Predicting the Equity Premium with the Implied Volatility Spread

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Abstract

We show that the call-put implied volatility spread (*IVS*) outperforms many well-known predictors of the equity premium at return horizons up to 6-months. The predictive ability of the *IVS* is unrelated to the dividend yield and is useful in explaining the cross-section of returns. Decomposing the *IVS*, we find the longer run predictive ability of the *IVS* operates primarily through a cash flow channel. We also find the *IVS* is significantly related to indicators of aggregate market direction and expected market conditions. Our results are consistent with the *IVS* reflecting market sentiment as well as information about informed trading.

Key Words: implied volatility spread, equity premium, prediction

Introduction

Deviations from put-call parity captured by option implied volatilities contain information about future stock returns. The intuition behind this relation provided by the current state of the literature is that price pressure from informed trading in both the options and equity markets causes violations of put-call parity resulting in the option implied volatilities differing from their no-arbitrage values. The spread between the implied volatilities of call and put options of individual firms (*IVS*) is a measure of the informed trading deviation from put-call parity. While the *IVS* predicts individual stock returns [Cremers and Weinbaum (2010)] and aggregate short-run market returns over horizons up to one week [Atilgan, Bali, and Demirtas (2015)], there is evidence that changes in implied volatilities [An, Ang, Bali, and Cakici (2014)] and the shape of the volatility smirk [Xing, Zhang, Zhao (2010)] predict portfolio returns for at least 6 months. The relations between implied volatilities and longer-horizon returns suggests that deviations from put-call parity may reflect information other than short-term price pressure of informed traders.

In models where informed traders choose to trade in the options market first [Easley, O'Hara, and Srinivas (1998) and An, Ang, Bali, and Cakici (2014)], options markets can predict stock returns. In these noisy rational expectations models of informed trading, the existence of noise traders allows informed traders to mask the information content of trades leading to inefficient, and hence predictable prices. If the information set of informed traders includes market sentiment, then trading in the options market may also reflect long-run information. The long-run information content of market sentiment is plausible behaviorally if people's optimism (pessimism) develops into a consensus view indicating the importance of sentiment may build over time, and rationally, if arbitrage forces which are likely to eliminate short-run mispricing, fail at longer horizons. An example of this limit-to-arbitrage is the noise trader risk described in DeLong, Shleifer, Summers, and Waldmann (1990). Indeed, Brown and Cliff (2005) find that while sentiment predicts longer-run returns, they find little predictive evidence for near-term returns. If the *IVS* captures the informed trader's assessment of market sentiment, then the *IVS* is an economically sensible predictor of the longer-run market risk premium.

Our first contribution is to demonstrate that the call-put implied volatility spread predicts the aggregate equity premium at return horizons well beyond one week. We first consider the in-sample predictive power of the *IVS* in comparison to other conventional variables investigated in Goyal and Welch (2008). We regress the equity premium on the individual lagged predictors for 1, 3, 6, and 12-month return horizons. Our results indicate that the *IVS* is a significant predictor of the market risk-premium for up to 12 months. In this experiment the *IVS* clearly dominates many of the other 14 predictors we examine.

Because in-sample prediction tests can suffer from several biases, including the Stambaugh (1999) coefficient bias caused by autocorrelated predictors, data snooping biases as in Ferson, Sarkissian, and Simin (2003), and finite sample biases described in Nelson and Kim (1993), we test the out-of-sample performance of the *IVS* as a predictor. We evaluate the predictive performance of each predictor based on univariate ordinary least squares regressions and the utility gains that a mean-variance utility investor would obtain by holding the portfolio formed based on the predictors relative to a portfolio based on the historical average benchmark forecast. A significant positive out-of-sample R-square (R_{OS}^2), in conjunction with a positive annualized utility gain, suggests that a predictor performs well out-of-sample. Compared to using the historical average return as a predictor, we find the *IVS* produces significantly smaller one-step-ahead mean square forecast errors and generates positive utility gains up to 6-months ahead. The *IVS* is the only predictor to produce significantly positive out-of-sample R^2's out of the set of 14 traditional predictors. We show that this result is robust to controls, model specification, and measurement of the *IVS*.

Our second contribution is to demonstrate that the *IVS* and the dividend yield contain different sources of predictive ability. We first show that the component of the risk premium that is uncorrelated with the *IVS* is predictable only by the dividend yield. When we orthogonalize the market risk premium relative to the other significant predictors, the *IVS* remains a significant predictor. These results indicate that the *IVS* and the dividend yield contain distinct information relevant to predicting future market returns. Next, we show that during expansionary periods, the dividend yield generates positive utility gains as a significant predictor of the market risk premium, while during recessions only the *IVS* remains a significant predictor while producing positive utility gains suggesting an important difference in predictability between the *IVS* and the dividend yield. Finally, we compare the ability of the *IVS*, versus the dividend yield, to explain a large cross-section of portfolios by utilizing the predictors as instrumental variables in conditional versions of the CAPM, Fama and French 3-factor, and the Carhart 4-factor models[1]. The conditional versions of these models where the time-varying expected market risk premium is modeled as a linear function of *IVS*, produce 71%-85% fewer significant intercepts relative to their unconditional versions. Using the

[1] Our test assets consist of monthly excess returns of 399 equally weighted portfolios from Ken French's database. These include five sets of decile portfolios sorted on past variance, residual variance, net share issues, beta, or accruals; three sets of portfolios double sorted into deciles base on size and book-to-market, size and operating profitability, or size and investment; and 49 industry portfolios.

dividend yield to model the expected risk premium, we find at most 65% fewer significant alphas and in the Carhart model conditioning on the dividend yield worsens the model's ability to explain the cross-section of returns.

Our third contribution is to show that the predictive ability of *IVS* captures more than just short-term impacts of informed trading. Decomposing the predictive power of the *IVS* into the expected return, cash flow, and discount rate innovations, we find that the predictive ability of the *IVS* comes through the cash-flow channel versus the expected return or discount rate channel. We then demonstrate that the predictive ability of *IVS* reflects information related to measures of market expectations and several measures of market uncertainty. Our proxies for market expectations come from three surveys: The Gallup investor survey, the American Association of Individual Investors survey, and the crash confidence index from the Yale School of Management. We also include a statistical measure of sentiment from Baker and Wurgler (2006). Our proxies for aggregate uncertainty come from Jurado, Ludvigson, and Ng (2015) and Baker, Bloom and Davis (2016). *IVS* is positively and significantly related to all the measures of market expectations. *IVS* is negatively and significantly related to all 8 proxies of macroeconomic, political, and financial uncertainty. We take these results to indicate that *IVS* captures the impact of market sentiment on the cash-flows of firms.

Historically, information from options markets is utilized to predict equity return volatility. Christoffersen, Jacobs, and Chang (2013) provide a comprehensive review of this literature. Increasingly, information extracted from option markets is used to predict market returns. For instance, Chordia, Kurov, Muravyev, and Subrahmanyam (2018) show how the order imbalance of stock index options predicts weekly S&P500 returns. Chen and Liu (2018) predict market returns using an estimate of implied volatility from bid and ask prices of deep out-of-the-money put options on the S&P500 index. Feunou, Fontaine, Taamouti, and Tédongap (2012) show that the term structure of option implied variances drives the equity premium. Bali, Cakici,and Chabi-Yo (2015) use a novel option implied measure of risk to predict the equity risk premium and So, Driouchi, and Trigeorgis (2016) generate an option implied measure of ambiguity to predict international market returns. The option-based predictor of the market risk premium that has garnered the most attention is the spread between option-implied and realized-volatility known as the variance risk premium. A few of the influential papers using the variance risk premium include Bollerslev, Tauchen and Zhou (2009), Bekaert, Hoerova, and Lo Duca (2013), Bollerslev, Marrone, Xu, and Zhou (2014), Zhou (2018), and Hollstein, Prokopczuk, Tharann, and Wese Simen (2019).

Our paper adds to a growing segment of this literature that shows that deviations from put-call parity captured by the *IVS* contain useful information for understanding equity returns. For instance, Bali and Hovakimian (2009) show that implied volatility spreads are positively related to the cross-section of expected returns, and An, Ang, Bali, and Cakici (2014) find an inverse relation between future returns and substantial changes in implied volatilities. Doran, Fodor, and Jiang (2013) use the *IVS* as a measure of informed trading relative to informed trading measures from the equity market. The *IVS* also roughly captures aggregate jump and tail risk [Bollerslev and Todorov (2011), Kelly and Jiang (2014)] and may contain nonlinear risk information across different economic states such as rare disasters [Gabaix (2012)]. Our contribution to this literature is to demonstrate that the *IVS* reflects market sentiment about the state of the economy, and through the cash-flow channel, provides longer run predictability of the market risk premium.

The organization of the paper is as follows. Section 1 defines variables and data sets, and methodologies used. Section 2 provides in-sample and out-of-sample prediction results. In Section 3 we perform three experiments to differentiate the source of the *IVS*' predictive ability from that of the other significant predictors. In Section 4 we explore why the *IVS* predicts future returns. Here we decompose returns based on Campbell and Shiller (1988) to see which components are predictable by the *IVS*. In this section we also show how the *IVS* is related to market sentiment and show how the *IVS* and the variance risk premium are complementary predictors. Section 5 concludes the paper.

