXO index (the predecessor to VIX that uses a slightly different computational methodology) is used in place of VIX from 1986 through 1989. Stock prices, monthly returns, and share volume are from the Center for Research in Security Prices (CRSP), as are the value-weighted CRSP index returns. Only stocks with CRSP share codes 10, 11, and 12 are kept in the sample. The share volumes for NASDAQ stocks are divided by two to adjust for double-counting trades. The market risk premium (MKT), Fama and French (1993) size and book-to-market factors (SMB and HML), risk-free rate, and NYSE size breakpoints are provided by Ken French’s website.

COMPUSTAT provides data for book equity and leverage. Book equity is the value of stockholders’ equity plus all deferred taxes and investment tax credit, minus the value of any preferred stock. The book-to-market equity ratio assigned to a firm from July of year $\tau$ to June of year $\tau+1$ is the book equity at the end of the fiscal year in calendar year $\tau-1$ divided by the market capitalization at the end of December of year $\tau-1$. Similarly, leverage in year $\tau$ is defined as the value of the total assets of the firm divided by the book equity, where both total assets and book value of equity are calculated at the end of the fiscal year in calendar year $\tau-1$. Only firms with positive book equity are kept in the sample. In order to avoid any COMPUSTAT firm bias, firms with less than two years of data on COMPUSTAT are removed from the sample. Pastor and Stambaugh (2003) liquidity factors are from Wharton Research Data Services (WRDS).

Panel A in Table I shows the simple correlations between MKT, SMB, HML, $\Delta$VIX, and the factor-mimicking portfolio FVIX, similar to that employed by Ang et al. (2006).

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7 The construction of the VIX index is detailed by Whaley (2000) and also in a white paper available at the CBOE’s website: http://www.cboe.com/micro/vix/vixwhite.pdf.
8 Ken French’s website is located at http://www.dartmouth.edu/~kfrench/.
9 The construction of FVIX and results from its use are discussed later.
highly negatively correlated with ΔVIX and FVIX. Panels B and C report the correlations conditional on whether MKT is positive or negative. These two panels demonstrate the nature of the asymmetric volatility phenomenon. The negative correlations of ΔVIX and FVIX with market returns are substantially larger in magnitude when MKT is negative (-0.6981 and -0.7197, respectively) than when it is positive (-0.1808 and -0.2681, respectively). These correlations, however, are just simple correlations, and there are occasions when market returns and ΔVIX are positively correlated. In 31 percent of the observations MKT has the same sign as ΔVIX; in two-thirds of these observations MKT and ΔVIX are both positive and in the remaining one-third they are both negative.

II. Methodology

A. Construction of Adjusted Factor Loadings on ΔVIX

The first step to empirically obtain adjusted factor loadings is to regress individual monthly stock returns, in excess of the risk-free rate, on ΔVIX and an interaction term composed of ΔVIX times a dummy variable reflecting if ΔVIX is positive or not. The interaction term allows for an asymmetric relation between returns and changes in implied market volatility, allowing for a different response to positive and negative innovations in VIX. This regression is:

$$r_{i,t} = \alpha_i + \beta_{\Delta VIX,i}\Delta VIX_t + \theta_i POS_t \Delta VIX_t + \epsilon_{i,t}$$

(1)

where $r_{i,t}$ is the excess return for firm i in month t, $\Delta VIX_t$ is the innovation in VIX from the end of month t-1 to the end of month t, $POS_t$ is a dummy variable that equals one in months when $\Delta VIX$ is positive and zero otherwise, and $\epsilon_{i,t}$ is an error term. This regression is estimated for
each firm for June of year \( \tau \) over 54 months ending in December of year \( \tau-1 \). We require at least 36 months of data and, thus, the earliest regressions end in December, 1988. The beta and theta estimates for each June of year \( \tau \) are assigned to July of year \( \tau \) through June of year \( \tau+1 \).

Although each firm’s parameter estimates are held constant for twelve-month periods, they are used to create adjusted factor loadings (AFL’s) for VIX innovations each month using the realized value of \( \text{POS}_t \) for each respective month from July of year \( \tau \) through June of year \( \tau+1 \). The computation of AFL’s is:

\[
AFL_{\Delta VIX,i,t} = \hat{\beta}_{\Delta VIX,i} + \hat{\theta}_i \text{POS}_t
\]

where \( AFL_{\Delta VIX,i,t} \) is the AFL representing the marginal effect of \( \Delta VIX \) for the returns of stock \( i \) for month \( t \). For example, the regression may be estimated for one firm over 54 months from June, 2001, to December, 2005, and the resulting parameter estimates (\( \hat{\beta}_{\Delta VIX} \) and \( \hat{\theta} \)) for June, 2006, are assigned to the firm from July, 2006, through June, 2007. The AFL for July, 2006, uses the assigned parameter estimates and the POS dummy value (0 or 1) corresponding to the sign of \( \Delta VIX \) that is realized for July, 2006. The AFL’s for August, 2006, through June, 2007, are similarly calculated, using the same \( \hat{\beta}_{\Delta VIX} \) and \( \hat{\theta} \) used for the AFL computation in July, 2006, but using the respective \( \text{POS}_t \) for each month. The analysis begins with July, 1988.

B. Portfolio Formation

Each month we sort the stocks into quintiles based on the \( \Delta VIX \) AFL’s. This method of portfolio formation is common to the size and book-to-market sorts of Fama and French (1993) and Daniel and Titman (1997). The important difference comes from the inclusion of the
interaction term in the regression, which allows each firm to have an asymmetric relation with $\Delta VIX$, and ensures that the firms are placed into quintile portfolios subject to the realization of the direction of $\Delta VIX$. If the asymmetric relation is large enough, the stock may change quintile portfolios depending on whether $\Delta VIX$ is positive or negative. If this is the case for a given stock, then the stock can be in one of two portfolios during the 12-month period that the parameters estimates are held constant, one portfolio when $\Delta VIX$ is negative and another when $\Delta VIX$ is positive. Ang et al.’s (2006) average $\Delta VIX$ loadings of the post-formation portfolios are not well dispersed and this could be due to the lack of accounting for the asymmetric volatility phenomenon. Much of our analysis is based on zero-cost portfolios formed from differences in returns between the fifth and first quintiles.

Similar to Daniel and Titman (1997), we initiate our pricing model tests by sorting the sample into size terciles based on NYSE breakpoints, and then sequentially sorting into book-to-market equity (B/M) terciles. The sorts are performed sequentially in order to guarantee that the number of stocks in each size-B/M bin is sufficiently large. The size of the firm is determined in June of calendar year $\tau$ and assigned to the firm from July of calendar year $\tau$ to June of year $\tau+1$. The B/M of each firm is determined by the book value at the fiscal year-end in calendar year $\tau-1$ divided by the market capitalization of the firm at the end December of year $\tau-1$ and assigning it to the firm from July of calendar year $\tau$ to June of calendar year $\tau+1$. This sorting procedure leads to nine separate size and B/M portfolio bins and in each bin the stocks have similar size and B/M characteristics, or are characteristic balanced. We analyze the returns of these portfolios both when VIX rises and when it falls.
Next, in each portfolio bin the stocks are divided into equal quintiles based on the pre-
formation AFL’s. Following Daniel and Titman (1997), we construct zero-cost characteristic-
balanced portfolios, that differ only in AFL’s, by buying stocks in the fifth quintile (loading the
highest on ΔVIX) and selling the stocks in the first quintile (loading the lowest on ΔVIX) in each
size-B/M bin. This procedure is done both for months when VIX rises and when it falls.

A characteristic-based returns model predicts that the returns of the five portfolios in each
size-B/M bin will not be significantly different from each other, since they all share the same
characteristics and loadings on ΔVIX do not matter. Conversely, a risk-based model predicts
that in each size-B/M bin the stocks with high loadings on ΔVIX will have different mean returns
than the low-loading stocks. This prediction reflects that, among stocks that have similar
characteristics, it is the AFL’s that generate cross-sectional differences in returns. Also, if cross-
sectional differences in returns due to AFL’s are risk-based with no residual unexplained
components, then the alphas from the Fama and French (1993) three-factor model, augmented
with ΔVIX, should be zero since the model explains all the risk components of portfolio returns.

We use two variations of the Fama and French (1993) three-factor model to estimate
abnormal returns, or alphas. The difference between the two models is if ΔVIX is included as an
independent variable. Expectations of market volatility may substantially affect market returns
and MKT in the traditional three-factor model. To isolate the effect of ΔVIX on portfolio
returns, we orthogonalize MKT to ΔVIX. We consider this essential to remove the effect of
volatility from MKT. As seen in Heston (1993) and others, volatility follows a stochastic, mean-
reverting process. The form of the discrete price and volatility processes are:

\[
\frac{\Delta S_t}{S_t} = \mu \Delta t + \sqrt{\Delta t} \Delta W_s
\] (3)
\[ \Delta V_t = k(\theta - V_t)\Delta t + \sigma \sqrt{V_t} \Delta W_v \]  

(4)

where \( S_t \) is the equity spot price at time \( t \), \( V_t \) is the variance of equity spot price at time \( t \), \( \mu \) is the rate of drift of the equity spot price, \( k \) is the rate of mean reversion of the variance, \( \theta \) is the long run mean of the variance, \( \sigma \) is the volatility of the variance, and \( W_s \) and \( W_v \) are standard Wiener processes that are correlated by \( \rho \) such that 

\[ \Delta W_s \cdot \Delta W_v = \rho \Delta t \]  

(5)

Note that the returns process (equation (3)) is explicitly a function of the variance \( V_t \) as well as implicitly a function of the variance through the correlation of the two Wiener processes (equation (5)). The variance process (equation (4)), however, is only influenced by the returns process through correlation of the Wiener processes. This is the motivation for orthogonalizing \( \text{MKT} \) to \( \Delta \text{VIX} \), and not vice versa.

