

Implied Volatility Spreads and Expected Market Returns

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Abstract

This paper investigates the intertemporal relation between volatility spreads and expected returns on the aggregate stock market. We provide evidence for a significantly negative link between volatility spreads and expected returns at the daily and weekly frequencies. We argue that this link is driven by the information flow from option markets to stock markets. The documented relation is significantly stronger for the periods during which (i) S&P 500 constituent firms announce their earnings; (ii) cash flow and discount rate news are large in magnitude; and (iii) consumer sentiment index takes extreme values. The intertemporal relation remains strongly negative after controlling for conditional volatility, variance risk premium and macroeconomic variables. Moreover, a trading strategy based on the intertemporal relation with volatility spreads has higher portfolio returns compared to a passive strategy of investing in the S&P 500 index, after transaction costs are taken into account.

Key words: expected market returns, volatility spreads, option markets, information flow.

JEL classification: G10, G12, C13.

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1. Introduction

This paper examines the intertemporal relation between expected returns on the aggregate stock market and implied volatility spreads containing information in the options markets. The empirical results indicate that the spread between the implied volatilities of out-of-the-money put and at-the-money call options written on the S&P 500 index has a robust and significant relation with the expected returns up to a one-week horizon. Aside from documenting this robust finding, we provide an information-based explanation for the relation between expected aggregate returns and volatility spreads.

Inefficiencies in the way investors process information and informed investors choosing option markets over stock markets may cause information spillover effects which result in predictability of returns by the spreads. The framework for this hypothesis is laid out by some influential papers and the literature suggests that option markets provide better opportunities for traders to exploit their private information compared to stock markets. Easley, O'Hara and Srinivas (1998) show that if some informed investors choose to trade in options before they trade in the underlying stock, possibly because of the leverage that options offer, then changes in option prices can carry information that is predictive of future stock price movements. More importantly, the demand-based option pricing models lend the strongest and most direct support for the information explanation. In these models developed by Bollen and Whaley (2004) and Garlenau, Pedersen and Poteshman (2009), when the demand for a particular option contract is strong, competitive risk-averse option market makers are not able to hedge their positions perfectly and they require a premium for taking this risk. As a result, the demand for an option affects its price. In this type of equilibrium, one would expect a positive relation between option expensiveness which can be measured by implied volatility and end-user demand. In our context, investors with positive (negative) expectations about the future market conditions will increase their demand for calls (puts) and/or reduce their demand for puts (calls), implying an increase in call (put) option volatility and/or decrease in put (call) option volatility. Therefore, if the put minus call implied volatility spread becomes lower (higher), this implies an increase (decrease) in expected returns.¹

This paper focuses on the time-series predictability of aggregate equity returns and documents that the implied volatility spread is significantly negatively related to future excess returns on the

¹There are certain empirical findings in the literature which document information spillover from the options market to the stock market at the firm-level. Xing, Zhang and Zhao (2009) find that the slope of the volatility smile has a cross-sectional relation with equity returns. Bali and Hovakimian (2009) show that lagged squared shocks to the option price processes affect the conditional stock return variance. An, Ang, Bali and Cakici (2013) find that unexpected news in call and put implied volatilities predict the cross-sectional variation in future stock returns, implying information flow from individual equity options to individual stocks. Ni, Pan, and Poteshman (2008) show that the trading volume of options is informative about the future realized volatility of the underlying asset.

market. Four measures of implied volatility spread are used in the paper. These measures are distinct in the way they weight the implied volatilities of out-of-the money put options and at-the-money call options. Parameter estimates from regressions of excess future returns on all four measures show that there is a significantly negative relation between implied volatility spreads and aggregate stock returns. When the daily implied volatility spread increases by 1%, the decrease in the excess return on the S&P 500 index is about 2.82% to 7.43% per annum depending on the method being used to measure volatility spreads. We also investigate the intertemporal relation between implied volatility spreads and future returns for horizons ranging from one week to one month and find that the significantly negative link between volatility spreads and market returns remains intact up to a horizon of one week. In contrast, excess market returns cannot predict future volatility spreads at any horizon, including one-day to one-week forecast horizons. We also simulate the return of a trading strategy which invests on the market portfolio or the risk-free asset to test for out-of-sample predictability and the economic significance of our results. We find that an optimal trading strategy that is based on the intertemporal relation between volatility spreads and market returns is able to generate higher returns compared to investing in the S&P 500 index itself even after transaction costs are taken into account.

We conduct several robustness checks to see whether the main finding of the paper remains strong. First, we include implied and physical measures of market variance and numerous macroeconomic variables as additional controls in our specifications. Second, we recognize the possibility that implied volatility spreads may be correlated with variance risk premium, defined as the difference between implied and realized variance.² Third, we test whether the relation between volatility spreads and expected returns is due to volatility spreads acting as a proxy for conditional skewness. Fourth, we orthogonalize the volatility spread measures with respect to conditional volatility and skewness measures and investigate the predictive power of the residual terms on market returns. Fifth, we orthogonalize the volatility spread measures with respect to implied variance and nonparametric value-at-risk to tease out the risk component of volatility spreads and investigate the predictive power of the fitted and residual terms on market returns. Sixth, we control for the non-normality of empirical return distributions by estimating the predictive regressions using the skewed t density of Hansen (1994) in a maximum likelihood framework. Seventh, we address the issue of small-sample bias by utilizing the randomization and bootstrapping methods under the null hypothesis of no predictability. Eighth, rather than compounding market returns for different time periods, we use several lags of the volatility spread measures as independent variables. Ninth, we take the possibility that outliers and nonlinearities may drive our results into account and we repeat our regressions by using logarithmic

²Bollerslev, Tauchen, and Zhou (2009) find that the variance risk premium significantly predicts future market returns, thus we control for this variable in our specifications.

excess market returns as dependent variables and controlling for squared volatility spreads. Finally, we include additional macroeconomic controls in our specifications. We show that the main findings of the paper remain qualitatively the same after running all these robustness checks.

We also conduct additional tests to provide further evidence for our information-based hypothesis. In order to identify periods of significant information releases for the aggregate market, we focus on the earnings announcements of the firms that constitute the S&P 500 index. We show that the intertemporal relation between volatility spreads and expected returns is driven by the announcement periods rather than the non-announcement periods. The fact that our main finding is driven by informationally intensive periods further supports the information explanation. Next, following Campbell (1991), we decompose the realized index returns into their expected return, cash flow news, and discount rate news components and find that the relation between implied volatility spreads and expected market returns is significantly more pronounced when the cash flow and discount rate news are large, implying that investors use the options market when they have a high degree of confidence in the information and the information is sizable in importance. Finally, we utilize the consumer sentiment variable. Dates of extremely low or high consumer sentiment mark periods during which market values deviate from their fundamental values the most. Hence, if information explanation is the more viable option for our findings, we would expect the intertemporal relation between implied volatility spreads and the future returns to be stronger during periods of extreme consumer sentiment. Indeed, we find that the relation between spreads and returns is significantly stronger during periods corresponding to the extreme values of the consumer sentiment index. Overall, these results show that the information explanation is supported by the empirical analysis.

The paper is organized as follows. Section 2 describes the data and empirical methodology. Section 3 presents the empirical results. Section 4 provides additional evidence for the information explanation. Section 5 concludes.

2. Data and Estimation Methodology

To investigate the intertemporal relation between volatility spreads and expected market returns, we consider the following specification:

$$R_{t+1} = \alpha + \beta VS_t + E_t[VAR_{t+1}] + \theta X_t + \varepsilon_{t+1}, \quad (1)$$

where R_{t+1} is the excess return on the market portfolio at time $t + 1$, VS_t is the volatility spread measure at time t , $E_t[VAR_{t+1}]$ is the time- t expected conditional variance of the market portfolio return, and X_t denotes a set of macroeconomic control variables.

The sample period is from January 4, 1996 to September 10, 2008. We use the one-period ahead excess S&P 500 index return obtained from the Center for Research in Security Prices (CRSP) for the dependent variable in eq. (1). The excess return on day $t + 1$ is measured as the excess return from the opening index level on day $t + 1$ to the closing index level on day $t + 1$.³ Equation (1) is estimated for different return horizons. Specifically, one-day, one-week, two-week and one-month ahead excess market returns are used. We estimate equation (1) using non-overlapping returns for all measurement horizons and report Newey-West (1987) t-statistics adjusted using optimal lag length throughout the paper.

The main variable of interest is the volatility spread (VS). Following Xing, Zhang and Zhao (2009), we use the implied volatility difference between OTM put options and ATM call options to measure VS which can also be interpreted as the slope of the volatility smile. The data on the implied volatilities of S&P 500 index options are obtained from the IvyDB database of OptionMetrics which provides implied volatility, end-of-day bid-ask quotes, open interest and volume information for all exchange traded options. This dataset begins in January 1996. Moneyness is defined as the ratio of the strike price to the stock price. A put option is defined as OTM if its moneyness is lower than or equal to 0.95, but higher than or equal to 0.80. A call option is defined as ATM if its moneyness is between 0.95 and 1.05. We also adopt various screens similar to Xing, Zhang and Zhao (2009) and drop an option from the sample if its annualized implied volatility is less than 3% or more than 200%, if its time to expiration is less than 10 days or more than 60 days, if its open interest is negative, if its price is less than \$0.125 or if its volume data is missing.

Since there are multiple OTM put and ATM call options being traded on a given day, we utilize several methods to calculate a single measure of implied volatility spread for each day. HVVS (HOVS) is the implied volatility difference between the OTM put option and the ATM call option that have the highest volumes (open interests). For VWVS, we calculate the difference between the volume-weighted average of the volatility spreads for all OTM put options and the volume-weighted average of the volatility spreads for all ATM call options. For OWVS, we calculate the difference between the open interest-weighted average of the volatility spreads for all OTM put options and the open interest-weighted average of the volatility spreads for all ATM call options.

