Implied Volatility and Future Portfolio Returns

Prithviraj S. Banerjee
Department of Finance
Florida State University

James S. Doran
Department of Finance
Florida State University

David R. Peterson
Department of Finance
Florida State University

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Communications

Author:	James S. Doran
Address:	Department of Finance College of Business Florida State University Tallahassee, FL. 32306
Tel.:	(850) 644-7868 (Office)
FAX:	(850) 644-4225 (Office)
E-mail:	jsdoran@cob.fsu.edu

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Abstract

Prior studies find that the CBOE Volatility Index (VIX) predicts returns on stock market indices, suggesting implied volatilities measured by VIX are a risk factor affecting security returns or an indicator of market inefficiency. We extend prior work in three important ways. First, we investigate the relationship between future returns and current implied volatility levels and innovations. Second, we examine portfolios sorted on book-to-market equity, size, and beta. Third, we control for the four Fama and French (1993) and Carhart (1997) factors. We find that VIX-related variables have strong predictive ability.

Keywords: Risk Premium, Implied Volatility, VIX Index, Portfolio Returns

JEL Classification: G11, G1

I. Introduction

The CBOE Volatility Index (VIX) is a measure of market expectations of stock return volatility over the next 30 calendar days and is calculated from S&P 100 (OEX) stock index options. It was introduced in 1993 and originally computed on a minute-by-minute basis from the implied volatility of eight option series that are near-the-money, nearby, and second- nearby OEX option series, and was weighted to reflect the implied volatility of a 30 calendar-day at-the-money OEX option.[1] The option valuation model used in the calculation is a cash dividend adjusted binomial method based on Black and Scholes (1973). VIX has been referred to as the 'investor fear gauge' (Whaley (2000)), since high levels of VIX coincided with high degrees of market turmoil. In addition to VIX being used to gauge market volatility, some traders advocate the use of VIX as a stock market timing tool. This is based on the observation that high levels of VIX often coincide with market bottoms, and seem to indicate "oversold" markets. Traders can take long positions in the market in anticipation of an increase after VIX is high.

Giot (2005) tests if high levels of VIX indicate oversold stock markets by dividing the VIX price history into 21 equally spaced rolling percentiles and examining the returns on the S&P 100 for various future holding periods up to 60 days for each of these 21 percentiles. He finds that for very high (low) levels of VIX, future returns are always positive (negative). His findings suggest that extremely high levels of VIX may signal attractive buying opportunities. This is surprising, since VIX information is readily available and should not allow for timing profits if market participants are rational.

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[1] Beginning in 2003, VIX is calculated from the S&P500 (SPX) index option prices, rather than from the S&P100. The calculation involves a wide range of strike prices and is independent of any option-pricing model. The CBOE calculates and distributes the original OEX VIX under the new ticker "VXO". The old and new VIX series are highly correlated (Carr and Wu (2004)).

Another explanation is that the volatility of the market, as represented by VIX, is a systematic risk factor, and there would be no abnormal returns after adjusting for this factor. A negative market price of volatility risk is found by Jackwerth and Rubinstein (1996), Coval and Shumway (2001), Bakshi and Kapadia (2003) and others. If investors have aversion to volatility, high levels of volatility will translate to high price risk premiums since prices and volatility are negatively correlated.

Giot's (2005) findings are based on the S&P 100, and not on segments of the market grouped by characteristics of stocks. Copeland and Copeland (1999) also focus on indices rather than portfolios; they examine BARRA's indices (value and growth stocks), S&P 500 futures (large stocks), and Value Line futures (small stocks). They advocate the use of VIX as a size and style rotation tool and find that large and value stocks earn high returns after VIX is high, attributing this to investors seeking safer portfolios after increases in implied volatility. Guo and Whitelaw (2006) find that market returns are positively related to implied volatilities.

We expand on prior studies in three important ways. First, we examine the relationship between future returns and both current levels and innovations of implied volatility. Second, we analyze portfolios grouped by characteristics. We examine the future returns of portfolios sorted by beta, size, and book-to-market equity. Beta is chosen as a grouping characteristic because of the positive relationship shown in prior studies between levels of VIX and future market returns. As such, we sort on beta to determine if high beta firms have a stronger return relationship with VIX than low beta firms. Size and book-to-market equity are chosen as grouping characteristics since these attributes are commonly associated with the cross-section of returns. Further, Copeland and Copeland (1999) find that alternative indices associated with firm size and value versus growth characteristics have different returns following high VIX levels. Finally, behavioral finance suggests that investor sentiment may affect stock returns differently depending on their size and book-to-market equity characteristics.[2] If VIX is associated with sentiment, then characteristic-based portfolios may respond differently to VIX.

Third, we control for the Fama and French (1993) factors consisting of the excess market return (MKT), the size premium (SMB), and the value premium (HML) and for the Carhart (1997) momentum factor (UMD). These factors are known to affect security returns and characteristic-sorted portfolios are known to have different sensitivities to these factors. No other study adjusts for these risk factors and explores portfolios grouped by firm characteristics.

Our objective is to learn if the implied volatility of the market has predictive power for future returns on portfolios sorted by the security characteristics beta, size, and book-to-market equity. This has implications for asset pricing and market efficiency. If implied volatility is a risk factor in the time series of returns, then it should have predictive ability for the future returns of all portfolios, even after appropriate adjustment for other risk factors. On the other hand, if markets are inefficient, then alternative portfolios may have sporadic or random patterns of return responses to implied volatilities. Our analysis is distinct from that in Ang, Hodrick, Xing, and Zhang (2006), where firms are sorted into portfolios based upon sensitivities to innovations in market volatility. They find a contemporaneous negative relationship between cross-sectional returns and these sensitivities. This result is consistent with a negative market price of volatility risk. A conclusion of a positive relationship between VIX and future returns in our study would be consistent with a negative volatility risk premium.

We find that future returns are significantly related to both VIX levels and innovations for most portfolios, even in the presence of the Fama and French (1993) and Carhart (1997) factors. Results tend to be stronger for high beta portfolios. Thus, VIX

[2] See, for example, Brown and Cliff (2005) and Baker and Wurgler (2006).

may be a priced risk factor for security returns and it may be necessary to consider broader measures of VIX than those that have traditionally been studied.

