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Predicting the Equity Market with Option-Implied Variables*

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Abstract

We comprehensively analyze the predictive power of several option-implied variables for monthly S&P 500 excess returns and realized variance. The correlation risk premium (*CRP*) and the variance risk premium (*VRP*) emerge as strong predictors of both excess returns and realized variance. This is true both in- and out-of-sample. Our results also reveal that statistical evidence of predictability does not necessarily lead to economic gains. However, a timing strategy based on the *CRP* leads to utility gains of more than 5.03% per annum. Forecast combinations provide stable forecasts for both excess returns and realized variance, and add economic value.

JEL classification: G10, G11, G17

Keywords: Equity Premium, Option-Implied Information, Portfolio Choice, Predictability, Timing Strategies

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I. Introduction

A growing literature, e.g. [Jiang & Tian \(2005\)](#), [Bollerslev et al. \(2009\)](#), and [Driessen et al. \(2013\)](#), documents the predictive power of option-implied variables for equity excess returns and realized variance. The growing number of option-implied predictors raises several questions: Which variables really forecast market excess returns? Do the variables that predict market excess returns also forecast realized variance? Does predictability lead to economic gains? These are some of the questions we want to study.

The main contribution of this paper is to provide a comprehensive analysis of the forecasting ability of variables separately proposed in the recent literature on option-implied predictors. We perform our analysis following the methodological background of [Goyal & Welch \(2008\)](#). Importantly, we do not only analyze return predictability, but consider the predictability of variance at the same time. This is important from a portfolio choice perspective, since both quantities are needed for a portfolio decision. As such, we do not only consider statistical predictability, but also analyze the economic significance of return and variance predictability. We find that several variables, including the correlation risk premium (*CRP*) and the variance risk premium (*VRP*), predict the monthly excess return of the S&P 500. This is the case both in- and out-of-sample. We also show that both the *CRP* and the *VRP* predict not only the market excess return but also its realized variance. On the other hand, while most predictors are based on the option-implied moments of [Bakshi et al. \(2003\)](#), we note that the risk-neutral moments themselves have strong predictive power only for realized variance but not for the market excess return.

When studying the economic effects of the documented predictability in the context of portfolio choice, we find that relative to the agent who assumes that the mean and variance of the market return are unpredictable, a mean–variance agent with a risk-aversion coefficient of 3 who uses the information content of the *CRP* would realize utility gains of 5.03% per

annum (p.a.). Relatedly, we find that a return timing strategy based on the *VRP* leads to lower utility gains than those afforded by the strategy based on the recursive mean. This indicates that the statistical evidence of predictability of excess returns and realized variance, respectively, by the *VRP* does not always translate into economic gains. We conjecture that this result is due to the fact that individual variables lead to a large dispersion in the forecast estimation. Forecast combinations instead appear to generate stable forecasts for both excess returns and realized variance, and add economic value. Further, we link this result also to the sign-switching behavior of the *VRP* around economically important periods.

A variable is considered to have predictive power if it passes two tests. First, it has to generate statistically significant forecasts. In this case the variable contains key information about the variation in the market risk premium and the realized variance, respectively. [Bollerslev et al. \(2009\)](#) and [Drechsler & Yaron \(2011\)](#) argue that time-varying economic uncertainty is captured by the variance risk premium and, thus, affects the variation in the market risk premium. [Driessen et al. \(2009, 2013\)](#) state that the time-varying correlation risk is linked to economic uncertainty and, thus, also relates to the market price of return risk. Second, the variable needs to add economic value. Since the predictability, measured by the R^2 is, in general, small in magnitude, the question arises whether it is economically meaningful. Does an investor obtain an increase in utility by taking the variable into account? This aspect is often ignored in the existing literature. Our results show that the *CRP* emerges as the only predictor that passes both tests.

For robustness, we analyze the predictability of different specifications of the *VRP*. We follow [Andersen & Bondarenko \(2010\)](#), [Andersen et al. \(2015\)](#), and [Feunou et al. \(2015\)](#) and decompose the total variance risk premium into the downside and upside components. The results show that the upside and downside variance risk premia significantly predict excess returns and realized variance in-sample and add economic value based on a timing strategy.

