Forecasting Stock Index Returns with Aggregate Stock Option Information

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Abstract

This study examines whether predictors that integrate option price information or volume information of individual stock options can effectively forecast stock index returns over various horizons (monthly, quarterly, and semi-annually). We compare their predictive performance with several conventional forecasting predictors from the stock market and macroeconomic perspectives. The empirical results demonstrate that the aggregate volatility spread possesses significant predictive power both in-sample and out-of-sample. Using the encompassing test, we find that the informational content of the volatility spread does not overlap with that of other forecasting predictors. When combined with the aggregate short interest predictor through a combination forecasting approach, it further enhances both statistical and economic significance out-of-sample, and the performance of the combination forecast surpasses all individual predictors. Additionally, we employ a vector autoregressive model to further analyze the source of information embedded in the option market predictors. The results indicate that this information primarily reflects future cash flow news and provides unique insights beyond those covered by conventional predictors.

Keywords: Stock index return predictability; Option price information; Aggregate volatility spread; Combination forecast; Encompassing test

1. Introduction

A large body of literature examines how trading activity in the option market conveys information about the future prices of the underlying stocks. Because the option market exhibits high leverage, good liquidity, and relatively low short-selling costs, informed traders may reflect future information about the underlying stocks in option prices. This is particularly evident ahead of specific corporate events, when active option trading anticipates news disclosures (e.g., Cao, Chen, and Griffin, 2005; Atilgan, 2014; Augustin, Brenner, and Subrahmanyam, 2015; Weinbaum et al., 2021). Since Easley, O'Hara, and Srinivas (1998) used a theoretical model to investigate whether informed trading arises in the option market, numerous subsequent studies have explored the ability of option trading to predict future stock returns. Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2012) use the ratio of option to spot trading volume to predict cross-sectional stock returns, while Pan and Poteshman (2006) and Ge, Lin, and Pearson (2016) employ directional option trading volume to forecast future spot returns. Beyond trading volume, some studies rely on the implied volatility extracted from option prices to predict underlying returns (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Xing, Zhang, and Zhao, 2010; An et al., 2014). By pairing call and put options on the same underlying stock and maturity, one can derive an implied volatility spread that may reflect information about the underlying stocks.

To forecast overall market returns, many finance studies use time-series regressions to test the predictive power of a single predictor. Koijen and Van Nieuwerburgh (2011) and Rapach and Zhou (2013) survey a range of such predictors and models. They note that, beyond conventional stock market predictors, variables extracted from derivatives markets (e.g., options or futures) also exhibit statistically significant forecasting power.

Unlike prior research that applies index-level options to forecast aggregate market returns (Bollerslev, Tauchen, and Zhou, 2009; Bollerslev, Todorov, and Xu, 2015; Martin, 2016; Chen and Liu, 2020; Chordia et al., 2021), this paper takes a cross-sectional approach using individual-stock option data aggregated into market-level predictors. We construct two categories of market-wide measures: first, implied volatility spreads based on pairing call and put options on the same underlying stock, weighted by open interest to obtain a daily cross-sectional average (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Xing, Zhang, and Zhao, 2010). Second, predictors built from option trading volume and open interest (Billingsley and Chance, 1988; Dennis and Mayhew, 2002; Cao, Chen, and Griffin, 2005; Pan and Poteshman, 2006; Blau, Nguyen, and Whitby, 2014). We follow Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2012) to calculate an equally weighted average put–call open interest ratio as one of our option predictors.

After constructing each option-based predictor, we conduct several empirical analyses. First, we evaluate both in-sample and out-of-sample forecasts for short, medium, and long horizons—monthly, quarterly, and semiannual data frequencies, respectively—using volatility spread (VS), volatility skew (SKEW), the put–call open interest ratio (PC), and the 14 predictors proposed by Welch and Goyal (2008): DP, DY, EP, DE, SVAR, BM, NTIS, TBL, LTY, LTR, TMS, DFY, DFR, and INFL. Our sample spans January 1996 through December 2021. In-sample results indicate that VS and three of the Welch–Goyal predictors (DP, DY, LTY) significantly predict excess market returns at monthly, quarterly, and semiannual horizons. Comparing in-sample R^2 values, VS is superior at monthly and quarterly horizons, while DP and DY slightly outperform at the semiannual horizon. Out-of-sample forecasts begin in January 2003, revealing that VS is the only predictor yielding significant out-of-sample R^2 at monthly or quarterly horizons, whereas the others generally fail to outperform the historical mean.

Next, we assess economic significance via the realized utility gain of Campbell and Thompson (2008), assuming investors have mean-variance preferences and allocate between a risky asset and a risk-free asset. We compare the utility gains from forecasts based on our option-based predictors with those from the historical mean. Most predictors fail to produce an annualized utility gain above 2% when compared to the historical benchmark. In contrast, VS achieves significant gains at the monthly, quarterly, and semiannual horizons, while SKEW and PC do not yield robust economic significance.

We also compare our option-based predictors to other recently developed predictors (e.g., Rapach, Ringgenberg, and Zhou, 2016; Cao, Simin, and Xiao, 2020; Han and Li, 2021; Dong et al., 2022). Overall, none of the option-based predictors generate a significant out-of-sample R^2, except for the implied volatility spread proposed by Cao, Simin, and Xiao (2020), which uses volatility surface data from OptionMetrics to predict quarterly excess returns. In terms of economic significance, that volatility spread outperforms the historical mean at monthly, quarterly, and semiannual horizons. Moreover, the aggregate short interest predictor (SII) of Rapach, Ringgenberg, and Zhou (2016) exhibits outstanding performance in both statistical and economic terms.

Beyond assessing statistical and economic significance, we examine whether the information content embedded in option-based predictors is already captured by conventional predictors. Following Harvey, Leybourne, and Newbold (1998), we perform an encompassing test to see if option market variables contribute distinct information relative to standard stock market predictors or if they merely replicate existing information. Specifically, we test predictors derived from our own option-based measures, Welch and Goyal (2008), the SII predictor of Rapach, Ringgenberg, and Zhou (2016), and the option market variables constructed by Han and Li (2021) as well as Cao, Simin, and Xiao (2020). Only the SII predictor provides information that is not contained in the implied volatility spread, and no predictor fully encompasses the information in the implied volatility spread. Thus, option-based volatility spreads and SII do not overlap in their predictive content; combining these two predictors broadens the information set and improves out-of-sample forecasts. We further investigate such a combination by applying the combining forecasts approach of Bates and Granger (1969), using average combination (AC), median combination (MC), truncated mean (TC), and variance-weighted combination (WC) to combine VS and SII. Empirical results confirm that combining these predictors successfully expands the information set, enhancing both statistical and economic significance out of sample.

Finally, we investigate why option market predictors predict future market returns. To identify the source of their predictive content, we adopt the vector autoregression model (Campbell, 1991; Campbell and Ammer, 1993) to decompose stock returns into expected returns, cash-flow news, and discount-rate news, and then regress each component on our option market predictors. The implied volatility spread incorporates information distinct from the 14 predictors in Welch and Goyal (2008), and it appears particularly informative for future overall cash-flow news.

This study contributes to the existing literature in several ways. First, to the best of our knowledge, we are the first to jointly incorporate option price and volume information from individual-stock options to forecast the stock market return. Building on Welch and Goyal (2008), who use stock fundamentals, interest rates, and macroeconomic variables to predict market returns, subsequent research has identified additional effective predictors. For instance, Li, Ng, and Swaminathan (2013) aggregate implied cost of capital from individual firms to forecast market excess returns over horizons from one month to four years, while Rapach, Ringgenberg, and Zhou (2016) follow a similar aggregation concept for short interest, revealing that aggregated short interests effectively forecast market returns by reflecting informed traders' views on future cash flows. Outside of stock-based predictors, Han and Li (2021) adopt the implied volatility spread of individual stock options for market return prediction. Like them, we construct a market-wide volatility spread but differ in a few respects. While they use at-the-money options for pairing, Xing, Zhang, and Zhao (2010) document that out-of-the-money puts also reflect negative information. Hence, we use all available option strikes to capture potentially different levels of news embedded across the option chain. Furthermore, unlike Han and Li (2021), who focus solely on price data, we incorporate both price and volume metrics to strengthen our analysis of option market trading behavior.