We develop the study as follows. Section II provides a theoretical foundation. Section III gives details of the data and methodology. Section IV reports the numerical results. Section V concludes the paper.

II. Theoretical Foundation

Substantial work has tested the relationship between volatility and returns, with mixed results. Most studies focus on the contemporaneous relationship between realized volatility and the risk premium, testing the theoretical implication of the CAPM that there is a positive relationship between the level of volatility and the size of the premium.[3] However, these studies make limited to no statements on the relationship between implied volatility and future returns. Our hypothesis contends that VIX possesses information content in forecasting future market returns. The recent cross-sectional analysis of Ang et al. (2006) documents a negative relationship between firms with high beta-loadings on VIX innovations and returns. They attribute this finding to a negative volatility risk premium. However, a negative volatility risk premium can also explain why current implied volatility may explain future returns.

We demonstrate the relation between implied volatility and future returns using the two-factor price, *S*, and variance, *V*, processes as shown in Heston (1993). The realized (real-world) data generating processes is given as,

[3] Campbell (1987) and Glosten, Jagannathan,and Runkle (1993) document a negative relationship between the conditional volatility and the risk premium, contrary to economic theory, while Harvey (1989) and Turner, Startz and Nelson (1989) find a positive relationship. Scruggs (1998) decomposes the CAPM into a partial relation in a two-stage estimation and explains away the negative relationship of Campbell (1987) and Glosten et al. (1993). Brandt and Kang (2004) resolve these differences regarding contemporaneous correlation by implementing a VAR technique. By incorporating time-varying volatility, their conclusions suggest that these differences can be explained by the conditional and unconditional correlations.

$$\frac{dS_t}{S_t} = \mu dt + V_t dz \qquad \textbf{(1)}$$

$$dV_t = \kappa(\theta - V_t)dt + \lambda_V \xi V_t dt + \xi\sigma(\rho dz + \sqrt{1-\rho^2}\,dz^V) \qquad \textbf{(2)}$$

where $\mu = r_f + \lambda V$. Using Girsanov's theorem to transform the realized processes into risk-neutral equivalents results in,

$$\frac{dS_t}{S_t} = r_f dt + V_t dz^* \qquad \textbf{(3)}$$

$$dV_t = \kappa(\theta - V_t)dt + \xi\sigma_t(\rho dz^* + \sqrt{1-\rho^2}\,dz^{V*}) \qquad \textbf{(4)}$$

where κ is the speed of mean-reversion, θ is the level to which the return variance reverts too, ξ is the variance of the volatility process, and ρ is the correlation between price and volatility innovations. There are four Brownian motions, dz, dz^*, dz^{V*}, and dz^{V*}. λ and λ_V are the market price of risk and the market price of volatility risk, respectively, and r_f represents the risk-free rate. The variance, V, represents an instantaneous variance that is unobservable within both the risk-neutral and realized variance processes. We treat the terms variance and volatility as synonymous.[4]

The implication of a positive (negative) volatility risk premium in equation (2) is to increase (decrease) the volatility drift of the realized volatility process. Consistent with of Coval and Shumay (2001), Bakshi and Kapadia (2003), and Ang et al. (2006), the volatility risk premium is negative for equities. This can explain why implied (risk-neutral) volatility is higher than realized volatility, as shown by Jackwerth and Rubinstein (1996), and the upward biased nature of implied volatility as a forecast of future realized

[4] Alternatively, we could have included a jump process with the price process, which helps improve pricing dynamics and model fit. However, it is not central to the estimation and does not change the theoretical predictions, and thus is not included.

volatility, as shown by Doran and Ronn (2006). Implied volatility is a risk-neutral volatility since it is inferred from option prices, which are priced under the risk-neutral measure. However, the effect of the volatility risk premium on returns is unclear.

We discretize the real-world continuous time processes shown in equations (1) and (2) and allow for the realized price and variance to vary through time as,

$$\frac{\Delta S_{t+1}}{S_t} = \mu \Delta t + V_t \varepsilon_t \tag{5}$$

$$\Delta V_{t+1} = \kappa(\theta - V_t)\Delta t + \lambda_V \xi V_t \Delta t + \xi \sigma_t (\rho \varepsilon_t + \sqrt{1-\rho^2}\varepsilon_t^V) \tag{6}$$

where ε and ε^V represent the discrete Brownian motions distributed $N \sim (0, \sqrt{\Delta t})$.

Equations (5) and (6) are modified to represent the holding period from day *t* to day τ, and assuming Δt equals one day, gives

$$\frac{1}{\tau - t}\sum_{i=t}^{\tau} r_i = r_f + \frac{\lambda}{\tau - t}\sum_{i=t}^{\tau} V_i + \frac{1}{\tau - t}\sum_{i=t}^{\tau} V_i \varepsilon_i \tag{7}$$

$$\frac{1}{\tau - t}\sum_{i=t}^{\tau} \Delta\sigma_{RV,i}^2 = \kappa\theta - \frac{\kappa}{\tau - t}\sum_{i=t}^{\tau} V_i + \frac{\lambda_V \xi}{\tau - t}\sum_{i=t}^{\tau} V_i + \frac{\rho\xi}{\tau - t}\sum_{i=t}^{\tau} \sigma_i \varepsilon_i + \frac{\sqrt{1-\rho^2}\xi}{\tau - t}\sum_{i=t}^{\tau} \sigma_i \varepsilon_i^V \tag{8}$$

where r_i is the return at time *i* and $\Delta\sigma_{RV,i}^2$ is the change in realized variance at time *i*. The same methodology is applied to the volatility risk-neutral analog in equation (4), resulting in a similar expression to equation (8) absent the volatility risk premium term,

$$\frac{1}{\tau - t}\sum_{i=t}^{\tau} \Delta\sigma_{IV,i}^2 = \kappa\theta - \frac{\kappa}{\tau - t}\sum_{i=t}^{\tau} V_i + \frac{\rho\xi}{\tau - t}\sum_{i=t}^{\tau} \sigma_i \varepsilon_i + \frac{\sqrt{1-\rho^2}\xi}{\tau - t}\sum_{i=t}^{\tau} \sigma_i \varepsilon_i^{V*} \tag{9}$$