We orthogonalize the traditional market factor to changes in \( \text{VIX} \) by regressing \( \text{MKT} \) on \( \Delta \text{VIX} \) and using the residual in month \( t \) plus the intercept to form \( \text{MKT}^\perp \). By orthogonalizing \( \text{MKT} \) to \( \Delta \text{VIX} \), we remove the expected market variance component from the market returns and isolate it in \( \Delta \text{VIX} \). \( \text{MKT} \) is decomposed into two parts, that due to market volatility innovations and an uncorrelated residual plus intercept component. We also orthogonalize \( \text{MKT} \) because it is highly negatively correlated with \( \Delta \text{VIX} \), as shown in Table I. The coefficient on \( \text{MKT}^\perp \) thus measures the effect on returns from the portion of the market factor unrelated to \( \Delta \text{VIX} \).

We then estimate the two variations of the traditional Fama and French (1993) three-factor model as:
\[ r_{p,t} = a_p + \beta_{MKT,p}^pMKT_t^p + s_pSMB_t + h_pHML_t + \epsilon_{p,t} \]  \hspace{1cm} (6)

and

\[ r_{p,t} = a_p + \beta_{MKT,p}^pMKT_t^p + s_pSMB_t + h_pHML_t + \beta_{\Delta VIX,p}^p\Delta VIX_t + \epsilon_{p,t} \]  \hspace{1cm} (7)

III. ΔVIX Results

A. Cross-Sectional Portfolio Returns and ΔVIX

The characteristics of the quintile portfolios single-sorted by AFL’s on ΔVIX are reported in Panel A of Table II. The sort produces smaller firms in the lowest and highest quintiles. The lowest quintile portfolio based on ΔVIX AFL’s sorts has a slightly lower B/M than the other portfolios. Overall, the B/M ratios for the five portfolios are very similar.

The pre-formation loadings are used to predict post-formation loadings. If the loadings are not stable through time, then tests are not reliable since the post-formation portfolios will not be ranked correctly. Post-formation loadings are obtained by performing the regression described in equation (1) for each firm, and rolling the regressions forward every month to obtain monthly parameter estimates for each firm in each month. Equation (2) is used to form the AFL’s for each firm each month. The portfolio post-formation AFL’s are averages of the post-formation AFL’s of the firms in the quintile portfolios sorted by the pre-formation AFL’s. After the single-sort quintile portfolios are formed, the post-formation loadings are examined to see if the loadings are stable through time. As shown in Panel A of Table II, the portfolios sorted on AFL’s maintain a good dispersion in the mean post-formation AFL’s that is very similar to the mean pre-formation AFL’s. Ang et al. (2006) find poor dispersion in the mean post-formation loadings when sorting on pre-formation loadings on ΔVIX. However, their study focuses on the
portfolio returns in the month following portfolio formation, while our study focuses on the contemporaneous returns with asymmetric volatility.

Concerned that ΔVIX may include components other than diffusion risk (such as jump risk and/or a stochastic volatility risk premium), Ang et al. (2006) create the factor-mimicking portfolio FVIX, replace ΔVIX with FVIX in their original regression relating returns to changes in implied market volatility, and find that the average FVIX loadings of portfolios sorted by ΔVIX loadings are well-dispersed. We repeat all analyses with FVIX, calculated as in Ang et al., and present these results in our robustness section.

In a manner similar to Ang et al., we first present results before forming size and B/M sorted portfolios. Equal and value-weighted returns are computed for the five quintiles of ΔVIX AFL’s and reported in Panel A of Table II. There are slight increases in returns from the low to the high quintiles of AFL’s. As discussed in the introduction, this is not contradictory to Ang et al.’s results since our table presents returns that are contemporaneous to the formation of AFL quintile portfolios and incorporate asymmetric volatility in the formation of the AFL’s. Note that only the stocks in the highest AFL quintile have positive average AFL’s. Since ΔVIX and market returns are negatively correlated, as seen in Table I, this is an expected result.\textsuperscript{10} A positive loading on ΔVIX is akin to a negative loading on the market risk premium, which is unusual. This property of the stocks in the fifth quintile makes them attractive as hedging

\textsuperscript{10} The negative correlation between market returns and volatility is documented by French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992).
instruments. The AFL’s indicate that returns on this quintile of stocks increases as market volatility increases. It is likely that only a small percentage of stocks would exhibit this property.

Panel A of Table II shows that a zero-cost portfolio of going long quintile five stocks and shorting quintile one stocks (hereafter such a portfolio is called a 5-1 portfolio) yields returns insignificantly different than zero. This result is expected. ΔVIX has a mean close zero, with about an equal number of positive and negative realizations. Because the average AFL in quintile one is negative and the average AFL in quintile five is positive, we expect that a 5-1 portfolio return will be positive when ΔVIX is positive and negative when ΔVIX is negative. Thus, a simple t-test of mean returns on a 5-1 portfolio can be inconclusive due to the aggregation of the positive and negative portfolio returns resulting in a mean return close to zero.

In Panels B and C of Table II, the equal- and value-weighted returns of the 5-1 portfolios are tabulated conditional on the contemporaneous ΔVIX. When ΔVIX is positive, the ten sorted portfolios have monthly negative returns that are close to zero for high-loading firms and range to -1.52% for low-loading firms. The 5-1 portfolios have statistically significant positive returns and the three-factor model with MKT\(^t\), SMB, and HML has significant alphas, suggesting that loadings matter and that a risk explanation may apply when VIX rises. When ΔVIX is negative, all ten sorted portfolios have monthly returns of at least 2.30%. There is little return discrepancy across the portfolios and the 5-1 returns and alphas are statistically insignificant. These results are not conducive to a risk explanation as loadings do not matter. Instead, there is a strong positive return to all stocks, irrespective of loadings, when VIX falls. The results in Panels B and C highlight the importance of asymmetric volatility.

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\(^{11}\) This point is also made by Bakshi and Kapadia (2003), Ang et al. (2006), Dennis et al. (2006), and Adrian and Rosenberg (2008).
The results thus far show that there is a relation between ΔVIX loadings and the cross-section of stock returns. In order to establish that the AFL’s on ΔVIX are stable through time within the nine size and B/M bins from tercile sorting, we examine the pre- and post-formation AFL’s for the entire sample and conditional on the direction of ΔVIX. These results are reported in Table III. The pre-formation AFL’s on ΔVIX are well dispersed, and the rankings and dispersion hold for post-formation AFL’s. The average pre-formation (post-formation) AFL’s are -1.00 and -0.96 (-1.04 and -0.99) for small and medium-size growth firms, respectively, which are more negative than those of the other size and B/M bins, which range from -0.67 to -0.79 (-0.69 to -0.80).

Panels A and B of Table IV present value-weighted returns for the nine size and B/M sorted portfolios from periods when ΔVIX is positive and negative, respectively. When VIX increases, all nine portfolios have significantly negative returns and three-factor alphas. A Gibbons, Ross, and Shanken (1989) multivariate test of the alphas shows that they are jointly highly significant. For characteristic-balanced portfolios, VIX increases negatively impact returns and this effect is not reduced in a factor model with MKT, SMB, and HML included. The three-factor alphas are more negative and strongly significant than the raw returns. When VIX decreases, all nine portfolios have positive and highly significant returns and three-factor alphas. The multivariate test of the alphas shows that they are jointly highly significant. The absolute values of returns are larger than when VIX increases, although the three-factor alphas are not. Thus, for characteristic-balanced portfolios, VIX decreases positively impact returns in

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12 Unreported results show that across all subsequent analyses, equal-weighted returns provide quantitatively and qualitatively similar findings to that of the value-weighted returns.
a strong manner, though a little less than half the impact is eliminated in a factor model with MKT\(^{⊥}\), SMB, and HML included.

B. The Impact of Asymmetric Volatility on \(\Delta VIX\) as a Risk Factor

We next examine returns for the nine portfolios, where each is divided into five portfolios based on AFL’s. Panel A of Table V presents results for months when VIX rises and Panel B has results for months when VIX falls. When VIX rises, all nine 5-1 returns are positive and five of the nine are significantly different from zero at the 5\% level or better. All alphas from the three-factor model with MKT\(^{⊥}\), SMB, and HML are positive, with eight significant at the 5\% level or better. They are similar in size to the 5-1 returns, and the joint alpha test is significant at the 1\% level. Significant three-factor alphas show the inability of the model to capture all the risk contained in the portfolios and, in an efficient market, suggest there is risk present other than that captured by MKT\(^{⊥}\), SMB, and HML. The average 5-1 return and alpha effects across portfolios are 25\%-35\% below the corresponding value-weighted numbers in Table II, Panel B. This highlights the importance of forming characteristic controlled portfolios. The three-factor model augmented with VIX innovations has eight of nine individual alphas insignificantly different than zero, and the joint test of significance cannot reject the null hypothesis of alphas equal to zero. Although only one is significant, typical augmented model alphas retain about one-half the value of the three-factor alphas and raw returns.