Second, we aim to address the difficulty noted in Welch and Goyal (2008), where strong in-sample performance rarely translates into improved out-of-sample forecasts or substantial realized utility gains. To this end, we combine multiple predictors following Bates and Granger (1969). This approach is analogous to diversification in asset management, where mixing multiple predictors may increase the informational set and reduce forecast uncertainty. Our model includes not only the 14 market and macroeconomic predictors of Welch and Goyal (2008) but also our two option-based predictors and the aggregate short interest predictor of Rapach, Ringgenberg, and Zhou (2016). We further apply encompassing tests to examine whether the option-based measures add unique information beyond conventional predictors. Ultimately, we seek to determine if these option-based predictors enhance both out-of-sample forecast accuracy and economic utility gains.

The remainder of this paper is organized as follows. Section 2 introduces the stock market predictors and data sources. Section 3 discusses various time-series forecasting models, evaluation measures, and methods for identifying the source of predictive information. Section 4 presents in-sample and out-of-sample forecasting results, encompassing tests, and analyses of where the predictive information originates. Finally, Section5 concludes the study.

2. Data description and predictors

2.1 Data

This study employs data from multiple sources. The option market price and volume measures are constructed using the OptionMetrics database, covering the period from January 1996 to December 2020. The dataset includes comprehensive U.S. option market trading information, such as underlying stocks, call/put labels, strike prices, expiration dates, daily closing bid/ask quotes, open interest, and trading volume. Daily implied volatilities are also obtained from OptionMetrics, which computes implied volatilities for various strike prices and maturities using a binomial tree model. To mitigate the influence of outliers, we apply the following selection rules: the option's ask price must exceed zero and be higher than its bid price; the midpoint of the option's bid and ask quotes must exceed 0.125; the option's daily trading volume must be non-missing, and its open interest must be greater than zero; and the option's time-to-maturity must range from 10 to 365 days.

Data on stock prices, returns, shares outstanding, and trading volume for individual firms are obtained from the CRSP database. On average, the underlying stocks of listed options comprise approximately one-third of the firms in CRSP. Following Welch and Goyal (2008), we collect market-level data from the authors' website, which provides detailed information on data construction.[1] Excess market returns are computed by taking the natural logarithm of CRSP's value-weighted market returns, subtracting the risk-free rate, and adjusting to an annualized basis according to the forecast horizon. The risk-free rate is proxied by the one-month Treasury bill rate.

2.2 Predictors

The key predictive variables in this study are constructed from option market trading data, incorporating both price- and volume-related metrics.

2.2.1 Put-call implied volatility spread

Numerous empirical studies suggest that informed traders may prefer the options market, where short-selling constraints and leverage opportunities exist (e.g., Bollen and Whaley, 2004). According to their demand-based option pricing framework, if informed traders use both calls and puts to reflect private information, their demand

[1] For the most up-to-date forecasting predictors and additional materials from Professor Amit Goyal, please visit: https://sites.google.com/view/agoyal145

pressure affects call and put prices differently, leading to asymmetric implied volatilities. Building on earlier work (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Xing, Zhang, and Zhao, 2010; An et al., 2014), we pair calls and puts on the same underlying stock and maturity to measure the difference in implied volatilities and capture the information content of options.

Following these studies, we construct a volatility spread measure by pairing call and put contracts with the same underlying stock and time to maturity, then weighting each pair by the corresponding average open interest:

$$VS_{i,t} = \sum_{j=1}^{N_{i,t}} w_{i,j,t}(IV_{i,j,t}^{Call} - IV_{i,j,t}^{Put}), \tag{1}$$

where $N_{i,t}$ is the number of call-put pairs for stock *i* on day *t*,[2] $w_{i,j,t}$ denotes the ratio of the pair's open interest to total open interest, and $IV_{i,j,t}^{Call}$ and $IV_{i,j,t}^{Put}$ are the implied volatilities of the call and put, respectively. A higher call-implied volatility relative to puts indicates that call options are more expensive, presumably reflecting informed traders' demand. Accordingly, a positive (negative) volatility spread is expected to signal favorable (unfavorable) future information.

We also compute a market-level volatility spread by averaging $VS_{i,t}$ across all firms on day *t*:

$$VS_t = \frac{1}{N_t}\sum_{i=1}^{N_t} VS_{i,t}, \tag{2}$$

where N_t is the total number of firms with available option data on day *t*. To reduce

[2] Unlike the volatility skew measures employed by Jones, Mo, and Wang (2018), Cao, Simin, and Xiao (2020), and Han and Li (2021), which rely on a single pair of at-the-money calls and puts based on their higher liquidity and more efficient price discovery, this study incorporates all options that satisfy the screening criteria. Xing, Zhang, and Zhao (2010) show that informed traders factor negative news into out-of-the-money puts, implying that options at different moneyness levels can reflect varying degrees of good or bad news. Accordingly, including all eligible contracts can capture a broader set of information in the predictor.

the impact of extreme values, we winsorize observations below the 1st percentile and above the 99th percentile. In line with Rapach, Ringgenberg, and Zhou (2016), we adopt an equal-weighted index rather than a value-weighted index, as smaller firms tend to convey stronger aggregate economic signals.[3] We then take the moving average of the last five trading days in each month as the monthly market volatility spread predictor.

To compare our newly proposed predictor with measures used in previous literature, we adopt the volatility skew (SKEW) approach of Xing, Zhang, and Zhao (2010), which computes the implied volatility deviation of out-of-the-money puts and at-the-money calls, averaged across all underlying stocks. We also construct the volatility spread surface (VVS) measure following Cao, Simin, and Xiao (2020), using OptionMetrics' volatility surface data, and the standardized volatility spread (SVS) following Han and Li (2021) by employing standardized options data from OptionMetrics.

2.2.2 Put-to-call open interest ratio

Since Easley, O'Hara, and Srinivas (1998) introduced a theoretical model and provided empirical evidence that informed traders may operate in the options market, many studies have examined whether option trading volume predicts future stock returns (Billingsley and Chance, 1988; Dennis and Mayhew, 2002; Cao, Chen, and Griffin, 2005; Pan and Poteshman, 2006; Blau, Nguyen, and Whitby, 2014). They generally find that put and call trading volume or open interest can forecast both cross-sectional and

[3] This study also tests a value-weighted volatility skew predictor (VS-VW) and a volatility skew predictor constructed from all option contracts of S&P 500 constituents (VS-SPX). Unreported empirical results indicate that both measures exhibit weaker predictive power than the equal-weighted volatility skew predictor (VS).

aggregate market returns. Dennis and Mayhew (2002) document that trading-volume-based put-call ratios may contain more noise than open-interest-based ratios, whereas Jena, Tiwari, and Mitra (2019) show that open-interest-based ratios can better predict returns on the Nifty Index. Accordingly, we use the equal-weighted average of the open-interest put-call ratio (PC) as our predictive variable. Further following Dong et al. (2022), we also form zero-cost portfolios based on the VS, SKEW, and PC measures—denoted AVS, ASKEW, and APC—to investigate their predictability.

2.2.3 Other Stock Market Predictors

Beyond the option-based predictors, we incorporate the aggregate short interest (SII) introduced by Rapach, Ringgenberg, and Zhou (2016) and the 14 macroeconomic and market-based predictors proposed by Welch and Goyal (2008): the log dividend–price ratio (DP), log dividend yield (DY), log earnings–price ratio (EP), log dividend–payout ratio (DE), stock variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), and inflation rate (INFL). Specifically, these variables are computed using data on S&P 500 dividends, earnings, and returns, along with measures of Treasury rates, corporate bond yields, and consumer prices. Because the inflation rate is published with a lag, we employ the previous month's inflation rate as the predictor in our model.