Our work relates to the literature on the predictability of the market excess return

and/or its associated realized variance using option-implied quantities. [Bollerslev et al. \(2009\)](#) document the predictive power of the variance risk premium for S&P 500 excess returns, and [Bollerslev et al. \(2014\)](#) document similar results for a broad range of international equity indices. [Pyun \(2016\)](#) provides evidence of a weak out-of-sample performance of the variance risk premium for S&P 500 excess returns. [Driessen et al. \(2009, 2013\)](#) show that the correlation risk premium predicts S&P 500 excess returns, whereas [Cosemans \(2011\)](#) points out that the correlation risk premium and the systematic part of individual variance risk premia drive the predictive power of the variance risk premium for market excess returns. [Zhou \(2013\)](#) documents the predictive power of the S&P 500 implied correlation index for S&P 500 index returns. [Xing et al. \(2010\)](#) find that the option-implied smirk contains information about the cross-section of equity returns. [Cremers & Weinbaum \(2010\)](#) document that deviations from the put–call parity, measured as the difference in implied volatility between pairs of call and put options of U.S. stocks, contain information about the cross-section of stock returns and have predictive power for these. [Rehman & Vilkov \(2012\)](#) and [Stilger et al. \(2016\)](#) show that implied skewness of individual U.S. stocks has predictive power for future returns. [Bali et al. \(2011\)](#) introduce an option-implied generalized measure of riskiness and provide evidence for its predictive power for the cross-section of individual stock returns. [Bali et al. \(2012\)](#) and [Bali et al. \(2015\)](#) extend the analysis and document the predictive power of the generalized measure for economic downturns and future market excess returns. [Leiss et al. \(2015\)](#) and [Leiss & Nax \(2018\)](#) examine non-parametric risk-neutral densities from S&P 500 index options. [Leiss & Nax \(2018\)](#) provide evidence for the predictive power of an option-implied riskiness measure based on [Foster & Hart \(2009\)](#) for future downturns. [Bali et al. \(2017\)](#) document a relation between the risk-neutral moments of [Bakshi et al. \(2003\)](#) and expected stock returns.

[Jiang & Tian \(2005\)](#) and [Kourtis et al. \(2016\)](#) establish the forecasting power of the S&P 500 option-implied variance for realized variance. The above mentioned studies use

different sample periods and statistical techniques to document their results, thus making the interpretation and comparison of the findings somewhat difficult. We use a common sample period and recent developments in the literature on predictability to thoroughly analyze all these variables.

Our study also relates to the literature on the economic value of predictability. Typically, the literature analyzes the implications of return predictability for a return timing strategy (e.g., [Campbell & Thompson, 2008](#); [Çakmaklı & van Dijk, 2016](#)). Similarly, studies on realized variance predictability only explore the implications for a volatility/variance timing strategy ([Fleming et al., 2001](#)). Unlike these studies, we jointly study the impact of return and variance timing. This is important because in a mean–variance framework, the optimal portfolio weight invested in the risky asset depends on both the expected return and the expected realized variance. If a forecasting variable predicts both the market excess return and the realized variance, it might be potentially important to account for these two effects when computing the optimal weight.

The remainder of this paper proceeds as follows. Section *II.* introduces the data and explains the construction of the main variables. Section *III.* presents the main empirical results. Section *IV.* discusses some further results. Section *V.* provides additional results. Finally, Section *VI.* concludes.

***II.* Data and Methodology**

***II.A* Data**

We obtain our data from three distinct sources. First, we retrieve the monthly time series of the S&P 500 total return index as well as the corresponding dividend payments from the Center for Research in Security Prices (CRSP) database. Second, we obtain S&P

500 index option data from OptionMetrics. The OptionMetrics dataset contains information about option contracts available in the market as well as standardized options, both of which are useful for our analysis (see Section *II.B*). Third, we use intraday data on the S&P 500 index sampled at the 5-minute frequency from Thomson Reuters Tick History (TRTH). In sampling the intraday data, we focus on the normal trading hours, i.e. from 09:30 AM to 04:00 PM Eastern Daylight Time (EDT). Our sample period extends from January 1996 to December 2014. It is worth pointing out that although the CRSP database covers a period starting before 1996, this is not the case for the OptionMetrics and TRTH. Starting our sample in January 1996 allows us to guarantee the availability of data from all three databases.