where $\Delta\sigma_{IV,i}^2$ is the change in implied variance at time *i*. In the continuous-time framework, the variance/volatility terms are instantaneous volatilities and are unobservable. Forming a discrete-time analog allows us to observe the left-hand side variables of equation (8) and (9), where $\frac{1}{\tau - t}\sum_{i=t}^{\tau}\Delta\sigma_{RV,i}^{2}$ and $\frac{1}{\tau - t}\sum_{i=t}^{\tau}\Delta\sigma_{IV,i}^{2}$ represent the average realized variance change and average implied variance change, respectively, over the holding period. Substituting the right-hand side of equation (9) into equation (8) results in,

$$\frac{1}{\tau - t}\sum_{i=t}^{\tau}\Delta\sigma_{RV,i}^{2} = \frac{1}{\tau - t}\sum_{i=t}^{\tau}\Delta\sigma_{IV,i}^{2} + \frac{\lambda_V \xi}{\tau - t}\sum_{i=t}^{\tau}V_i \tag{10}$$

The average realized variance change is a function of the average implied variance change and the market price of volatility risk. More negative values for the volatility risk premium result in a larger difference between implied and realized volatility, consistent with the findings in Jackwerth and Rubinstein (1996). For simplicity we assume that the random error terms $\varepsilon_t^V = \varepsilon_t^{V*}$.[5]

To assess the impact volatility risk has on returns, it is necessary to make an assumption about the relationship between the price and volatility risk premiums. We assume that the price risk premium is equal to the volatility risk premium plus some constant, resulting in the following relationship

$$\lambda = \lambda_V + \delta \tag{11}$$

where δ is a positive constant, greater than the absolute value of the volatility risk premium. This guarantees that the price risk premium is positive when the volatility risk premium is negative, consistent with substantial empirical evidence. Using the relationship in equation (11), we substitute the expression for the volatility risk premium in equation (10) for the price risk premium in equation (7), yielding

[5] This assumption will not change the final results, but reduces the number of terms in the final expression. Explicitly, if the assumption were relaxed, an additional expression containing the difference between the risk-neutral and real-world price and volatility error terms multiplied by the correlations would be present.

$$\frac{1}{\tau-t}\sum_{i=t}^{\tau} r_i = r_f + \frac{1}{\xi}\left[\frac{\delta+1}{\tau-t}\sum_{i=t}^{\tau}\Delta\sigma_{RV,i}^2 - \frac{1}{\tau-t}\sum_{i=t}^{\tau}\Delta\sigma_{IV,i}^2\right] + \frac{1}{\tau-t}\sum_{i=t}^{\tau} V_i\varepsilon_i$$

or

$$\frac{1}{\tau-t}\sum_{i=t}^{\tau} r_i = r_f + \frac{1}{\xi(\tau-t)}\left[(\delta+1)(\sigma_{RV,\tau}^2 - \sigma_{RV,t}^2) - (\sigma_{IV,\tau}^2 - \sigma_{IV,t}^2)\right] + \frac{1}{\tau-t}\sum_{i=t}^{\tau} V_i\varepsilon_i \quad \textbf{(12)}$$

where $\sigma_{RV,t}^2$ is the realized variance, known at time *t*, measured over the period prior to *t*, $\sigma_{RV,\tau}^2$ is the realized variance, known at time τ, measured over the period *t* to τ, $\sigma_{IV,t}^2$ is the implied (future) variance, observed at time *t*, and $\sigma_{IV,\tau}^2$ is the implied (future) variance, observed at time τ. Since literature shows that implied volatility is the most efficient, but upward-biased predictor of future realized volatility, we express realized volatility as,

$$\sigma_{RV,\tau}^2 = \alpha + \psi\sigma_{IV,t}^2 \quad \textbf{(13a)}$$

$$\sigma_{RV,t}^2 = \alpha + \psi\sigma_{IV,t*}^2 \quad \textbf{(13b)}$$

where $\sigma_{IV,t*}^2$ is the implied volatility in the period prior to time *t*. Substituting into equation (12) yields,

$$\frac{1}{\tau-t}\sum_{i=t}^{\tau} r_i = r_f + \frac{1}{\xi(\tau-t)}\left[(\psi+\delta\psi)(\sigma_{IV,t}^2 - \sigma_{IV,t*}^2) + \sigma_{IV,t}^2 - \sigma_{IV,\tau}^2\right] + \frac{1}{\tau-t}\sum_{i=t}^{\tau} V_i\varepsilon_i \quad \textbf{(14)}$$

Thus, the returns from time *t* to τ are negatively related to the level of time τ implied volatility but positively related to the level of time *t* implied volatility and innovations of implied volatility from t^* to t. This leads to an empirical framework for testing the information content of implied volatility levels and innovations on future excess returns,

$$\bar{r}_{t,\tau} = \alpha^* + \beta_1^* \sigma_{IV,t}^2 + \beta_2^* \Delta\sigma_{IV,t}^2 + \beta_3^* \sigma_{IV,\tau}^2 + \nu_t \qquad \textbf{(15)}$$

where $\bar{r}_{t,\tau} = \frac{1}{\tau - t}\sum_{i=t}^{\tau} r_i - r_f$, $\beta_1^* = \frac{1}{\xi(\tau - t)}$, $\beta_2^* = \frac{\psi\delta + \psi}{\xi(\tau - t)}$, $\beta_3^* = -\frac{1}{\xi(\tau - t)}$, and

$\nu_t = \frac{1}{(\tau - t)} V_t \varepsilon_t$. Since both δ and ψ are positive, we expect that $\beta_1^* > 0$, $\beta_2^* > 0$, and $\beta_3^* < 0$. However, to estimate equation (15) and test whether implied volatility is related to future returns, we can directly observe $\sigma_{IV,t}^2$ and $\Delta\sigma_{IV,t}^2$ but $\sigma_{IV,\tau}^2$ is unobservable. Since our motivation is to examine the information content in implied volatility for future returns, we do not include $\sigma_{IV,\tau}^2$ in the empirical analysis because it has a contemporaneous relationship to returns. Thus, we focus on the effect of time t implied volatility levels and innovations on returns over the t to τ period.[6]