All of these results suggest that when VIX rises, factor loadings matter, consistent with the conclusion that VIX innovations represent a priced risk factor. Zero-cost characteristic-balanced portfolios can be constructed, albeit based on ex-post information, that generate both
statistically and economically significant mean returns. But since these returns can be explained by a model that includes VIX innovations, ΔVIX appears to be a risk factor. The sensitivity to changes in implied market volatility has a cross-sectional effect on stock returns that follows a risk-based returns process, and this risk is not captured by the three-factor model. However, an augmented model that incorporates ΔVIX seems to explain most of the return. There is, perhaps, a hint of some residual return left over that is captured in the augmented model alphas, which may suggest part of the 5-1 returns cannot be explained by the four factors in the model.

When VIX falls, all nine 5-1 returns are negative, but none are significant. None of the alphas are significant either. These results are not consistent with a risk story; loadings do not matter. Instead, all portfolios have similar returns that are quite high, ranging from 2.14% to 3.55% per month. These results, consistent with those in Table II, suggest that when VIX falls, there is a large positive premium for the characteristic of being a stock, with no differentiation based on loadings. All stocks rise substantially and similarly when VIX falls.

C. Effects of Other Firm Characteristics on the Role of ΔVIX

We next examine if the previous results are robust to liquidity, momentum, price, volume, and leverage. In order to get loadings on the Pastor and Stambaugh (2003) liquidity factor (LIQ), a rolling regression is estimated (in a similar manner to equation (1)) as:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + l_i LIQ_t + \epsilon_{i,t}$$

(8)

The regression is estimated over 54 months ending in December of year τ-1 with at least 36 months of data required. The loadings are assigned to stock i from July of year τ to June of year
The stocks are sorted into quintile portfolios based on their loadings on LIQ. Six (twelve) month momentum is constructed for each firm in June of year $\tau$ by accumulating the monthly returns from December (June) of year $\tau-1$ to April of year $\tau$. The accumulated returns are assigned to stock $i$ from July of year $\tau$ to June of year $\tau+1$, and the stocks are sorted into quintile portfolios based on their six (twelve) month momentum. The quintile portfolios based on stock price are created by sorting at the end of June of year $\tau$ and assigning the rankings from July of year $\tau$ to June of year $\tau+1$. To control for volume effects, firms are sorted into quintiles based on the dollar trading volume over June of year $\tau$ and the rankings are assigned from July of year $\tau$ to June of year $\tau+1$. We define leverage as the ratio of the total book value of assets to the total book value of equity at the fiscal year end occurring in calendar year $\tau-1$. Firm leverage ratios are sorted into quintiles and the rankings assigned from July of year $\tau$ to June of year $\tau+1$.

In a manner similar to our original sorting procedure, a 3x3x3 triple sort is performed every 12 months involving each of the robustness characteristics. The first sort is on size, the second on B/M, and the third on the respective characteristic. Thus, we form 27 characteristic-balanced portfolios. Next, in each portfolio bin the stocks are divided into equal quintiles based on the pre-formation AFL’s. As before, we construct zero-cost characteristic-balanced portfolios in each bin, differing only in AFL’s, by buying stocks in the fifth quintile and selling the stocks in the first quintile. This is done both for months when VIX rises and when it falls. Each month the value-weighted returns of the zero-cost portfolios are computed and averaged across the 27 bins. This average return is used in the regressions.

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13 Jegadeesh and Titman (1993) document the momentum effect.
14 Equal-weighted returns (unreported) provide similar results.
Results for months when VIX increases are in Table VI, Panel A, and findings for months when VIX decreases are in Table VI, Panel B. When \( \Delta VIX \) is positive, all 5-1 returns and three-factor alphas are positive and significant at the 5% level or better, while in the augmented model all alphas are insignificant. When \( \Delta VIX \) is negative, all 5-1 returns and alphas are insignificant. All of these results are very similar to those in Table V and suggest that when VIX rises there is substantial evidence indicating it is a risk factor, while when VIX falls there is very little evidence that VIX innovations are a priced risk factor. These results confirm that liquidity, momentum, price, volume, and leverage are not driving the results from the size and B/M characteristic-balanced portfolio tests.

Finally, we estimate Fama and MacBeth (1973) cross-sectional regressions with firm-level data. Consistent with the earlier portfolio analysis, the first monthly cross-sectional regression is for July, 1989, and independent variables include the AFL on \( \Delta VIX \), log of size, B/M, six-month momentum, beta on MKT\( ^{\perp} \), and liquidity beta. The construction of all variables is as defined earlier. Separate estimations are performed for months when \( \Delta VIX \) is positive and for months when it is negative. We employ Newey and West (1987) standard errors in the construction of t-statistics.

Table VII, Panel A, has results when VIX rises and Panel B has results for when VIX falls. When VIX rises, the coefficient on VIX loadings is positive and significant at the 5% level. This is consistent with prior results indicating that when VIX rises, loadings on VIX matter. When VIX falls, the coefficient on VIX loadings is negative and insignificant. The absolute value of the coefficient is more than four times higher when VIX rises than when it
falls. These results are consistent with prior results and suggest a lesser role for loadings when ∆VIX is negative.

IV. Results with FVIX

Ang et al. (2006) suggest that using ∆VIX at the monthly level is a poor approximation for changes in aggregate volatility due to the role that the conditional mean of VIX plays in the determination of the unanticipated change in VIX, as well as the possibility that jump risk and the stochastic volatility risk premium may be incorporated in VIX. This inspires them to create a factor mimicking portfolio, FVIX, that proxies for innovations in aggregate volatility and can be used at any frequency. In order to ensure that our results are not due to an inappropriate proxy for innovations in aggregate volatility, we create FVIX as detailed by Ang et al., and perform the same analysis as in the previous section, replacing ∆VIX with FVIX. All steps in the analysis are identical, except that FVIX replaces ∆VIX in the models and equations.

Panel A of Table VIII shows the equal- and value-weighted returns, the pre-formation and post-formation AFL’s, and the size and B/M of the quintile portfolios single-sorted by AFL’s on FVIX. The FVIX AFL’s are slightly less dispersed than those based on ∆VIX. The size and B/M characteristics of the quintiles portfolios are similar between the quintile portfolios based on the FVIX AFL’s and those based on ∆VIX AFL’s. The 5-1 portfolio returns are not significantly different from zero and similar in magnitude to ∆VIX results in Table II.

In Panels B and C of Table VIII, the equal- and value-weighted returns of the 5-1 portfolios are given conditional on the contemporaneous sign of FVIX. When FVIX is positive,
the 5-1 returns and three-factor alphas are positive and significant at the 1% level. Their magnitudes are about twice the corresponding measures for ΔVIX in Table II. When FVIX is negative, the 5-1 returns are negative and significant. The three-factor alphas are negative, but only the value-weighted alpha is significant, and the alphas are about half the 5-1 returns. These results are different from the ΔVIX results in Table II where there was no significance.\textsuperscript{15}

The story is somewhat different when FVIX is negative than when VIX declines. With FVIX, a partial risk explanation is warranted because loadings seem to matter. However, two things should be noted. First, the 5-1 returns and alphas are much smaller when FVIX is negative than when it is positive; thus, the risk explanation is stronger in the latter than the former. Second, when FVIX is negative there is still a strong positive effect on returns irrespective of loadings; the smallest return of the ten portfolios is 2.68%, which is actually slightly larger than the smaller corresponding returns in Table II for a negative ΔVIX. Our prior conclusion, that when implied volatility falls there is a substantial positive return effect just for being a stock and irrespective of loadings, remains; however, risk matters too. The asymmetric volatility phenomenon remains intact when substituting FVIX for ΔVIX as the proxy for innovations in aggregate volatility.

As with ΔVIX, we examine the stability of the FVIX AFL’s from the pre-formation period to the post-formation period. The methodology is the same and results are in Table IX. The pre-formation AFL’s on FVIX are well dispersed, and the rankings and dispersion generally hold for post-formation AFL’s. The dispersion is not as great, however, as it was for ΔVIX.

\textsuperscript{15} FVIX has a greater mean, standard deviation, and range than ΔVIX. This may lead to greater dispersion in returns with FVIX than ΔVIX.
This is the same conclusion as when the ΔVIX loadings in Table II, Panel A, are compared with the FVIX loadings in Table VI, Panel A.

Panels A and B of Table X present value-weighted returns for the nine size and B/M sorted portfolios from periods when FVIX is positive and negative, respectively. Results are very similar to those for ΔVIX in Table IV. When FVIX is positive (negative), portfolio returns and three-factor alphas are negative (positive) and highly significant. Magnitudes of returns and alphas are slightly greater with FVIX. FVIX strongly affects portfolio returns in a similar way that ΔVIX does.

We now look at returns for the nine portfolios where each is divided into five portfolios based on AFL’s. Panel A of Table XI presents results for months when FVIX is positive and Panel B has results for months when FVIX is negative. When FVIX is positive, all nine 5-1 returns and alphas from the three-factor model with MKT⊥ (the MKT factor orthogonalized to FVIX), SMB, and HML are positive and significant at the 1% level, except for two alphas that are significant at 5%. The joint alpha test is significant at the 1% level. The three-factor model augmented with FVIX has six of nine alphas insignificantly different from zero and the joint alpha test is insignificant. Typical augmented model alphas keep about one-half the value of the three-factor alphas, even though only three are significant. These results are very similar to those with ΔVIX, indicating a strong market volatility risk component and a possible residual unexplained effect too.