1. Data and Methodology

Our monthly data come from several sources. The option implied volatility is from OptionMetrics. The conventional predictors, value-weighted CRSP stock returns and risk-free rate are from Amit Goyal's website.[2] The index for business cycle comes from the NBER.[3] The common risk factors for the Fama-French model and the other portfolio returns are from Kenneth French's online data library.[4] Due to restrictions in the option data, our main empirical results are based on monthly data from 1996:1 to 2017:12. To be comparable with Atilgan, Bali and Demirtas (2015), we apply the variance risk premium as a covariate to control for conditional variance risk, which comes from Hao Zhou's website.[5] We test the source of

[2] http://www.hec.unil.ch/agoyal/.
[3] http://www.nber.org/cycles.html
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[5] https://sites.google.com/site/haozhouspersonalhomepage/

the predictive ability of the *IVS* using conventional predictors from Amit Goyal and implied volatility computed using CRSP.

1.1 The Call/Put Implied Volatility Spread (IVS)

We construct our monthly *IVS* measure using daily option implied volatilities in OptionMetrics. The volatility surface represents the separately interpolated implied volatility surface for puts and calls, computed using a methodology based on a kernel smoothing algorithm with expirations of 30 to 730 calendar days, at deltas of 0.20 to 0.80 (negative deltas for puts). The underlying implied volatilities of individual options are computed using binomial trees that account for the early exercise of individual stock options and the dividends expected to be paid over the lives of the options. Using the volatility surface avoids having to make potentially arbitrary decisions on which strikes or maturities to include when computing an implied call or put volatility for each stock. Here we use implied volatilities with an absolute delta of 0.5*, i.e.*, at-the-money options, and an expiration of 30 days.[6]

The *IVS* for individual stocks is defined as the difference between their call option volatility and put option volatility. We then calculate the equally weighted average of the *IVS*. Since we focus on predicting the return on the value-weighted market portfolio, it seems natural to use a value-weighted version of the *IVS* or directly use option implied volatilities from the S&P 500 index options (*SPX*) as in Atilgan *et al.* (2015). Our choice to utilize the equally weighted *IVS* is supported by the intuition outlined in Rapach Ringgenberg, and Zhou (2016) who make the compelling argument that equal-weighting reflects more information concerning the trades of informed market participants relative to value-weighting given the skewness in the distribution of market capitalization. They argue that if informed trading is less important for large cap stocks, then equally weighting predictive measures that reflect the information content of the informed trading will provide a better predictive signal. We confirm the intuition of Rapach *et al.* (2016) in the out-of-sample analysis below and focus our results on an equally weighted version of *IVS*.[7]

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[6] Our construction of the *IVS* differs from Atilgan, *et al.* (2015) where they use OTM put options and ATM call options, *i.e.* their method uses the slope of the volatility smile to create the *IVS.*

[7] In the appendix, we check the robustness of the equally weighted *IVS* compared to several other possible specifications. In particular, we present the in- and out-of-sample results for versions of the *IVS* calculated using the implied volatility for options with 91, 182, 273, and 365 days to expiration and two versions of the *IVS* that account for a potential look-ahead bias caused by using historical dividend payments.

1.2 Common Predictors

Following Goyal and Welch (2008), we define the equity premium as the logarithm of the CRSP value-weighted market return minus the logarithm of the prevailing short-term Treasury-bill rate. The log of equity premium has a mean (standard deviation) of 0.015 (0.085) from 1996 to 2017.

The set of predictor variables includes the following.

(1) Fundamental valuations:

- Logarithm of dividend-price ratio (ln(DP)): the log of 12-month moving sum of dividends paid on the S&P 500 index minus the log of S&P 500 index price.
- Logarithm of dividend-yield ratio (ln(DY)): the log of 12-month moving sum of dividends paid on the S&P 500 index minus the log of lagged S&P 500 index price.
- Logarithm of earning-price ratio (ln(EP)): the log of 12-month moving sum of earnings on the S&P 500 index minus the log of S&P 500 index price.
- Logarithm of dividend-payout ratio (ln(DE)): the log of 12-month moving sum of dividends paid on the S&P 500 index minus the log of 12-month moving sum of earnings on the S&P 500 index.
- Stock Variance (SVAR): the sum of squared daily returns on the S&P 500.
- Book-to-Market Ratio (BM): the ratio of book value to market value for the Dow Jones Industrial Average.
- Net Equity Expansion (NTIS): the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks.

(2) Interest rate related variables:

- Treasury Bills (TBL): the 3-Month Treasury Bill Secondary Market Rate.
- Long Term Yield (LTY): the long-term government bond yield.
- Long Term Rate of Returns (LTR): the rate of return on long-term government bond.
- Term Spread (TMS): the difference between the yield on long-term government bonds and the Treasury-bill.
- Default Yield Spread (DFY): the difference between BAA and AAA-rated corporate bond yields.
- Default Return Spread (DFR): the difference between long-term corporate bond return and long-term government bond returns.

(3) Macroeconomic indicators

- Inflation (INFL): the lag of the inflation calculated from the Consumer Price Index (All Urban Consumers).
- Investment to Capital Ratio (*i/k*): the ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy.

We report the detailed statistics of the predictor variables, the equity premium across quantiles, and the correlation matrix in the appendix. Table 1 provides the mean, standard deviation and autocorrelation summary statistics. The monthly equal weighted *IVS* has the mean (standard errors) of -0.008 (0.005), with first-order autocorrelation 0.372. The lagged predictor variables are often highly persistent, namely 9 of the predictors have first-order autocorrelations of at least 0.90.

1.3 Methodology

In this section we define the OLS regressions for the in-sample and step-ahead tests. For the step-ahead experiments, we test the hypothesis that the out-of-sample R^2 is significant based on Clack-West (2007) adjusted mean-square forecast error (MSFE) *F*-test. We also evaluate the step-ahead forecasts with a utility-based method as a measure of the economic value. By considering the difference between forecasts of predictors versus the historical average forecast in the asset allocation decision, any utility gain can be interpreted as the portfolio management fee an investor would be willing to pay to have access to the predictive information.

1.3.1 OLS prediction.

We first consider the in-sample predictive regression:

$$r_{t+h} = \alpha_{i,h} + \beta_{i,h} x_{i,t} + \varepsilon_{i,t+h} \tag{1}$$

where $r_{t+h} = \left(\prod_{i=1}^{h} 1 + r_{t+i}\right) - 1$, for h = 1, 3, 6, 12 month, represents the return on a stock market index in excess of the risk-free interest rate from $t+1$ to $t+h$, and $x_{i.t}$ represents the i^{th} predictor where X = {*IVS*, ln(DP), …} and $\varepsilon_{i,t+1}$ is the error term of the variable i's prediction for t = 1, 2, …, T-h. We use the autocorrelation-heteroskedasticity-consistent (HAC) standard errors from Newey and West (1987), with an automatic lag selection procedure as suggested in Ferson, Sarkissian, and Simin (2003) to account for overlapping issues. The number of lags is chosen by computing the autocorrelations of the estimated residuals and truncating the lag length when the sample auto-correlations become "insignificant" at longer lags. Explicitly, we compute 12 sample autocorrelations and compare the values with a cutoff at two approximate standard errors: $2/\sqrt{T}$, where T is the sample size. The number of lags chosen is the minimum lag length at which no higher order autocorrelation is larger than two standard errors.

As in Goyal and Welch (2008), we generate out-of-sample forecasts of the equity premium using an expanding estimation window. More specifically, we first divide the total sample of T observations into a training period composed of the first n_1 observations and an out-of-sample portion composed of the $n_2 = T - n_1$ observations. The initial out-of-sample forecast of the equity premium using the predictor $x_{i.t}$ is given by

$$\hat{r}_{i,m+1} = \hat{\alpha}_{i.m} + \hat{\beta}_{i.m} x_{i.m} \tag{2}$$

where $\hat{\alpha}_{i.m}$ and $\hat{\beta}_{i.m}$ are the OLS estimates of α_i and β_i, respectively, generated by regressing $\left\{r_t\right\}_{t=2}^{m}$ on a constant and $\left\{x_{i,t}\right\}_{t=1}^{m-1}$. The out-of-sample forecast is given by

$$\hat{r}_{i,m+2} = \hat{\alpha}_{i.m+1} + \hat{\beta}_{i.m+1} x_{i.m+1} \tag{3}$$

where $\hat{\alpha}_{i.m+1}$ and $\hat{\beta}_{i.m+1}$ are generated by regressing $\left\{r_t\right\}_{t=2}^{m+1}$ on a constant and $\left\{x_{i,t}\right\}_{t=1}^{m}$. Proceeding in this manner through the end of the out-of-sample period, we generate a series of n_2 out-of-sample forecasts of the equity premium based on $x_{i.t}$, $\left\{\hat{r}_{i,t+1}\right\}_{t=m}^{T-1}$. Our training period is 1996:1 to 2006:12. Tests of forecast evaluation are done for the period, 2007:1–2017:12. Alternative divisions of in-sample and out-of-sample periods produce similar results.