III. Data and Methodology

A. Dependent and Independent Variables

We employ daily data from June, 1986, through June, 2005. We use excess returns (return minus the risk-free rate) on twelve portfolios formed on size (market value of equity, ME), book-to-market equity (B/M), and beta as dependent variables in the

[6] Our objective is to test the ex-ante predictive power of implied volatility. However, we also estimated an ex-post regression including implied volatility at time τ and found the coefficient to be negative and significant. This is not surprising since there is a well documented negative *contemporaneous* relationship between implied volatility and returns.

regressions. The portfolios are in the Fama and French (1993) style. Specifically, at the end of June of each year t from 1986 to 2005, we independently sort NYSE stocks on CRSP by beta, ME and B/M.[7] Book equity is for fiscal year end t-1 and is defined as the COMPUSTAT book value of shareholders' equity, plus balance sheet deferred-taxes and investment tax credits, minus the book value of preferred stock. ME is measured at the end of June of year t. B/M is the ratio of the book equity divided by the market value of equity. Beta is measured at the end of June of year t by estimating the market model over the prior 200 trading days. The CRSP value-weighted index is the market proxy.

We use the NYSE breakpoints for ME, B/M, and beta to allocate NYSE, AMEX and Nasdaq stocks to two size, two book-to-market, and three beta categories.[8] The ME and BE/ME breakpoint is the 50th percentile and beta breakpoints are the 30th and 70th NYSE percentiles. We construct twelve portfolios from the intersection of the size, book-to-market equity, and beta categories and calculate the daily value-weighted returns on these portfolios from July of year t through June of year t+1.[9] Excess holding period returns on these twelve portfolios, from July 1986 through June 2005, are the dependent variables. We obtain the daily risk-free rates from Kenneth French's website.[10]

The independent variables include either 30 or 60 calendar day holding period returns for the three Fama and French (1993) factors (MKT, SMB, HML) and the Carhart (1997) momentum factor (UMD). They are contemporaneous with the portfolio returns and obtained from the webpage of Kenneth French. Independent variables also include daily measures of the level and innovation of squared VIX. The innovations in squared VIX are measured over the prior 30 (60) calendar days for tests with 30 (60) day holding periods. Implied volatilities are from the CBOE website *(www.cboe.com/vix)*.

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[7] Similar to Fama and French (1993), we delete negative book equity firms, financial firms, and utilities.
[8] Only firms with ordinary common equity (as classified by CRSP) are used. Thus, ADRs, REITS, and units of beneficial interest are excluded.
[9] We also formed equally-weighted portfolios. The results are even stronger than the value weighted returns, and are available upon request.
[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

We choose 30 and 60 calendar days as the lengths of our holding periods. The 30 day holding period corresponds with the forecast horizon of VIX. Giot (2005) finds that the 60 day holding period has the greatest forecasting power for VIX for future returns. In addition we estimate 44.1 trading days as the average time for mean reversion for VIX for our sample period, which is extremely close to 60 calendar days.[11] Thus, 60 days is a close approximation to the number of days it takes for VIX to revert back to its mean long-term volatility.

B. Regression Analyses

Before testing for the information content in squared VIX levels and innovations, it is necessary to account for stationarity and persistence in VIX, and the potential correlation between the levels and innovations. While there is little concern for stationarity in the squared volatility innovations, we test for the presence of stationarity of squared VIX levels using an augmented Dickey-Fuller test. The test statistic is 7.49, rejecting the null hypothesis of a unit root. Additionally, Stambaugh (1999) points out that coefficients from a predictive regression are subject to a small sample bias when an independent variable, such as VIX, follows an AR(1) process. However, Bali and Peng (2006) show that the magnitude of this bias decreases as the sample size increases. They find no significant bias in their sample of sixteen years of daily data. Since we use daily data over nineteen years, the effect of this bias on our estimates is very small.[12]

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[11] This estimate comes from the estimation of a discrete time Ornstein-Uhlenbeck process of the form $\Delta\sigma_t^2 = \kappa(\theta - \sigma_t^2)\Delta t + \sigma_t \xi \varepsilon_t$, as given in Heston (1993) using daily variance changes. The half-life for the mean-reversion is calculated as $\frac{\ln(2)}{\kappa}$ where κ is the speed of mean-reversion.

[12] To determine that the bias was negligible, we estimate the bias adjusted slope coefficient using the expression in Stambaugh (1999), $\hat{\beta} = \beta + \phi(1+\rho 3)/n$, where β is the OLS estimate, ρ is the first-order autocorrelation coefficient of a lagged stochastic regressor, *n* is the number of observations, and ϕ is equal to the sum of the cross-equation residual products between the predictive regression and the regression of

Implied variance levels and innovations are highly correlated; our correlation coefficient is 0.6. If both variables are included in the regressions, multicollinearity could be a problem. To alleviate the impact of this correlation we estimate the regression,

$$\sigma^2_{IV,t} = \alpha + \beta \Delta \sigma^2_{IV,t} + \nu_t \quad \textbf{(16)}$$

The regression residuals ν_t are used as a measure for the implied variance levels, orthogonal to the variance innovations, as an independent variable in the portfolio return regressions. For each day t we estimate equation (16) using all observations through day t. The estimated intercept and slope are used with day t observations of squared VIX levels and innovations to form ν_t. We require a minimum of one year's worth of data to estimate equation (16). Thus, our analysis starts on July 1, 1987. Throughout the remainder of the paper we use the term "VIX level" to refer to ν_t, even though ν_t is actually the squared VIX level orthogonal to innovations of squared VIX.

As a preliminary check to examine if VIX levels and innovations have forecasting power for the future returns of the portfolios, we regress the 30 and 60 day future holding-period excess returns for each of the twelve portfolios on daily levels and innovations of VIX. We employ Newey and West (1987) standard errors in the two equations below, and all regressions that follow, to account for residual correlation due to overlapping portfolio returns.[13] The regression equations are given as:

$$R^{30}_{pt} = \alpha^*_p + \beta^*_{1,p}\nu_t + \beta^*_{2,p}\Delta\sigma^2_{IV,t} + \varepsilon_{p,t} \quad \textbf{(17a)}$$

$$R^{60}_{pt} = \alpha^*_p + \beta^*_{1,p}\nu_t + \beta^*_{2,p}\Delta\sigma^2_{IV,t} + \varepsilon_{p,t} \quad \textbf{(17b)}$$

the predictive variable on its lagged value, divided by the sum of the squared predictive residuals. The biased-adjusted slopes differ from OLS estimates by less than 1%.