When FVIX is negative, eight of nine 5-1 returns are negative and significant at the 5% level or better. This is different from results with ΔVIX where all 5-1 returns are insignificant.

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16 As with ΔVIX, unreported results with equal-weighted returns for FVIX are similar to value-weighted returns.
Two of nine alphas from the three-factor model with MKT, SMB, and HML are significant, one each at the 1% and 5% levels, respectively. The joint test alpha is insignificant. Thus, much of the 5-1 return differences are explained by the three-factor model, reducing the chances that the 5-1 differences are due to FVIX loadings. However, the typical three-factor alpha is about 40% of the typical 5-1 return difference. This, coupled with two significant alphas, suggests that there may be a minor risk-based explanation for 5-1 return differences. This conclusion is slightly different than with ΔVIX, where there is no significance and no risk story. Like with ΔVIX, alphas from the augmented three-factor model with FVIX are insignificant. Finally, all 45 portfolio returns are strongly positive, even more so than they are with ΔVIX. Thus, the message when FVIX is negative is fairly similar to that when ΔVIX is negative. There are strong positive returns across all portfolios, suggesting a positive effect on the returns of all stocks, irrespective of loadings, when FVIX or ΔVIX is negative. When expected market volatility changes are measured by FVIX, there may be a minor risk aspect to the explanation.

V. Conclusion

We examine the effect of innovations in implied volatility on stock returns and whether the relation is best described as due to risk or characteristics. Importantly, we address these relations in the context of asymmetric volatility. We use returns contemporaneous to the portfolio formation and account for the asymmetric volatility phenomenon by using a model that allows different loadings for positive and negative innovations in implied market volatility. We apply a test from Daniel and Titman (1997) to distinguish risk from characteristics. We find that a firm’s sensitivity to changes in market volatility is a cross-sectionally priced risk factor when
volatility increases, but not when it decreases. Loadings matter when volatility rises, but when volatility falls there is a positive uniform effect on all stock returns.

Monthly loadings of stock returns on $\Delta$VIX are obtained via rolling regressions from January 1986 through December 2007. Portfolios are constructed based on their past loadings and then examined to see if there is a difference in returns among them. Sensitivities to $\Delta$VIX are found to have a cross-sectional effect on returns. Next, stocks are sorted into portfolios with like size and B/M characteristics, and then sorted into portfolios based on their adjusted factor loadings on $\Delta$VIX. Inside of each size and B/M bin, a characteristic-balanced zero-cost portfolio is formed that is long in stocks that load high on $\Delta$VIX and short stocks that load low on $\Delta$VIX. We examine results separately for months when $\Delta$VIX is positive and for months when it is negative.

When $\Delta$VIX is positive the zero-cost portfolios have significantly positive returns, alphas from a three-factor model, including an orthogonalized market factor, that are also positive and significant, and alphas from a three-factor model augmented with VIX innovations that are generally positive and insignificant. These results suggest that $\Delta$VIX loadings are a priced risk factor. There are some minor positive abnormal returns that tend to remain in the augmented model alphas, however. When $\Delta$VIX is negative, zero-cost returns and all alphas are insignificant. Further, all characteristically balanced non-zero cost portfolios have strongly positive returns that are roughly equivalent. These results suggest that when $\Delta$VIX is negative, risk related to VIX innovations does not matter, with positive returns just for being a stock. Our results are robust to liquidity, momentum, price, volume, and leverage.
We examine results from Fama and MacBeth (1973) firm-level regressions and reach similar conclusions to our portfolio analysis. We then examine portfolio results based on the FVIX measure derived by Ang et al. (2006). For increasing volatility, results are similar to those with ΔVIX. When volatility decreases, a minor risk component appears with FVIX that was not present with ΔVIX. However, there is an even stronger positive effect on returns, fairly uniform across portfolios, just for being a stock, than there was with ΔVIX. Overall, the pricing of volatility risk is more complex than previously thought and warrants further study.
References


Table I
Monthly Factor Correlations

The table reports the correlations between the Fama and French (1993) factors MKT, SMB, and HML, the first differences in VIX (ΔVIX), and the factor mimicking portfolio FVIX (constructed similar to Ang et al. (2006)). Panel A reports the correlations over the entire sample period of January 1986 to December 2007. Panel B reports the correlations during the months when MKT is positive. Panel C reports the correlations during the sample period when MKT is negative.

### Panel A: Monthly Correlations for the Entire Sample Period

<table>
<thead>
<tr>
<th></th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>ΔVIX</th>
<th>FVIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>MKT</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.1926</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>-0.5013</td>
<td>-0.3152</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔVIX</td>
<td>-0.5558</td>
<td>-0.2864</td>
<td>0.1274</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>FVIX</td>
<td>-0.5961</td>
<td>-0.1937</td>
<td>0.2358</td>
<td>0.6510</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

### Panel B: Monthly Correlations When Excess Market Returns Are Positive

<table>
<thead>
<tr>
<th></th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>ΔVIX</th>
<th>FVIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>MKT</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>-0.0060</td>
<td>1.0000</td>
<td></td>
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<tr>
<td>HML</td>
<td>-0.4186</td>
<td>-0.4213</td>
<td>1.0000</td>
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<td></td>
</tr>
<tr>
<td>ΔVIX</td>
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<td>-0.1364</td>
<td>0.0101</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>FVIX</td>
<td>-0.2681</td>
<td>0.0544</td>
<td>0.2952</td>
<td>-0.0287</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

### Panel C: Monthly Correlations When Excess Market Returns Are Negative

<table>
<thead>
<tr>
<th></th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>ΔVIX</th>
<th>FVIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>MKT</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.2531</td>
<td>1.0000</td>
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</tr>
<tr>
<td>HML</td>
<td>-0.3692</td>
<td>-0.1014</td>
<td>1.0000</td>
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</tr>
<tr>
<td>ΔVIX</td>
<td>-0.6981</td>
<td>-0.3620</td>
<td>0.0175</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>FVIX</td>
<td>-0.7197</td>
<td>-0.2688</td>
<td>0.1095</td>
<td>0.7924</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
### Table II
Portfolios Sorted by Sensitivity to Innovations in Implied Market Volatility

For each firm a regression is estimated of the form:

\[ r_{i,t} = \alpha_i + \beta_i \Delta VIX_t + \theta_i POS_t \Delta VIX_t + \epsilon_{i,t} \]

where \( r_{i,t} \) is the excess return for firm \( i \) in month \( t \), \( \Delta VIX_t \) is the innovation in VIX from the end of month \( t-1 \) to the end of month \( t \), \( POS_t \) is a dummy variable that equals one in months when \( \Delta VIX \) is positive and equals zero otherwise, and \( \epsilon_{i,t} \) is an error term. This regression is estimated for each firm for June of year \( \tau \) on a monthly basis over 54 months (a minimum of 36 months of data are required) ending in December of year \( \tau-1 \). The beta and theta estimates for each June of year \( \tau \) are assigned to July of year \( \tau \) through June of year \( \tau+1 \). Although each firm’s parameter estimates are held constant for twelve-month periods, they are used to create \( \Delta VIX \) adjusted factor loadings (\( \Delta VIX \) AFL’s) each month using the realized value of \( POS_t \) for each respective month from July of year \( \tau \) through June of year \( \tau+1 \). The \( \Delta VIX \) AFL’s are computed as:

\[ AFL_{\Delta VIX,i,t} = \beta_i \Delta VIX_t + \theta_i POS_t \]

Firms are sorted each month into quintiles based on their \( \Delta VIX \) AFL’s. Post-formation monthly returns are averages of stock returns (either equal- or value-weighted) in each portfolio every month. Post-formation loadings are found by rolling the regressions every month to obtain monthly parameter estimates for each firm. AFL’s are computed for each firm each month. The portfolio post-formation AFL’s are averages of the post-formation AFL’s of the firms in the quintile portfolios sorted by the pre-formation AFL’s. Panel A presents equal- and value-weighted average monthly returns in the post-formation period, the mean \( \Delta VIX \) AFL’s for the pre- and post-formation periods, average natural log of mean size (total market capitalization) and the average book-to-market equity ratio (B/M) of the firms in each quintile portfolio. The row “5-1” refers to the mean difference in returns between quintile portfolios 5 and 1. Panels B and C report the equal and value-weighted portfolio returns and the mean difference in returns between quintile portfolios 5 and 1, but limit the sample to months where either the \( \Delta VIX \) is positive or negative, respectively. The alpha from regressing the 5-1 portfolio returns on the Fama and French (1993) three-factor model, with a market factor orthogonalized to \( \Delta VIX \), is reported in the row labeled “Ortho FF-3 Alpha.” \( t \)-statistics are reported in parentheses.