3. Methodology

3.1 Predictive regression

After constructing the option- and stock-based predictors, we incorporate each predictor into a forecasting regression to generate expected market returns. The following univariate linear model is commonly employed to predict excess stock market returns:

$$r_{i,t+1} = a_i + b_i x_{it} + \varepsilon_{t+1}, \tag{3}$$

where $r_{i,t+1}$ is the excess market return, x_{it} is the i-th predictive variable, and ε_{t+1} is the regression residual. We run separate regressions for each predictor to obtain one-step-ahead forecasts of excess returns. The in-sample forecasting power is gauged by the significance of the slope coefficient and the R^2. Stronger evidence of predictability arises when the slope coefficient is significantly different from zero or when the R^2 is materially greater than zero.

For out-of-sample forecasting, we adopt the recursive estimation approach of Welch and Goyal (2008). To generate $\hat{r}_{i,m+1}$, we estimate the linear model using data from time 0 through *m* and obtain:

$$\hat{r}_{i,m+1} = \hat{a}_{i,m} + \hat{b}_{i,m} x_{im}, \tag{4}$$

where $\hat{a}_{i,m}$ and $\hat{b}_{i,m}$ are the intercept and slope estimated from the in-sample data ending at time mmm. To generate $\hat{r}_{i,m+2}$, we expand the estimation window to time *m+1*, and so forth.

3.2 Combination forecast

Using equation (4), we obtain out-of-sample forecasts $\hat{r}_{i,t+1}$ for each predictor *i*. Because single predictors often provide limited information and may perform poorly, one alternative is a multivariate regression that includes multiple predictors. However, high-dimensional issues such as collinearity can undermine performance. Welch and

Goyal (2008) show that including too many predictors may actually deteriorate out-of-sample results. Hence, following Bates and Granger (1969), we employ a combination forecast approach, which merges forecasts from multiple predictors to form an out-of-sample forecast of excess returns. Empirical evidence indicates that such combination methods often outperform individual predictors. Specifically, we first estimate univariate regressions for each of the *N* predictors as in equation (3), then combine their forecasts as follows:

$$\hat{r}_{c,t+1} = \sum_{i=1}^{N} \omega_{i,t} \hat{r}_{i,t+1}, \tag{5}$$

where $\{\omega_{i,t}\}_{i=1}^{N}$ are the combination weights.

We consider four weighting schemes. First, the simple average method (AC) sets $\omega_{i,t} = 1/N$. Second, the median combination (MC) selects the median among the *N* individual forecasts. Third, to mitigate extreme values, we implement a trimmed mean (TC), which discards the largest and smallest forecasts before computing the equal-weighted mean. Fourth, the weighted combination (WC) follows Stock and Watson (2004), assigning lower weights to predictors with higher residual variance. We employ these four methods to predict excess returns and compare their out-of-sample performance.

3.3 Evaluating Predictive Performance

The following subsections detail the commonly used methods in the existing literature for evaluating predictive accuracy and comparing the informational content of different predictors.

3.3.1 Statistical significance

To assess out-of-sample forecasting performance, we follow Campbell and Thompson (2008) by employing the out-of-sample R^2 measure, defined as:

$$R_{OS}^2 = 1 - \frac{\sum_{j=q_0+1}^{T-1}(r_{j+1}-\hat{r}_{j+1})^2}{\sum_{j=q_0+1}^{T-1}(r_{j+1}-\bar{r}_{j+1})^2}, \tag{6}$$

where q_0 is the starting point for out-of-sample forecasts, r_{j+1} is the realized excess return at time $j+1$, $\hat{r}_{j+1}$ is the predicted excess return from the model, and $\bar{r}_{j+1}$ is the out-of-sample forecast based on the historical mean of realized excess returns from the first observation up to time *j*. The statistic R_{OS}^2 measures the mean-squared prediction error (MSPE) of the forecasting regression relative to that of the historical average. A positive R_{OS}^2 indicates that $\hat{r}_{t+1}$ performs better than $\bar{r}_{t+1}$.

To further verify whether a predictor's MSPE is lower than that of the historical average, we adopt the MSPE-adjusted statistic proposed by Clark and West (2007). The null hypothesis is $H_0: R_{OS}^2 \leq 0$ against the alternative $H_1: R_{OS}^2 > 0$. The adjusted statistic is given by:

$$e_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2], \tag{7}$$

We then regress this statistic on a constant term and use the *t*-value of the coefficient to determine whether it significantly differs from zero.

3.3.2 Economic significance

Because the above measures focus solely on statistical significance without accounting for risk, Campbell and Thompson (2008) propose an economically motivated performance measure. Suppose investors follow a mean-variance utility model and allocate their wealth between a risky asset and a risk-free asset. At each time *t*, the optimal weight ω_t in the risky asset is chosen to maximize expected utility:

$$\max_{\omega_t} E_t[U(W_{t+1})] = \omega_t(\hat{r}_{i,t+1} + r_{f,t+1}) - \frac{\gamma}{2}\omega_t^2\hat{\sigma}_{i,t+1}, \tag{8}$$

where ω_t is the weight on the risky asset,[4] $1-\omega_t$ is the weight on the risk-free asset, $\hat{r}_{i,t+1}$ is the forecasted excess return from model i, $r_{f,t+1}$ is the risk-free rate,[5] γ is the investor's risk aversion coefficient,[6] and $\hat{\sigma}_{i,t+1}$ is the estimated variance at time *t*.

From this optimization, the optimal portfolio weight is:

$$\omega_t^* = \frac{1}{\gamma}\frac{\hat{r}_{i,t+1}}{\hat{\sigma}_{i,t+1}}, \tag{9}$$

The realized utility from model *i* can be written as $\hat{v}_i = \hat{\mu}_i - (1/2)\gamma\hat{\sigma}_i^2$, where $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the sample mean and variance of the portfolio constructed using model *i*. The realized utility from the historical average benchmark is $\hat{v}_0 = \hat{\mu}_0 - (1/2)\gamma\hat{\sigma}_0^2$. The difference $\hat{v}_i - \hat{v}_0$ reflects the utility gain to the investor when using model *i* rather than the historical average. Following Rapach, Strauss, and Zhou (2010), we classify an out-of-sample result as having economic significance if the realized utility gain exceeds 2%.

3.3.3 Encompassing test

To compare the informational content of option-based predictors with that of other equity market predictors, we employ the encompassing test proposed by Harvey, Leybourne, and Newbold (1998). The null hypothesis states that the forecasts from the

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[4] Following Campbell and Thompson (2008), this study restricts weights to the 0%–150% range. Specifically, if the estimated optimal weight exceeds 150%, we set it to 150%; if it falls below 0%, we set it to 0%.

[5] This study employs the U.S. Treasury bill rate as a proxy for the risk-free rate.

[6] Following Rapach, Strauss, and Zhou (2010), we set the risk aversion coefficient to 3.

option-based predictor (Model 1) encompass the information contained in other predictors (Model 2). The alternative hypothesis is that the forecasts from Model 2 already incorporate the option-based information, implying no additional information is offered by Model 1. We first compute:

$$e_{t+1} = (\hat{u}_{1,t+1} - \hat{u}_{2,t+1})\hat{u}_{1,t+1}, \tag{10}$$

where $\hat{u}_{1,t+1} = r_{t+1} - \hat{r}_{1,t+1}$ and $\hat{u}_{2,t+1} = r_{t+1} - \hat{r}_{2,t+1}$ are the forecast errors from Models 1 and 2, respectively. We then compute the following statistic:

$$HLN = \frac{T-q_0-2}{T-q_0-1}\left[\hat{V}(\bar{e})^{-1/2}\right]\bar{e}, \tag{11}$$

where $\bar{e} = \frac{1}{T-1-q_0}\sum_{t=q_0}^{T-1} e_{t+1}$ and $\hat{V}(\bar{e}) = \frac{1}{(T-q_0-1)^2}\sum_{t=q_0}^{T-1}(e_{t+1} - \bar{e})^2$. The HLN statistic follows a *t*-distribution with $T - q_0 - 2$ degrees of freedom, and we use it to determine whether Model 1's forecasts fully encompass the information in Model 2.