[13] For the 30 and 60 day specifications, 15 and 30 lags are chosen, respectively. We also tested higher lags, with similar conclusions. We found more significant results without the Newey and West correction.

where R_{pt}^{30} is the 30-day compounded future holding period excess returns at time t for portfolio p and R_{pt}^{60} is the 60-day compounded future holding period excess returns at time t for portfolio p. ν_t is the residual from the regression of implied variances on implied variance innovations given in equation (16), $\Delta\sigma_{IV,t}^{2}$ is the innovation in squared VIX from t-30 to t for the 30-day regression, and t-60 to t for the 60-day regression, and $\varepsilon_{p,t}$ is the error term. β_1^* represents the marginal effect of implied variance levels on returns while β_2^* represents the incremental effect of implied variance innovations.

It is important to know if VIX levels and innovations have an effect on returns independent of known explanatory factors. To examine whether the ability of VIX to forecast returns holds in the presence of risk factors, we estimate for each of our twelve portfolios the following regressions:

$$R_{pt}^{30} = \alpha_p^* + \beta_{1,p}^* \nu_t + \beta_{2,p}^* \Delta\sigma_{IV,t}^2 + \beta_p MKT_t^{30} + \gamma_p HML_t^{30} + \varsigma_p SMB_t^{30} + \mu_p UMD_t^{30} + \varepsilon_{p,t} \qquad \textbf{(18a)}$$

$$R_{pt}^{60} = \alpha_p^* + \beta_{1,p}^* \nu_t + \beta_{2,p}^* \Delta\sigma_{IV,t}^2 + \beta_p MKT_t^{60} + \gamma_p HML_t^{60} + \varsigma_p SMB_t^{60} + \mu_p UMD_t^{60} + \varepsilon_{p,t} \qquad \textbf{(18b)}$$

MKT_t^{30} and MKT_t^{60} are the 30-day and 60-day geometric future returns, respectively, on the Fama and French (1993) market factor formed by compounding the daily MKT values. HML_t^{30} and HML_t^{60} are corresponding measures on the Fama and French HML factor, SMB_t^{30} and SMB_t^{60} are corresponding measures on the Fama and French SMB factor, and UMD_t^{30} and UMD_t^{60} are corresponding measures on the Carhart (1997) momentum factor.[14] If VIX is a predictor of portfolio returns, then β_1^* and β_2^* should be positive and significant, even in the presence of the Fama and French and Carhart factors.

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[14] The HML, SMB, MKT, and UMD variables are measured over the same time period as R_{pt}^{30} and R_{pt}^{60}.

IV. Empirical Results

A. VIX and the S&P 500

Before testing the characteristic portfolios, we examine if VIX levels and innovations predict future market excess returns. To test this hypothesis, and confirm the results in Giot (2005), the 30-day and 60-day excess returns on the S&P 500 are regressed on the VIX variables.[15] The regressions are identical to those in equations (17a) and (17b), except the dependent variable is the return on the S&P 500. The results are reported in table 1 and show significantly positive coefficients on the VIX level at the 5% level. They are not surprising and consistent with prior findings related to VIX and future returns, and the notion of a significant negative volatility risk premium. VIX innovations, however, are unrelated to future market returns.

B. Book-to-Market Equity, Size, and Beta Sorted Portfolios

We now examine the impact that VIX levels and innovations have on our twelve portfolios. Before conducting our statistical analyses, we present in table 2 the mean returns and standard deviations of returns for the twelve portfolios formed on book-to-market, size, and beta sorting. High book-to-market firms tend to have larger returns than low book-to-market firms, while small firms beat large firms. The relationship between returns and betas varies depending on the size and book-to-market equity ratio. These relationships are consistent across 30-day and 60-day returns.

We next estimate equations (17a) and (17b) for each of our twelve portfolios and present findings in table 3, panel A, for the 30-day results and in table 4, panel A, for the

[15] Additionally, tests were run on the S&P 100 with similar conclusions.

60-day results. All 24 coefficients on the VIX level are positive. For the 30-day (60-day) returns, nine (eleven) of twelve VIX coefficients are significant at the 5% level or higher. Also note that there is a monotonic increase in the VIX level coefficient from low beta to high beta portfolios in all four book-to-market equity and size groups for the 30-day returns and for three of four groups for the 60-day returns. Sorting on beta reveals that high beta firms are more response to VIX than low beta firms. Results for the VIX innovations are less impressive. Coefficients are often negative, significantly so three times for 30-day returns. For 60-day returns all twelve coefficients are insignificant.

Our next estimation for the twelve portfolios is for the full model expressed in equations (18a) and (18b). Results for the 30-day returns are presented in table 3, panel B, and for the 60-day returns in table 4, panel B. For the 30-day returns, the coefficient on VIX levels is positive all twelve times, and significant at the 5% level or higher six times. Based on the four book-to-market equity and size groupings, all six significant coefficients are in medium and high beta portfolios. Thus, we continue to observe a stronger relationship between VIX levels and returns for higher beta portfolios. The results for VIX innovations are only slightly improved. Four of twelve coefficients are significant at the 5% level or higher; two are negative and two are positive. Even in the presence of the four factors, for the 30-day returns VIX levels, but not innovations, tend to be positively related to future returns. This is especially so for higher beta portfolios.

Overall, findings for the 60-day returns are stronger. Eleven of twelve VIX level coefficients are positive, the negative coefficient is insignificant, and five of the eleven positive coefficients are significant at the 5% level or higher. Based on the four book-to-market equity and size groupings, four of those significant coefficients are for medium or high beta portfolios. The big difference from the 30-day results is the positive strength of the VIX innovations. Eleven of twelve coefficients are positive, the negative coefficient is insignificant, and seven of the eleven positive coefficients are significant at the 5%

level or higher. The innovation coefficients tend to be greater for higher beta portfolios, and for the four book-to-market equity and size groupings, all four of the high beta coefficients are significant at the 5% level or higher. An explanation for this significance is the mean-reversion in VIX. Our finding for how quickly VIX mean-reverts (44 trading days) helps explain the increased significance of the innovations. There are only three portfolios without a significant VIX variable and none of these are high beta portfolios. Thus, even in the presence of the four factors there is strong evidence that VIX levels and innovations predict future 60-day returns, especially for higher beta portfolios.