#### Panel A: Portfolios sorted by the AFL’s on \( \Delta VIX \) for the entire sample period.

<table>
<thead>
<tr>
<th>( \Delta VIX ) AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th>Mean of Pre-formation ( \Delta VIX ) AFL</th>
<th>Mean of Post-formation ( \Delta VIX ) AFL</th>
<th>Log of size</th>
<th>B/M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Low)</td>
<td>Equal weighted 1.38  Value weighted 0.76</td>
<td>-3.21</td>
<td>-2.85</td>
<td>4.68</td>
<td>0.75</td>
</tr>
<tr>
<td>2</td>
<td>1.25</td>
<td>0.96</td>
<td>-1.39</td>
<td>-1.32</td>
<td>5.38</td>
</tr>
<tr>
<td>3</td>
<td>1.23</td>
<td>0.92</td>
<td>-0.71</td>
<td>-0.73</td>
<td>5.60</td>
</tr>
<tr>
<td>4</td>
<td>1.28</td>
<td>0.93</td>
<td>-0.11</td>
<td>-0.23</td>
<td>5.46</td>
</tr>
<tr>
<td>5 (High)</td>
<td>1.72</td>
<td>1.24</td>
<td>1.25</td>
<td>0.86</td>
<td>4.65</td>
</tr>
<tr>
<td>5-1</td>
<td>0.34</td>
<td>0.48</td>
<td>(1.44)</td>
<td>(1.62)</td>
<td></td>
</tr>
</tbody>
</table>

** **p<0.01, * p<0.05
Panel B: Portfolios sorted by the AFL’s on ΔVIX when ΔVIX is positive.

<table>
<thead>
<tr>
<th>ΔVIX AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equal weighted</td>
<td>Value weighted</td>
<td></td>
</tr>
<tr>
<td>1 (Low)</td>
<td>-1.04</td>
<td>-1.52</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.68</td>
<td>-0.76</td>
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</tr>
<tr>
<td>3</td>
<td>-0.47</td>
<td>-0.56</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.33</td>
<td>-0.50</td>
<td></td>
</tr>
<tr>
<td>5 (High)</td>
<td>-0.07</td>
<td>-0.17</td>
<td></td>
</tr>
<tr>
<td>5-1</td>
<td>0.97*</td>
<td>1.34**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.35)</td>
<td>(2.90)</td>
<td></td>
</tr>
<tr>
<td>Ortho FF-3 Alpha</td>
<td>0.71*</td>
<td>1.21**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.56)</td>
<td>(3.42)</td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Portfolios sorted by the AFL’s on ΔVIX when ΔVIX is negative.

<table>
<thead>
<tr>
<th>ΔVIX AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equal weighted</td>
<td>Value weighted</td>
<td></td>
</tr>
<tr>
<td>1 (Low)</td>
<td>3.72</td>
<td>2.97</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3.12</td>
<td>2.62</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2.87</td>
<td>2.34</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2.82</td>
<td>2.30</td>
<td></td>
</tr>
<tr>
<td>5 (High)</td>
<td>3.45</td>
<td>2.61</td>
<td></td>
</tr>
<tr>
<td>5-1</td>
<td>-0.27</td>
<td>-0.36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.26)</td>
<td>(-1.03)</td>
<td></td>
</tr>
<tr>
<td>Ortho FF-3 Alpha</td>
<td>-0.01</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.05)</td>
<td>(-0.02)</td>
<td></td>
</tr>
</tbody>
</table>

**p<0.01, * p<0.05
Table III
Stability of ∆VIX Adjusted Factor Loadings

This table reports the pre- and post-formation mean ∆VIX AFL’s in each portfolio that is sequentially sorted by size, book-to-market equity ratio (B/M), and ∆VIX AFL’s. We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. The size of the firm is determined at the end of June in calendar year t and assigned to the firm from July in calendar year t to June in year t+1. B/M is the book value at fiscal year-end in calendar year t-1 divided by the market capitalization of the firm at the end of December in year t-1 and it is assigned to the firm from July in calendar year t to June in t+1. In each size and B/M portfolio bin the stocks are divided into equal quintiles based on their pre-formation ∆VIX AFL’s formed from estimated parameters in June of year t. Post-formation loadings are obtained by estimating equation (1) for each firm and rolling the regressions every month to obtain monthly parameter estimates. AFL’s are computed for each firm each month using equation (2). The portfolio post-formation AFL’s are averages of post-formation AFL’s of the firms in the quintile portfolios sorted by the pre-formation AFL’s.

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>Pre-formation Mean ∆VIX AFL</th>
<th>Post-formation Mean ∆VIX AFL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>∆VIX AFL Quintiles</td>
<td>1 (Low) 2 3 4 5 (High) Average</td>
</tr>
<tr>
<td>1 (Low)</td>
<td>1 (Low)</td>
<td>-4.20 -1.84 -0.87 0.01 1.88 -1.00</td>
<td>-3.70 -1.74 -0.92 -0.17 1.32 -1.04</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>-3.11 -1.34 -0.65 -0.05 1.22 -0.79</td>
<td>-2.75 -1.27 -0.67 -0.17 0.86 -0.80</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>-3.16 -1.39 -0.66 0.00 1.34 -0.77</td>
<td>-2.77 -1.29 -0.66 -0.12 0.97 -0.77</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>-3.12 -1.51 -0.85 -0.25 0.94 -0.96</td>
<td>-2.78 -1.45 -0.89 -0.34 0.52 -0.99</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>-2.39 -1.24 -0.70 -0.23 0.68 -0.78</td>
<td>-2.16 -1.16 -0.70 -0.31 0.42 -0.78</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>-2.26 -1.18 -0.68 -0.25 0.55 -0.76</td>
<td>-2.05 -1.13 -0.72 -0.36 0.30 -0.79</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>-2.31 -1.14 -0.66 -0.22 0.64 -0.74</td>
<td>-2.06 -1.12 -0.70 -0.33 0.35 -0.77</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>-2.00 -1.08 -0.65 -0.26 0.48 -0.70</td>
<td>-1.83 -1.04 -0.66 -0.33 0.24 -0.72</td>
</tr>
<tr>
<td>3 (High)</td>
<td>3 (High)</td>
<td>-1.88 -1.03 -0.63 -0.24 0.45 -0.67</td>
<td>-1.71 -0.98 -0.66 -0.35 0.23 -0.69</td>
</tr>
</tbody>
</table>
Table IV
Mean Returns and Alphas of the Nine Portfolios Formed on the Basis of Size and Book-to-Market Ratio

We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. Firm size is determined at the end of June in calendar year \( t \) and assigned from July in calendar year \( t \) to June in year \( t+1 \). B/M is the book value at fiscal year-end in calendar year \( t-1 \) divided by the market capitalization of the firm at the end of December in year \( t-1 \) and it is assigned from July in calendar year \( t \) to June in calendar year \( t+1 \). Value-weighted returns for each portfolio are calculated every month from July 1989 to December 2007. Panel A contains months where VIX increases and Panel B has months where it decreases. Alphas are from the Fama and French (1993) three-factor model where MKT is orthogonalized to \( \Delta VIX \) ("Ortho FF-3 Alpha"). The row labeled “Joint test p-value” presents the p-value from a Gibbons, Ross, and Shanken (1989) multivariate test of alphas. The last row shows the mean returns and alphas when the characteristic-balanced portfolio returns are averaged across size and B/M sorted portfolios each month. \( t \)-statistics are in parentheses.