1.3.2 Forecast evaluation.

We use the mean squared forecast error (*MSFE*), the out-of-sample R-squared $\left(R_{OS}^2\right)$, and a utility-based measure to evaluate the quality of the different forecasts. For a given predictor x_i, The *MSFE* is given by

$$MSFE_i = \frac{1}{n_2} \sum_{s=1}^{n_2} \left(r_{n_1+s} - \hat{r}_{i,n_1+s}\right)^2 . \tag{4}$$

where i is the index of predictors. We use the historical equity mean as a benchmark, *i.e.*, we assume a constant expected excess return $\overline{r}_{t+1}$, and calculate its *MSFE* as,

$$MSFE_0 = \frac{1}{n_2} \sum_{s=1}^{n_2} \left(r_{n_1+s} - \overline{r}_{n_1+s}\right)^2 . \tag{5}$$

The out-of-sample R_{OS}^2 statistic, suggested by Campbell and Thompson (2008) measures the proportional reduction in *MSFE* for the predictive regression forecast relative to the historical average:

$$R_{OS}^2 = 1 - \left(MSFE_i / MSFE_0 \right). \tag{6}$$

If $R_{OS}^2 > 0$, then $MSFE_i < MSFE_0$ and the predictor is more accurate than the historical mean. We calculate the *p*-value for the Clark-West (2007) *MSFE*-adjusted statistic to evaluate the statistical significance of R_{OS}^2. To test $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$ we first calculate

$$\tilde{d}_{i,n1+s} = \left(r_{n1+s} - \overline{r}_{n1+s} \right)^2 - \left[\left(r_{n_1+s} - \hat{r}_{i,n_1+s} \right)^2 - \left(\overline{r}_{n1+s} - \hat{r}_{i,n_1+s} \right)^2 \right] \tag{7}$$

then regress $\tilde{d}_{i,n1+s}$ on a constant. The *MSFE*-adjusted statistic is the *t*-statistic corresponding to the constant. When comparing forecasts from non-nested models, Diebold and Mariano (2002) and West (1996) show that *MSFE*-adjusted statistic has an asymptotic standard normal distribution.

For our utility-based forecast evaluation, we consider a mean-variance investor with relative risk aversion *γ* who allocates wealth between stocks and risk-free bills based on the forecast of the equity premium. At time *t*, the investor allocates the following share of the portfolio to equities during *t+1*:

$$a_{i,t} = \left(\frac{1}{\gamma} \right) \left(\frac{\hat{r}_{i,t+1}}{\hat{\sigma}_{t+1}^2} \right) \tag{8}$$

where $\hat{\sigma}_{t+1}^2$ is a forecast of the stock return's variance. Over the forecast evaluation period, the investor realizes the average utility:

$$\hat{v}_i = \hat{\mu}_i - 0.5\gamma\hat{\sigma}_i^2 \tag{9}$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the sample mean and variance of the portfolio formed on the basis of $\hat{r}_{i,t+1}$ and $\hat{\sigma}_{t+1}^2$ over the forecast evaluation period. If the investor instead relies on the historical average forecast of the equity premium, $\overline{r}_{i,t+1}$, the realized average utility over the forecast evaluation period is

$$\hat{v}_0 = \hat{\mu}_0 - 0.5\gamma\hat{\sigma}_0^2 \tag{10}$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance of the portfolio formed on the basis of $\overline{r}_{i,t+1}$ and $\hat{\sigma}_{t+1}^2$ over the forecast evaluation period. We set the risk aversion parameter to 5 and define the utility gain as $\Delta = \hat{v}_i - \hat{v}_0$.[8]

2. Prediction Results

2.1 In-sample Tests

Table 2 contains the in-sample regressions of the equity premium on the lagged predictor variables up to 12-month ahead based on our predictive specification Equation (1). We use Newey-West heteroscedasticity-autocorrelation consistent standard errors with lags chosen as in Ferson *et al*. (2003) to calculate *t* statistics. The results are consistent if we use Hansen-Hodrick *t*-statistics. Market excess returns and predictors are standardized to have a mean zero and standard deviation of one, thus the coefficients are comparable. For our 1996:1 to 2017:12 sample, we have 264, 262, 259, and 253 overlapping observations for estimating Equation (1) at one-month (h=1), three-month (h=3), semi- annual (h=6), and annual (h=12) horizons, respectively.

The results indicate that at monthly horizon (Column 2 – 3), *IVS* has significant predictive ability for up to 12 months. In sample, *IVS* is one of four significant predictors along with ln(DP), ln(DY) and SVAR at the monthly frequency. A one standard error increase in *IVS* predicts a 19 basis-point higher market excess returns in the next month. For the conventional predictors, only ln(DY), Ln(DP, and SVAR exhibit significant coefficients for the one-month horizon. While not tabulated, the R^2 of the implied volatility spread is the largest (3.3%) among Goyal and Welch (2008) predictors. Campbell and Thompson (2008) argue that a monthly R^2 statistic of approximately 0.5% represents an economically meaningful degree of return predictability. The monthly R^2 statistics for the significant predictors are above this threshold.

At longer predictive horizons, the implied volatility spread maintains a strong predictive ability. At the three-month horizon, the coefficient for *IVS* is 0.26 in Column 4 with Newey-West *t*-statistics of 4.33. Here, a one-standard-deviation increase in *IVS* corresponds to an increase of 26 basis-point more excess market returns in the following quarter. Among remaining predictors, only ln(DP), ln(DY), SVAR, BM, and NTIS have significant predictions.

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[8] Rapach, Strauss and Zhou (2010) use a risk aversion value of 3. Bliss and Panigirtzoglou (2004) use a CRRA utility function with risk aversion implied from option prices, varying the representative agent's relative risk aversion coefficient from 3.04 to 9.52. Changing the risk aversion parameter has little qualitative effect on our results.

Moreover, the *IVS*'s R^2 is 6.8% compared to 4.3% for the next highest R^2 (NTIS). The semi-annual and annual predictions of the implied volatility spread are substantially significant. Even though there are some predictors (e.g., ln(DP), ln(DE), and BM) that gain significant predictability after 6 months, the results come from high autocorrelation and overlapping effects. Most of the standard predictors fail to predict the equity premium at the longer horizons.

2.2 Out-of-sample Tests

Table 3 reports one-month to 12-month ahead forecasts from the set of predictor variables relative to forecasts based on the historical average. Column (1) – (3) include one-month ahead predictions, and Column (4) – (12) represent predictions using three to twelve months ahead market excess returns. R^2_{OS} is the out of sample R^2 in Equation (6), and *pval* is the corresponding *p*-value based on Clark-West (2007) MSFE-adjusted test in Equation (8). Here Δ is the utility gain measure calculated from the difference between Equations (9) and (10).

The significantly positive R^2_{OS} for the *IVS* for one-month ahead forecasts indicates that the *IVS* produces a significantly smaller mean-squared-error compared to the benchmark historical mean. The higher the R^2_{OS} represents the better predictor performance. Moreover, the positive utility gain (Δ) implies that if the mean-variance investor allocates between the market portfolio and the risk-free bond based on the predictor, the utility will be higher than that of a portfolio allocation based on the benchmark historical average. A higher utility gain indicates a more valuable predictor.

The results imply that the *IVS* is the only predictor out of 15 predictors with the positive R^2_{OS} one-month ahead, while conventional predictors, for example ln(DP), underperformed out-of-sample. The *IVS* produces a significantly large increase (146 bps) in utility over the benchmark forecast at the one-month frequency, comparing to the next highest 87 bps (ln(EP)). That means that investors prefer to pay more fees on learning from the *IVS* and can get a higher utility level by holding a mean-variance portfolio based on the *IVS*. Both out-of-sample R^2 and utility gain measures support the predictive ability of the *IVS*.

Notably, the *IVS* continues to predict significantly better than the benchmark historical average in the three- (R^2_{OS}=3.18) and six-month ahead (R^2_{OS}=2.58) at the 5% significance level. The positive utility gain (310bps and 44 bps, respectively) supports the results. However, unlike the in-sample prediction, the out-of-sample prediction finds no 12-month ahead prediction (R^2_{OS}=-1.41, and the utility gain is -218 bps). The results are consistent with results of Ang *et* *al*. (2014) where they find changes in option implied volatility provide predictability up to six months.

Consistent with Goyal and Welch (2008), the conventional predictors exhibit no significant out-of-sample predictability in terms of both R_{OS}^2 and utility gains. Several of the conventional predictors occasionally exhibit either positive R_{OS}^2 or positive utility gains at longer horizons, however these two measures are either insignificant or contradictory. For example, SVAR has insignificantly positive (0.22 with 23% significance) in three-month horizon yet the utility gain is negative (-254 bps). The dividend yield (ln(DY)) produces strong forecasts at the six-month horizon (3.19 with 1% significance), nevertheless the utility gain is -43.34%. The results are consistent with the high autocorrelation underlying these predictors.