The descriptive statistics for the volatility spread measures are presented in Panel A of Table 1. The mean (median) volatility spreads vary between 8.3% and 9.5% (7.8% and 9.2%) indicating that, on average, S&P 500 index put options have about eight to nine percent higher volatility than index call

³Vijh (1988) argues that non-synchronous trading can induce spurious positive cross-correlation between options and stock markets. Battalio and Schultz (2006) also argue that ignoring the non-synchronicity between the option and stock markets can bias empirical results. We take this issue into account by skipping the overnight returns to calculate one-period ahead market returns.

options during our sample period. For the highest open interest- and highest volume-based volatility spread measures, the standard deviations are about half of the mean and median volatility spreads. For the open interest- and volume-weighted volatility spread measures, the standard deviations are about a quarter of the mean and median volatility spreads. The skewness and kurtosis estimates of the volatility spread measures indicate that the volatility spreads are mildly right-skewed and extreme deviations from the median are rare. As reported in Panel B of Table 1, the correlations between the implied volatility measures vary between 0.30 and 0.79.

The main measure used to control for the conditional volatility in equation (1) is VIXSQ. VIX is the implied volatility which measures the market’s forecast of the volatility of the S&P 500 index and is obtained from the Chicago Board Options Exchange (CBOE). VIX is computed from the European style S&P 500 index option prices and incorporates information from the volatility smile by using a wide range of strike prices. The implied variance denoted by VIXSQ is equal to the square of VIX. In some specifications, we use an alternative measure of conditional volatility, realized variance (REALVAR), calculated as the sum of squared five-minute returns adjusted for fifth-order autocorrelation as in Andersen, Bollerslev, Diebold and Ebens (2001).⁴ The intra-day price data are obtained from Olsen Data Corporation.⁵ Panel A of Table 1 shows that the daily means (medians) are 1.86 (1.62) and 0.85 (0.49) in percentages squared terms for VIXSQ and REALVAR, respectively. VIXSQ exhibits mild skewness and kurtosis, whereas the deviations from normality are more extreme for REALVAR. The correlation between daily (monthly) implied and realized volatility is 0.55 (0.81).

Furthermore, to make sure that our results are not affected by model misspecification, we add a set of control variables (X_t) that are expected to have a predictive relation with the excess market return.⁶ DEF is the change in the default spread calculated as the change in the difference between the yields on BAA- and AAA-rated corporate bonds. TERM is the change in the term spread calculated as the change in the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. RREL is the detrended riskless rate defined as the yield on the one-month Treasury bill minus its

⁴We use this autocorrelation adjustment to control for the microstructure noise in high-frequency returns. Blume and Stambaugh (1983) show that zero-mean noise in prices leads to strictly positive bias in mean returns. Similarly, Asparouhova, Bessembinder and Kalcheva (2013) investigate how noisy prices can impart bias to mean return estimates and regression parameters. Bandi and Russell (2006) and Andersen, Bollerslev and Meddahi (2011) study the impact of noisy prices on realized volatility estimates. We base our realized variance measures on varying past five-minute return windows according to the forecasting horizon. For example, when we forecast one-month ahead returns, we base our realized variance measure on the summation of the within-day five-minute squared returns over the preceding month adjusted for fifth-order serial correlation.

⁵At an earlier stage of the study, we also use RANGEVAR, the range volatility defined as the square of the difference between the logarithm of the highest price and the logarithm of the lowest price in each period. As discussed in Brandt and Diebold (2006), range volatility is highly efficient, robust to microstructural noise and approximately Gaussian. All results presented in the paper also hold for range volatility and they are available upon request.

⁶See, for example, Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988, 1989), Harvey (1989), and Ferson and Harvey (1991, 1999).

one-year backward moving average.⁷ DP is the dividend-to-price ratio calculated by using the returns on the S&P 500 index with and without dividends. Finally, we include the lagged return on the index, RET, to control for the serial correlation in market returns. The set of macroeconomic controls used in regressions changes as the measurement window of the expected market returns changes. We measure DEF and TERM as the change in the default and term premia over the last period, RET as the return over the last period and RREL and DP as the detrended riskless rate and the dividend-to-price ratio at the end of the last period. Panel B of Table 1 shows that there is no strong correlation between the volatility spread measures and the macroeconomic control variables. For daily (monthly) data, the R^2 from a contemporaneous regression of volatility spreads on implied variance and the macroeconomic variables is about 3.00% (4.66%).

3. Empirical Results

3.1 Intertemporal Relation between Volatility Spreads and Market Returns

Table 2 presents results from the univariate time-series regressions of one-period ahead excess returns of the S&P 500 index on various volatility spread measures. In Panel A (Panel B), the dependent variable is the one-day, one-week, two-week and one-month ahead value-weighted (equal-weighted) excess returns on the S&P 500 index. The first row in each regression gives the intercepts and slope coefficients. The second row presents the Newey-West (1987) adjusted t-statistics using optimal lag length.⁸

The first set of results in Table 2 pertain to the regression of one-day ahead excess market returns on the lagged volatility spreads. The results show that all volatility spread measures have significantly negative coefficients, reflecting the fact that when put options are relatively more expensive with respect to call options written on the S&P 500 index, one-day ahead market returns are expected to be lower. This is consistent with the idea that investors with favorable (unfavorable) expectations about future index movements will buy more call (put) options before price increases (decreases). For the value-weighted returns in Panel A, the coefficients of the volatility spread measures range from -0.0112 to -0.0295, implying considerable economic significance as well. When volatility spreads increase by 1%, one-day ahead excess market returns decrease by 1.12 to 2.95 basis points, which corresponds to 2.82% to 7.43% per annum assuming 252 trading days in a year. Moreover, the Newey-

⁷The time-series data on daily 10-year Treasury bond yields and BAA- and AAA-rated corporate bond yields are available at the Federal Reserve Statistical Release website. Daily yields on the one-month Treasury bill are downloaded from Kenneth French's online data library.

⁸Following Newey and West (1994), we use automatic lag length selection in the covariance matrix estimation of Newey-West (1987) standard errors. Newey and West (1994) employ a nonparametric approach (a Truncated kernel estimator) to estimating the optimal bandwidth from the data, rather than specifying a value a priori.

West t-statistics are high in absolute magnitude ranging from -2.71 (for HOVS) to -3.70 (for OWVS). Hence, we observe both economically and statistically significant parameter estimates. For the equal-weighted returns in Panel B, the results are even stronger. The coefficients of the volatility spread measures range from -0.0120 to -0.0332 and the t-statistics for these coefficients are between -2.81 and -4.08.

Second set of regressions in both panels test weekly predictability using non-overlapping weekly observations. For the value-weighted returns in Panel A, the coefficients of the volatility spread measures are still significantly negative ranging from -0.0311 to -0.0826. In other words, when volatility spread measures increase by 1%, one-week ahead aggregate stock returns decrease by 3.11 to 8.26 basis points. However, two of the four volatility spread measures are not significant at conventional levels. When we focus on equal-weighted market returns in Panel B, we find that all volatility spread measures have a significantly negative relation with expected weekly market returns. The coefficient estimates are between -0.0418 and -0.1156 and the corresponding t-statistics are between -1.92 and -2.64. Extending the measurement window for expected market returns to non-overlapping two weeks or one month takes away significance of the slope coefficients on volatility spread measures. For the value-weighted returns, at the two-week horizon, the coefficient of HOVS (HVVS) has the lowest (highest) statistical significance with a t-statistic of -0.09 (-1.31), whereas for the one-month horizon, the coefficients of the volatility spread measures become positive but they are still insignificant. For the equal-weighted returns reported in Panel B, although we observe some significantly negative coefficients at the two-week horizon, the results are qualitatively similar to those reported for the value-weighted returns in Panel A. Collectively, these results suggest that there is an economically and statistically significant relation between volatility spreads and market returns and this predictability extends to a weekly horizon. We believe that the weekly predictability that the results indicate is consistent with our information-based explanation as option and equity markets typically assimilate information quickly and it is not likely that it would take more than one week for any information revealed in the option market to be reflected in the stock market.

Table 3 presents results from the multivariate time-series regressions of one-period ahead excess returns of the S&P 500 index on various volatility spread measures and control variables as in eq. (1). We expect to find significantly positive slope coefficients for the conditional variance measures as documented by Bali and Peng (2006) at the daily frequency and Guo and Whitelaw (2006) at the monthly frequency. We also control for various macroeconomic variables. Again, Panels A and B present results for value- and equal-weighted expected market returns, respectively.

The daily regressions in both panels show that the negative relation between volatility spreads and excess market returns is robust to the inclusion of the control variables in the regression specifications.

The t-statistics for the volatility spreads vary between -3.26 and -4.06 for value-weighted returns and -3.07 and -4.36 for equal-weighted returns. The weekly predictability documented in Table 2 also extends to the multivariate setting. The volatility spread measures have t-statistics that range from -1.86 to -2.40 for value-weighted returns and from -2.32 to -2.94 for equal-weighted returns at the one-week horizon. Although three of the four volatility spread measures can forecast equal-weighted market returns at the two-week horizon as shown in Panel B of Table 3, bi-weekly predictability does not exist for value-weighted returns. Neither panel displays any predictive power of volatility spreads for monthly excess market returns. To summarize, with the addition of the macroeconomic variables, the noise in the index returns is reduced and, if anything, the negative relation between volatility spreads and expected market returns becomes even stronger.

Going forward, we only report results for value-weighted returns both to be more conservative and to take into account the possibility that equal-weighted returns are more sensitive to microstructure noise.

The results in Table 3 also show that the implied variance measured by VIXSQ is positively and significantly related to one-period ahead excess S&P 500 returns.⁹ In the regressions of one-day ahead excess market returns, the estimated coefficients on the lagged implied volatility are in the range of 7.74 and 8.30. The t-statistics associated with these coefficients range from 2.89 to 3.09. When the excess returns are extended to longer horizons, VIXSQ remains a significant predictor of future returns. One can also see that the estimated coefficients on the dividend-to-price ratio and the detrended riskless rate are significantly positive. Also, the change in the term premium is significant for the one-month horizon.