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>Log of Size</th>
<th>B/M</th>
<th>Portfolio Returns</th>
<th>Ortho FF-3 Alpha</th>
<th>Panel A: Mean Returns and Alphas in Months When ( \Delta VIX ) is Positive</th>
<th>Panel B: Mean Returns and Alphas in Months When ( \Delta VIX ) is Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(Low)</td>
<td>1(Low)</td>
<td>4.32</td>
<td>0.28</td>
<td>-1.84**</td>
<td>-2.11**</td>
<td>2.90**</td>
<td>1.58**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-3.03)</td>
<td>(-8.49)</td>
<td>(5.54)</td>
<td>(5.02)</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4.21</td>
<td>0.70</td>
<td>-0.75</td>
<td>-1.40**</td>
<td>2.64**</td>
<td>1.57**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-1.69)</td>
<td>(-6.84)</td>
<td>(7.67)</td>
<td>(7.19)</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>3.48</td>
<td>1.74</td>
<td>-0.81</td>
<td>-1.51**</td>
<td>2.85**</td>
<td>1.56**</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td>(-1.65)</td>
<td>(-6.08)</td>
<td>(6.84)</td>
<td>(5.55)</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>6.79</td>
<td>0.23</td>
<td>-1.59**</td>
<td>-2.00**</td>
<td>2.90**</td>
<td>1.76**</td>
</tr>
<tr>
<td></td>
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<td>(6.91)</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>6.77</td>
<td>0.48</td>
<td>-0.95*</td>
<td>-1.74**</td>
<td>2.49**</td>
<td>1.51**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-2.12)</td>
<td>(-7.50)</td>
<td>(7.72)</td>
<td>(7.17)</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>6.75</td>
<td>0.92</td>
<td>-0.93*</td>
<td>-1.86**</td>
<td>2.62**</td>
<td>1.58**</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td>(-2.13)</td>
<td>(-7.86)</td>
<td>(8.27)</td>
<td>(8.32)</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>8.94</td>
<td>0.18</td>
<td>-1.03*</td>
<td>-1.47**</td>
<td>2.16**</td>
<td>1.54**</td>
</tr>
<tr>
<td></td>
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<td>(-2.27)</td>
<td>(-7.23)</td>
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<td>(6.68)</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>8.71</td>
<td>0.40</td>
<td>-0.91*</td>
<td>-1.65**</td>
<td>2.24**</td>
<td>1.57**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-2.32)</td>
<td>(-7.07)</td>
<td>(7.28)</td>
<td>(6.91)</td>
</tr>
<tr>
<td>3(High)</td>
<td>3(High)</td>
<td>8.52</td>
<td>0.76</td>
<td>-0.89*</td>
<td>-1.91**</td>
<td>2.30**</td>
<td>1.59**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-2.16)</td>
<td>(-8.95)</td>
<td>(7.52)</td>
<td>(7.14)</td>
</tr>
<tr>
<td>Joint test p-value</td>
<td></td>
<td></td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Average across portfolios</td>
<td></td>
<td></td>
<td></td>
<td>-1.08*</td>
<td>-1.74**</td>
<td>2.57**</td>
<td>1.58**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-2.50)</td>
<td>(-8.34)</td>
<td>(8.13)</td>
<td>(9.06)</td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05
We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. Firm size is determined at the end of June in calendar year $\tau$ and assigned from July in calendar year $\tau$ to June in calendar year $\tau+1$. B/M is the book value at fiscal year-end in calendar year $\tau-1$ divided by the market capitalization of the firm at the end of December in year $\tau-1$ and it is assigned from July in calendar year $\tau$ to June in calendar year $\tau+1$. In each size and B/M portfolio bin the stocks are divided into equal quintiles each month based on the pre-formation $\Delta$VIX AFL’s. Value-weighted returns are calculated for each portfolio every month from July 1989 to December 2007. Mean returns for each triple-sorted portfolio and the 5-1 characteristic-balanced portfolios are presented. Alphas are from the Fama and French (1993) three-factor model where MKT is orthogonalized to $\Delta$VIX (“Ortho FF-3 Alpha”), as given in equation (6), and a modified version augmented with $\Delta$VIX (“Augmented FF-3 Alpha”), as represented in equation (7). The row labeled “Joint test p-value” presents the p-value from a Gibbons, Ross, and Shanken (1989) multivariate test of alphas. The last row shows the mean returns and alphas when the characteristic-balanced portfolio returns are averaged across size and B/M sorted portfolios each month. Panels A and B report portfolio returns for months when $\Delta$VIX is positive or negative, respectively. $t$-statistics are in parentheses.

### Panel A: Mean Returns of Portfolios Sorted on Size, B/M, and $\Delta$VIX AFL’s In Months When $\Delta$VIX is Positive

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>1 (Low)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 (High)</th>
<th>5-1</th>
<th>Ortho FF-3 Alpha</th>
<th>Augmented FF-3 Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Low)</td>
<td>1 (Low)</td>
<td>-2.16</td>
<td>-1.61</td>
<td>-1.11</td>
<td>-1.00</td>
<td>-0.80</td>
<td>1.36**</td>
<td>1.13**</td>
<td>0.45</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>-0.78</td>
<td>-0.22</td>
<td>-0.29</td>
<td>-0.17</td>
<td>-0.02</td>
<td>0.75</td>
<td>0.67</td>
<td>-0.17</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>-0.44</td>
<td>-0.58</td>
<td>-0.43</td>
<td>-0.33</td>
<td>0.57</td>
<td>1.01**</td>
<td>1.25**</td>
<td>0.83</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>-1.53</td>
<td>-1.13</td>
<td>-1.44</td>
<td>-0.54</td>
<td>-0.57</td>
<td>0.96*</td>
<td>0.90*</td>
<td>0.62</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>-1.03</td>
<td>-0.21</td>
<td>-0.47</td>
<td>-0.56</td>
<td>-0.23</td>
<td>0.80</td>
<td>0.82*</td>
<td>0.42</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>-0.70</td>
<td>-0.48</td>
<td>-0.61</td>
<td>-0.38</td>
<td>-0.14</td>
<td>0.56</td>
<td>0.64*</td>
<td>0.10</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>-1.75</td>
<td>-0.53</td>
<td>-0.64</td>
<td>-0.52</td>
<td>-0.09</td>
<td>1.66**</td>
<td>1.52**</td>
<td>1.52*</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>-0.91</td>
<td>-0.80</td>
<td>-0.68</td>
<td>-0.32</td>
<td>-0.16</td>
<td>0.75</td>
<td>0.71*</td>
<td>0.08</td>
</tr>
<tr>
<td>3 (High)</td>
<td>3 (High)</td>
<td>-0.66</td>
<td>-0.49</td>
<td>-0.64</td>
<td>-0.42</td>
<td>0.32</td>
<td>0.98*</td>
<td>1.09**</td>
<td>0.62</td>
</tr>
<tr>
<td>Joint test p-value</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0031</td>
<td>0.1289</td>
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<tr>
<td>Average across portfolios</td>
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<td></td>
<td></td>
<td></td>
<td>0.98**</td>
<td>0.97**</td>
<td>0.50</td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05
Panel B: Mean Returns of Portfolios Sorted on Size, B/M, and ΔVIX AFL’s In Months When ΔVIX is Negative

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>ΔVIX AFL Quintiles</th>
<th>Ortho FF-3 Alpha</th>
<th>Augmented FF-3 Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Low)</td>
<td>1 (Low)</td>
<td>1 (Low)</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>3.29</td>
<td>3.03</td>
<td>-0.41</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>3.19</td>
<td>3.55</td>
<td>0.36</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>3.20</td>
<td>3.09</td>
<td>-0.12</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2.98</td>
<td>2.63</td>
<td>-0.35</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>3.01</td>
<td>2.61</td>
<td>-0.40</td>
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<tr>
<td>3</td>
<td>1</td>
<td>2.73</td>
<td>2.31</td>
<td>-0.41</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>2.81</td>
<td>2.34</td>
<td>-0.46</td>
</tr>
<tr>
<td>3 (High)</td>
<td>3 (High)</td>
<td>2.94</td>
<td>2.51</td>
<td>-0.42</td>
</tr>
</tbody>
</table>

Joint test p-value
Average across portfolios

** p<0.01, * p<0.05
Robustness of ΔVIX Results to Liquidity, Momentum, Price, Volume, and Leverage

We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. Firm size is determined at the end of June in calendar year τ and assigned from July in calendar year τ to June in year τ+1. B/M is the book value at fiscal year-end in calendar year τ-1 divided by the market capitalization of the firm at the end of December in year τ-1 and it is assigned from July in calendar year τ to June in calendar year τ+1. Portfolios are sequentially sorted into terciles by the control variable and then into quintiles on ΔVIX AFL’s. The tercile sorts on the control variables occur in June of year τ and the rankings are assigned to the firms from July of year τ to June of year τ+1. The 5-1 portfolio returns are averages of the twenty-seven 5-1 portfolio returns each month over the control variables’ quintiles. Alphas are from the Fama and French (1993) three-factor model where MKT is orthogonalized to ΔVIX (“Ortho FF-3 Alpha”), as given in equation (6), and a modified version augmented with ΔVIX (“Augmented FF-3 Alpha”), as represented in equation (7). The control variables are the liquidity beta, six-month momentum, twelve-month momentum, price, volume, and leverage. Liquidity beta is the coefficient on the Pastor and Stambaugh (2003) liquidity variable in their four-factor model. Six-month momentum is the cumulative returns from the end of December in year τ-1 to the end of April in year τ, while twelve-month momentum is the cumulative returns from the end of June in year τ-1 to the end of April in year τ. Price is the price per share of stock. Volume is the one-month dollar volume (NASDAQ stock volumes are divided by 2). Leverage is the total book value of assets at the end of the fiscal year in calendar year τ-1 divided by the book value of equity at the end of the fiscal year of calendar year τ-1. Panel A presents results from months when VIX increases and Panel B presents results from months when VIX decreases. t-statistics are in parentheses.

<table>
<thead>
<tr>
<th>Panel A: Portfolios Sorted on Control Variables and ΔVIX AFL’s In Months When ΔVIX is Positive</th>
<th>Panel B: Portfolios Sorted on Control Variables and ΔVIX AFL’s In Months When ΔVIX is Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average 5-1 Portfolio Returns</td>
<td>Ortho FF-3 Alpha</td>
</tr>
<tr>
<td>Liquidity Beta</td>
<td>0.76*</td>
</tr>
<tr>
<td></td>
<td>(2.32)</td>
</tr>
<tr>
<td>Momentum (6-month)</td>
<td>0.86**</td>
</tr>
<tr>
<td></td>
<td>(2.84)</td>
</tr>
<tr>
<td>Momentum (12-month)</td>
<td>0.82**</td>
</tr>
<tr>
<td></td>
<td>(2.68)</td>
</tr>
<tr>
<td>Price</td>
<td>0.88**</td>
</tr>
<tr>
<td></td>
<td>(2.74)</td>
</tr>
<tr>
<td>Volume</td>
<td>0.72*</td>
</tr>
<tr>
<td></td>
<td>(2.47)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.81*</td>
</tr>
<tr>
<td></td>
<td>(2.58)</td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05
### Fama-MacBeth Regressions with ΔVIX AFL’s, Size, B/M, Momentum, Orthogonalized Market Betas, and Liquidity Betas