4. Empirical results

4.1 Descriptive statistics of the predictors

Table 1 presents the descriptive statistics of the 14 predictors from Welch and Goyal (2008), the call–put implied volatility spread (VS), the skew (SKEW), and the put–call open interest ratio (PC) over the sample period from January 1996 to December 2021. VS is the equally weighted average difference in implied volatilities between call options and their corresponding put options for individual stocks. SKEW is the equally weighted average difference in implied volatilities between out-of-the-money put options and at-the-money call options. PC is the equally weighted average of each stock's put-to-call open interest ratio. As shown in Table 1, the volatility of most predictors is relatively small and their means are close to zero, with the exception of the put–call ratio.

[Insert Table 1 about here]

Table 2 reports the Pearson correlation coefficients among the 14 predictors of Welch and Goyal (2008), the call–put implied volatility spread, the call–put implied volatility skew, and the put–call ratio. The implied volatility spread is positively correlated with PC, EP, NTIS, DFR, and INFL, but negatively correlated with the other predictors. Notably, because DP and DY are both calculated using the S&P 500 Index, their correlation coefficient is very close to 1.

[Insert Table 2 about here]

Figure 1 plots the time series of the S&P 500 excess monthly returns and the call–put implied volatility spread. The shaded gray areas represent recessions as defined by the National Bureau of Economic Research. The figure shows that both market returns and the implied volatility spread exhibit noticeably higher volatility during the three recession periods.

[Insert Figure 1 about here]

4.2 In-sample forecasting results

Table 3 reports the results of univariate in-sample forecasting regressions. The dependent variable is the average monthly excess return of the S&P 500 over one-month, one-quarter, and one-half-year forecasting horizons, covering January 1996 to December 2021. The results indicate that VS, DP, DY, and LTY significantly predict the S&P 500 excess return at the monthly, quarterly, and semiannual frequencies.

Comparing the R^2 values of these predictors shows that VS performs best for the monthly and quarterly horizons, while DP and DY slightly outperform VS for the semiannual horizon.

[Insert Table 3 about here]

4.3 Out-of-sample forecasting results

Table 4 summarizes the out-of-sample forecasting performance of the predictors at the monthly, quarterly, and semiannual horizons. The sample period spans January 1996 to December 2021, with out-of-sample forecasts beginning in January 2003. We measure out-of-sample performance using the out-of-sample R^2 statistic and employ the Clark and West (2007) test to evaluate whether each predictor's out-of-sample R^2 is significantly greater than zero. An out-of-sample R^2 significantly above zero indicates that the predictive model outperforms the historical average benchmark. Except for VS, most predictors do not achieve a significantly positive out-of-sample R^2 at the monthly or quarterly horizons. VS, however, obtains an out-of-sample R^2 of nearly 2% for the monthly and semiannual horizons and as high as 11.34% for the quarterly horizon.

[Insert Table 4 about here]

4.4 Economic significance

The above methods focus on statistical significance, considering returns without incorporating risk. Therefore, we further examine economic significance by adopting the concept of annualized realized utility gains, measured as the utility difference between each predictor's forecasts and those based on the historical average.[7]

[Insert Table 5 about here]

Table 5 shows that most independent predictors fail to deliver annualized utility gains of 2% or more relative to the historical average, whereas VS consistently yields significant annualized utility gains at the monthly, quarterly, and semiannual horizons. By contrast, the alternative option-based predictors SKEW and PC do not exhibit significant economic gains.

4.5 Predictive Performance of Other Predictors

Tables 4 and 5 reveal that VS, constructed from option price information, can generate both statistically and economically significant forecasts of excess stock market returns. We further investigate whether additional predictors or modeling approaches proposed in recent studies can also generate significant out-of-sample predictive gains (e.g., Rapach, Ringgenberg, and Zhou, 2016; Cao, Simin, and Xiao, 2020; Han and Li, 2021; Dong et al., 2022).

[Insert Table 6 about here]

[7] Building on prior research, this study sets the risk aversion coefficient at 3 and constrains the optimal weight between −50% and 150%.

Table 6 reports the out-of-sample forecast statistics (Panel A) and annualized utility gains (Panel B) at the monthly, quarterly, and semiannual horizons, from January 1996 to December 2021, with out-of-sample forecasts starting in January 2003. The following predictors are included: AVS, ASKEW, and APC from Dong et al. (2022), which are zero-cost portfolios constructed using the same logic as VS, SKEW, and PC; OS, the ratio of total S&P 500 index option trading volume to its ETF trading volume; VVS, constructed from the OptionMetrics volatility surface data as in Cao, Simin, and Xiao (2020); SVS, constructed from standardized option data as in Han and Li (2021); and SII, the cumulative short interest of Rapach, Ringgenberg, and Zhou (2016). The results show that most of these option-based predictors fail to generate a significantly positive out-of-sample R^2, with the exception of VVS at the quarterly horizon. In terms of economic significance (Panel B), VVS and SVS produce higher annualized utility gains than the historical average at all three horizons, while SII excels in both statistical and economic significance, outperforming other predictors.

4.6 Encompassing test results

Table 7 presents the encompassing test statistics of Harvey, Leybourne, and Newbold (1998), which evaluate whether the out-of-sample predictive information in the implied volatility spread (VS) encompasses that of other predictors, and vice versa. We consider Welch and Goyal (2008)'s 14 predictors, the SII predictor of Rapach, Ringgenberg, and Zhou, 2016, SVS from Han and Li (2021), VVS from Cao, Simin, and Xiao (2020), and AVS, ASKEW, and APC constructed from the methodology of Dong et al. (2022).

[Insert Table 7 about here]

The null hypothesis in the first three columns posits that the forecasts based on VS (Model 1) encompass the information content of the other predictors (Model 2). The results show that most predictors provide insufficient evidence to reject this null, except for SII, indicating that SII contains predictive information beyond that captured by VS. Conversely, the null hypothesis in the last three columns states that other predictors (Model 1) encompass VS (Model 2). The sixth column shows no evidence that any predictor fully encompasses the information contained in VS. Overall, these findings suggest that the information embedded in VS and SII does not overlap, and combining the two predictors can expand the information set and improve out-of-sample forecasting performance.

4.7 Performance of combination forecasting methods

Because VS and SII do not overlap in predictive information, this study combines them to improve forecasts of stock market returns. Table 8 shows the out-of-sample R^2 (Panel A) and annualized utility gains (Panel B) for combination forecasts at monthly, quarterly, and semiannual horizons. The sample period runs from January 1996 to December 2021, with out-of-sample forecasts beginning in January 2003. We implement four combination methods—average combination (AC), median combination (MC), truncated-mean combination (TC), and variance-weighted combination (WC).[8]

[Insert Table 8 about here]

[8] Because only two sets of predictors are combined, AC, MC, and TC exhibit identical forecasting performance. Accordingly, the average combination approach (AC) serves as the representative method in the subsequent analysis.

Panel A shows that, at the monthly horizon, AC and WC achieve an out-of-sample R^2 of 5.08% and 5.03%, respectively, exceeding the 1.96% and 2.56% from VS and SII alone. The combination methods also outperform the individual predictors for the quarterly and semiannual horizons. Panel B demonstrates that the combination forecasts deliver annualized utility gains above 6% relative to the historical average, surpassing the gains achieved by VS or SII individually. Taken together, these results indicate that combining VS and SII meaningfully expands the information set and enhances both statistical and economic significance in out-of-sample forecasts.