Next, we answer the question whether expected market returns can predict the volatility spread measures, or in other words, whether the predictability runs the other way around. Table 4 presents results from the regressions of one-period ahead volatility spread measures on the value-weighted excess S&P index returns, implied variance and macroeconomic variables. The results show that the lagged stock returns computed using windows ranging from one day to one month cannot predict volatility spreads. The t-statistics for the coefficients of lagged daily returns vary from -0.32 to -1.72 and the t-statistics for the coefficients of lagged monthly returns vary from 0.16 to 1.29. None of the control variables can forecast volatility spreads with the exception of VIXSQ that has a significantly positive relation with future volatility spreads at the daily horizon. Although not reported in the paper to save space, similar results are obtained without controlling for implied variance (VIXSQ) and macroeconomic variables, i.e., lagged market returns do not predict future volatility spreads.

⁹The significantly positive relation between implied variances and expected market returns also holds for the realized and range variances, and they are available upon request.

These results collectively suggest that the implied volatility spreads can predict aggregate equity returns up to a one-week horizon; however, there is no predictability in the opposite direction.

3.2 Controlling for Variance Risk Premium

Bollerslev, Tauchen, and Zhou (2009) argue that the long-run risk in consumption growth is a fundamental determinant of the equity premium and dynamic dependencies among asset returns over the long-run. Bollerslev et al. (2009) show that the variance risk premium, defined as the difference between expected variance under the risk-neutral measure and expected variance under the physical measure, predicts future market returns, especially at the quarterly horizon.

Our volatility spread measure is constructed as the difference between the volatilities of OTM put options and ATM call options written on the S&P 500 index. As such, it is a difference between two market volatility measures and is potentially correlated with the variance risk premium. To ensure that our results are not driven by a correlation between implied volatility spreads and variance risk premium, we first test a generalized version of the specification in Bollerslev et al. (2009) and include both the implied variance and the realized variance in the regressions:

$$R_{t+1} = \alpha + \beta VS_t + \gamma VIXSQ_t + \delta REALVAR_t + \theta X_t + \varepsilon_{t+1}. \quad (2)$$

The results are presented in Table 5. First set of regressions show that, at the daily forecasting horizon, all four volatility spread measures have significantly negative coefficients in the presence of VIXSQ and REALVAR in the specification. The coefficients vary between -0.0141 and -0.0324 and the t-statistics vary between -3.15 and -3.96. Due to the high correlation between VIXSQ and REALVAR, both conditional volatility measures lose their significance albeit retaining their positive coefficients. Extending the forecasting horizon to one week indicates that the significantly negative relation between volatility spreads and expected market returns continues to hold. The t-statistics associated with the coefficients of the volatility spread measures range from -2.45 and -3.22 at the weekly horizon. At the two-week and one-month horizons, there is no robust relation between volatility spreads and expected market returns. Also, the high correlation between VIXSQ and REALVAR becomes more pronounced at return horizons longer than one day. This multicollinearity problem causes VIXSQ to have a higher and more significantly positive coefficient compared to earlier specifications in which VIXSQ is the only variance proxy. Moreover, the coefficient of REALVAR turns negative and becomes highly significant, whereas it is significantly positive when included in the specification in isolation.

In Table 6, we include the variance risk premium, denoted as VRP, directly in the regressions.

$$R_{t+1} = \alpha + \beta VS_t + \gamma VRP_t + \theta X_t + \varepsilon_{t+1}. \quad (3)$$

The correlation between VRP and VIXSQ is 0.83 and the correlation between VRP and REALVAR is 0.36 at the monthly frequency, in line with the findings of Bollerslev et al. (2009). The correlation between the variance risk premium and our implied volatility measures range from 0.09 and 0.14 (0.12 and 0.19) at the daily (monthly) frequency indicating that the two types of measures capture different information. Supporting this finding, all the volatility spread measures have significantly negative coefficients up to a return forecasting horizon of one week. The t-statistics associated with the coefficients of the volatility spreads range from -2.65 to -3.58 at the one-day horizon and from -2.43 to -3.16 at the one-week horizon. The coefficients of VRP indicate a significantly positive intertemporal relation between variance risk premia and excess market returns starting from the one-week horizon complementing the results of Bollerslev et al. (2009).

3.3 Out-of-Sample Evidence and Economic Significance

Goyal and Welch (2008) examine the performance of a wide variety of factors that have been suggested by the literature to be significant predictors of the equity premium. Their conclusion is that the in-sample performance of many of these predictors is weak. Moreover, the out-of-sample performance of the predictors indicates that they would not have helped investors to profitably time the market. Hence, we need to investigate the out-of-sample significance of the volatility spread measures by simulating the return of a trading strategy which invests on the market portfolio or the risk-free asset. Yet another issue is the significance of trading costs. Since our findings suggests a straightforward mispricing, we need to understand if the predictability is big enough to exceed transaction cost bounds.

To be able to address the issues of out-of-sample predictability and transaction cost bounds, we use a rolling window trading analysis. The trading strategy uses the out-of-sample one step ahead forecasts of the excess market return using one of our volatility spread measures, namely VWVS. The first forecasting regression uses the first half of the sample, i.e., the first regression uses the first 1593 observations of the overall sample and then the one-step ahead estimations use an expanding window. Specifically, on each day t after the midpoint of the data set, the data available up to day t are used to estimate our baseline predictive regression. The estimated coefficients are recorded and used to forecast the excess market return at time $t+1$. Then for each day t , the investment strategy invests 100% in the equity index if the forecasted excess market return is positive or it invests 100% on the risk free rate if the forecasted excess return is negative. On day $t+1$, the return of this portfolio is realized and a new cycle of predictive regressions is estimated using an expanded window. We denote

this strategy as the optimal strategy. Consequently, we obtain a time series of returns for this strategy.

However, there are certain transaction costs when this switching trading algorithm is utilized. One cost is the brokerage fees and the other is the bid-ask spread. Exchange traded funds (ETFs) are popularly used to invest in market indices. There is a fixed brokerage fee when one invests in ETFs, which can be diluted by the amount invested in the fund since it is a fixed fee. In other words, the fee as a percentage of the investment decreases by the total amount invested. However, the bid-ask spreads are real costs that the switching investors need to bear. When we investigate the most famous ETF that invests in the S&P 500 index (ticker: SPY), we find that the bid-ask spread is 1 basis point. Hence, an investor bears this cost every time he/she switches between investments (in both directions). Therefore, after we find the optimal trading strategy, we decrease investment returns by the bid-ask spread amount each time the strategy switches between investments.

We find that, when one allocates all his/her wealth to the equity index portfolio, the strategy earns a daily return of %0.021. This passive investment strategy has a Sharpe ratio of 0.020. To better understand this performance, we follow the growth path of an investment of \$100 using this strategy and find that it grows to \$129 by the end of the data period. When one invests in the optimal strategy, he/she earns an average daily return of %0.032 with a Sharpe ratio of 0.036. To compare the relative performance of the optimal strategy to the passive strategy of investing in the S&P 500 index, we track the growth of an investment of \$100 to the optimal strategy and find that it grows to \$158 by the end of the estimation period. In other words, there is a significant difference between the optimal and the static portfolios. Finally, to be able to evaluate the effect of the bid-ask spreads, we identify the number of switching trades and decrease the optimal portfolio returns by the magnitude of the bid-ask spreads. This helps us obtain the net optimal returns. We find that the optimal strategy yields a higher return compared to the passive strategy even after taking the bid-ask spreads into account. Specifically, the daily average return becomes %0.030 which corresponds to a Sharpe ratio of 0.033. An investment of \$100 into the optimal strategy grows to \$151.6 after transaction costs are deducted. Hence, we conclude that even after taking the transaction costs into account, the optimal portfolio has a significantly better performance than the S&P 500 index itself both in a nominal sense and a risk-adjusted sense.

When we repeat the analysis for the other spread measures, we find qualitatively similar results.

4. Information Explanation

4.1 Earnings Announcements

In this section, we provide additional evidence for the information-based explanation of the significant link between volatility spreads and future returns.¹⁰ Admittedly, it is difficult to pinpoint periods of significant information releases that have the potential to impact the aggregate stock market. Nevertheless, we focus on the earnings announcements of the firms that constitute the S&P 500 index motivated by the idea that earnings announcements are informationally intensive periods for individual firms and such informational events have the potential to affect the aggregate stock market as well. Moreover, the earnings announcements of firms in the same industry tend to be clustered in time and this makes it easier to identify periods of significant information releases for empirical purposes.

We obtain the list of S&P 500 constituent firms from CRSP. The earnings announcement dates of these firms come from COMPUSTAT.¹¹ If the negative relation between volatility spreads and aggregate returns is due to information flow from options to stock markets, we would expect this relation to be stronger during informationally intensive periods such as the earnings announcement periods of S&P 500 constituent firms. To test this hypothesis, we first define a dummy variable that is equal to one for a given trading day if a firm that is a constituent of the S&P 500 index makes an earnings announcement in that period and zero otherwise. Then, we estimate the following regression model for one-day ahead market returns:

$$R_{t+1} = \alpha + \beta_1 VSPLUS_t + \beta_2 VSMINUS_t + \gamma VIXSQ_t + \theta X_t + \varepsilon_{t+1}. \quad (4)$$

where $VSPLUS$ is equal to the volatility spread if the the dummy variable is equal to one and 0 otherwise; and $VSMINUS$ is equal to the volatility spread if the dummy variable is equal to zero and 0 otherwise. We expect β_1 to be more negative (larger in absolute magnitude) than β_2 if the earnings announcements of S&P 500 constituent firms have an impact on the negative link between volatility spreads and excess market returns.

The coefficients of $VSPLUS$ in Panel A of Table 7 vary between -0.0157 and -0.0352. The lowest t-statistic in absolute magnitude is associated with $HVVS$ and is equal to -3.53. On the other hand, the coefficients of $VSMINUS$ are never significantly different from zero and the t-statistics range from -1.54

¹⁰Rather than drawing on the potential preference of informed traders for the option market, the information explanation can also be supported by the idea that the option market incorporates available information to the prices more efficiently than the stock market. In this case, the mispricing in the stock market would lead to apparent volatility spreads in the options market, and the reversal of the mispricing would result in the predictive power of volatility spreads.