This table reports the Fama and MacBeth (1973) estimated premiums associated with the ΔVIX AFL’s, natural log of size, B/M, 6-month momentum, beta on MKT⊥ (where MKT⊥ is the MKT factor orthogonalized to ΔVIX), and the beta on liquidity (the coefficient on the Pastor and Stambaugh (2003) liquidity variable in their four-factor model). Firm size is determined at the end of June in calendar year τ and assigned from July in calendar year τ to June in year τ+1. B/M is the book value at fiscal year-end in calendar year τ-1 divided by the market capitalization of the firm at the end of December in year τ-1 and it is assigned from July in calendar year τ to June in calendar year τ+1. Six-month momentum is the cumulative returns from the end of month t-6 to the end of month t-2. The beta on MKT⊥ is estimated by using the regression:

\[ r_{i,t} = a_i + \beta_i \text{MKT}_{t} + \epsilon_{i,t} \]

where \( r_{i,t} \) is the return of stock \( i \) in month \( t \), \( \text{MKT}_{t} \) is market factor in month \( t \) that is orthogonalized to ΔVIX, and \( \epsilon_{i,t} \) is an error term. This regression is estimated for each firm for June of year τ on a monthly basis over 54 months (a minimum of 36 months of data are required) ending in December of year τ-1. The beta estimates for each June of year τ are assigned to July of year τ through June of year τ+1. The liquidity betas are estimated using the regression:

\[ r_{i,t} = \alpha_i + \beta_i \text{MKT}_{t} + s_i \text{SMB}_{t} + h_i \text{HML}_{t} + l_i \text{LIQ}_{t} + \epsilon_{i,t} \]

where MKT, SMB, and HML are the Fama-French (1993) factors and LIQ is the Pastor and Stambaugh liquidity factor. The sample is from July 1989 to December 2007. Panel A reports the results when VIX increases. Panel B reports the results when VIX decreases. Robust Newey-West (1987) \( t \)-statistics are in parentheses.

<table>
<thead>
<tr>
<th>Panel A: Months When ΔVIX is Positive</th>
<th>Panel B: Months When ΔVIX is Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔVIX AFL</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(2.13)</td>
</tr>
<tr>
<td>Log of Size</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>(-1.57)</td>
</tr>
<tr>
<td>B/M</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
</tr>
<tr>
<td>Momentum (6-month)</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(-0.73)</td>
</tr>
<tr>
<td>MKT⊥ Beta</td>
<td>0.73**</td>
</tr>
<tr>
<td></td>
<td>(3.98)</td>
</tr>
<tr>
<td>Liquidity Beta</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(1.39)</td>
</tr>
</tbody>
</table>

\* p<0.05, \*\* p<0.01
Table VIII
Portfolios Sorted by Sensitivity to FVIX

For each firm a regression is estimated of the form:

\[ r_{i,t} = \alpha_i + \beta_{FVIX,i} FVIX_t + \theta_i POS_t FVIX_t + \epsilon_{i,t} \]

where \( r_{i,t} \) is the excess return for firm \( i \) in month \( t \), \( FVIX_t \) is the tracking portfolio for the innovation in VIX from the end of month \( t-1 \) to the end of month \( t \) as created by Ang et al. (2006), \( POS_t \) is a dummy variable that equals one in months when FVIX is positive and equals zero otherwise, and \( \epsilon_{i,t} \) is an error term. This regression is estimated for each firm for June of year \( \tau \) on a monthly basis over 54 months (a minimum of 36 months of data are required) ending in December of year \( \tau-1 \). The beta and theta estimates for each June of year \( \tau \) are assigned to July of year \( \tau \) through June of year \( \tau+1 \). Although each firm’s parameter estimates are held constant for twelve-month periods, they are used to create FVIX adjusted factor loadings (FVIX AFL’s) each month using the realized value of \( POS_t \) for each respective month from July of year \( \tau \) through June of year \( \tau+1 \). The FVIX AFL’s are computed as:

\[ AFL_{FVIX,i,t} = \hat{\beta}_{FVIX,i} + \hat{\theta}_i POS_t \]

Firms are sorted each month into quintiles based on their FVIX AFL’s. Post-formation monthly returns are averages of stock returns (either equal- or value-weighted) in each portfolio every month. Post-formation loadings are found by rolling the regressions every month to obtain monthly parameter estimates for each firm. AFL’s are computed for each firm each month. The portfolio post-formation AFL’s are averages of the post-formation AFL’s of the firms in the quintile portfolios sorted by the pre-formation AFL’s. Panel A presents equal- and value-weighted average monthly returns in the post-formation period, the mean AFL’s for the pre- and post-formation periods, average natural log of mean size (total market capitalization) and the average book-to-market equity ratio (B/M) of the firms in each quintile portfolio. The row “5-1” refers to the mean difference in returns between quintile portfolios 5 and 1. Panels B and C report the equal and value-weighted portfolio returns and the mean difference in returns between quintile portfolios 5 and 1, but limit the sample to months where either FVIX is positive or negative, respectively. The alpha from regressing the 5-1 portfolio returns on the Fama and French (1993) three-factor model, with a market factor orthogonalized to FVIX, is reported in the row labeled “Ortho FF-3 Alpha.” \( t \)-statistics are in parentheses.

Panel A: Portfolios sorted by the AFL’s on FVIX for the entire sample period.

<table>
<thead>
<tr>
<th>FVIX AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th>Mean of Pre-formation FVIX AFL</th>
<th>Mean of Post-formation FVIX AFL</th>
<th>Log of size</th>
<th>B/M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Low)</td>
<td>Equal weighted 0.75</td>
<td>-2.29</td>
<td>-1.55</td>
<td>4.89</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>Value weighted 0.90</td>
<td>-1.01</td>
<td>-0.81</td>
<td>5.48</td>
<td>0.76</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>-0.53</td>
<td>-0.53</td>
<td>5.59</td>
<td>0.77</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>-0.13</td>
<td>-0.27</td>
<td>5.29</td>
<td>0.81</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0.69</td>
<td>0.10</td>
<td>4.51</td>
<td>0.83</td>
</tr>
<tr>
<td>5 (High)</td>
<td>Equal weighted 1.20</td>
<td>0.43</td>
<td>0.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Value weighted 1.61</td>
<td>(1.61)</td>
<td>(1.31)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**p<0.01, * p<0.05
Panel B: Portfolios sorted by the AFL’s on FVIX when FVIX is positive.

<table>
<thead>
<tr>
<th>FVIX AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equal weighted</td>
<td>Value weighted</td>
<td></td>
</tr>
<tr>
<td>1 (Low)</td>
<td>-2.88</td>
<td>-3.49</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-1.83</td>
<td>-2.43</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-1.37</td>
<td>-1.82</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.96</td>
<td>-1.38</td>
<td></td>
</tr>
<tr>
<td>5 (High)</td>
<td>-0.71</td>
<td>-0.95</td>
<td></td>
</tr>
<tr>
<td>5-1</td>
<td>2.16**</td>
<td>2.54**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.46)</td>
<td>(4.56)</td>
<td></td>
</tr>
<tr>
<td>Ortho FF-3 Alpha</td>
<td>1.48**</td>
<td>1.92**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.71)</td>
<td>(4.87)</td>
<td></td>
</tr>
</tbody>
</table>

** p<0.01, * p<0.05

Panel C: Portfolios sorted by the AFL’s on FVIX when FVIX is negative.

<table>
<thead>
<tr>
<th>FVIX AFL Quintiles</th>
<th>Post-formation Monthly Returns (%)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equal weighted</td>
<td>Value weighted</td>
<td></td>
</tr>
<tr>
<td>1 (Low)</td>
<td>4.58</td>
<td>4.07</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3.60</td>
<td>3.18</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>3.20</td>
<td>2.86</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>3.06</td>
<td>2.68</td>
<td></td>
</tr>
<tr>
<td>5 (High)</td>
<td>3.64</td>
<td>2.88</td>
<td></td>
</tr>
<tr>
<td>5-1</td>
<td>-0.93**</td>
<td>-1.20**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.28)</td>
<td>(-3.39)</td>
<td></td>
</tr>
<tr>
<td>Ortho FF-3 Alpha</td>
<td>-0.36</td>
<td>-0.67*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.83)</td>
<td>(-2.16)</td>
<td></td>
</tr>
</tbody>
</table>
Table IX
Stability of FVIX Adjusted Factor Loadings

This table reports the pre- and post-formation mean ΔVIX AFL’s in each portfolio that is sequentially sorted by size, book-to-market equity ratio (B/M), and FVIX AFL’s. We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. The size of the firm is determined at the end of June in calendar year \( \tau \) and assigned to the firm from July in calendar year \( \tau \) to June in year \( \tau + 1 \). B/M is the book value at fiscal year-end in calendar year \( \tau - 1 \) divided by the market capitalization of the firm at the end of December in year \( \tau - 1 \) and it is assigned to the firm from July in calendar year \( \tau \) to June in \( \tau + 1 \). In each size and B/M portfolio bin the stocks are divided into equal quintiles based on their pre-formation FVIX AFL’s formed from estimated parameters in June of year \( \tau \). Post-formation loadings are obtained by estimating equation (1) for each firm and rolling the regressions every month to obtain monthly parameter estimates. AFL’s are computed for each firm each month using equation (2). The portfolio post-formation AFL’s are averages of post-formation AFL’s of the firms in the quintile portfolios sorted by the pre-formation AFL’s.