Coefficients on the Fama and French (1993) and Carhart(1997) four factors are similar to prior studies. For example, Fama and French sort portfolios on the basis of size and book-to-market equity, as do we. Based on these sorts, our coefficients across categories are similar to those of Fama and French. Further, the beta coefficients exhibit the expected monotonic ordering across portfolios sorted on beta and the momentum coefficients are similar to those in prior studies.

C. Results Based on Market States

We next conduct two additional analyses. First, we examine if the relationship between returns and VIX variables is dependent upon the level of market performance. Models in behavioral finance, such as Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999), find that stock market returns may behave differently depending on the state of the market. If VIX levels and/or innovations are related to behavioral parameters, then they may influence returns differently depending on whether the market is performing well or poorly.

We independently rank both the 30-day and 60-day MKT returns in our sample. Those above the median are labeled a “bull market” and those below the median are labeled a “bear market”. For each of our twelve portfolios, we estimate equations (18a) and (18b) separately for each of the two market types. Next, we compute the difference in coefficients, bull minus bear, for the VIX levels and innovations for each portfolio.

Second, we also explore whether the relationship between returns and VIX levels and innovations is contingent on whether volatility is relatively high or low. For both the 30-day and 60-day samples we rank our observations based on the median level of VIX during the sample. Volatilities above the median are said to be in a “high volatility” period and those below the median in a “low volatility” period. For each of our twelve portfolios, we estimate equations (18a) and (18b) separately for the two volatility groupings. We then compute the difference in coefficients as high volatility minus low volatility.

In results not shown, we find a general lack of significant differences in coefficients for our two analyses. This suggests that the market states based on directional movement or volatility levels do not make a difference.

D. The Value of VIX Information

Last, we examine how much VIX contributes to returns. For each of the twelve portfolios, we use coefficient estimates on VIX levels and innovations from the 60-day results reported in table 4, panel B. We multiply these coefficients by values of the VIX levels (orthogonalized squared residuals) and innovations, and then annualize the products. The means of the two variables are both zero. Thus, on average they make no contribution to returns, but deviations of the variables from their means do affect returns.

In table 5 we report the effects on returns, for each of our twelve portfolios, of a one standard deviation increase above the mean for each of our two variables. Results for the VIX levels are in panel A and results for the VIX innovations are in panel B. We also provide estimated standard errors for our return contributions. We use the variance-covariance matrix of the estimate, the VIX variable, and the delta method to generate the estimated standard errors.

For VIX levels, the annual contribution to returns of a value one standard deviation above the mean varies across portfolios from close to zero to 4.44%. For innovations the annual contribution to returns varies from near zero to 2.97%. For both levels and innovations ten of twelve returns are more than two standard errors above zero. Since eleven of twelve coefficients (from table 4) are positive for both the levels and innovations, the directional forecasting ability of VIX variables is high. The two (three) highest contributions for levels (innovations) are for high beta portfolios, consistent with prior findings. Thus, VIX information makes a meaningful economic contribution to returns.

V. Conclusion

Prior studies examine the effect of VIX levels on stock market index returns and find a positive relationship. We make three important extensions to this prior work. First, we examine returns as a function of both implied volatility levels and innovations. Second, we examine the forecasting power of implied volatility for future returns of portfolios grouped by the characteristics book-to-market equity, size, and beta. Third, we control for the factors MKT, SMB, HML, and UMD.

We find VIX variables significantly affect returns for most portfolios, with the relationship stronger for high beta portfolios. Both levels and innovations are important. Results are stronger for 60-day returns than 30-day returns, probably because VIX takes about 60 days to mean revert. The generally pervasive results suggest that VIX may be a priced risk factor, although the weaker relation for lower beta portfolios leaves open the possibility of market inefficiency. Regardless, it appears necessary to examine both volatility levels and innovations. While the literature suggests a negative volatility risk premium, there has been no statement about whether volatility risk itself has multiple parts. In other words, should there be a separate premium for volatility levels and innovations? Our results suggest the notion of volatility risk may need to be expanded.

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TABLE 1

30-Day and 60-Day Excess Return Regression Estimates for the Market

This table shows the results of the Newey-West regression of equations (17a, 17b) of the future S&P 500 excess returns on implied variance, ν, and the implied variance innovations, $\Delta\sigma^2_{IV,t}$. ν is our measure for the implied variance level, orthogonal to innovations and calculated from equation (16). $\Delta\sigma^2_{IV,t}$ is the innovation in squared VIX from t-30 to t for the 30-day regression, and t-60 to t for the 60-day regression. Newey-West regressions use fifteen (thirty) lags to correct the standard errors for the 30-day (60-day) regression. The returns to the S&P 500 are the 30-day and 60-day geometric returns, beginning the day after the observation of VIX, over the period from July, 1987, through June, 2005. Absolute values of the t-statistics are shown in parentheses.

	30-day S&P 500	60-day S&P 500
ν	**0.064**	**0.119**
	(1.97)*	**(2.22)***
$\Delta\sigma^2_{IV,t}$	**-0.003**	**0.011**
	(0.17)	**(0.34)**
α	0.007	0.013
	(3.19)**	(3.21)**
Observations	4490	4446

*significance at 5%, **significance at 1%

Table 2
Descriptive Statistics

The table shows the mean returns and standard deviations for the twelve 30-day and 60-day book-to-market equity (B/M), size, and beta portfolios. All returns are calculated over the sample period July, 1987, through June, 2005.