***II.B* Variables**

Armed with the dataset introduced above, we are now able to construct our main variables.

Market Excess Return We compute the excess return on the S&P 500 index by subtracting the riskless rate for the corresponding period from the total return on the equity index:

$$ER_{t+1} = 12 \times \log \left(\frac{P_{t+1}}{P_t} \right) - rf_t, \quad (1)$$

where ER_{t+1} is the (annualized) monthly excess return on the S&P 500 index at the end of month $t + 1$. P_{t+1} and P_t denote the total return price index at the end of months $t + 1$ and t , respectively. rf_t refers to the (annualized) riskless rate observed at the end of month t .¹ Following [Goyal & Welch \(2008\)](#), we use the 1-month T-bill rate to proxy for the riskless rate.

¹Throughout this paper, we use the convention that the riskless rate is given the subscript for the time when it is observed. Thus, the riskless rate is observed at time t even though it is realized at time $t + 1$.

Realized Variance In order to estimate the realized variance of the stock market, we exploit developments in the literature on high-frequency financial econometrics. [Andersen et al. \(2003\)](#) show that by sampling data at the intraday level, one can improve the accurate measurement of realized variance. Building on this insight, we use intraday prices sampled at the 5-minute frequency to compute the realized variance of the asset:

$$RV_{t+1} = \frac{360}{N} \times \left[\sum_{i=1}^N \left(\sum_{j=1}^{m-1} \log \left(\frac{S_{t+\frac{i}{N},j+1}}{S_{t+\frac{i}{N},j}} \right)^2 \right) + \log \left(\frac{S_{t+\frac{i}{N},1}}{S_{t+\frac{i-1}{N},m}} \right)^2 \right], \quad (2)$$

where RV_{t+1} is the realized variance at the end of month $t + 1$. The first term to the right of the equality sign simply annualizes the variance estimate, where N is the number of days between the end of month t and that of month $t + 1$. Each day contains m intraday observations. $S_{t+\frac{i}{N},j+1}$ and $S_{t+\frac{i}{N},j}$ are the spot prices observed on day $t + \frac{i}{N}$ at times $j + 1$ and j , respectively. The last term to the right of the equality sign simply reflects the effect of overnight returns. In particular, it captures the impact of the return from the end of the previous day to the opening of the following day.

Option-Implied Moments Recent studies document the information content of option-implied moments, e.g. [Jiang & Tian \(2005\)](#), [Prokopczuk & Wese Simen \(2014\)](#), and [Kourtis et al. \(2016\)](#), for realized variance. We exploit the theoretical results of [Bakshi et al. \(2003\)](#) to construct the risk-neutral (i) variance (VAR^{BKM}), (ii) skewness ($SKEW^{BKM}$), and (iii) excess kurtosis ($EXKURT^{BKM}$):

$$VAR^{BKM} = \frac{e^{r\tau}V - \mu^2}{\tau}, \quad (3)$$

$$SKEW^{BKM} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{3/2}}, \quad (4)$$

$$EXKURT^{BKM} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3, \quad (5)$$

where r denotes the continuously compounded (annualized) interest rate for the period from t to $t+\tau$. We use the Ivy curve from OptionMetrics to proxy for the interest rate. Essentially, this curve is based on London Interbank Offered Rate (LIBOR) and Eurodollar futures.² τ indicates the time to expiration of each option, expressed as a fraction of a year. Note that all variables are contemporaneously observed. In the expressions above V , W , X , and μ are defined as follows:

$$V = \int_{K=0}^S \frac{2(1 + \log[\frac{S}{K}])}{K^2} P(K) dK + \int_{K=S}^{\infty} \frac{2(1 - \log[\frac{K}{S}])}{K^2} C(K) dK, \quad (6)$$