¹¹The results are qualitatively similar when the earnings announcement dates are collected from I/B/E/S.

to 0.02. The last column presents the p-values associated with the Wald test for the equality of the coefficients of VSPLUS and VSMINUS. In all the specifications, VSPLUS is significantly more negative than VSMINUS such that the p-values are all lower than 2%. The fact that the predictive ability of volatility spreads for future market returns is constrained to the periods of earnings announcements by S&P 500 constituent firms lends support to the idea that the negative intertemporal relation between volatility spreads and aggregate returns is driven by the trading activities of informed investors.

Next, we further refine the earnings announcement periods and focus on the first announcement done by an S&P 500 constituent firm in a given industry for a particular month. Specifically, we define a dummy variable that is equal to one for a given trading day, if a firm that is a constituent of the S&P 500 index makes the first earnings announcement in a particular industry-month and accordingly estimate equation (4). In this test, we are motivated by the idea that the first earnings announcement in an industry will have the most informational impact since the stock returns of the firms in the same industry tend to be correlated. The results are presented in Panel B of Table 7. Again, the coefficients of VSPLUS are significantly negative and their t-statistics vary between -3.65 and -4.53. In contrast, the coefficients of VSMINUS are statistically insignificant without any exception. The p-values reported in the last column range from 2.58% to 4.70% and indicate that the predictive ability of volatility spreads for excess market returns is significantly stronger during periods of significant information releases by S&P 500 constituent firms.

4.2 Cash Flow and Expected Return News

It is well-known that three sources explain variation in stock returns: variation in expected returns, change in expected future cash flows (cash flow news) and change in expected future returns (expected return news). For example, Fama (1990), Schwert (1990) and others regress stock returns on the change in cash flow variables. In these regressions, coefficient estimates and explained variances are considered to be a measure of how well those variables proxy for change in expected cash flows. However, as argued in the literature, explanatory power of cash flow proxies may arise from the correlation of cash flow proxies with expected returns, cash flow news and/or expected return news.

In a similar spirit, we argue that the statistically significant explanatory power of implied volatility spreads may be due to market participants' predicting extreme news in cash flows and/or expected returns and incorporating these predictions to implied volatilities and hence to the volatility spreads. To test this hypothesis, we decompose index returns into cash flow news and expected return news using Campbell's log-linearization framework.

In Campbell's (1991) log-linearization framework, stock returns can be written as linear combinations of revisions in expected future dividends and returns:

$$r_{i,t} = E_{t-1}[r_{i,t}] + \Delta E_t \left[\sum_{j=0}^{\infty} \rho^j \Delta d_{i,t+j} \right] - \Delta E_t \left[\sum_{j=1}^{\infty} \rho^j r_{i,t+j} \right] \quad (5)$$

where ΔE_t is the change in expectations from the end of period $t-1$ to the end of period t , $d_{i,t+j}$ is the dividends paid during period $t+j$ and ρ is a discount factor close to one. We can define the two components of unexpected return as,

$$N_{i,t}^c \equiv \Delta E_t \left[\sum_{j=0}^{\infty} \rho^j \Delta d_{i,t+j} \right], \quad N_{i,t}^r \equiv \Delta E_t \left[\sum_{j=1}^{\infty} \rho^j r_{i,t+j} \right] \quad (6)$$

where $N_{i,t}^c$ is the change in expected cash flows (cash flow news) and $N_{i,t}^r$ is the change in expected returns (expected return news). In order to decompose unexpected returns ($r_{i,t} - E_{t-1}[r_{i,t}]$) into cash flow news ($N_{i,t}^c$) and expected return news ($N_{i,t}^r$), we use a vector autoregression (VAR) setting following Campbell (1991). Assuming that the index specific state vector follows a linear law, we consider the VAR equation,

$$y_{i,t}^p = Ay_{i,t-1}^p + \epsilon_{i,t} \quad (7)$$

where $y_{i,t}^p$ is the VAR state vector for the index at time t containing p 'demeaned' variables and A is the $p \times p$ coefficient matrix. Since the VAR setting is a collection of time-series regressions, the coefficient matrix is assumed to be constant in time. The first element of the state vector $y_{i,t}^p$ is the demeaned stock returns. As in Campbell (1991), define $e1' \equiv [1 \ 0 \ \dots \ 0]$ and $\lambda' \equiv e1' \rho' A (I - \rho A)^{-1}$, where I is $p \times p$ identity matrix. Using these simplified definitions, the one-period expected returns and infinite sums in equation (5) can be written as functions of λ' , the residual vector of the VAR ($\epsilon_{i,t}$) and the VAR coefficient matrix (A). Specifically, one-period expected returns is $E_{t-1}[r_{i,t}] = e1' Ay_{i,t-1}^p$, expected return news is $N_{i,t}^r = \lambda' \epsilon_{i,t}$, and expected cash flow news is $N_{i,t}^c = (e1' + \lambda') \epsilon_{i,t}$.

Specifically, dividend yield, stochastically detrended riskless rate, term premium and default premium are used in the state vector. To test the robustness of our estimations, we further use several state vectors as determinants of one period expected returns and find that the conclusions remain intact across a variety of explanatory variables.

After decomposing aggregate stock returns into one-period expected returns, cash flow news and expected return news, we test whether days associated with extreme news in cash flows and/or expected returns drive the significant negative link between future index returns and implied volatility spreads. If informed investors trade in the options market based on their information about future cash flow

and expected return news, we would expect the intertemporal relation between volatility spreads and aggregate returns to be stronger when the magnitude of the unexpected cash flow and/or expected return news is larger. To test this conjecture, we define dummy variables equal to one if the daily cash flow or expected return news are less than the 25th percentile or greater than the 75th percentile among the observed cash flow and expected return news over the sample period. Then, we estimate the asymmetric regression model in equation (4). We expect β_1 to be more negative (larger in absolute magnitude) than β_2 if the information about future cash flow and expected return news affect informed investors' trades in the options market.

Panels A and B of Table 8 present results for cash flow and expected return news, respectively. The dependent variable in all specifications is the one-day ahead excess market returns. The last column presents the p-values associated with the Wald test of the equality of the coefficients of VSPLUS and VSMINUS. For cash flow news, we find that the coefficient of VSPLUS is more negative than the coefficient of VSMINUS for all implied volatility spread measures. For example, the results for the highest open interest volatility spread measure show that the coefficients for VSPLUS and VSMINUS are -0.0211 and -0.0096, respectively and the p-value associated with the equality of these coefficients is equal to 0.0035. The highest p-value in this panel is 0.0082. The same pattern also holds for all volatility spread measures when VSPLUS and VSMINUS are defined based on the extreme values of the expected return news. The p-values in Panel B vary between 0.0005 and 0.0045. These results support the conjecture that the predictive power of volatility spreads on aggregate stock returns is at least partially driven by the information possessed by investors regarding future cash flow and expected return news that potentially carry sizable and important information.

4.3 Consumer Sentiment

We further focus on the consumer sentiment index. The consumer sentiment index is compiled by the University of Michigan through a nationally representative survey based on telephonic household interviews and published monthly.¹² The data are available for download from the Federal Reserve statistical release website. Periods of extremely high or low consumer sentiment index are important because these are the periods during which asset prices deviate from their fundamental values the most. Hence, if information flow across markets is the main explanation of our findings, then one would expect the intertemporal relation between implied volatility spreads and expected returns to be stronger during periods of extreme consumer sentiment. To test this hypothesis, we again estimate the asymmetric regression model in eq. (4). However, this time VSPLUS is equal to the volatility spread

¹²We should note that the relationship between investor sentiment and stock returns is originally documented by Baker and Wurgler (2006).

if the consumer sentiment index is greater than its 90th percentile or less than its 10th percentile over the sample period, and 0 otherwise; and VSMINUS is equal to the volatility spread if the consumer sentiment index is less than its 90th percentile and greater than its 10th percentile over the sample period, and 0 otherwise. Alternatively, we define the extreme levels of the consumer sentiment index based on the 25th and 75th percentiles of its distributions. If the information in volatility spreads related to consumer sentiment is instrumental in the predictive power of the volatility spreads on expected market returns, then β_1 is expected to be negative and larger in absolute magnitude than β_2 .

Panel A (Panel B) of Table 9 reports the results based on the 10th and 90th (25th and 75th) percentiles of the consumer sentiment index. The dependent variable in all specifications is the one-day ahead excess market returns. The last column presents the p-values associated with the Wald test for the equality of the coefficients of VSPLUS and VSMINUS. We find that, for all four measures of volatility spread, the coefficient of VSPLUS is significantly more negative than VSMINUS. For example, when the highest open interest volatility spread measure is used in the empirical specification in Panel A, the coefficient of VSPLUS is -0.0266 and the coefficient of VSMINUS is -0.0135. In other words, the coefficient of VSPLUS is about twice as large as the coefficient of VSMINUS in absolute magnitude. The p-value associated with the equality of these two coefficients is 0.0241 confirming the conjecture that the predictive ability of volatility spreads on expected market returns is at least partially driven by the information embedded in volatility spreads related to sentiment. The p-values associated with the Wald tests for the equality of the coefficients of VSPLUS and VSMINUS are between 0.0036 and 0.0485 in Panel A and between 0.0281 and 0.0462 in Panel B.