	30-Day Returns			60-Day Returns		
Low B/M, Small Size	**Low Beta**		**High Beta**	**Low Beta**		**High Beta**
Mean Return	1.48%	1.46%	1.33%	3.00%	2.98%	2.68%
Standard Deviation	4.90%	5.94%	9.28%	7.41%	8.88%	13.47%
High B/M, Small Size						
Mean Return	1.87%	1.75%	2.05%	3.83%	3.57%	4.21%
Standard Deviation	4.76%	5.78%	8.42%	7.51%	8.76%	12.69%
Low B/M, Large Size						
Mean Return	0.99%	1.11%	1.05%	2.00%	2.21%	2.05%
Standard Deviation	4.22%	4.39%	6.20%	5.98%	6.06%	8.59%
High B/M, Large Size						
Mean Return	1.29%	1.39%	1.25%	2.57%	2.76%	2.47%
Standard Deviation	4.94%	4.77%	6.09%	7.18%	6.71%	8.63%

TABLE 3

30-Day Excess Return Regression Estimates for the Twelve Portfolios Sorted on Book-to-Market Equity, Size, and Beta

The table below shows the regression results of the 12 portfolio excess returns, sorted on book-to-market equity (B/M), size, and beta. The returns to the portfolios are the 30-day geometric returns, beginning the day after the observation of the implied variance level orthogonal to innovations, ν, over the period from July, 1987, through June, 2005. Newey-West regressions are estimated, using fifteen lags to correct the standard errors. Portfolio numerical labelings represent orderings based on B/M, size, and beta. Portfolio *r111* represents low B/M, low size, and low beta, portfolio *r113* is low B/M, low size, and high beta, and portfolio *r223* is high B/M, high size, and high beta. The number of observations is 4490. Panel A reports the coefficient estimates from the regression of equation (17a) for the implied variance, ν, and the implied variance innovations, $\Delta\sigma^2_{IV,t}$. Panel B reports the coefficient estimates from the regression of equation (18a) for the implied variance, ν, the implied variance innovations, and four factors; MKT, SMB, HML, and UMD. Absolute values of the t-statistics are shown in parentheses.

Panel A

	Low B/M, Small Size			Low B/M, Large Size			High B/M, Small Size			High B/M, Large Size		
	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
ν	0.058	0.115	0.229	0.060	0.062	0.121	0.053	0.083	0.207	0.07	0.073	0.112
	(1.24)	(2.06)*	(2.36)*	(2.11)*	(2.09)*	(2.39)*	(1.11)	(1.52)	(2.31)*	(2.43)*	(2.34)*	(2.21)*
$\Delta\sigma^2_{IV,t}$	-0.055	-0.059	-0.038	-0.026	0.011	0.018	-0.065	-0.052	-0.075	-0.033	-0.004	-0.012
	(2.01)*	(1.65)	(0.61)	(1.89)	(0.68)	(0.58)	(2.23)*	(1.58)	(1.29)	(2.56)*	(0.23)	(0.42)
α	0.012	0.012	0.010	0.007	0.008	0.007	0.016	0.015	0.018	0.009	0.010	0.009
	(5.24)**	(4.31)**	(2.42)*	(3.46)**	(3.95)**	(2.59)**	(7.19)**	(5.52)**	(4.66)**	(4.23)**	(4.87)**	(3.38)**

Panel B

	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
ν	0.013	0.051	0.087	0.027	0.014	0.013	0.018	0.034	0.107	0.050	0.030	0.042
	(1.04)	(3.16)**	(5.08)**	(1.05)	(1.11)	(1.12)	(1.59)	(3.04)**	(5.55)**	(1.90)	(2.13)*	(2.55)*
$\Delta\sigma^2_{IV,t}$	-0.015	-0.014	0.02	-0.021	0.003	0.012	-0.021	-0.005	-0.008	-0.025	0.001	0.006
	(3.05)**	(1.92)	(2.15)*	(1.47)	(0.64)	(2.29)*	(3.47)**	(0.98)	(0.66)	(1.78)	(0.10)	(0.91)
MKT	0.882	1.040	1.302	0.786	0.910	1.082	0.865	1.094	1.366	0.879	0.975	1.195
	(36.16)**	(41.65)**	(43.06)**	(15.95)**	(25.79)**	(54.59)**	(37.66)**	(45.23)**	(46.31)**	(15.15)**	(32.52)**	(42.38)**
SMB	0.734	0.819	1.167	0.018	-0.246	-0.159	0.800	0.846	1.259	0.045	-0.005	0.281
	(18.41)**	(18.99)**	(28.14)**	(0.33)	(6.37)**	(4.61)**	(21.57)**	(17.86)**	(24.87)**	(0.76)	(0.14)	(6.67)**
HML	0.428	0.329	-0.387	0.370	0.265	-0.465	0.657	0.709	0.392	0.786	0.642	0.439
	(12.11)**	(7.73)**	(7.68)**	(6.76)**	(5.29)**	(14.92)**	(20.17)**	(17.22)**	(7.54)**	(12.07)**	(12.97)**	(8.38)**
UMD	-0.085	-0.140	-0.446	-0.042	-0.091	-0.228	-0.130	-0.164	-0.370	-0.086	-0.224	-0.226
	(3.02)**	(4.09)**	(10.57)**	(0.93)	(2.63)**	(9.14)**	(4.67)**	(5.30)**	(8.88)**	(1.82)	(6.57)**	(6.91)**
α	0.005	0.005	0.008	0.000	0.002	0.004	0.009	0.007	0.011	0.002	0.004	0.002
	(6.40)**	(5.23)**	(6.02)**	(0.29)	(1.43)	(4.57)**	(11.56)**	(7.64)**	(8.52)**	(0.91)	(3.44)**	(1.52)

*significance at 5%, **significance at 1%

TABLE 4
60-Day Excess Return Regression Estimates for the Twelve Portfolios Sorted on Book-to-Market Equity, Size, and Beta

The table below shows the regression results of the 12 portfolio excess returns, sorted on book-to-market equity (B/M), size, and beta. The returns to the portfolios are the 60-day geometric returns, beginning the day after the observation of the implied variance level orthogonal to innovations, ν, over the period from July, 1987, through June, 2005. Newey-West regressions are estimated, using thirty lags to correct the standard errors. Portfolio numerical labelings represent orderings based on B/M, size, and beta. Portfolio *r111* represents low B/M, low size, and low beta, portfolio *r113* is low B/M, low size, and high beta, and portfolio *r223* is high B/M, high size, and high beta. The number of observations is 4446. Panel A reports the coefficient estimates from the regression of equation (17a) for the implied variance, ν, and the implied variance innovations, $\Delta\sigma^2_{IV,t}$. Panel B reports the coefficient estimates from the regression of equation (18a) for the implied variance, ν, the implied variance innovations, and four factors; MKT, SMB, HML, and UMD. Absolute values of the t-statistics are shown in parentheses.