$$W = \int_{K=S}^{\infty} \frac{6 \log[\frac{K}{S}] - 3(\log[\frac{K}{S}])^2}{K^2} C(K) dK - \int_{K=0}^S \frac{6 \log[\frac{S}{K}] + 3(\log[\frac{S}{K}])^2}{K^2} P(K) dK, \quad (7)$$

$$X = \int_{K=S}^{\infty} \frac{12(\log[\frac{K}{S}])^2 + 4(\log[\frac{K}{S}])^3}{K^2} C(K) dK + \int_{K=0}^S \frac{12(\log[\frac{S}{K}])^2 + 4(\log[\frac{S}{K}])^3}{K^2} P(K) dK, \quad (8)$$

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V - \frac{e^{r\tau}}{6} W - \frac{e^{r\tau}}{24} X, \quad (9)$$

where K and S are the strike and spot prices, respectively. $C(K)$ and $P(K)$ denote the call and put prices of strike K , respectively. All other variables are as previously defined.

At the end of each calendar month, we use the OptionMetrics database to extract the standardized options data of 1-month maturity, the contemporaneous spot price, and the interest rate of corresponding maturity. We retain only out-of-the-money option prices. It is worth pointing out that the integrals in the formulas above implicitly assume the existence of a wide range of strike prices. Alas, this is not perfectly true in the market. Thus, we follow [Chang et al. \(2012\)](#) by computing a fine grid of 1,000 equidistant interpolated moneyness levels, i.e. K/S , ranging from 1% to 300%. For each moneyness level on that grid, we interpolate the implied volatility using a spline interpolation method. For moneyness levels outside of the moneyness range observed in the market, we extrapolate the implied volatilities

²We use this interest rate curve to be consistent with the empirical literature on option prices (e.g., [Bali & Hovakimian, 2009](#); [McGee & McGroarty, 2017](#)). Obviously, one may wonder if our main results hold if we substitute the OptionMetrics curve with the term-structure of Treasury rates. The effect on our main findings is negligible. The intuition behind this result is that most of our analysis focuses on options of short time to maturity. Because the interest rate is always multiplied by the time to maturity, we find that the interest rate proxy has very little impact on our results.

(Jiang & Tian, 2005). In practice, this means that if a moneyness level is lower (higher) than the lowest (highest) moneyness level available in the market, we simply use the implied volatility corresponding to the lowest (highest) level of moneyness available in the market. Next, we plug the implied volatilities into the Black & Scholes (1973) option pricing model to obtain the corresponding out-of-the-money option prices. Finally, we follow Bali et al. (2017) by using a trapezoidal rule to approximate the integrals that appear in the formulas above and obtain the risk-neutral moments of 1-month maturity.

Variance Risk Premium The variance risk premium is defined as the difference between the risk-neutral and physical expectations of variance:

$$VRP_t = E_t^{\mathbb{Q}}(\sigma_{t+1}^2) - E_t^{\mathbb{P}}(\sigma_{t+1}^2), \quad (10)$$

where $E_t(\cdot)$ is the expectation operator conditional on the information available at time t . The superscripts \mathbb{Q} and \mathbb{P} indicate that the expectation is computed under the risk-neutral and physical measures, respectively. In order to proxy for the risk-neutral expectation of variance, we use VAR^{BKM} . This choice is motivated by Du & Kapadia (2012) who show that the risk-neutral variance of Bakshi et al. (2003) is robust to jumps.

While the expression above clearly defines the variance risk premium, it is of very little practical use. The reason for this is that it involves the physical expectation of future variance, which is not directly observable. Therefore, we follow the lead of Bollerslev et al. (2009) and Driessen et al. (2013) in positing a simple random walk model for the future variance under the physical measure. That is, we assume that the expectation of the future variance under the physical measure equals its most recent realization. Thus, we can compute the VRP as follows:

$$VRP_t = VAR_t^{BKM} - RV_t. \quad (11)$$

Note that all variables are annualized and observed at the end of each calendar month.