We also run a battery of robustness checks that are presented in the online appendix. In Section I of the online appendix, we entertain the possibility that the intertemporal relation between market returns and volatility spreads is due to volatility spreads acting as a proxy for the conditional skewness of aggregate returns. In Section II, we orthogonalize the implied volatility spread measures with respect to the implied variance, realized variance, physical skewness and risk-neutral skewness measures, and we show that the results remain qualitatively the same when the orthogonalized measures of volatility spreads are used in the predictive regressions. In Section III, we orthogonalize the volatility spread measures with respect to implied variance and nonparametric value-at-risk to tease out the risk component of volatility spreads (e.g., Kelly and Jiang (2013)) and investigate the predictive power of the fitted and residual terms on market returns. In Section IV, we control for the non-normality of empirical return distributions by estimating the predictive regressions using the skewed t density of Hansen (1994) in a maximum likelihood framework. In Section V, we address the issue of small-sample bias by utilizing the randomization and bootstrapping methods of Nelson and Kim (1993) under the

null hypothesis of no predictability. We also perform an alternative small-sample bias analysis by exploiting information about the autocorrelation structure of the volatility spread measures following Lewellen (2004). In Section VI, rather than compounding market returns for different time periods, we use several lags of the volatility spread measures as independent variables. In Section VII, we use logarithmic excess market returns as dependent variables and control for squared volatility spreads to account for outliers and nonlinearities. In Section VIII, we include additional macroeconomic controls in our specifications. The online appendix shows that the main findings of the paper remain qualitatively the same after running all these robustness checks.

5. Conclusion

We examine the intertemporal relation between implied volatility spreads and expected market returns. Our analyses show that the spread between the implied volatilities of out-of-the-money put and at-the-money call options written on the S&P 500 index is significantly negatively related to the expected market returns up to a one-week horizon. The main findings of the paper remain intact after running a battery of robustness checks. Specifically, the intertemporal relation between volatility spreads and aggregate stock returns remains strongly negative after controlling for various measures of conditional volatility, variance risk premium, physical and risk-neutral skewness, a large set of macroeconomic variables, and after correcting for non-synchronicity, small sample biases, non-normality in the return distribution, outliers and nonlinearity.

We attribute our findings to the information spillover from the options market to the stock market. Indeed, demand based option pricing models indicate a positive relation between option expensiveness which can be measured by implied volatility and end-user demand, hence investors with positive (negative) expectations about future stock prices will increase their demand for call (put) options. Consistent with this information-based argument, we show that the relation between volatility spreads and expected market returns is only significant for the periods that S&P 500 constituent firms announce their earnings. Hence, it is the informationally intense periods that drive our findings. We also find that the documented predictability is significantly more pronounced when the cash flow and expected return news are sizable and the consumer sentiment index takes extreme values. The finding that the documented predictability does not extend to horizons longer than one week is consistent with the fact that options and equity markets typically assimilate information quickly. Finally, we construct a trading strategy based on the relation between volatility spreads and expected market returns and show that this strategy has higher returns compared to a passive strategy after transaction costs are taken into account.

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Table 1. Descriptive Statistics

This table presents descriptive statistics for various volatility spread measures, implied variance, realized variance, volatility risk premium and macroeconomic variables. Panel A presents the summary statistics for volatility spreads, variance measures and macroeconomic variables. Panel B presents the correlation matrix between the volatility spreads, variance measures and macroeconomic control variables. HOVS (HVVS) is the implied volatility difference between the OTM put option and the ATM call option that have the highest open interest (volume) in a given trading day. VWVS (OWVS) is equal to the difference between the volume-weighted (open interest-weighted) average of the volatility spreads for all OTM put options and the volume-weighted (open interest-weighted) average of the volatility spreads for all ATM call options. VIXSQ is the implied variance which measures the market's forecast of the volatility of the S&P 500 index. REALVAR is the realized variance calculated as the sum of squared five-minute returns adjusted for fifth-order autocorrelation. VRP is the volatility risk premium defined as the difference between VIXSQ and REALVAR. DEF is the change in the default spread calculated as the change in the difference between the yields of BAA- and AAA-rated corporate bonds. TERM is the change in the term spread calculated as the change in the difference between the yields of the 10-year Treasury bond and the 1-month Treasury bill. RREL is the detrended riskless rate defined as the 1-month Treasury bill rate minus its 1-year backward moving average. DP is the aggregate dividend price ratio obtained by using the S&P 500 index return with and without dividends.

Panel A. Summary Statistics for Volatility Spreads, Variance Measures and Macroeconomic Variables

	HOVS	HVVS	OWVS	VWVS	VIXSQ	REALVAR	VRP	DEF	TERM	RREL	DP
Mean	0.083	0.086	0.095	0.089	1.8550	0.8490	1.0050	0.0001	0.0002	-0.0005	0.0167
Median	0.078	0.078	0.092	0.088	1.6220	0.4940	0.9100	0.0000	0.0000	-0.0002	0.0171
StDev	0.044	0.043	0.025	0.027	1.2010	1.3020	1.1970	0.0062	0.0492	0.0034	0.0031
Min	-0.041	-0.053	0.007	-0.002	0.3880	0.0030	-19.4890	-0.0379	-0.6112	-0.0112	0.0107
P25	0.052	0.055	0.078	0.071	0.9630	0.2440	0.4750	-0.0036	-0.0151	-0.0021	0.0140
P75	0.107	0.109	0.110	0.104	2.3590	0.9720	1.4550	0.0036	0.0115	0.0018	0.0190
Max	0.390	0.323	0.232	0.215	8.3020	22.2970	6.2260	0.1517	0.8810	0.0057	0.0240
Skew	0.797	1.064	0.524	0.558	1.6210	6.9609	-4.1414	4.8561	2.5868	-0.6898	-0.0276
Kurt	4.585	5.091	4.024	4.285	6.7119	79.8234	65.0548	122.6957	79.4656	3.2946	2.0607

Panel B. Correlations for Volatility Spreads, Variance Measures and Macroeconomic Variables

	HOVS	HVVS	OWVS	VWVS	VIXSQ	REALVAR	VRP	DEF	TERM	RREL	DP
HOVS	1.000										
HVVS	0.304	1.000									
OWVS	0.636	0.495	1.000								
VWVS	0.440	0.759	0.785	1.000							
VIXSQ	0.118	0.088	0.114	0.154	1.000						
REALVAR	0.018	-0.013	0.027	0.018	0.545	1.000					
VRP	0.099	0.101	0.085	0.135	0.410	-0.541	1.000				
DEF	0.017	0.028	0.029	0.027	0.039	0.052	-0.017	1.000			
TERM	-0.017	-0.001	-0.001	0.012	0.009	-0.013	0.023	-0.029	1.000		
RREL	0.048	0.014	0.045	0.009	-0.318	-0.109	-0.201	-0.036	-0.106	1.000	
DP	-0.006	0.001	-0.062	-0.027	-0.253	-0.093	-0.153	0.018	-0.005	0.022	1.000

Table 2. Volatility Spreads and Market Returns: Univariate Regressions

This table presents parameter estimates from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads. Panel A presents results for the value-weighted market returns and Panel B presents results for the equal-weighted market returns. Volatility spread measures are defined in Table 1. In each regression, the dependent variable is the 1-day, 1-week, 2-week or 1-month excess market returns, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length. The last column reports the number of non-overlapping observations used in predictive regressions.

Panel A. Value-Weighted Market Returns

	Constant	HOVS	HVVS	OWVS	VWVS	# of obs.
1-day	0.0012	-0.0112				3,189
	(3.10)	(-2.71)				
	0.0013		-0.0125			3,189
	(3.13)		(-2.91)			
1-week	0.0030			-0.0295		3,189
	(3.92)			(-3.70)		
	0.0022				-0.0229	3,189
	(3.37)				(-3.17)	
2-week	0.0044	-0.0413				638
	(2.28)	(-2.04)				
	0.0036		-0.0311			638
	(1.78)		(-1.41)			
1-month	0.0088			-0.0826		638
	(2.27)			(-2.07)		
	0.0059				-0.0544	638
	(1.84)				(-1.57)	
1-month	0.0024	-0.0039				319
	(0.62)	(-0.09)				
	0.0070		-0.0564			319
	(1.87)		(-1.31)			
1-month	0.0076			-0.0590		319
	(1.03)			(-0.74)		
	0.0077				-0.0623	319
	(1.21)				(-0.84)	
1-month	-0.0074	0.1475				152
	(-0.85)	(1.47)				
	-0.0075		0.1360			152
	(-0.97)		(1.79)			
1-month	-0.0139			0.1920		152
	(-0.79)			(1.08)		
	-0.0130				0.1954	152
	(-0.81)				(1.13)	

Panel B. Equal-Weighted Market Returns

	Constant	HOVS	HVVS	OWVS	VWVS	# of obs.
1-day	0.0015	-0.0145				3,189
	(3.76)	(-3.13)				
	0.0013		-0.0120			3,189
	(3.23)		(-2.81)			
1-week	0.0035			-0.0332		3,189
	(4.41)			(-4.08)		
	0.0027				-0.0265	3,189
	(3.90)				(-3.59)	
2-week	0.0060	-0.0545				638
	(2.91)	(-2.22)				
	0.0051		-0.0418			638
	(2.37)		(-1.92)			
1-month	0.0125			-0.1156		638
	(2.91)			(-2.64)		
	0.0088				-0.0806	638
	(2.59)				(-2.23)	
2-week	0.0076	-0.0539				319
	(1.74)	(-1.06)				
	0.0109		-0.0877			319
	(2.68)		(-1.98)			
1-month	0.0204			-0.1830		319
	(2.41)			(-2.06)		
	0.0169				-0.1523	319
	(2.47)				(-1.97)	
1-month	0.0002	0.0815				152
	(0.02)	(0.74)				
	0.0035		0.0354			152
	(0.43)		(0.45)			
1-month	0.0091			-0.0262		152
	(0.49)			(-0.14)		
	0.0077				-0.0127	152
	(0.48)				(-0.07)	

Table 3. Volatility Spreads and Market Returns: Multivariate Regressions

This table presents parameter estimates from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. Volatility spread measures, implied variance and macroeconomic variables are defined in Table 1. Panel A presents results for the value-weighted market returns and Panel B presents results for the equal-weighted market returns. In each regression, the dependent variable is the 1-day, 1-week, 2-week or 1-month ahead excess market returns, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length.