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>Pre-formation Mean FVIX AFL</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Post-formation Mean FVIX AFL</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Low)</td>
<td>1 (Low)</td>
<td>-2.93</td>
<td>-1.34</td>
<td>-0.67</td>
<td>-0.08</td>
<td>1.04</td>
<td>-0.80</td>
<td>-1.87</td>
<td>-1.09</td>
<td>-0.76</td>
<td>-0.36</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>-2.18</td>
<td>-0.91</td>
<td>-0.43</td>
<td>-0.05</td>
<td>0.70</td>
<td>-0.57</td>
<td>-1.45</td>
<td>-0.62</td>
<td>-0.35</td>
<td>-0.12</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>-2.13</td>
<td>-0.92</td>
<td>-0.43</td>
<td>-0.02</td>
<td>0.78</td>
<td>-0.54</td>
<td>-1.20</td>
<td>-0.53</td>
<td>-0.33</td>
<td>-0.11</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>-2.36</td>
<td>-1.23</td>
<td>-0.74</td>
<td>-0.33</td>
<td>0.38</td>
<td>-0.86</td>
<td>-1.97</td>
<td>-1.25</td>
<td>-0.90</td>
<td>-0.68</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>-1.82</td>
<td>-0.90</td>
<td>-0.54</td>
<td>-0.24</td>
<td>0.34</td>
<td>-0.63</td>
<td>-1.43</td>
<td>-0.76</td>
<td>-0.56</td>
<td>-0.37</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>-1.65</td>
<td>-0.82</td>
<td>-0.48</td>
<td>-0.19</td>
<td>0.31</td>
<td>-0.57</td>
<td>-1.18</td>
<td>-0.68</td>
<td>-0.41</td>
<td>-0.24</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>-1.99</td>
<td>-1.05</td>
<td>-0.69</td>
<td>-0.38</td>
<td>0.17</td>
<td>-0.79</td>
<td>-1.91</td>
<td>-1.21</td>
<td>-0.93</td>
<td>-0.70</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>-1.61</td>
<td>-0.89</td>
<td>-0.60</td>
<td>-0.33</td>
<td>0.12</td>
<td>-0.66</td>
<td>-1.45</td>
<td>-0.86</td>
<td>-0.65</td>
<td>-0.52</td>
</tr>
<tr>
<td>3 (High)</td>
<td>3 (High)</td>
<td>-1.46</td>
<td>-0.79</td>
<td>-0.50</td>
<td>-0.23</td>
<td>0.20</td>
<td>-0.55</td>
<td>-1.19</td>
<td>-0.69</td>
<td>-0.49</td>
<td>-0.29</td>
</tr>
</tbody>
</table>
**Table X**

Mean Returns and Alphas of the Nine Portfolios Formed on the Basis of Size and Book-to-Market Ratio - FVIX

We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. Firm size is determined at the end of June in calendar year \( \tau \) and assigned from July in calendar year \( \tau \) to June in calendar year \( \tau +1 \). B/M is the book value at fiscal year-end in calendar year \( \tau -1 \) divided by the market capitalization of the firm at the end of December in year \( \tau -1 \) and it is assigned from July in calendar year \( \tau \) to June in calendar year \( \tau +1 \). Value-weighted returns for each portfolio are calculated every month from July 1989 to December 2007. Panel A contains months where FVIX increases and Panel B has months where it decreases. Alphas are from the Fama and French (1993) three-factor model where MKT is orthogonalized to FVIX (“Ortho FF-3 Alpha”). The row labeled “Joint test \( p \)-value” presents the \( p \)-value from a Gibbons, Ross, and Shanken (1989) multivariate test of alphas. The last row shows the mean returns and alphas when the characteristic-balanced portfolio returns are averaged across size and B/M sorted portfolios each month. \( t \)-statistics are in parentheses.

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>Log of B/M</th>
<th>Portfolio Returns</th>
<th>Ortho FF-3 Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(Low)</td>
<td>1(Low)</td>
<td>4.32</td>
<td>0.28</td>
<td>-3.22**</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4.21</td>
<td>0.7</td>
<td>-1.52**</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>3.48</td>
<td>1.74</td>
<td>-1.66**</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>6.79</td>
<td>0.23</td>
<td>-3.12**</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>6.77</td>
<td>0.48</td>
<td>-1.86**</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>6.75</td>
<td>0.92</td>
<td>-1.62**</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>8.94</td>
<td>0.18</td>
<td>-2.37**</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>8.71</td>
<td>0.4</td>
<td>-1.91**</td>
</tr>
<tr>
<td>3(High)</td>
<td>3(High)</td>
<td>8.52</td>
<td>0.76</td>
<td>-1.77**</td>
</tr>
<tr>
<td>Joint test ( p )-value</td>
<td></td>
<td></td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>Average across portfolios</td>
<td></td>
<td></td>
<td></td>
<td>-2.12**</td>
</tr>
</tbody>
</table>

Panel A: Mean Returns and Alphas in Months When FVIX is Positive

<table>
<thead>
<tr>
<th>Portfolio Returns</th>
<th>Ortho FF-3 Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>3.47**</td>
<td>1.75**</td>
</tr>
<tr>
<td>(7.73)</td>
<td>(5.94)</td>
</tr>
<tr>
<td>2.90**</td>
<td>1.72**</td>
</tr>
<tr>
<td>(7.67)</td>
<td>(8.53)</td>
</tr>
<tr>
<td>3.15**</td>
<td>1.92**</td>
</tr>
<tr>
<td>(8.69)</td>
<td>(7.58)</td>
</tr>
<tr>
<td>3.59**</td>
<td>2.20**</td>
</tr>
<tr>
<td>(9.62)</td>
<td>(8.29)</td>
</tr>
<tr>
<td>2.84**</td>
<td>1.95**</td>
</tr>
<tr>
<td>(10.23)</td>
<td>(8.46)</td>
</tr>
<tr>
<td>2.80**</td>
<td>2.00**</td>
</tr>
<tr>
<td>(10.12)</td>
<td>(8.93)</td>
</tr>
<tr>
<td>2.88**</td>
<td>2.27**</td>
</tr>
<tr>
<td>(10.33)</td>
<td>(9.09)</td>
</tr>
<tr>
<td>2.72**</td>
<td>2.28**</td>
</tr>
<tr>
<td>(10.95)</td>
<td>(9.06)</td>
</tr>
<tr>
<td>2.71**</td>
<td>2.30**</td>
</tr>
<tr>
<td>(10.45)</td>
<td>(9.29)</td>
</tr>
</tbody>
</table>

Panel B: Mean Returns and Alphas in Months Where FVIX is Negative

<table>
<thead>
<tr>
<th>Portfolio Returns</th>
<th>Ortho FF-3 Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>-2.60**</td>
<td>3.01**</td>
</tr>
<tr>
<td>(-8.14)</td>
<td>(11.50)</td>
</tr>
<tr>
<td>2.05**</td>
<td>(10.36)</td>
</tr>
</tbody>
</table>

** \( p<0.01 \), * \( p<0.05 \)
Table XI  
Mean Returns and Alphas of Portfolios Formed on the Basis of Size, Book-to-Market, and FVIX Adjusted Factor Loadings

We first sort the sample into size terciles based on NYSE breakpoints, and then sequentially sort into book-to-market equity (B/M) terciles. Firm size is determined at the end of June in calendar year $t$ and assigned from July in calendar year $t$ to June in year $t+1$. B/M is the book value at fiscal year-end in calendar year $t-1$ divided by the market capitalization of the firm at the end of December in year $t-1$ and it is assigned from July in calendar year $t$ to June in calendar year $t+1$. In each size and B/M portfolio bin the stocks are divided into equal quintiles each month based on the pre-formation FVIX AFL’s. Value-weighted returns are calculated for each portfolio every month from July 1989 to December 2007. Mean returns for each triple-sorted portfolio and the 5-1 characteristic-balanced portfolios are presented. Alphas are from the Fama and French (1993) three-factor model where MKT is orthogonalized to FVIX (“Ortho FF-3 Alpha”) and a modified version augmented with FVIX (“Augmented FF-3 Alpha”). The row labeled “Joint test $p$-value” presents the $p$-value from a Gibbons, Ross, and Shanken (1989) multivariate test of alphas. The last row shows the mean returns and alphas when the characteristic-balanced portfolio returns are averaged across size and B/M sorted portfolios each month. Panels A and B report portfolio returns for months when FVIX is positive or negative, respectively. $t$-statistics are in parentheses.

Panel A: Mean Returns of Portfolios Sorted on Size, B/M, and FVIX AFL’s In Months When FVIX is Positive

<table>
<thead>
<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>FVIX AFL Quintiles</th>
<th>1 (Low)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 (High)</th>
<th>5-1</th>
<th>Ortho FF-3 Alpha</th>
<th>Augmented FF-3 Alpha</th>
</tr>
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** $p<0.01$, * $p<0.05$
Panel B: Mean Returns of Portfolios Sorted on Size, B/M, and FVIX AFL’s In Months When FVIX is Negative

<table>
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<tr>
<th>Size Rank</th>
<th>B/M Rank</th>
<th>FVIX AFL Quintiles</th>
<th>Ortho FF-3 Alpha</th>
<th>Augmented FF-3 Alpha</th>
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<td>-0.26 0.51</td>
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Joint test p-value: 0.0827 0.9249
Average across portfolios: -1.12** -0.49* 0.05

** p<0.01, * p<0.05