4.8 Source of predictability

In the subsequent analysis, we investigate the ability of option-based predictors not only to forecast stock market excess returns but also to explain fundamental market news. Following Campbell and Shiller (1988), stock returns are decomposed into three components: expected returns, cash-flow news, and discount-rate news. Let $r_{t+1} = log[(p_{t+1} + D_{t+1})/p_t]$, where p_t and D_t denote the stock price and dividend at time t. Campbell and Shiller (1988) derive the following approximate expression:

$$p_t \approx \kappa + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t, \tag{12}$$

where $\rho = 1/\left(1 + e^{\overline{d-p}}\right)$ (with $\overline{d-p}$ denoting the average log dividend–price ratio) and $\kappa = -\,log(\rho) - (1-\rho)\,log[(1/\rho) - 1]$). Campbell and Shiller (1988) show that the log return can then be decomposed into:

$$r_{t+1} = E_t[r_{t+1}] + \eta_{t+1}^{CF} - \eta_{t+1}^{DR}, \tag{13}$$

where η_{t+1}^{CF} captures cash-flow news and η_{t+1}^{DR} captures discount-rate news. Empirically, following Campbell (1991) and Campbell and Ammer (1993), we can estimate these components using a VAR(1) model of the form:

$$Y_{t+1} = AY_t + u_{t+1}, \tag{14}$$

where $Y_t = (r_t, d_t - p_t, z_t')'$ includes the stock return r_t, the log dividend yield $(d_t - p_t)$, and n additional predictors z_t. The vector u_{t+1} is a mean-zero disturbance. Let e_1 be an (n+2)-dimensional vector whose first element is 1 and all others are 0. Then,

$$\eta_{t+1}^{r} = r_{t+1} - E_t[r_{t+1}] = e_1' U_{t+1}, \tag{15}$$
$$\eta_{t+1}^{DR} = e_1' \rho A (1 - \rho A)^{-1} U_{t+1}, \tag{16}$$
$$\eta_{t+1}^{CF} = \eta_{t+1}^{r} + \eta_{t+1}^{DR}. \tag{17}$$

Using OLS on the sample observations y_t for $t = 1, \dots, T$, we obtain estimates $\hat{A}$ and $\hat{u}_{t+1}$, which can be substituted into these equations to derive $\hat{\eta}_{t+1}^{r}$, $\hat{\eta}_{t+1}^{DR}$, and $\hat{\eta}_{t+1}^{CF}$, and $\widehat{E}_t[r_{t+1}]$.

To analyze the ability of the options-implied volatility spread to forecast future stock returns, we examine how it predicts each return component. First, we use the volatility spread (VS_t) in a predictive regression for log stock returns:

$$r_{t+1} = \alpha + \beta VS_t + \varepsilon_{t+1}. \tag{18}$$

We then consider the following predictive regressions to estimate the three components in Equation (13):

$$\widehat{E}_t[r_{t+1}] = \alpha_E + \beta_E VS_t + \varepsilon_{t+1}^{E}, \tag{19}$$
$$\hat{\eta}_{t+1}^{CF} = \beta_{CF} VS_t + \varepsilon_{t+1}^{CF}, \tag{20}$$
$$\hat{\eta}_{t+1}^{DR} = \beta_{DR} VS_t + \varepsilon_{t+1}^{DR}, \tag{21}$$

where the intercept in the cash-flow and discount-rate regressions is set to zero. From Equation (18), the estimated coefficients satisfy

$$\hat{\beta} = \hat{\beta}_E + \hat{\beta}_{CF} - \hat{\beta}_{DR}. \quad (22)$$

By comparing the slope coefficients in Equations (18)–(21), we can assess how the volatility spread predicts total returns and, specifically, the separate components of Equation (13). In Equation (14), we include the 14 predictors from Welch and Goyal (2008) as proxies for market information, which highlights the unique information content of the options volatility spread.

Table 9 reports OLS estimates for the expected return, cash-flow news, and discount-rate news components derived from separate VAR specifications, as well as a VAR incorporating the log dividend–price ratio and the first three principal components of the full set of predictors. In the baseline regression, $\hat{\beta}$ is estimated to be 0.78. Most estimates of $\hat{\beta}_E$ are insignificant, indicating a limited contribution to the overall predictive slope. By contrast, $\hat{\beta}_{\mathrm{CF}}$ is larger and statistically significant for most specifications, suggesting that the predictive power of VS primarily stems from its

ability to anticipate cash-flow news. While some estimates of $\hat{\beta}_{\mathrm{DR}}$ are also significant, their magnitudes are smaller, thus contributing less to the overall $\hat{\beta}$. Collectively, these findings highlight that VS contains unique predictive information distinct from that embedded in Welch and Goyal (2008)‘s 14 predictors and underscore the significance of VS in forecasting future cash-flow news.

5. Conclusion

This study systematically investigates the predictive power and economic significance of implied volatility spread and other option predictors for future stock index returns by integrating individual stock option implied volatility or open interest information and incorporating multiple conventional forecasting predictors. The empirical results demonstrate that implied volatility spreads exhibit both in-sample and out-of-sample statistical significance across various time horizons, including monthly, quarterly, and semi-annual periods, and their information content does not overlap with other predictors. Comprehensive tests further indicate that the information embedded in the options market cannot be fully captured by conventional stock market or macroeconomic predictors. Moreover, combining implied volatility spread with SII predictor not only enhances out-of-sample predictive accuracy but also generates significant economic utility gains.

In terms of model application, this study employs a combination forecasting approach based on Bates and Granger (1969) to combine option-related predictive variables with other conventional stock predictors in various forms. The empirical evidence confirms that incorporating predictive predictors constructed from option prices significantly enhances out-of-sample predictive performance and utility gains.

Furthermore, to investigate the specific sources of information in the options market, this study employs a VAR model to decompose stock returns into expected returns, cash flow news, and discount rate news, and further analyzes the predictive relationship between options market predictors and each subcomponent. The results highlight the crucial role of option volatility spreads in explaining future cash flow news, underscoring their informational value beyond conventional predictors and suggesting that the options market may play a vital role in capturing potential information at both the firm and market levels.

The overall empirical findings demonstrate that the price and trading volume signals embedded in individual stock options have a significant effect on predicting market returns and exhibit unique and non-negligible informational content even when combined with other stock and macroeconomic predictors.

References

An, Byong-Je, Andrew Ang, Turan G. Bali, and Nusret Cakici, 2014, The joint cross section of stocks and options, *The Journal of Finance* 69, 2279-2337.

Atilgan, Yigit, 2014, Volatility spreads and earnings announcement returns, *Journal of Banking & Finance* 38, 205-215.

Augustin, Patrick, Menachem Brenner, and Marti G Subrahmanyam, 2015, Informed options trading prior to m&a announcements: Insider trading?, *Available at SSRN 2441606*.

Bali, Turan G., and Armen Hovakimian, 2009, Volatility spreads and expected stock returns, *Management Science* 55, 1797-1812.

Bates, John M, and Clive WJ Granger, 1969, The combination of forecasts, *Journal of the Operational Research Society* 20, 451-468.

Billingsley, Randall S, and Don M Chance, 1988, Put-call ratios and market timing effectiveness, *Journal of Portfolio Management* 15, 25.

Blau, Benjamin M, Nga Nguyen, and Ryan J Whitby, 2014, The information content of option ratios, *Journal of Banking & Finance* 43, 179-187.

Bollen, Nicolas P. B., and Robert E. Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions?, *The Journal of Finance* 59, 711-753.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *The Review of Financial Studies* 22, 4463-4492.

Bollerslev, Tim, Viktor Todorov, and Lai Xu, 2015, Tail risk premia and return predictability, *Journal of Financial Economics* 118, 113-134.

Campbell, John Y, and Robert J Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *The Review of Financial Studies* 1, 195-228.

Campbell, John Y., 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157-179.

Campbell, John Y., and John Ammer, 1993, What moves the stock and bond markets? A variance decomposition for long-term asset returns, *The Journal of Finance* 48, 3-37.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *The Review of Financial Studies* 21, 1509-1531.

Cao, Charles, Zhiwu Chen, and John M Griffin, 2005, Informational content of option volume prior to takeovers, *The Journal of Business* 78, 1073-1109.

Cao, Charles, Timothy Simin, and Han Xiao, 2020, Predicting the equity premium with the implied volatility spread, *Journal of Financial Markets* 51, 100531.