Panel A. Value-Weighted Market Returns

	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	RET	DEF	TERM	RREL	DP
1-day	-0.0034	-0.0150				8.0354	-0.0251	-4.8339	-0.0699	0.1207	0.2071
	(-2.57)	(-3.46)				(3.04)	(-1.35)	(-1.52)	(-0.17)	(2.16)	(3.25)
	-0.0034		-0.0145			7.7379	-0.0253	-4.7299	-0.0547	0.1109	0.2057
	(-2.50)		(-3.26)			(2.89)	(-1.37)	(-1.50)	(-0.13)	(1.98)	(3.19)
	-0.0013			-0.0333		8.1006	-0.0262	-4.5953	-0.0438	0.1242	0.1920
			(-4.06)		(3.09)	(-1.42)	(-1.46)	(-0.10)	(2.18)	(2.99)	
					-0.0285	8.2958	-0.0263	-4.7020	-0.0293	0.1171	0.2044
					(-3.75)	(3.09)	(-1.42)	(-1.50)	(-0.07)	(2.06)	(3.16)
1-week	-0.0165	-0.0529				6.7234	-0.1029	-5.6714	1.7656	0.7567	0.9633
	(-2.88)	(-2.46)				(3.31)	(-2.29)	(-0.98)	(1.46)	(2.42)	(3.25)
	-0.0174		-0.0389			6.4958	-0.0987	-5.4147	1.8690	0.7492	0.9661
	(-2.95)		(-1.86)			(3.17)	(-2.19)	(-0.95)	(1.50)	(2.41)	(3.23)
	-0.0112			-0.0966		6.7271	-0.1009	-4.8415	1.7372	0.7627	0.9303
			(-2.40)		(3.35)	(-2.20)	(-0.83)	(1.44)	(2.42)	(3.12)	
					-0.0710	6.7878	-0.0977	-5.4169	1.8021	0.7386	0.9537
					(-2.06)	(3.30)	(-2.13)	(-0.94)	(1.46)	(2.36)	(3.18)
2-week	-0.0368	-0.0109				5.9242	0.0210	1.8656	1.8460	1.4492	1.7710
	(-3.96)	(-0.25)				(3.34)	(0.36)	(0.28)	(1.58)	(2.57)	(3.62)
	-0.0317		-0.0590			5.9272	0.0154	3.1181	1.9235	1.4709	1.7225
	(-3.29)		(-1.53)			(3.37)	(0.26)	(0.46)	(1.63)	(2.62)	(3.53)
	-0.0312			-0.0645		5.9779	0.0188	2.7253	1.7728	1.4662	1.7353
			(-0.84)		(3.44)	(0.32)	(0.39)	(1.54)	(2.61)	(3.61)	
					-0.0700	6.0339	0.0200	2.6275	1.7938	1.4607	1.7358
					(-1.00)	(3.45)	(0.34)	(0.38)	(1.55)	(2.62)	(3.56)
1-month	-0.0806	0.1176				4.8100	0.0808	11.8367	4.0414	3.0672	3.4541
	(-3.67)	(1.21)				(2.76)	(0.77)	(1.11)	(2.70)	(3.75)	(3.75)
	-0.0805		0.1072			4.8774	0.0727	10.6258	4.1781	3.0052	3.4343
	(-3.89)		(1.46)			(2.74)	(0.70)	(0.98)	(2.87)	(3.57)	(3.74)
	-0.0830			0.1076		4.8994	0.0755	9.1204	4.0542	2.9609	3.5228
			(0.61)		(2.95)	(0.71)	(0.82)	(2.62)	(3.62)	(3.62)	
					0.0999	4.9266	0.0726	10.2974	4.1576	3.0085	3.3799
					(0.64)	(2.83)	(0.69)	(0.96)	(2.83)	(3.64)	(3.68)

Panel B. Equal-Weighted Market Returns

	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	RET	DEF	TERM	RREL	DP
1-day	-0.0021	-0.0169				7.0622	0.0162	-3.7306	0.0319	0.1075	0.1550
	(-1.59)	(-3.76)				(2.57)	(0.85)	(-1.16)	(0.08)	(1.83)	(2.44)
	-0.0023		-0.0135			6.6256	0.0167	-3.6668	0.0467	0.0948	0.1526
	(-1.68)		(-3.07)			(2.38)	(0.87)	(-1.16)	(0.12)	(1.61)	(2.38)
	0.0002			-0.0362		7.1011	0.0152	-3.4788	0.0606	0.1106	0.1383
(0.11)			(-4.36)		(2.59)	(0.80)	(-1.10)	(0.15)	(1.84)	(2.16)	
1-week	-0.0008				-0.0308	7.3118	0.0154	-3.5970	0.0758	0.1029	0.1518
	(-0.55)				(-4.00)	(2.60)	(0.81)	(-1.14)	(0.19)	(1.72)	(2.36)
	-0.0113	-0.0627				6.1634	-0.0571	-5.2982	1.5904	0.6857	0.7632
	(-1.87)	(-2.76)				(2.77)	(-1.23)	(-0.89)	(1.20)	(2.08)	(2.58)
	-0.0122		-0.0478			5.8742	-0.0547	-4.9981	1.7182	0.6778	0.7658
(-2.02)		(-2.32)			(2.60)	(-1.20)	(-0.86)	(1.26)	(2.06)	(2.58)	
2-week	-0.0038			-0.1270		6.1924	-0.0574	-4.1674	1.5445	0.6995	0.7197
	(-0.57)			(-2.94)		(2.79)	(-1.23)	(-0.69)	(1.17)	(2.08)	(2.44)
	-0.0079				-0.0950	6.2735	-0.0543	-4.9224	1.6288	0.6684	0.7505
	(-1.25)				(-2.67)	(2.74)	(-1.16)	(-0.84)	(1.20)	(2.00)	(2.53)
	-0.0273	-0.0567				6.0301	0.0301	1.4860	2.7055	1.4912	1.4809
(-2.82)	(-1.13)				(2.99)	(0.53)	(0.20)	(1.87)	(2.42)	(3.07)	
1-month	-0.0228		-0.0901			5.8603	0.0273	3.0691	2.9549	1.5104	1.4201
	(-2.33)		(-2.17)			(2.94)	(0.50)	(0.42)	(1.92)	(2.44)	(3.03)
	-0.0131			-0.1852		6.0633	0.0265	3.7417	2.5844	1.5305	1.3846
	(-1.14)			(-2.14)		(3.04)	(0.48)	(0.47)	(1.81)	(2.48)	(2.95)
	-0.0168				-0.1569	6.1122	0.0296	2.9002	2.7074	1.5050	1.4099
(-1.58)				(-2.10)	(3.01)	(0.54)	(0.38)	(1.82)	(2.48)	(3.01)	
1-month	-0.0639	0.0406				5.1414	0.0771	8.4209	4.3259	3.0738	2.8720
	(-2.43)	(0.40)				(2.81)	(0.66)	(0.82)	(2.57)	(3.07)	(2.82)
	-0.0607		0.0018			5.2674	0.0756	8.1065	4.4108	3.0786	2.8382
	(-2.50)		(0.02)			(2.72)	(0.65)	(0.80)	(2.64)	(3.08)	(2.83)
	-0.0419			-0.1670		5.6950	0.0728	10.8117	4.7787	3.2654	2.5669
(-1.27)			(-0.92)		(3.11)	(0.64)	(0.97)	(2.74)	(3.30)	(2.47)	
1-month	-0.0505				-0.1194	5.5567	0.0755	8.7389	4.5688	3.1635	2.7989
	(-1.88)				(-0.79)	(2.93)	(0.66)	(0.85)	(2.73)	(3.27)	(2.88)

Table 4. Market Returns Predicting Volatility Spreads

This table presents parameter estimates from the time-series predictive regressions of one-period ahead volatility spreads on the value-weighted excess S&P 500 index returns, implied variance and macroeconomic variables. Volatility spread measures, implied variance and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day, 1-week, 2-week or 1-month ahead volatility spreads. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length.

		Constant	LAGRET	VIXSQ	DEF	TERM	RREL	DP
1-day	HOVS	0.0680 (6.61)	-0.1115 (-1.51)	52.1026 (3.13)	3.5684 (0.26)	-0.6837 (-0.47)	1.1981 (2.36)	0.3571 (0.67)
	HVVS	0.0744 (10.09)	-0.0213 (-0.32)	33.7225 (2.20)	-3.3347 (-0.32)	0.0010 (0.00)	0.5503 (1.35)	0.3146 (0.88)
	OWVS	0.0963 (15.13)	-0.0841 (-1.72)	22.5400 (2.00)	9.7262 (1.10)	0.2941 (0.33)	0.6132 (1.89)	-0.3288 (-1.05)
	VWVS	0.0817 (12.80)	-0.0337 (-0.76)	34.6118 (2.80)	1.9637 (0.28)	-0.1052 (-0.10)	0.4785 (1.55)	0.0734 (0.24)
1-week	HOVS	0.0801 (5.19)	-0.1039 (-1.18)	3.6578 (0.74)	8.8157 (0.85)	-1.4131 (-0.88)	0.6153 (0.78)	-0.0473 (-0.06)
	HVVS	0.0792 (5.70)	0.0144 (0.17)	1.5367 (0.30)	-4.3598 (-0.39)	-1.5163 (-1.04)	0.6658 (1.08)	0.2458 (0.35)
	OWVS	0.1002 (9.20)	-0.0456 (-0.85)	0.8358 (0.22)	8.8827 (1.24)	-0.9262 (-0.91)	0.2874 (0.55)	-0.3889 (-0.71)
	VWVS	0.0877 (7.65)	0.0039 (0.07)	3.7157 (0.90)	-1.3227 (-0.20)	-1.3952 (-1.25)	0.1616 (0.33)	-0.1090 (-0.19)
2-week	HOVS	0.0942 (5.10)	-0.1038 (-1.10)	1.1501 (0.38)	5.7366 (0.52)	1.0661 (0.67)	0.0180 (0.02)	-0.8511 (-0.91)
	HVVS	0.0997 (5.38)	-0.0319 (-0.45)	0.7519 (0.24)	-2.1501 (-0.23)	3.4661 (1.85)	0.5047 (0.62)	-0.8009 (-0.86)
	OWVS	0.1106 (8.48)	-0.0551 (-1.06)	-0.9067 (-0.49)	19.6758 (2.93)	-0.1656 (-0.20)	-0.0895 (-0.16)	-0.9153 (-1.36)
	VWVS	0.1006 (7.51)	0.0049 (0.08)	0.5416 (0.21)	8.7869 (1.20)	-0.2144 (-0.25)	-0.1645 (0.28)	-0.7031 (-1.04)
1-month	HOVS	0.0799 (2.99)	0.0559 (0.73)	4.3508 (2.06)	-3.7145 (-0.38)	-1.2785 (-0.57)	0.0167 (0.01)	-1.1243 (-0.81)
	HVVS	0.0805 (2.89)	0.1105 (1.29)	3.0536 (1.28)	3.6876 (0.35)	-1.0845 (-0.55)	-0.1503 (-0.11)	-0.4024 (-0.31)
	OWVS	0.1139 (7.10)	0.0096 (0.16)	2.1438 (1.73)	-4.5754 (-0.70)	-0.9842 (-0.86)	0.2175 (0.36)	-1.6634 (-2.09)
	VWVS	0.0868 (4.46)	(0.0257 (0.45)	1.9501 (1.33)	-0.5307 (-0.08)	-0.5253 (-0.47)	0.1283 (0.19)	-0.3733 (-0.39)