We also confirm the intuition of Rapach Ringgenberg, and Zhou (2016) that equally-weighing the *IVS* reflects more information on the informed buys or sells rather than value-weighting or the *IVS* constructed from the *SPX* index. We find that both the value-weighted version of the *IVS* and the *IVS* constructed from the *SPX* index options fail to provide any predictive ability as measured by R_{OS}^2 or utility gains at any of the time horizons. These results suggest why our equally weighted version of the *IVS* exhibits predictive ability while other papers such as An, Ang, Bali, and Cakici (2014), who use a value-weighted version of the *IVS*, and Atilgan *et al.* (2015) who create a version of the *IVS* utilizing implied volatilities from call and put options on the S&P 500 index, do not.[9]

3. Does *IVS* Capture New Information?

In this section we perform three experiments to differentiate the source of the *IVS*' predictive ability from that of the other significant predictors. First, we isolate the part of the equity premium that is unrelated to the *IVS* and check if that component is predictable by the other predictor variables. If any of these variables can predict the part of the market risk premium that is orthogonal to the *IVS*, then we conclude they are capturing information that is different from what the *IVS* captures. For completeness we reverse the process to see if the *IVS* can predict the part of the risk premium that is orthogonal to the other returns. Next, we use subsamples to determine if the *IVS* predicts the market risk premium at the same points in the

[9] In the appendix we compare the in- and out-of-sample performance to several risk-based predictors that have shown promise as predictors of the market risk premium. These include: The aggregate short interest index (SII) in Rapach, Ringgenberg, and Zhou, (2016), the time-varying tail risk of Kelly and Jiang (2014), the aggregate liquidity measure of Pástor and Stambaugh (2003), and the aggregate systematic risk (CATFIN) of Allen, Bali, and Tang (2012) which is based on bank specific risks. The *IVS* outperforms these risk-based measures as a predictor of the market risk premium.

business cycle as the other predictors. Finally, we compare the cross-sectional pricing ability of three linear factor models that utilize predictor variables as instruments for the conditional expected market risk premium.

3.1 Orthogonality comparison

In Table 4 we perform the orthogonality tests of the information content in the predictors. In the first test we use the residuals from a regression of market returns on lagged *IVS* as the part of returns that is orthogonal to *IVS*. We regress these orthogonalized returns on each of the other predictors individually to see if there is any predictable information remaining in returns after controlling for *IVS*. In the second test we reverse the process and first orthogonalize returns to the each of the other predictors and then regress those orthogonalized returns on *IVS* to see if there is any remaining information that is predictable by *IVS*. That is, in the first step, we regress

$$r_{t+1} = \alpha_{i,h} + \beta_{i,h} x_{i,t} + \varepsilon_{i,t+1} \tag{11}$$

where $x_{i,t}$ represents one of the predictors. In the second step, we run the following regression:

$$\varepsilon_{i,t+1} = a_{i,t} + b_{i,t} \tilde{x}_{j,t} + u_{i,t+1} \tag{12}$$

where $\tilde{x}_{j,t}$ is the predictor $j \neq i$. If b_i is significant, then there is predictable information not being accounted for by x_i. Note that to make the magnitude of coefficients comparable among these regressions, we first standardize the level of residuals and predictors such that they are of mean zero and standard deviation one.

The first three columns of Table 4 contain the results from regressing returns that have been orthogonalized to the *IVS* on the other predictors. We focus on the DP, DY, and SVAR since they are the only variables besides the *IVS* that significantly predict the market risk premium at the 1-month frequency. Using monthly data, we find that the dividend to price ratio and dividend yield are related to returns after controlling for the *IVS* while SVAR has no predictive ability after removing the predictable component of the risk premium related to the *IVS*. In Panel B, all the predictors leave information that is predictable by the *IVS*. These results indicate that the predictors involving dividends contain information important for predicting returns not contained in the *IVS*.

3.2 Predicting Over the Business Cycle

Da, Jagannathan, and Shen (2014) show that stock return predictability varies with the business cycle. To examine how the predictability of the *IVS* changes across business cycles, we partition our data into two sub-samples based on the business cycle. Asset returns are functions of the state variables of the real economy. If these state variables are linked to economic fluctuations, then the time-varying expected returns and return predictability are expected and variables that measure and/or predict the state of the economy should display different patterns across business cycle. Recessions are identified according to the time periods in the NBER business cycle indicator, which is the dates from peak to trough, and expansions are periods outside the indicator. We have two recessions in our sample period: March 2001 to November 2001 (8 months), and December 2007 to June 2009 (18 months).

We find that in Table 5 the one step ahead predictive ability of *IVS* during expansionary periods is insignificant, but during recessionary periods the *IVS* is the strongest predictor based on (R^2_{OS}=15.65 with 6% significance) or utility gains (345 bps). For the conventional predictors, we find that the dividend yield (ln(DY)) is the strongest predictor during expansion (5.19 with 1% significance, and 321 bps utility gain), but is a poor predictor during recessions. This provide more evidence that the *IVS* is capturing different information relative to the dividend yield.

3.3 Explaining the Cross-Section of Returns

A common use of variables shown to exhibit predictive ability is as informational variables in conditional versions of asset pricing models. In this section we utilize the *IVS* as an information variable in conditional versions of linear asset pricing models. If the *IVS* contains information that is valuable for predicting the market risk premium, then utilizing this information in a conditional framework should improve the pricing ability of the model relative to the unconditional version of the model. Because the focus of our paper is predicting the equity risk premium, we consider three models that include the market as a factor; the CAPM, the 3-factor model of Fama and French (FF3), and the 4-factor model of Carhart. For the CAPM we estimate the parameters for the following model

$$E_t(r_{t+1} \mid Z_t) = \alpha + \beta E_t(rm_{t+1} \mid Z_t) \quad (13)$$

where Z_t is the set of lagged information variables. For the multifactor models we estimate

$$E_t(r_{t+1} \mid Z_t) = \alpha + \beta E_t(rm_{t+1} \mid Z_t) + b'F \quad (14)$$

where F is the $k \times 1$ vector of factor realizations not including the market risk premium and b is the $k \times 1$ vector of loadings. Based on our previous results and because DY and DP are highly correlated, we only include the dividend yield and *IVS* in the information set, *i.e.* Z = {ln(DY), *IVS*}. For the unconditional versions of the models $Z = \{\varnothing\}$.[10] We model the time-variation in the conditional expected market risk premium as a linear function of the instruments. That is, we regress the market premium on the instruments as

$$rm_{t+1} = \gamma_0 + \gamma_1 ' Z_t + u_{t+1} \tag{15}$$

and then calculate the time-varying premium as $E_t\left(rm_{t+1} \mid Z_t\right) = \hat{\gamma}_0 + \hat{\gamma}_1 ' Z_t$.

Our test assets consist of monthly excess returns of 399 portfolios. All the portfolios are equally weighted and are available from Ken French's database. The test assets include five sets of decile portfolios sorted on past variance, residual variance, net share issues, beta, or accruals; three sets of portfolios double sorted into deciles base on size and book-to-market, size and operating profitability, or size and investment; and 49 industry portfolios. The risk-free rate, market return, SMB and HML factors, as well as the momentum factor are all from the same source.

Table 6 contains the number and percentage of significant intercepts from the unconditional and conditional versions of the three models using different sets of information. For the CAPM and FF3 model we see that modelling the time-varying market risk premium as a function of both *IVS* and the dividend yield reduces the number of significant alphas across the 399 test assets. For the CAPM the unconditional version of the model produces 68 significant alphas indicating that the CAPM fails to price 17% of the portfolios. The conditional version of the CAPM using both the dividend yield and the *IVS* reduces the number of significant alphas to 65. Using only the dividend yield as an instrument has a large impact on the ability of the CAPM to explain the cross-section of returns as the number of significant alphas falls to 24 or 6% of the portfolios. Using only the *IVS* as a conditioning variable brings the number of significant alphas to 20 or only 5% of the portfolios, reducing the number of significant alphas by 71% relative to the unconditional version of the model.

A similar pattern emerges for the FF3 model. Here the conditional versions of the model all produce many fewer significant intercepts but utilizing the *IVS* as a sole instrument has the largest impact. The unconditional FF3 model generates significant intercepts for 89 (22%) of the portfolios while using only the *IVS* as a conditioning variable for the market risk premium reduces that number by 85% with only 13 (3%) of the portfolios having a significant alpha. For the four factor Carhart model conditioning on DY alone or in conjunction with the *IVS*

[10] We estimate the models via iterated GMM with a Newey-West spectral density using $T^{1/3} \cong 6$ lags. The estimators produce two-stage least-squares estimates of the coefficients. For the multifactor models we do not include all the exogenous variables in the first stage estimate of the conditional expected market risk premium. We adjust the standard errors to account for the bias based on Gujarati (2003)

reduces the ability of the model to price these assets relative to the unconditional version. Using only the *IVS* to model the market risk premium reduces that number by 74% with 33 (8%) of the portfolios exhibiting a significant alpha.

Overall, when using the *IVS* to model the time-varying conditional expected market risk premium we find a dramatic reduction in the number of significant alphas relative to unconditional versions of the models. This improvement in model performance is larger than when using the log of the dividend price ratio, which was the next best predictor of the market risk premium in our earlier experiments. We take these results as further evidence that the *IVS* contains information different from that found in the other predictors which important for predicting returns.

4. The Source of the *IVS* Predictive Power

In this section we explore why the *IVS* predicts future returns on the market portfolio at longer horizons. Towards this end we perform three experiments. First, we decompose the market return into three components related to expected returns, cash flows, and the discount rate and test which component(s) is predictable by the *IVS*. Next, we relate the *IVS* to several surveys of market participants to show market sentiment is related to the *IVS*. Finally, we test the relation between the *IVS* and several measures of aggregate market uncertainty.