Chen, Jian, and Yangshu Liu, 2020, Bid and ask prices of index put options: Which predicts the underlying stock returns?, *Journal of Futures Markets* 40, 1337-1353.

Chordia, Tarun, Alexander Kurov, Dmitriy Muravyev, and Avanidhar Subrahmanyam, 2021, Index option trading activity and market returns, *Management Science* 67, 1758-1778.

Clark, Todd E., and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291-311.

Cremers, Martijn, and David Weinbaum, 2010, Deviations from put-call parity and stock return predictability, *Journal of Financial and Quantitative Analysis* 45, 335-367.

Dennis, Patrick, and Stewart Mayhew, 2002, Risk-neutral skewness: Evidence from stock options, *Journal of Financial and Quantitative Analysis* 37, 471-493.

Dong, Xi, Yan Li, David E Rapach, and Guofu Zhou, 2022, Anomalies and the expected market return, *The Journal of Finance* 77, 639-681.

Easley, David, Maureen O'Hara, and P.S. Srinivas, 1998, Option volume and stock prices: Evidence on where informed traders trade, *The Journal of Finance* 53, 431-465.

Ge, Li, Tse-Chun Lin, and Neil D. Pearson, 2016, Why does the option to stock volume ratio predict stock returns?, *Journal of Financial Economics* 120, 601-622.

Han, Bing, and Gang Li, 2021, Information content of aggregate implied volatility spread, *Management Science* 67, 1249-1269.

Harvey, David I., Stephen J. Leybourne, and Paul Newbold, 1998, Tests for forecast encompassing, *Journal of Business & Economic Statistics* 16, 254-259.

Jena, Sangram Keshari, Aviral Kumar Tiwari, and Amarnath Mitra, 2019, Put–call ratio volume vs. Open interest in predicting market return: A frequency domain rolling causality analysis, *Economies* 7, 24.

Johnson, Travis L., and Eric C. So, 2012, The option to stock volume ratio and future returns, *Journal of Financial Economics* 106, 262-286.

Jones, Christopher S, Haitao Mo, and Tong Wang, 2018, Do option prices forecast aggregate stock returns?, *Available at SSRN 3009490*.

Koijen, Ralph SJ, and Stijn Van Nieuwerburgh, 2011, Predictability of returns and cash flows, *Annu. Rev. Financ. Econ.* 3, 467-491.

Li, Yan, David T. Ng, and Bhaskaran Swaminathan, 2013, Predicting market returns using aggregate implied cost of capital, *Journal of Financial Economics* 110, 419-436.

Martin, Ian, 2016, What is the expected return on the market?, *Quarterly Journal of Economics* 132, 367-433.

Pan, Jun, and Allen M. Poteshman, 2006, The information in option volume for future stock prices, *The Review of Financial Studies* 19, 871-908.

Rapach, David E, Matthew C Ringgenberg, and Guofu Zhou, 2016, Short interest and aggregate stock returns, *Journal of Financial Economics* 121, 46-65.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2010, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *The Review of Financial Studies* 23, 821-862.

Rapach, David, and Guofu Zhou, 2013, Forecasting stock returns, in *Handbook of economic forecasting* (Elsevier).

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, 2010, O/s: The relative trading activity in options and stock, *Journal of Financial Economics* 96, 1-17.

Stock, James H, and Mark W Watson, 2004, Combination forecasts of output growth in a seven-country data set, *Journal of Forecasting* 23, 405-430.

Weinbaum, David, Andy Fodor, Dmitriy Muravyev, and Martijn Cremers, 2021, How do informed option traders trade? Option trading activity, news releases, and stock return predictability, *Available at SSRN 2544344*.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *The Review of Financial Studies* 21, 1455-1508.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao, 2010, What does the individual option volatility smirk tell us about future equity returns?, *Journal of Financial and Quantitative Analysis* 45, 641-662.

Table 1. Summary statistics

This table presents summary statistics for 14 predictors from Welch and Goyal (2008), implied volatility spread, volatility skew, and put-call ratio. The sample period is from January 1996 to December 2021. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate.

Predictor	Mean	Std. dev.	1st percentile	Median	99th percentile
VS	-0.01	0.01	-0.04	-0.01	0.01
SKEW	0.05	0.01	0.03	0.05	0.09
PC	5.03	1.77	1.84	4.77	10.39
DP	-4.02	0.20	-4.48	-3.99	-3.42
DY	-4.01	0.20	-4.48	-3.98	-3.43
EP	-3.17	0.36	-4.78	-3.11	-2.67
DE	-0.85	0.41	-1.24	-0.92	1.25
SVAR	0.00	0.01	0.00	0.00	0.03
BM	0.26	0.07	0.13	0.26	0.41
NTIS	0.00	0.02	-0.05	0.00	0.03
TBL	0.02	0.02	0.00	0.01	0.06
LTY	0.04	0.02	0.01	0.04	0.07
LTR	0.01	0.03	-0.06	0.01	0.08
TMS	0.02	0.01	-0.00	0.02	0.04
DFY	0.01	0.00	0.01	0.01	0.03
DFR	0.00	0.02	-0.06	0.00	0.06
INFL	0.00	0.00	-0.01	0.00	0.01

Table 2. Correlation matrix

This table presents Pearson correlation coefficients for 14 predictors from Welch and Goyal (2008), implied volatility spread, volatility skew, and put-call ratio. The sample period is from January 1996 to December 2021. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate.

Predictor	VS	SKEW	PC	DP	DY	EP	DE	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL
VS	1																
SKEW	-0.25	1															
PC	0.31	-0.34	1														
DP	-0.10	0.55	-0.24	1													
DY	-0.08	0.54	-0.16	0.98	1												
EP	0.10	-0.17	0.04	0.02	0.01	1											
DE	-0.14	0.42	-0.16	0.47	0.47	-0.87	1										
SVAR	-0.33	0.43	-0.27	0.26	0.17	-0.20	0.30	1									
BM	-0.02	0.53	-0.32	0.70	0.68	0.41	-0.01	0.08	1								
NTIS	0.16	-0.47	0.26	-0.51	-0.49	0.07	-0.31	-0.19	-0.26	1							
TBL	-0.18	-0.68	0.12	-0.49	-0.50	0.03	-0.27	-0.08	-0.60	0.28	1						
LTY	-0.34	-0.55	-0.08	-0.35	-0.37	-0.09	-0.10	-0.03	-0.45	0.47	0.76	1					
LTR	-0.17	0.11	-0.21	0.05	-0.00	0.06	-0.03	0.21	0.06	0.03	0.03	-0.04	1				
TMS	-0.15	0.36	-0.28	0.31	0.30	-0.15	0.29	0.08	0.36	0.17	-0.58	0.09	-0.09	1			
DFY	-0.34	0.69	-0.41	0.59	0.57	-0.47	0.71	0.48	0.35	-0.48	-0.36	-0.18	0.04	0.34	1		
DFR	0.07	0.02	0.17	-0.02	0.09	-0.19	0.16	-0.37	-0.05	0.01	-0.08	-0.04	-0.47	0.08	0.10	1	
INFL	0.12	-0.27	0.06	-0.20	-0.19	0.05	-0.14	-0.17	-0.11	0.08	0.09	0.07	-0.08	-0.05	-0.28	-0.08	1

Table 3. In-sample predictive regression

This table presents the results of univariate predictive regressions. The dependent variable is the average monthly S&P500 stock market excess return over the monthly, quarterly, and semiannually forecast horizons. The sample period is from January 1996 to December 2021. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate. $\hat{\beta}$ and R^2 statistics are reported in the table. *t*-statistics are reported in the parentheses. ***, **, * represent significance at the 1%, 5%, and 10% levels.