Table 5. Controlling for Implied and Realized Variance

This table presents parameter estimates from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, implied variance, realized variance and macroeconomic variables. Volatility spread measures, implied variance, realized variance and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day, 1-week, 2-week or 1-month ahead excess value-weighted market returns, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length.

	Constant	HOVS	HVVS	OWVS	VWVS	VIXSQ	REAL VAR	RET	DEF	TERM	RREL	DP
1-day	-0.0032	-0.0143				6.0197	2.9340	-0.0273	-4.9007	-0.0540	0.1109	0.1989
	(-2.39)	(-3.26)				(1.83)	(1.02)	(-1.44)	(-1.54)	(-0.13)	(1.93)	(3.09)
	-0.0032		-0.0141			5.7711	2.8818	-0.0275	-4.7889	-0.0394	0.1019	0.1977
	(-2.32)		(-3.15)			(1.76)	(1.01)	(-1.46)	(-1.52)	(-0.09)	(1.77)	(3.04)
	-0.0011			-0.0324		6.0830	2.9513	-0.0283	-4.6772	-0.0292	0.1145	0.1842
			(-3.96)		(1.91)	(1.03)	(-1.52)	(-1.49)	(-0.07)	(1.97)	(2.85)	
					-0.0276	6.4011	2.7367	-0.0284	-4.7615	-0.0155	0.1082	0.1967
					(-3.64)	(1.96)	(0.95)	(-1.51)	(-1.52)	(-0.04)	(1.86)	(3.01)
1-week	-0.0168	-0.0621				19.3279	-25.1261	-0.1670	-2.5898	1.2954	0.9116	0.9640
	(-2.74)	(-3.10)				(5.35)	(-4.96)	(-3.60)	(-0.42)	(1.31)	(3.43)	(3.18)
	-0.0177		-0.0471			18.9672	-24.9288	-0.1617	-2.2829	1.4199	0.9032	0.9679
	(-2.81)		(-2.45)			(5.25)	(-4.80)	(-3.51)	(-0.38)	(1.42)	(3.38)	(3.17)
	-0.0096			-0.1235		19.5989	-25.5817	-0.1662	-1.4175	1.2386	0.9274	0.9232
			(-3.22)		(5.61)	(-5.10)	(-3.52)	(-0.23)	(1.26)	(3.48)	(3.03)	
					-0.0943	19.5809	-25.3451	-0.1617	-2.1396	1.3215	0.8969	0.9533
					(-3.08)	(5.48)	(-4.93)	(-3.43)	(-0.35)	(1.33)	(3.37)	(3.11)
2-week	-0.0290	-0.0307				16.6907	-23.9814	-0.0928	2.7343	1.3131	1.5383	1.4412
	(-3.45)	(-0.84)				(6.61)	(-6.97)	(-1.69)	(0.41)	(1.33)	(3.44)	(3.14)
	-0.0240		-0.0745			16.6969	-24.1442	-0.0979	4.1814	1.4611	1.5606	1.3841
	(-2.73)		(-2.29)			(6.87)	(-7.12)	(-1.77)	(0.65)	(1.50)	(3.54)	(3.04)
	-0.0181			-0.1307		17.0161	-24.5474	-0.0984	4.4213	1.1808	1.5718	1.3644
			(-1.88)		(7.11)	(-7.25)	(-1.77)	(0.63)	(1.21)	(3.56)	(2.99)	
					-0.1048	16.8957	-24.2063	-0.0930	3.7631	1.2758	1.5515	1.3908
					(-1.68)	(6.96)	(-7.18)	(-1.66)	(0.56)	(1.32)	(3.53)	(3.03)
1-month	-0.0443	0.0505				11.8832	-20.1011	-0.0455	16.7125	1.8514	2.5883	2.1040
	(-2.36)	(0.62)				(6.57)	(-5.90)	(-0.47)	(1.63)	(1.54)	(3.52)	(2.40)
	-0.0435		0.0379			11.9535	-20.1508	-0.0488	16.2294	1.9126	2.5666	2.0866
	(-2.16)		(0.57)			(6.31)	(-5.80)	(-0.51)	(1.60)	(1.63)	(3.52)	(2.31)
	-0.0342			-0.0497		12.3470	-20.5592	-0.0487	17.2870	2.0127	2.6437	1.9580
			(-0.34)		(6.65)	(-5.81)	(-0.52)	(1.68)	(1.67)	(3.72)	(2.10)	
					-0.0183	12.2138	-20.4299	-0.0479	16.5309	1.9435	2.6031	2.0382
					(-0.14)	(6.60)	(-5.88)	(-0.50)	(1.63)	(1.65)	(3.62)	(2.25)

Table 6. Controlling for Variance Risk Premium

This table presents parameter estimates from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, volatility risk premium and macroeconomic variables. Volatility spread measures, volatility risk premium and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day, 1-week, 2-week or 1-month ahead excess value-weighted market returns, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length.

	Constant	HOVS	HVVS	OWVS	VWVS	VRP	RET	DEF	TERM	RREL	DP
1-day	-0.0009	-0.0120				-0.1355	-0.0372	-4.2303	-0.0889	0.0301	0.1292
	(-0.83)	(-2.65)				(-0.05)	(-1.94)	(-1.27)	(-0.20)	(0.56)	(2.18)
	-0.0009		-0.0127			-0.1371	-0.0372	-4.1366	-0.0754	0.0252	0.1303
	(-0.75)		(-2.91)			(-0.05)	(-1.94)	(-1.26)	(-0.17)	(0.47)	(2.19)
	0.0010			-0.0289		-0.0958	-0.0383	-4.0138	-0.0677	0.0334	0.1157
(0.77)			(-3.58)		(-0.04)	(-2.01)	(-1.22)	(-0.15)	(0.61)	(1.95)	
	0.0002				-0.0233	0.0846	-0.0383	-4.0993	-0.0571	0.0266	0.1261
	(0.15)				(-3.15)	(0.03)	(-2.00)	(-1.24)	(-0.13)	(0.49)	(2.11)
1-week	-0.0217	-0.0635				19.7431	-0.1341	-3.7644	1.4407	1.0555	1.1105
	(-3.57)	(-3.13)				(5.49)	(-2.88)	(-0.64)	(1.45)	(3.79)	(3.67)
	-0.0229		-0.0472			19.3799	-0.1276	-3.5039	1.5727	1.0499	1.1183
	(-3.65)		(-2.43)			(5.37)	(-2.73)	(-0.61)	(1.54)	(3.71)	(3.67)
	-0.0148			-0.1234		20.0113	-0.1320	-2.6475	1.3921	1.0744	1.0740
(-2.09)			(-3.16)		(5.74)	(-2.78)	(-0.45)	(1.42)	(3.81)	(3.55)	
	-0.0182				-0.0971	20.0069	-0.1288	-3.2875	1.4654	1.0400	1.0986
	(-2.73)				(-3.04)	(5.60)	(-2.71)	(-0.57)	(1.46)	(3.71)	(3.61)
2-week	-0.0422	-0.0329				17.0428	-0.0255	0.9758	1.5594	1.8899	1.8545
	(-5.43)	(-0.89)				(6.46)	(-0.49)	(0.15)	(1.59)	(3.96)	(4.22)
	-0.0379		-0.0715			17.0328	-0.0283	2.2964	1.7183	1.9174	1.8102
	(-4.78)		(-2.18)			(6.55)	(-0.54)	(0.37)	(1.74)	(4.00)	(4.15)
	-0.0329			-0.1208		17.3239	-0.0277	2.4405	1.4600	1.9302	1.7986
(-3.72)			(-1.76)		(6.78)	(-0.52)	(0.37)	(1.50)	(4.07)	(4.17)	
	-0.0348				-0.1055	17.2368	-0.0251	1.9891	1.5293	1.9035	1.8060
	(-4.05)				(-1.72)	(6.67)	(-0.47)	(0.31)	(1.57)	(4.03)	(4.14)
1-month	-0.0774	0.0513				11.9496	0.0619	13.4920	3.1432	3.5573	3.2041
	(-4.65)	(0.58)				(7.17)	(0.75)	(1.34)	(2.38)	(5.42)	(4.06)
	-0.0769		0.0432			11.9981	0.0581	12.9897	3.2000	3.5295	3.1881
	(-4.51)		(0.60)			(6.82)	(0.72)	(1.29)	(2.49)	(5.33)	(3.97)
	-0.0666			-0.0553		12.4406	0.0585	14.1629	3.3143	3.6179	3.0464
(-2.80)			(-0.36)		(7.36)	(0.72)	(1.37)	(2.46)	(5.40)	(3.58)	
	-0.0707				-0.0263	12.3162	0.0595	13.3655	3.2430	3.5771	3.1331
	(-3.64)				(-0.19)	(7.21)	(0.73)	(1.33)	(2.50)	(5.47)	(3.83)

Table 7. Earnings Announcements

This table presents results from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. In Panel A, we define a dummy variable equal to one for a given trading day if a firm that is a constituent of the S&P 500 index makes an earnings announcement. In Panel B, we define a dummy variable equal to one for a given trading day if a firm that is a constituent of the S&P 500 index makes the first earnings announcement in a particular industry-month. VSPLUS is equal to the value of the volatility spread if the dummy variable is equal to one and 0 otherwise. VSMINUS is equal to the value of the volatility spread if the dummy variable is equal to zero and 0 otherwise. Volatility spread measures, implied variance and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day ahead excess value-weighted market return, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length. The final column presents p-values associated with the F-test for the equality of the coefficients of VSPLUS and VSMINUS.