4.1 Stock Return Decomposition

Following Campbell and Shiller (1988) we decompose the stock return into innovations of expected return, cash flow and the discount rate, controlling for dividend-price ratio and other conventional variables in vector autoregression (VAR) framework. Then, we analyze whether investors, who trade based on the *IVS*, can anticipate future stock returns by anticipating shocks in discount rate and/or cash flow. Taking the set of conventional predictors in Goyal and Welch (2008) as a proxy for the market information set this analysis provides a deeper understanding of the sources of the forward-looking information in the *IVS*.

To understand the Campbell and Shiller (1988) method we begin with the definition of the log stock return, $r_{t+1} = \log[(P_{t+1} + D_{t+1})/P_t]$, where P_t (D_t) is the monthly stock price (dividend). The Campbell-Shiller log-linear approximation of r_{t+1} is given by

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t \tag{16}$$

where p_t (d_t) is the log stock price (divided), $\rho = \frac{1}{1+\exp(\overline{d-p})}$ where $(\overline{d-p})$ is the mean of log dividend ratio, and $k = -\log(\rho) - (1-\rho)\log[(1/\rho)-1]$. Thus, we can rewrite Equation (16) as

$$p_t \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - r_{t+1} \tag{17}$$

Solving Equation (17) forward and imposing the boundary condition, the stock price decomposition is given by

$$p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^j (1-\rho) d_{t+1} - \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \tag{18}$$

Letting E_t denote the expectation operator conditional on information through month t, Equation (16) and (18) imply the following decomposition for the log stock return innovation:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \tag{19}$$

According to equation (19), the stock return innovation can be decomposed into cash flow news and discount rate news components:

$$\eta_{t+1}^{r} = \eta_{t+1}^{CF} - \eta_{t+1}^{DR} \tag{20}$$

where:

$\eta_{t+1}^{r} = r_{t+1} - E_t r_{t+1}$ (expected return shock)

$\eta_{t+1}^{CF} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$ (cash flow shock)

$\eta_{t+1}^{DR} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j}$ (discount rate shock).

We use a VAR framework to extract the cash flow and discount shock components. Consider the following VAR(1) model:

$$Y_{t+1} = AY_t + U_{t+1} \tag{21}$$

where $Y_t = (r_t, d_t - p_t, z_t)$, the N-vector z_t contains predictor variables, and A is the $(N+2)$-by-$(N+2)$ matrix of VAR slope coefficients, and U_t is the vector of mean-zero innovations. Denote e_1 as $(N+2)$ vector with one as its first element and zeros for the remaining elements, the stock return innovation and discount rate shocks can be expressed as

$$\eta_{t+1}^{r} = e_1' U_{t+1} \tag{22}$$

and

$$\eta_{t+1}^{DR} = e_1' \rho A (I - \rho A)^{-1} U_{t+1} \tag{23}$$

The cash flow shock is then residually defined using Equation (20):

$$\eta_{t+1}^{CF} = \eta_{t+1}^{r} + \eta_{t+1}^{DR} \tag{24}$$

In terms of Equation (20), the expected stock return for *t + 1* based on information through *t* is given by

$$E_t r_{t+1} = e_1' A Y_t \tag{25}$$

Using $r_{t+1} = E_t r_{t+1} + \eta_{t+1}^{r}$ and Equation (20), the log stock return can then be decomposed as

$$r_{t+1} = E_t r_{t+1} + \eta_{t+1}^{CF} - \eta_{t+1}^{DR} \tag{26}$$

With sample observations for Y_t for $t = 1, \ldots, T$, we can use OLS to estimate A and U_{t+1} ($t=1, \ldots, T-1$) for the VAR model given by Equation (21). Thus we can estimate all coefficients, denoted as $\hat{A}$, $\hat{U}_{t+1}$, and $\hat{\rho}$. Plugging into Equations (22), (23), (24), and (25) yields $\hat{\eta}_{t+1}^{r}$, $\hat{\eta}_{t+1}^{DR}$, $\hat{\eta}_{t+1}^{CF}$, and $\hat{E}_t r_{t+1}$, respectively.

We analyze the source of *IVS*'s predictive power for future stock returns by examining its ability to predict the individual components comprising the total stock return. We begin with an in-sample predictive regression model for the market excess return on *IVS*:

$$r_{t+1} = \alpha + \beta IVS_t + \varepsilon_{t+1} \tag{27}$$

We then consider the following predictive regression models for the estimation of the individual components on the RHS of Equation (26):

$$\begin{aligned} r_{t+1} &= \alpha + \beta IVS_t + \varepsilon_{t+1} \\ \hat{\eta}_{t+1}^{CF} &= \beta_{CF} IVS_t + \varepsilon_{t+1}^{CF} \\ \hat{\eta}_{t+1}^{DR} &= \beta_{DR} IVS_t + \varepsilon_{t+1}^{DR} \end{aligned} \tag{28}$$

The properties of OLS imply the following relation between the OLS estimation of β in Equation (27) and those of β_E, β_{CF}, and β_{DR} in Equations (28): $\hat{\beta} = \hat{\beta}_{\hat{E}} + \hat{\beta}_{CF} - \hat{\beta}_{DR}$. By comparing the estimated slope coefficients in Equation (28), we can ascertain the extent to which *IVS*'s ability to predict total stock returns relates to its ability to anticipate the individual components on the RHS of Equation (26).

Table 7 reports OLS estimation when the expected return shock, cash flow shock, and discount rate shock are estimated based on individual VAR constructed from market excess returns, dividend price ratio, and one of conventional predictors. We always include the dividend price ratio in the VAR to properly estimate the cash flow and discount rate shocks. From the OLS estimation in Equation (27) is $\beta = 0.19$, the same as the estimation in the first column of Table 2. The results in Table 7 show that nearly all the $\hat{\beta}_{CF}$ estimates are significant except for NTIS and DFY indicating that innovations in cash flows contribute to the size of $\hat{\beta}_{IVS}$. Moreover, the magnitude for the coefficients of the innovation in the discount rate makes up 50% of that in the regression of the *IVS*. A weaker situation occurs for $\hat{\beta}_{DR}$. Innovations in cash flows explain most of the predictive power in the *IVS*. In contrast, the $\hat{\beta}_{E}$ coefficients are smaller and much less often significant. The intuition is the information underlying the option market influences market returns primarily through changes of cash flows in these markets.

4.2 Market Sentiment and the IVS

Greenwood and Shleifer (2014) argue that investor's belief about future market returns are correlated to predictors such as the dividend yield. Since sophisticated traders incorporate sentiment while trading both equity and options, we test if aggregated market sentiment is related to deviations in put-call parity that result in the predictive power captured by the *IVS*. Market sentiment is difficult to measure quantitatively.[11] Greenwood and Shleifer (2014) propose using surveys of investor's subjective forecast to the future economy. We use three survey-based return expectations as proxies of market sentiment: (1) the Gallup investor survey, (2) the American Association of Individual Investors (AAII) survey, and (3) the crash confidence index from the Yale School of Management. The time horizon of survey expectations for Gallup survey is the next 12 months. The AAII and crash index survey reports six-month expectations. For comparison we include a version of the statistically derived sentiment index of Baker and Wurgler (2006) from Huang, Jiang. Tu and Zhou (2015) which is adjusted for estimation error.

The Gallup survey (1996 – 2012) asks participants whether they were "very optimistic," "optimistic," "neutral," "pessimistic," or "very pessimistic" about stock returns over the next year. The Gallup survey is widely used in the economics and finance literature given its large sample size and consistent methodology. Our measure of expectations based on Gallup survey is:

$$Gallup = Bullish\% - Bearish\%$$

where Bullish% represent% the percentage of investors who are at least "optimistic" about the future stock market performance and Bearish% are those who are no more than "pessimistic". A non-zero Gallop measure indicates disparity among optimistic and pessimistic investors.

[11] Previous literature uses option open interest [Bessembinder, Chan, and Seguin (1996)] and turnover to identify investor's sentiment, assuming that trading activity is driven by beliefs about market trends [Hong and Stein (2007)].

i,t

The American Association of Individual Investors Investor Sentiment Survey (1987 – 2016) measures the percentage of individual investors who are bullish, neutral, or bearish on the stock market for the next six months. The survey is administered weekly to members of the American Association of Individual Investors. The main differences between American Association of Individual Investors survey and Gallup include: (1) a shorter prediction horizon, (2) fewer response levels, (3) the subjects of the survey, and (4) a shorter survey frequency. We construct two time-series of sentiment using this survey. First, we subtract the percentage of "bearish" investors from the percentage of "bullish" investors and denote this as AAII. We also take the moving average over the past eight weeks of the Bullish index in the survey (Bull8MA). We use monthly averages of the weekly data. The former measure is similar that of the Gallup in terms of the intuition, whereas the latter measure captures the momentum of the optimistic sentiment. The higher moving average of bullish index, the stronger aggregate sentiment in better future stock market performance.