	Monthly		Quarterly		Semiannually	
Predictor	$\hat{\beta}$	R^2	$\hat{\beta}$	R^2	$\hat{\beta}$	R^2
VS	103.92***	3.38	106.60***	10.23	73.34***	8.94
	(3.29)		(5.92)		(5.46)	
SKEW	2.48	0.01	1.29	0.00	11.39	0.66
	(0.13)		(0.12)		(1.42)	
PC	0.20	0.62	0.16*	1.23	0.20***	3.44
	(1.39)		(1.96)		(3.29)	
DP	2.47**	1.27	2.61***	4.11	2.88***	9.10
	(1.99)		(3.63)		(5.52)	
DY	2.71**	1.52	2.70***	4.36	2.95***	9.44
	(2.18)		(3.74)		(5.63)	
EP	0.47	0.14	0.13	0.03	0.00	0.00
	(0.67)		(0.33)		(0.01)	
DE	0.24	0.05	0.53	0.69	0.68**	2.13
	(0.39)		(1.46)		(2.57)	
SVAR	-2.78	0.00	-7.57	0.03	17.75	0.35
	(-0.07)		(-0.32)		(1.03)	
BM	4.15	0.42	5.67***	2.26	7.43***	7.14
	(1.14)		(2.67)		(4.84)	
NTIS	20.23	0.73	23.03***	2.76	22.19***	4.74
	(1.51)		(2.95)		(3.89)	
TBL	-16.14	0.54	-15.89**	1.54	-17.45***	3.42
	(-1.30)		(-2.19)		(-3.28)	
LTY	-30.02**	1.26	-28.79***	3.34	-28.26***	5.82
	(-1.99)		(-3.26)		(-4.34)	
LTR	3.76	0.07	-0.54	0.00	2.90	0.21
	(0.45)		(-0.11)		(0.81)	
TMS	-9.28	0.08	-7.47	0.14	-2.12	0.02

	(-0.48)		(-0.67)		(-0.26)	
DFY	-53.55	0.24	-29.02	0.21	12.49	0.07
	(-0.86)		(-0.80)		(0.46)	
DFR	16.36	0.47	2.07	0.02	4.84	0.22
	(1.20)		(0.26)		(0.82)	
INFL	96.27	0.59	-32.81	0.20	-74.40**	1.87
	(1.36)		(-0.78)		(-2.41)	

Table 4. Out-of-sample results

This table presents the out-of-sample R^2 of the forecast by stock predictors at the monthly, quarterly, and semiannually horizons. The sample period is from January 1996 to December 2021. The out-of-sample forecast starts from January 2003. The individual predictors are as follows. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate. The statistical significance of out-of-sample R^2 is based on the Clark and West (2007) statistic. ***, **, * represent significance at the 1%, 5%, and 10% levels.

Predictor	Monthly	Quarterly	Semiannually
VS	1.96**	11.34***	2.50***
SKEW	-1.64	-2.83	-8.88
PC	-0.45	-1.42	-5.34
DP	-2.70	-3.67	-1.80
DY	-1.55	-2.68	-0.43
EP	-6.09	-11.84	-17.46
DE	-4.61	-5.43	-3.27
SVAR	-9.60	-7.01	-5.80
BM	-0.68	0.76**	3.52***
NTIS	-1.85	-3.63	-11.94
TBL	-1.20	-1.38	-1.56
LTY	-0.44	1.36	0.73**
LTR	-1.30	-1.22	-1.03
TMS	-1.05	-1.62	-2.16*
DFY	-4.14	-10.30	-23.74
DFR	-4.06	-4.45	-6.24*
INFL	-0.37	-1.85	1.31

Table 5. Economic significance

This table presents the annualized utility gains of predictors at the monthly, quarterly, and semiannually horizons. The sample period is from January 1996 to December 2021. The out-of-sample forecast starts from January 2003. The individual predictors are as follows. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate.

Predictor	Monthly	Quarterly	Semiannually
VS	3.33	4.08	2.85
SKEW	-2.31	-1.66	-0.39
PC	-0.39	0.14	-0.54
DP	0.14	0.98	1.23
DY	0.99	1.5	1.41
EP	0.77	0.34	-0.49
DE	1.09	1.62	1.2
SVAR	0.6	-1.45	-0.44
BM	0.59	2.57	2.77
NTIS	-2.93	-3.11	-3.21
TBL	-0.17	0.73	1.46
LTY	1.17	2.05	2.41
LTR	-1.86	-0.57	-0.72
TMS	-1.48	-0.62	-0.28
DFY	-0.41	-0.24	0.2
DFR	0.82	-1.17	-1.35
INFL	-1.61	-0.78	-0.41

Table 6. Out-of-sample performance of other predictors

This table presents the out-of-sample R^2 (Panel A) and the annualized utility gains (Panel B) of predictors at the monthly, quarterly, and semiannually horizons. The sample period is from January 1996 to December 2021. The out-of-sample forecast starts from January 2003. The individual predictors are as follows. AVS, ASKEW, and APC are the long-short portfolio returns of VS, SKEW, and PC, respectively, constructed following the methodology described by Dong et al. (2022). OS is the ratio of the total trading volume of options on the S&P 500 index to the trading volume of ETFs. VVS is the implied volatility spread constructed using volatility surface data, following the approach adopted by Cao, Simin, and Xiao (2020). SVS is the aggregate implied volatility spread constructed using Standardized Options data, following the methodology of Han and Li (2021). SII is the aggregate short interest from Rapach et al. (2016). The statistical significance of out-of-sample R^2 is based on the Clark and West (2007) statistic. ***, **, * represent significance at the 1%, 5%, and 10% levels.

Panel A: Out-of-sample R^2			
Predictor	Monthly	Quarterly	Semiannually
AVS	-0.29	-0.60	-0.64
ASKEW	-0.71**	-0.42	-0.05
APC	-0.61	-2.64	-2.79
OS	-0.62	-1.22	-2.31*
VVS	-2.81	2.69**	-5.95**
SVS	-4.09	-1.47**	-10.92**
SII	2.56**	9.58***	18.36***
Panel B: Economic significance			
Predictor	Monthly	Quarterly	Semiannually
AVS	-0.85	-0.47	-0.28
ASKEW	-1.13	-0.07	-0.05
APC	-0.81	-2.14	-1.22
OS	-1.45	-1.05	-1.04
VVS	3.65	3.55	2.24
SVS	3.27	3.40	2.08
SII	5.92	6.49	6.80

Table 7. Encompassing tests

This table reports the *p*-values of the Harvey et al. (1998) statistics for the null hypothesis that the out-of-sample forecast of model 1 encompasses the out-of-sample forecast of model 2. The sample period is from January 1996 to December 2021. The out-of-sample forecast starts from January 2003. The individual predictors are as follows. VS is the equal-weighted average of the differences between the implied volatilities of calls and corresponding puts across individual stocks. SKEW is the equal-weighted average of the differences between the implied volatilities of out-of-the-money puts and at-the-money calls. PC is the equal weighted average ratio of call open interest to one plus the put open interest across individual stocks. DP is the logarithm of the dividend-price ratio, DY is the logarithm of the dividend yield, EP is the logarithm of the earnings-price ratio, DE is the logarithm of the dividend ratio, SVAR is the volatility of S&P500 excess returns, BM is the book-to-market ratio, NTIS is the net equity expansion, TBL is the treasury bill rate, LTY is the long-term yield, LTR is the long-term return, TMS is the term spread, DFY is the default yield spread, DFR is the default return spread, INFL is the lagged term of the inflation rate. AVS, ASKEW, and APC are the long-short portfolio returns of VS, SKEW, and PC, respectively, constructed following the methodology described by Dong et al. (2022). OS is the ratio of the total trading volume of options on the S&P 500 index to the trading volume of ETFs. VVS is the implied volatility spread constructed using volatility surface data, following the approach adopted by Cao, Simin, and Xiao (2020). SVS is the aggregate implied volatility spread constructed using Standardized Options data, following the methodology of Han and Li (2021). SII is the aggregate short interest from Rapach et al. (2016).