Panel A

	Low B/M, Small Size			Low B/M, Large Size			High B/M, Small Size			High B/M, Large Size		
	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
ν	**0.182**	**0.265**	**0.446**	**0.112**	**0.098**	**0.165**	**0.207**	**0.248**	**0.452**	**0.138**	**0.146**	**0.204**
	(2.74)**	**(3.22)****	**(2.78)****	**(2.48)***	**(2.39)***	**(1.94)**	**(3.17)****	**(3.09)****	**(3.05)****	**(2.71)****	**(3.09)****	**(2.38)***
$\Delta\sigma^2_{IV,t}$	**-0.050**	**-0.020**	**0.025**	**0.010**	**0.023**	**0.070**	**-0.074**	**-0.055**	**-0.010**	**0.009**	**0.008**	**0.026**
	(1.02)	**(0.32)**	**(0.23)**	**(0.41)**	**(0.96)**	**(1.31)**	**(1.48)**	**(0.94)**	**(0.09)**	**(0.39)**	**(0.26)**	**(0.47)**
α	0.025	0.024	0.021	0.013	0.016	0.015	0.033	0.030	0.037	0.019	0.020	0.018
	(5.03)**	(4.21)**	(2.44)*	(3.50)**	(4.07)**	(2.66)**	(6.53)**	(5.22)**	(4.47)**	(3.96)**	(4.77)**	(3.28)**

Panel B

	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
ν	**0.027**	**0.068**	**0.115**	**0.024**	**0.003**	**-0.006**	**0.053**	**0.062**	**0.152**	**0.059**	**0.030**	**0.031**
	(1.32)	**(2.64)****	**(3.18)****	**(0.63)**	**(0.16)**	**(0.41)**	**(2.55)***	**(2.66)****	**(3.36)****	**(1.53)**	**(1.24)**	**(0.92)**
$\Delta\sigma^2_{IV,t}$	**0.000**	**0.031**	**0.057**	**0.021**	**0.015**	**0.030**	**-0.007**	**0.012**	**0.063**	**0.040**	**0.029**	**0.048**
	(0.03)	**(2.29)***	**(2.85)****	**(0.94)**	**(1.67)**	**(3.11)****	**(0.66)**	**(1.07)**	**(2.30)***	**(2.13)***	**(3.31)****	**(2.75)****
MKT	0.874	0.990	1.219	0.758	0.874	1.082	0.871	1.058	1.302	0.853	0.910	1.150
	(27.39)**	(26.84)**	(31.25)**	(13.79)**	(17.99)**	(50.57)**	(26.49)**	(31.82)**	(33.14)**	(12.17)**	(20.53)**	(28.76)**
SMB	0.757	0.881	1.205	0.040	-0.219	-0.163	0.843	0.880	1.337	0.026	0.009	0.287
	(13.60)**	(15.18)**	(20.64)**	(0.59)	(4.92)**	(4.08)**	(16.54)**	(13.97)**	(18.41)**	(0.36)	(0.15)	(4.21)**
HML	0.442	0.345	-0.428	0.361	0.258	-0.441	0.703	0.706	0.367	0.835	0.623	0.412
	(10.11)**	(6.14)**	(6.41)**	(6.04)**	(3.85)**	(11.85)**	(16.47)**	(13.72)**	(5.20)**	(10.28)**	(10.23)**	(5.39)**
UMD	-0.094	-0.176	-0.426	-0.090	-0.148	-0.206	-0.146	-0.183	-0.380	-0.140	-0.271	-0.230
	(2.57)*	(4.18)**	(8.89)**	(1.64)	(3.39)**	(6.75)**	(4.44)**	(4.68)**	(7.46)**	(2.44)*	(6.09)**	(5.01)**
α	0.012	0.012	0.017	0.003	0.005	0.007	0.019	0.015	0.025	0.004	0.009	0.005
	(6.52)**	(5.51)**	(6.80)**	(0.81)	(2.04)*	(4.21)**	(11.08)**	(7.43)**	(8.28)**	(1.09)	(3.57)**	(1.64)

*significance at 5%, **significance at 1%

TABLE 5

Annualized Contribution of VIX to Returns

The table shows the annualized contribution to returns from implied variance levels and innovations; both measured using VIX, for the 12-portfolios sorted on book-to-market equity (B/M), size, and beta. Portfolio numerical labelings represent orderings based on B/M, size, and beta. Portfolio *r111* represents low B/M, low size, and low beta, portfolio *r113* is low B/M, low size, and high beta, and portfolio *r223* is high B/M, high size, and high beta. Panel A reports the marginal impacts from a one standard deviation increase above the mean in the implied variance levels orthogonal to innovations, ν. Panel B reports the marginal impacts from a one standard deviation increase above the mean in the implied variance innovations. The results are generated using the coefficient estimates from Panel B in Table 4. The standard errors are given in parentheses and are calculated using the delta method.

Panel A:VIX Levels

	Low B/M, Small Size			**Low B/M, Large Size**			**High B/M, Small Size**			**High B/M, Large Size**		
	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
One Standard Deviation Increase From Mean	0.79%	1.98%	3.36%	0.73%	0.08%	-0.19%	1.55%	1.81%	4.44%	1.68%	0.90%	0.98%
Standard Error	(0.18%)	(0.59%)	(0.77%)	(0.32%)	(0.14%)	(0.29%)	(0.41%)	(0.47%)	(0.98%)	(0.76%)	(0.38%)	(0.30%)

Panel B:VIX Innovations

	Low B/M, Small Size			**Low B/M, Large Size**			**High B/M, Small Size**			**High B/M, Large Size**		
	r111	r112	r113	r121	r122	r123	r211	r212	r213	r221	r222	r223
One Standard Deviation Increase From Mean	0.00%	1.50%	2.67%	0.96%	0.72%	1.43%	-0.34%	0.58%	2.97%	1.96%	1.30%	2.17%
Standard Error	(0.20%)	(0.66%)	(0.86%)	(0.35%)	(0.12%)	(0.32%)	(0.17%)	(0.20%)	(1.14%)	(0.79%)	(0.27%)	(0.60%)