The Investor Behavior Project at Yale University led by Robert Shiller releases surveys of individual investor confidence in the stock market. We use the one-year individual Crash Confidence Index. The Crash Confidence Index is the percentage of institutional respondents who think that the probability of a market crash is strictly less than 10%. Data are available only sporadically between 1989 and July 2001. After that, the surveys are conducted monthly. The main difference between crash confidence index and the other two surveys is that we use institutional investors' responses to construct an aggregated measure of market expectations. We also include a version of the ubiquitous market sentiment measure of Baker and Wurgler (2006) suggested by Huang, Jiang, Tu, and Zhou (2015) called the Aligned Investor Sentiment Index.[12] The Aligned Investor Sentiment Index adjustment utilizes a partial least square method to focus the Baker and Wurgler measure on information that more closely relates to expected market returns by removing a substantial amount of approximation errors that are not relevant for forecasting returns.

If market sentiment contributes to market return prediction and is measured with little noise, then investor sentiment and predictors will have a significant positive correlation. To test this, we regress the *IVS* on the contemporaneous standardized sentiment measures from surveys, *i.e.,*

$$IVS_t = \alpha + \beta Sent_{i,t} + \varepsilon_{i,t} \tag{29}$$

[12] We thank Goufu Zhou for making The Aligned Investor Sentiment Index available at his webpage: http://apps.olin.wustl.edu/faculty/zhou/PLS_BW_investor_sentiment_indexes.xls

where *Sent* represents the i^{th} market sentiment measures defined above. The results in Table 8 support the prediction that the *IVS* is related to the market participant's view of future market performance. For each survey there is a positive and significant relation between market sentiment and the *IVS*. The positive and significant relation also exist between the *IVS* and the aligned sentiment index. We take these results, along with those of the previous section, as evidence that the *IVS* captures investors' perspective of future cash flows or cash flow growth.

4.4 Macroeconomic Uncertainty and the IVS

The results above focus on the connection between the longer-run predictive ability of the *IVS* and the sentiment concerning future performance of the equity markets. We conjecture that the *IVS* also reflects reactions of option investors to innovations in the aggregate level of uncertainty which impacts firms through cash flows, investment opportunities, and earning management and through monetary and fiscal policy shocks which have a significant impact on market returns. In this section we explore whether the *IVS* reflects information concerning linkages between the state of the economy and financial markets [Dew-Becker, Giglio, and Kelly (2018)].

For this experiment we test the contemporaneous relation between the *IVS* and broad measures of macroeconomic and financial uncertainty from Jurado, Ludvigson, and Ng (2015). MUx and FUx are macroeconomic uncertainty and financial uncertainty about next x-month horizon (x=1, 3, 12), respectively. The econometric estimates of their uncertainty measure do not rely on model structure or economic indicators because they use innovations from a factor augmented VAR with a large set of time series. Specifically, MUx and FUx are created using 132 macroeconomic and 147 financial variables, respectively.

We also consider measures of policy uncertainty from Baker, Bloom and Davis (2016). Their measure is based on newspaper coverage frequency. They find that policy uncertainty is associated with greater stock price volatility and reduced investment and employment. They count key words frequency within three main sources to construct the measure: (1) 10 large newspapers, (2) reports by the Congressional Budget Office (CBO), and (3) the Federal Reserve Bank of Philadelphias Survey of Professional Forecasters. We apply their news measure (*News*, using Newspaper source) and baseline measure (*baseline,* using all three sources).

We estimate and test for significance of the slope parameter in the following model:

$$IVS_t = \alpha + \beta Uncertainty_{i,t} + \varepsilon_{i,t} \tag{30}$$

where *Uncertainty* ∈ {MU1, MU3, MU12, FU1, FU3, FU12, Baseline, News}[13]. Here, *Uncertainty* and *IVS* are standardized to have a mean zero and standard deviation of one. The sample period is 1996:1 to 2017:12. The results in Table 9 indicate a consistently negative relation between the *IVS* and aggregate levels of macroeconomic, financial, and political uncertainty. We interpret these findings and the results in the previous section as evidence that the *IVS* captures general market sentiment.

4.5 Controlling for the Variance Risk Premium

Bollerslev, Tauchen, and Zhou (2009) demonstrate the ability of the variance risk premium, *i.e.* the difference between the expected variance under the risk-neutral and the physical measure, to predict future market returns. Atilgan *et al.* (2015) find that after controlling for conditional variance, the volatility spread (OTM put versus ATM call based on the SPX) cannot predict the market excess returns longer than one-week horizon. Since both the *IVS* and the *VRP* derive their predictive abilities by utilizing information from the options markets, we explore if there is any incremental predictive power in the *IVS* beyond the *VRP*.

In Table 10 we demonstrate that our implied volatility spread measure calculated using individual stock option implied volatilities is robust to accounting for the variance risk premium. In Panel A we present the in-sample prediction results when we include the variance risk premium (*VRP*) in the *IVS* predictive regressions. We conduct one- to twelve-month ahead predictions and evaluate the in-sample prediction results. The coefficients of *IVS* are 0.14, 0.19, 0.19, and 0.09 for one- to twelve-month horizons and only slightly smaller than those in Table 2. The coefficients for *IVS* are significant up to three months and the coefficients on *VRP* are significant up to twelve months out.

In Panel B we present the out-of-sample results for a predictive regression using only *VRP*, a predictive regression using both the *VRP* and *IVS*, the combining the forecasts of *VRP* and the *IVS* as a simple average and the discounted mean square prediction error (DMSPE) which combines *IVS* and *VRP* using the weights defined in Rapach, Strauss, and Zhou (2010).[14] *VRP* exhibits significant out-of-sample R^2 and positive utility gains over the entire sample and for expansions and recessionary periods. Including the *IVS* in the predictive regression continues

[13] We download the data from: https://www.sydneyludvigson.com/s/MacroFinanceUncertainty_2019Feb_update.zip and http://www.policyuncertainty.com/media/US_Policy_Uncertainty_Data.xlsx.

[14] DMSPE combines the *m* forecast of *i* = *IVS* and VRP using the weights: $\omega_{i,t} = \varphi_{i,t}^{-1} \Big/ \sum_{j=1}^{N} \varphi_{i,t}^{-1}$, where $\varphi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1})^2$ is the discounted squared forecast using θ = 0.75 as the discount factor.

to produce significant out-of-sample R^2, but we find larger utility gains overall and in both sub-samples. For the full sample and recessionary sample, including the *IVS* nearly doubles the increase in utility. Averaging the forecasts of the *IVS* and the *VRP* using a simple average or the DMSPE method also increases the out-of-sample R^2 and utility gains.

While both the *VRP* and the *IVS* exhibit significant out-of-sample predictive ability, we are unable to deduce whether the *VRP* or the *IVS* is a better predictor of the market risk premium. We can conclude that they are complementary predictors. An investor who combines the predictability of these two variables will see large gains in utility especially during recessionary periods.

5. Conclusion

We show that the *IVS* can robustly predict the equity risk premium over the sample period of 1996 to 2017. We first consider in-sample predictive performance using monthly data to predict 1, 3, 6, and 12 months ahead equity risk premium. We find that in-sample results are significant under most forward periods, even after controlling for the variance risk premium. We also examine the out-of-sample prediction of the *IVS*. We find that the *IVS* is a strong predictor of the equity risk premium under various specifications, in-sample and out-of-sample, and for longer horizons than has been previously demonstrated in the literature. Part of the predictive ability is due to using an equally weighted version of the *IVS* suggested by the intuition of Rapach *et al.* (2016). We also show that the *IVS* predictive ability is the strongest during recessions while the predictive ability of the dividend yield is the strongest during expansions. Utilizing the *IVS* as an information variable in conditional versions of the CAPM significantly improves pricing of portfolios that are difficult to price unconditionally.

The source of prediction is due to forward-looking information underlying the *IVS*. We show that the *IVS* predictive ability is primarily related to cash flow innovations relative to innovations in expected returns or innovations in the discount rate. We also demonstrate a significant relation between the *IVS* and measures of aggregate market performance as well as uncertainty concerning the macroeconomy and financial markets. Together the evidence of longer-term predictive ability and relation to aggregate market expectations indicate that the *IVS* captures information important for predicting the market risk premium beyond the short-term impacts arising from informed trading in the options and equity markets. The *IVS* also appears to capture general market sentiment.

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Tables

Table 1: Summary statistics

This table displays summary statistics of market returns, implied volatility spread (*IVS*), and 14 predictors from Goyal and Welch (2008), where AR(1) is the 1st order autocorrelation, respectively. Market excess returns are the logarithm of the return on the value weighted CRSP index minus logarithm of the prevailing short-term interest rate. *IVS* is the equal-weighted average of call and put option implied volatility spread across individual stocks. ln(DP) is the log dividend-price ratio, ln(DY) is the log dividend yield, ln(EP) is the log earnings-price ratio, ln(DE) is the log dividend-payout ratio, SVAR is sum of squared daily returns on the S&P 500, BM is the book-to-market ratio for the Dow Jones Industrial Average, NTIS is net equity expansion, TBL is the interest rate on a three-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA- and AAA-rated corporate bond yields, DFR is the long-term corporate bond return minus the long-term government bond return, and INFL is inflation calculated from the CPI for all urban consumers. The sample contains 264 observations for the monthly sample for the period 1996:1 to 2017:12.