Model 1	Model 2	*p*-values	Model 1	Model 2	*p*-values
VS	DP	0.15	DP	VS	0.01
VS	DY	0.12	DY	VS	0.01
VS	EP	0.25	EP	VS	0.00
VS	DE	0.23	DE	VS	0.01
VS	SVAR	0.61	SVAR	VS	0.02
VS	BM	0.11	BM	VS	0.01
VS	NTIS	0.10	NTIS	VS	0.00
VS	TBL	0.12	TBL	VS	0.02
VS	LTY	0.12	LTY	VS	0.03
VS	LTR	0.13	LTR	VS	0.01
VS	TMS	0.13	TMS	VS	0.02
VS	DFY	0.27	DFY	VS	0.02
VS	DFR	0.20	DFR	VS	0.02
VS	INFL	0.10	INFL	VS	0.01
VS	SKEW	0.20	SKEW	VS	0.02
VS	PC	0.12	PC	VS	0.02
VS	AVS	0.10	AVS	VS	0.02
VS	ASKEW	0.13	ASKEW	VS	0.01
VS	APC	0.13	APC	VS	0.02
VS	OS	0.11	OS	VS	0.01
VS	VVS	0.81	VVS	VS	0.01
VS	SVS	0.88	SVS	VS	0.01
VS	SII	0.04	SII	VS	0.04

Table 8. Out-of-sample performance of combination forecasts

This table presents the out-of-sample R^2 (Panel A) and the annualized utility gains (Panel B) of combination forecasts at the monthly, quarterly, and semiannually horizons. The sample period is from January 1996 to December 2021. The out-of-sample forecast starts from January 2003. We combine the VS and SII predictors through various combination methods. AC is the average combination forecast, MC is the median combination forecast, TC is the trim-mean combination forecast, and WC is the weighted average combination forecast. The statistical significance of out-of-sample R^2 is based on the Clark and West (2007) statistic. ***, **, * represent significance at the 1%, 5%, and 10% levels.

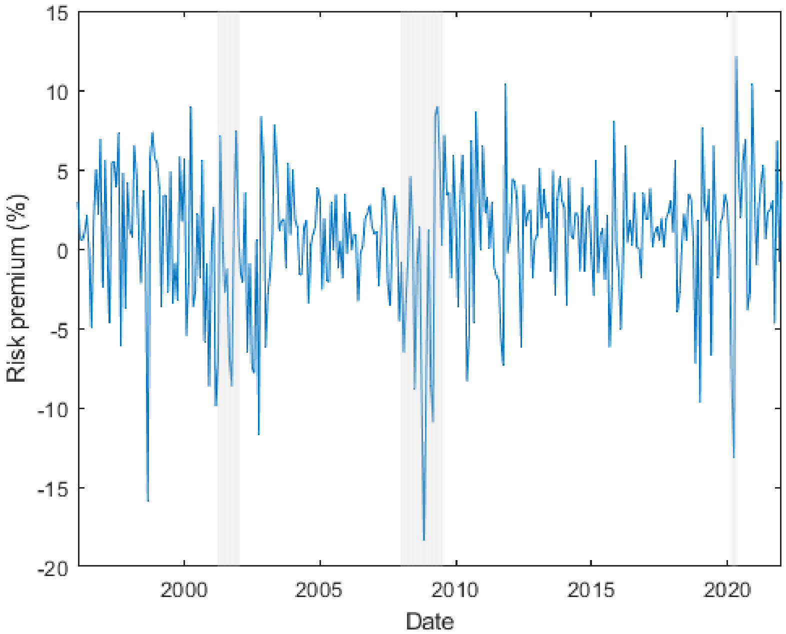
Panel A: Out-of-sample R^2			
Predictor	Monthly	Quarterly	Semiannually
AC	5.08***	21.62***	24.38***
MC	5.08***	21.62***	24.38***
TC	5.08***	21.62***	24.38***
WC	5.03***	21.50***	24.04***
Panel B: Economic significance			
Predictor	Monthly	Quarterly	Semiannually
AC	6.19	7.50	7.04
MC	6.19	7.50	7.04
TC	6.19	7.50	7.04
WC	6.12	7.14	7.10

Table 9 Sources of predictive power

This table presents the OLS estimate of β for the predictive regression model,
$y_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1}$ for $t = 1,\ldots,T$ -1 ,
where y_t is one of three estimated components of the log return for month *t* and x_t is the option implied volatility predictor. The three estimated components of the S&P 500 log return are the expected return ($E_t r_{t+1}$), cash flow news (η^{CF}_{t+1}), and discount rate news (η^{DR}_{t+1}), corresponding to β_E, β_{CF}, and β_{DR} respectively. The heteroskedasticity- and autocorrelation-robust t-statistics are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Expected Return	Cash Flow News	Discount Rate News
r, DP	-0.02	0.43**	-0.37*
	(-0.62)	(2.33)	(-1.95)
r, DP, DY	-0.01	0.43**	-0.36*
	(-0.24)	(2.36)	(-1.90)
r, DP, EP	-0.01	1.05***	0.26
	(-0.19)	(3.00)	(1.28)
r, DP, DE	-0.01	1.05***	0.26
	(-0.19)	(3.00)	(1.28)
r, DP, SVAR	-0.01	0.39**	-0.39**
	(-0.14)	(2.04)	(-2.15)
r, DP, BM	-0.03	0.42**	-0.40**
	(-0.78)	(2.13)	(-2.17)
r, DP, NTIS	0.07	0.19	-0.53**
	(1.11)	(0.85)	(-1.98)
r, DP, TBL	-0.04	0.43**	-0.39**
	(-1.15)	(2.34)	(-2.06)
r, DP, LTY	0.06	0.35	-0.37*
	(1.31)	(1.57)	(-1.92)
r, DP, LTR	-0.05	0.44**	-0.39**
	(-1.05)	(2.38)	(-2.06)
r, DP, TMS	0.02	0.41*	-0.35*
	(0.48)	(1.89)	(-1.81)
r, DP, DFY	0.20***	0.56	-0.03
	(3.64)	(1.60)	(-0.12)
r, DP, DFR	-0.02	0.42**	-0.38**
	(-0.32)	(2.28)	(-2.05)
r, DP, INFL	0.02	0.46**	-0.30
	(0.44)	(2.48)	(-1.52)

Panel A: S&P 500 risk premium



Panel B: Implied volatility spread

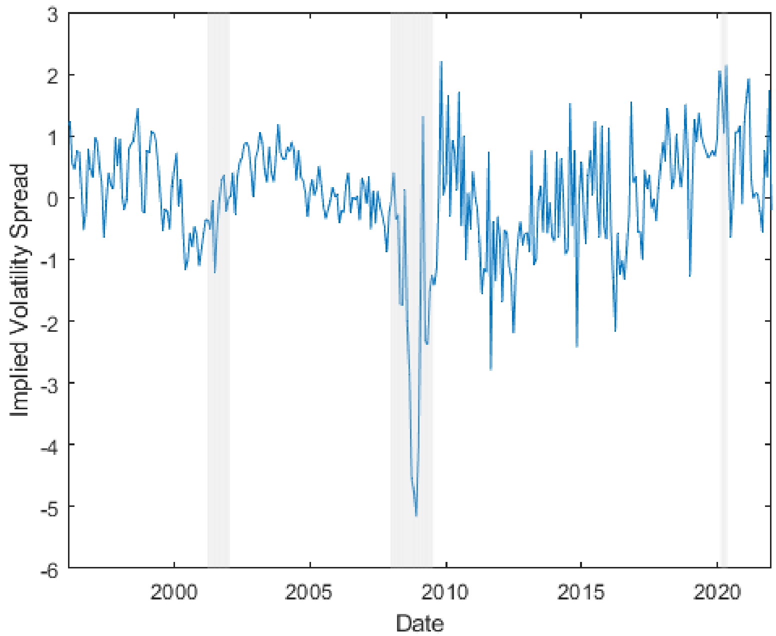


Figure 1. Market excess returns and implied volatility spread, January 1996 - December 2021

Panel A illustrates the time-series trend of the S&P 500 index excess returns. Panel B presents the time-series plot of the detrended implied volatility spread. Vertical bars indicate recessions, as dated by the National Bureau of Economic Research (NBER).