Panel A. All announcements

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0034 (-2.57)	-0.0158 (-3.67)	0.0002 (0.02)	8.0770 (3.04)	-0.0252 (-1.36)	-4.8176 (-1.52)	-0.0500 (-0.12)	0.1216 (2.17)	0.2084 (3.28)	0.0013
HVVS	-0.0033 (-2.49)	-0.0157 (-3.53)	-0.0013 (-0.12)	7.7746 (2.89)	-0.0253 (-1.37)	-4.6919 (-1.49)	-0.0425 (-0.10)	0.1118 (1.99)	0.2079 (3.22)	0.0045
OWVS	-0.0012 (-0.77)	-0.0352 (-4.31)	-0.0193 (-1.54)	8.1428 (3.10)	-0.0263 (-1.44)	-4.5805 (-1.46)	-0.0263 (-0.06)	0.1251 (2.19)	0.1927 (3.01)	0.0105
VWVS	-0.0021 (-1.46)	-0.0299 (-3.93)	-0.0144 (-1.17)	8.3299 (3.09)	-0.0263 (-1.43)	-4.6893 (-1.50)	-0.0160 (-0.04)	0.1176 (2.07)	0.2057 (3.18)	0.0129

Panel B. First announcement in the industry

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0035 (-2.59)	-0.0165 (-3.77)	0.0010 (0.10)	8.1361 (3.06)	-0.0250 (-1.34)	-4.9651 (-1.55)	-0.0310 (-0.07)	0.1211 (2.16)	0.2105 (3.30)	0.0258
HVVS	-0.0033 (-2.49)	-0.0164 (-3.65)	-0.0029 (-0.31)	7.7918 (2.89)	-0.0253 (-1.36)	-5.0608 (-1.58)	-0.0405 (-0.10)	0.1105 (1.97)	0.2094 (3.24)	0.0394
OWVS	-0.0011 (-0.75)	-0.0367 (-4.53)	-0.0171 (-1.46)	8.2008 (3.12)	-0.0263 (-1.43)	-4.7786 (-1.50)	-0.0092 (-0.02)	0.1245 (2.19)	0.1953 (3.04)	0.0332
VWVS	-0.0021 (-1.44)	-0.0310 (-4.08)	-0.0128 (-1.12)	8.3777 (3.10)	-0.0262 (-1.42)	-4.9270 (-1.55)	-0.0084 (-0.02)	0.1166 (2.05)	0.2077 (3.21)	0.0470

Table 8. Cash Flow and Discount Rate News

This table presents results from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. In Panel A, we define a dummy variable equal to one if the daily cash flow news is less than the 25th percentile or greater than the 75th percentile among the observed cash flow news over the sample period. In Panel B, we define a dummy variable equal to one if the daily discount rate news is less than the 25th percentile or greater than the 75th percentile among the observed discount rate news over the sample period. VSPLUS is equal to the value of the volatility spread if the dummy variable is equal to one and 0 otherwise. VSMINUS is equal to the value of the volatility spread if the dummy variable is equal to zero and 0 otherwise. Volatility spread measures, implied variance and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day ahead excess value-weighted market return, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length. The final column presents p-values associated with the F-test for the equality of the coefficients of VSPLUS and VSMINUS.

Panel A. Cash Flow News

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0033 (-2.44)	-0.0211 (-4.05)	-0.0096 (-2.24)	8.3530 (3.20)	-0.0252 (-1.36)	-4.5447 (-1.43)	-0.0766 (-0.18)	0.1132 (2.02)	0.1950 (3.06)	0.0035
HVVS	-0.0033 (-2.44)	-0.0198 (-3.85)	-0.0096 (-2.14)	8.1272 (3.05)	-0.0256 (-1.39)	-4.3415 (-1.38)	-0.0565 (-0.13)	0.1043 (1.87)	0.1977 (3.07)	0.0061
OWVS	-0.0012 (-0.76)	-0.0383 (-4.40)	-0.0284 (-3.46)	8.4201 (3.25)	-0.0262 (-1.43)	-4.2857 (-1.36)	-0.0481 (-0.11)	0.1173 (2.06)	0.1820 (2.83)	0.0082
VWVS	-(0.0020 (-1.38)	-0.0346 (-4.24)	-0.0236 (-3.13)	8.6812 (3.26)	-0.0264 (-1.43)	-4.3629 (-1.39)	-0.0302 (-0.07)	0.1100 (1.94)	0.1943 (3.00)	0.0054

Panel B. Discount Rate News

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0038 (-2.82)	-0.0202 (-3.81)	-0.0094 (-2.38)	8.8399 (3.38)	-0.0254 (-1.37)	-4.5759 (-1.43)	-0.0731 (-0.17)	0.1148 (2.06)	0.2186 (3.42)	0.0045
HVVS	-0.0038 (-2.81)	-0.0210 (-3.94)	-0.0080 (-1.90)	8.8619 (3.29)	-0.0261 (-1.42)	-4.5430 (-1.42)	-0.0745 (-0.17)	0.1018 (1.82)	0.2204 (3.38)	0.0005
OWVS	-0.0017 (-1.13)	-0.0380 (-4.38)	-0.0273 (-3.41)	9.0053 (3.46)	-0.0270 (-1.47)	-4.3242 (-1.36)	-0.0578 (-0.14)	0.1156 (2.04)	0.2057 (3.18)	0.0034
VWVS	-0.0026 (-1.78)	-0.0347 (-4.26)	-0.0223 (-3.01)	9.3354 (3.48)	-0.0274 (-1.48)	-4.4492 (-1.41)	-0.0449 (-0.10)	0.1078 (1.90)	0.2188 (3.35)	0.0012

Table 9. Consumer Sentiment

This table presents results from the time-series predictive regressions of excess returns of the S&P 500 index on volatility spreads, implied variance and macroeconomic variables. In Panel A, we define a dummy variable equal to one if the consumer sentiment index is less than the 10th percentile or greater than the 90th percentile among the observed consumer sentiment values over the sample period. In Panel B, we define a dummy variable equal to one if the consumer sentiment index is less than the 25th percentile or greater than the 75th percentile among the observed consumer sentiment values over the sample period. VSPLUS is equal to the value of the volatility spread if the dummy variable is equal to one and 0 otherwise. VSMINUS is equal to the value of the volatility spread if the dummy variable is equal to zero and 0 otherwise. Volatility spread measures, implied variance and macroeconomic variables are defined in Table 1. In each regression, the dependent variable is the 1-day ahead excess value-weighted market return, where the returns start accruing from the opening of the next trading day. For each regression, the first row gives the intercepts and slope coefficients. The second row presents Newey-West adjusted t-statistics using optimal lag length. The final column presents p-values associated with the F-test for the equality of the coefficients of VSPLUS and VSMINUS.

Panel A. 10th and 90th percentiles

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0035 (-2.61)	-0.0266 (-3.96)	-0.0135 (-3.11)	8.4838 (3.09)	-0.0253 (-1.36)	-4.6331 (-1.44)	-0.0618 (-0.15)	0.1252 (2.29)	0.2101 (3.31)	0.0241
HVVS	-0.0036 (-2.61)	-0.0266 (-4.52)	-0.0120 (-2.64)	8.2497 (2.95)	-0.0256 (-1.38)	-4.6388 (-1.46)	-0.0625 (-0.15)	0.1087 (2.00)	0.2139 (3.30)	0.0036
OWVS	-0.0014 (-0.89)	-0.0422 (-4.54)	-0.0319 (-3.87)	8.5131 (3.12)	-0.0263 (-1.44)	-4.5052 (-1.42)	-0.0439 (-0.10)	0.1244 (2.25)	0.1959 (3.05)	0.0485
VWVS	-0.0023 (-1.57)	-0.0393 (-4.49)	-0.0265 (-3.46)	8.7670 (3.13)	-0.0266 (-1.44)	-4.6105 (-1.46)	-0.0342 (-0.08)	0.1161 (2.11)	0.2103 (3.24)	0.0167

Panel B. 25th and 75th percentiles

	Constant	VSPLUS	VSMINUS	VIXSQ	RET	DEF	TERM	RREL	DP	p-value
HOVS	-0.0034 (-2.57)	-0.0193 (-3.74)	-0.0115 (-2.48)	8.8719 (3.20)	-0.0245 (-1.32)	-4.9119 (-1.54)	-0.0688 (-0.16)	0.1359 (2.40)	0.2003 (3.16)	0.0281
HVVS	-0.0034 (-2.51)	-0.0191 (-3.68)	-0.0100 (-2.17)	8.6964 (3.08)	-0.0250 (-1.35)	-4.9597 (-1.56)	-0.0625 (-0.15)	0.1243 (2.20)	0.1978 (3.08)	0.0305
OWVS	-0.0013 (-0.86)	-0.0373 (-4.34)	-0.0296 (-3.54)	9.0193 (3.25)	-0.0254 (-1.38)	-4.7063 (-1.49)	-0.0455 (-0.11)	0.1395 (2.43)	0.1854 (2.90)	0.0255
VWVS	-0.0022 (-1.51)	-0.0330 (-4.11)	-0.0240 (-3.11)	9.2907 (3.26)	-0.0256 (-1.39)	-4.8672 (-1.54)	-0.0337 (-0.08)	0.1316 (2.29)	0.1963 (3.04)	0.0462