	Mean	Std	AR(1)
Market excess returns	0.005	0.043	-0.043
IVS	-0.008	0.005	0.372
ln(DP)	-4.016	0.209	0.949
ln(DY)	-4.010	0.209	0.949
ln(EP)	-3.156	0.381	0.929
ln(DE)	-0.860	0.436	0.940
SVAR	0.003	0.005	0.438
BM	0.268	0.073	0.926
NTIS	0.002	0.019	0.936
TBL	0.022	0.021	0.983
LTY	0.045	0.014	0.958
LTR	0.006	0.030	-0.182
TMS	0.023	0.013	0.939
DFY	0.010	0.004	0.888
DFR	0.001	0.018	-0.087
INFL	0.002	0.004	0.038

Table 2: In-sample Predictability

This table reports the estimation results of in-sample predictive regressions. The prediction model is

$$r_{t+h} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t+h}$$

where r_{t+h} is h-month-ahead market excess returns, including 1-month ahead predictions and overlapping 3, 6, and 12-month predictions, and X_i represents each predictor in the first column. See the notes of Table 1 for variable definitions. The columns labeled t_{NW} contains t-statistics using Newey-West heteroscedasticity-autocorrelation consistent standard errors with lags chosen as in Ferson *et al.* (2003). Market excess returns and predictors are standardized to have a mean zero and standard deviation of one. The sample period is 1996:1 to 2017:12.

	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
Predictor	β	t_{NW}	β	t_{NW}	β	t_{NW}	β	t_{NW}
IVS	0.19	3.02	0.26	4.33	0.25	4.09	0.13	2.03
ln(DP)	0.13	2.10	0.20	3.35	0.31	5.21	0.43	7.48
ln(DY)	0.14	2.37	0.22	3.54	0.32	5.39	0.44	7.80
ln(EP)	0.06	0.93	0.04	0.58	0.02	0.34	0.08	1.19
ln(DE)	0.01	0.19	0.07	1.07	0.13	2.10	0.14	2.22
SVAR	-0.16	-2.57	-0.15	-2.51	-0.03	-0.53	0.05	0.74
BM	0.07	1.19	0.13	2.05	0.24	4.03	0.31	5.22
NTIS	0.10	1.59	0.21	3.42	0.27	4.52	0.30	4.95
TBL	-0.05	-0.76	-0.02	-0.28	-0.05	-0.80	-0.11	-1.73
LTY	-0.08	-1.26	-0.06	-0.98	-0.08	-1.28	-0.06	-1.02
LTR	0.03	0.53	-0.02	-0.36	0.03	0.55	0.02	0.32
TMS	-0.01	-0.14	-0.04	-0.63	0.00	-0.08	0.11	1.76
DFY	-0.08	-1.23	-0.08	-1.24	0.01	0.14	0.08	1.24
DFR	0.08	1.23	0.06	0.91	0.06	0.90	0.06	1.01
INFL	0.09	1.50	-0.05	-0.79	-0.13	-2.15	-0.14	-2.16

Table 3:Out-of-sample Predictability

This table reports estimation results of out-of-sample predictive regression for next 1-, 3-, 6-, and 12-month (cumulative) market excess returns. Out-of-sample R^2 (R_{OS}^2 (%)) is defined as one minus the ratio of mean square forecast error (MSFE) of predictive regression versus MSFE of historical average up to the current period. *p* represents the *p*-value associated with Clark-West MSFE-adjusted statistic, testing the null hypothesis, H_0: $R_{OS}^2 \leq 0$, and the alternative H_1: $R_{OS}^2 > 0$; that is, the historical average MSFE is less than or equal to the predictive regression MSFE. Δ (%) is the annualized utility gain, the difference between predicted utility and historical average utility, calculated from the CARA utility of holding mean-variance portfolios. See the notes of Table 1 for variable definitions and *IVS* (*VW*) is the value-weighted version of the IVS where the weights are based on market capitalization. *SPX* is the *IVS* constructed from the index options (*SPX*). The sample period is 1996:1 to 2017:12.

	h = 1			*h* = 3			*h* = 6			*h* = 12		
	R_{OS}^2	*pval*	Δ	R_{OS}^2	*pval*	Δ	R_{OS}^2	*pval*	Δ	R_{OS}^2	*pval*	Δ
IVS	3.23	0.08	1.46	3.18	0.04	3.10	2.58	0.01	0.44	-1.41	0.12	-2.18
ln(DP)	-5.01	0.83	-6.18	-9.30	0.82	-13.83	0.93	0.03	-45.81	-2.26	0.15	-62.34
ln(DY)	-3.10	0.65	-3.76	-6.94	0.67	-10.92	3.19	0.01	-43.34	0.43	0.12	-54.19
ln(EP)	-8.04	0.65	0.87	-15.90	0.82	0.40	-7.64	0.08	-13.23	-15.32	0.24	-36.06
ln(DE)	-6.93	0.43	-0.28	-8.35	0.33	0.80	-15.40	0.51	-10.17	-28.82	0.71	-26.48
SVAR	-3.04	0.27	-7.35	0.22	0.23	-2.54	-4.86	0.27	-1.47	-5.36	0.27	0.27
BM	-1.10	0.78	-0.94	-0.49	0.28	-0.02	-2.92	0.01	-13.00	-12.00	0.02	-15.90
NTIS	-1.45	0.26	-2.87	-0.04	0.07	-1.82	-4.48	0.00	1.30	-5.17	0.08	7.68
TBL	-0.92	0.59	-0.49	-1.72	0.50	-0.18	-10.98	0.61	-11.62	-16.35	0.64	-13.65
LTY	-0.58	0.43	-0.03	-1.17	0.41	0.38	-1.98	0.11	3.97	-4.95	0.28	3.13
LTR	-1.53	0.96	-1.13	-1.45	0.78	-1.34	-1.07	0.79	-0.06	-1.08	0.94	-0.27
TMS	-0.61	0.72	-0.76	-0.67	0.55	0.22	-10.90	0.90	-12.24	-19.00	0.79	-16.47
DFY	-4.50	0.22	-0.70	-10.99	0.09	-1.88	-11.41	0.00	1.16	-11.45	0.11	4.52
DFR	-5.21	0.79	-4.79	-5.64	0.90	-6.13	-3.56	0.65	-7.90	-2.60	0.74	-1.18
INFL	-0.26	0.34	-2.17	-1.31	0.67	-1.95	-0.04	0.21	-2.81	-0.84	0.31	-5.22
IVS (*VW*)	-1.08	0.79	-0.91	-2.26	0.97	-2.33	-0.26	0.32	-1.28	-0.57	0.47	-1.96
SPX	-0.90	0.54	-1.21	-0.45	0.59	-0.42	-4.48	0.97	-6.29	-6.77	0.92	-4.97

Table 4: Information content of *IVS*

The table presents the predictive power for all predictors, using an "orthogonal two-step" method. The first step is to use the predictor *IVS* to predict the equity premium, i.e.,

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1}.$$

Using ε_{t+1} as the part of the equity premium not explained by *x,* the second step is to regress the residual on other predictors, i.e.,

$$\varepsilon_{t+1} = \delta + \gamma \tilde{x}_t + \omega_{t+1}.$$

In Panel A, Column (1) to (3) represent to orthogonality regression of the call-put option implied volatility spread residual on other predictors, and Panel B Column (1) to (3) represent a test of whether *IVS* can explain other predictor's residuals. The sample period is 1996:1 to 2017:12.

Panel A: Other predictor on *IVS*'s residual			
Second Step: $\varepsilon_{t+1}^{IVS} = \delta + \gamma X_t + \omega_{t+1}$	γ	t_{NW}	R^2 (%)
ln(DP)	0.17	2.80	2.91
ln(DY)	0.19	3.17	3.70
SVAR	-0.09	-1.46	0.81
Panel B: *IVS* on other predictor's residual			
Second Step: $\varepsilon_{t+1}^{X} = \delta + \gamma IVS_t + \omega_{t+1}$	γ	t_{NW}	R^2 (%)
ln(DP)	0.22	1.99	4.53
ln(DY)	0.23	2.10	4.88
SVAR	0.13	1.86	1.61

Table 5: Expansions and Recessions

We use the business cycles defined by the NBER to separate the sample into expansive and recessive periods. See the notes to Table 1 for the variable definitions. Out-of-sample R^2 is defined as one minus the ratio of mean square forecast error (MSFE) of prediction versus MSFE of historical average up to the current period. Clark-West *p*-values are reported The Clark-West MSFE-adjusted statistic tests the null hypothesis, H_0: $R_{OS}^2 \leqslant 0$, and the alternative H_1: $R_{OS}^2 > 0$; that is, the historical average MSFE is less than or equal to the predictive regression MSFE. The sample period is 1996:1 to 2017:12.

	Expansion			Recession		
Predictor	R_{OS}^2	*pval*	Δ (%)	R_{OS}^2	*pval*	Δ (%)
IVS	-6.17	0.48	1.15	15.65	0.06	3.45
ln(DP)	4.33	0.00	2.70	-17.37	0.99	-61.25
ln(DY)	5.19	0.00	3.21	-14.06	0.99	-47.34
SVAR	2.61	0.07	0.42	-10.52	0.35	-58.76

Table 6: Conditioning on *IVS* and Dividend Yield

This table contains the number and percentage of significant intercepts from regressing the 399 monthly excess portfolio returns described in the text on excess market returns for conditional and unconditional versions of the CAPM, Fama and French 3-factor model (FF3), and the Carhart 4-factor model (Carhart). All the portfolios are equally weighted. The factors for three models and the portfolio data are all available from Ken Frenchs web page. The row labeled Unconditional contains number and percentage of the sample of alphas significantly different from zero using Newey-West (1987) standard errors from the unconditional versions of the models. The rows labeled $E[R_M|\{DY, IVS\}]$ contain the results for conditional versions of the where the market risk premium is a linear function of the instruments both DY and *IVS*. The data are for the period 1996:1 to 2016:12.

Model	Number of $|t\text{-stat}| \geq 1.96$	Percent of Sample
CAPM Unconditional	68	0.17
CAPM with $E[R_M|\{DY, IVS\}]$	65	0.16
CAPM with $E[R_M|DY]$	24	0.06
CAPM with $E[R_M|IVS]$	20	0.05
FF3 Unconditional	89	0.22
FF3 with $E[R_M|\{DY, IVS\}$	35	0.09
FF3 with $E[R_M|DY]$	34	0.08
FF3 with $E[R_M|IVS]$	13	0.03
Carhart Unconditional	125	0.31
Carhart with $E[R_M|\{DY, IVS\}]$	168	0.42
Carhart with $E[R_M|DY]$	198	0.50
Carhart with $E[R_M|IVS]$	33	0.08

Table 7: Decomposing Market Returns

This table investigates the sources of prediction power in call-put implied volatility spread. Based on Campbell and Shiller (1988), we first regress the equity premium on the logarithm of dividend-price ratio and other conventional predictors. The innovation is the difference between raw discount data and expected discount variables. Lastly, we regress three innovations on the call-put implied volatility spread respectively. See the notes in Table 1 for the variable definitions. The sample period is 1996:1 to 2017:12.

	Expected Return Channel		Cash Flow Channel		Discounted Rate Channel	
Predictor	$\hat{\beta}_E$	*pval*	$\hat{\beta}_{CF}$	*pval*	$\hat{\beta}_{DR}$	*pval*
ln(DP)	-0.04	0.04	0.12	0.01	-0.12	0.06
ln(DP),SVAR	0.04	0.38	0.10	0.01	-0.06	0.22
ln(DP), BM	-0.04	0.04	0.10	0.01	-0.13	0.04
ln(DP), NTIS	0.00	0.96	0.03	0.23	-0.15	0.03
ln(DP), TBL	-0.04	0.07	0.11	0.02	-0.12	0.04
ln(DP), LTY	-0.04	0.04	0.12	0.03	-0.11	0.06
ln(DP), LTR	-0.04	0.07	0.12	0.01	-0.11	0.07
ln(DP), TMS	-0.03	0.15	0.12	0.01	-0.10	0.12
ln(DP), DFY	0.03	0.20	0.08	0.32	-0.08	0.04
ln(DP), DFR	-0.05	0.02	0.12	0.01	-0.12	0.04
ln(DP), INFL	-0.04	0.09	0.12	0.02	-0.11	0.05

Table 8: Sentiment and the implied volatility spread

This table reports regressions of the implied volatility spread (*IVS*) on the measures of sentiment calculated from survey-based data. The Gallup Spread is computed as the fraction of investors who are bullish (optimistic or very optimistic) minus the fraction of investors who are bearish. This series spans monthly 1996:10 to 2011:12, with a notable gap between 2009:11 and 2011:2. AAII Bull8MA is the last-eight-week moving average of the percentage of "bullish" investors, weekly 1996:1 to 2016:12. AAII Spread is calculated by subtracting the percentage of "bearish" investors from the percentage of "bullish" investors monthly 1996:1 to 2011:12. Crash Confidence is one of the Yale School of Management Stock Market Confidence Indexes based on survey data reporting the confidence that there will be no stock market crash in the succeeding six months. Crash confidence is available between 1989:10 and 2016:12. BW AIS is the Baker and Wurgler (2006) sentiment index aligned for forecasting by Huang, Jiang, Tu, and Zhou (2015) between 1996:1 to 2016:12. We regress sentiment on contemporaneous *IVS*

$$IVS_t = \alpha + \beta\, Sent_{i,t} + \varepsilon_{i,t}$$

where *IVS* is the implied volatility spread at time *t*, and *Sent* includes Gallup Spread, AAII Spread, AAII Bull8MA, Crash or BW AIS. The represented results are coefficients estimate of β and three statistics. t(NW) is calculated using Newey-West heteroscedasticity-autocorrelation consistent standard errors with twelve-month lags, t(HH) corrects overlapping observation bias with twelve-month lags, and R^2 (%) associates with OLS regression.

Sentiment Measure	β	t_{NW}	t_{HH}	R^2 (%)
Gallup Spread	0.45	5.20	6.07	20.40
AAII Bull8MA	0.15	2.69	2.26	2.15
AAII Spread	0.23	2.04	2.20	12.45
Crash	0.35	2.76	2.25	11.98
BW AIS	0.29	3.32	2.93	8.45

Table 9: *IVS* and Macroeconomic, Financial, and Political Uncertainty

This table contains test results of the relationship between uncertainty measures and the implied volatility spread (*IVS*). MU*x* and FU*x* are macroeconomic uncertainty and financial uncertainty about next *x*-month horizon (*x*=1, 3, 12), respectively (Jurado, Ludvigson and Ng, 2015). Political uncertainty about the next one month includes Baseline and News, economic policy uncertainty (EPU) measures based on Baker, Bloom and Davis (2016). The reported results are coefficient estimates of β and corresponding *t*-statistics and R^2. t(NW) is calculated using Newey-West (1987) heteroscedasticity-autocorrelation consistent standard errors with twelve-month lags modified by Ferson *et al.* (2003). The prediction model is

$$IVS_t = \alpha + \beta\ Uncertainty_{it} + \omega_t$$

where $Uncertainty_{it}$ is the i^{th} uncertainty measure, and *Uncertainty∈{MU1, MU3, MU12, FU1, FU3, FU12, Baseline, News}*. Uncertainty and *IVS* are standardized to have a mean zero and standard deviation of one. The sample period is 1996:1 to 2017:12.

Uncertainty	β	t_{NW}	R^2 (%)
MU1	-0.46	-2.25	21.42
MU3	-0.46	-2.19	20.90
MU12	-0.44	-2.16	19.38
FU1	-0.39	-2.56	14.94
FU3	-0.38	-2.60	14.48
FU12	-0.36	-2.66	12.91
Basline (h=1)	-0.28	-3.45	7.70
News (h=1)	-0.22	-2.71	4.97

Table 10: Controlling for Variance Risk Premium

Panel A reports estimation results of in-sample predictive regressions including the *IVS* and the *VRP*. The prediction model is

$$r_{t+1} = \alpha_i + \beta_i IVS_{i,t} + \gamma_i VRP_t + \varepsilon_{i,t+1}$$

where r_{t+1} is one-month ahead market excess returns, and *VRP* is the variance risk premium, defined as the difference between model-free implied volatility and realized volatility calculated using historical market returns, and the data is from Zhou's website. Panel B contains out-of-sample results for a predictive regression using only *VRP*, a predictive regression using both the *VRP* and *IVS*, the forecast of combining the forecasts of *VRP* and the *IVS* as a simple average and the discounted mean square prediction error (DMSPE) which combines *IVS* and *VRP* using the weights defined in Rapach et. al (2010). Here t_{NW} is calculated using Newey-West heteroscedasticity-autocorrelation consistent standard errors with 12-month lags modified by Ferson *et al.* (2003). R^2 is the percentage of adjusted R^2. Market excess returns and predictors are standardized to have a mean zero and standard deviation of one. Out-of-sample R^2 is defined as one minus the ratio of mean square forecast error (MSFE) of prediction versus MSFE of historical average up to the current period. Clark-West *p*-values are reported The Clark-West MSFE-adjusted statistic tests the null hypothesis, H_0: $R_{OS}^2 \leqslant 0$, and the alternative H_1: $R_{OS}^2 > 0$; that is, the historical average MSFE is less than or equal to the predictive regression MSFE. The sample period is 1996:1 to 2017:12.

Panel A: In-sample Prediction with *VRP*

	β	t_{NW}	β_{VRP}	t_{NW}	R^2
One-month	0.14	2.23	0.21	3.51	7.76
Three-month	0.19	2.01	0.30	4.39	15.17
Six-month	0.19	1.68	0.25	2.94	11.85
Twelve-month	0.09	0.86	0.15	1.72	3.85

Panel B: Out-of-sample Prediction with *VRP*

	Overall			Expansion			Recession		
	R_{OS}^2	*pval*	Δ(%)	R_{OS}^2	*pval*	Δ(%)	R_{OS}^2	*pval*	Δ (%)
VRP	5.13	0.02	2.29	3.94	0.03	1.14	7.08	0.10	8.65
VRP + IVS	4.57	0.02	4.44	2.19	0.05	1.82	8.51	0.06	19.89
Simple average	6.59	0.02	4.31	3.06	0.04	1.81	12.44	0.05	19.04
DMSPE	6.72	0.02	4.82	3.07	0.04	2.04	12.76	0.05	21.30