Correlation Risk Premium [Driessen et al. \(2013\)](#) establish the predictive power of the correlation risk premium for future aggregate stock returns. The authors observe that the equity index is a portfolio of individual equities ([Driessen et al., 2009](#)). An upshot of this is that the variance of the market index return is equal to the weighted average variance of individual stocks and covariance terms. Assuming further that the pairwise correlation between different stocks is the same for all stocks, they are able to derive the following formula:

$$IC_t = \frac{E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds] - \sum_{\psi=1}^{\Theta} \omega_{\psi}^2 E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]}{\sum_{\psi=1}^{\Theta} \sum_{\chi \neq \psi} \omega_{\psi} \omega_{\chi} \sqrt{E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]} \sqrt{E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\chi,s}^2 ds]}}, \quad (12)$$

where IC_t is the implied correlation at time t . Θ denotes the number of stocks in the stock market. $E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds]$ and $E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]$ are the risk-neutral expected variance of the index (Ψ) and of the individual stock (ψ), respectively. As before, we proxy these expectations with the risk-neutral variance of [Bakshi et al. \(2003\)](#). w_{ψ} and w_{χ} are the weights of stocks ψ and χ in the market index Ψ , respectively.

The intuition developed above also holds under the physical measure, thus yielding the following formula for the realized correlation at time t :

$$RC_t = \frac{E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds] - \sum_{\psi=1}^{\Theta} \omega_{\psi}^2 E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]}{\sum_{\psi=1}^{\Theta} \sum_{\chi \neq \psi} \omega_{\psi} \omega_{\chi} \sqrt{E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]} \sqrt{E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\chi,s}^2 ds]}}, \quad (13)$$

where RC_t is the realized correlation at time t . All other variables are as previously defined. As before, we use the historical variance computed over the most recent period to proxy for the physical expectation of the future variance.

The CRP at time t is then defined as the difference between the risk-neutral and physical

expectations of future correlation, yielding the following result:

$$CRP_t = IC_t - RC_t. \quad (14)$$

To obtain this variable, we use standardized options (of time to maturity of one month) on the S&P 500 index as well as options data on all constituents of the index. All options are observed at the end of each calendar month.

Implied Volatility Smirk Measure Xing et al. (2010) document the predictive power of the implied volatility smirk.³ Our construction of this variable broadly mirrors theirs. At the end of each calendar month, we retain all S&P 500 index options with positive open interest and a time to maturity between 10 and 60 days. We discard all option prices with a midquote price below \$0.125. We also purge all options with implied volatility outside of the interval [3%; 200%]. We define the out-of-the-money put options as the put options with a moneyness level between 0.8 and 0.95. Note that by moneyness level, we understand the ratio of the strike price over the stock price, i.e. K/S . Relatedly, we define at-the-money call options as call options with a moneyness level between 0.95 and 1.05. The smirk measure is simply computed as follows:

$$SMIRK_t = VOL_t^{OTMP} - VOL_t^{ATMC}, \quad (15)$$

where $SMIRK_t$ is the smirk measure at time t . VOL_t^{OTMP} denotes the implied volatility of out-of-the-money puts. To be more precise, this is the volume-weighted average of the implied volatilities of all out-of-the-money put options. VOL_t^{ATMC} refers to the volume-weighted

³Xing et al. (2010) analyze the predictive ability of the implied volatility smirk in the cross-section of stock returns. Motivated by the intertemporal capital asset pricing model (ICAPM) of Merton (1973), if SMIRK is priced in the cross-section, it also has to predict the investment opportunity set in the time series (Maio & Santa-Clara, 2012).

average of all implied volatilities of at-the-money calls at time t .

Risk-Neutral Riskiness Leiss & Nax (2018) apply the result of Foster & Hart (2009) to the risk-neutral density of the S&P 500 index to derive an option-implied riskiness measure. We follow Leiss & Nax (2018) and first obtain the risk-neutral density of the S&P 500 using the approach of Figlewski (2010). That is, for the center of the distribution, i.e. the moneyness range observed in the market, we interpolate the implied volatilities using a 4th order spline with one knot at-the-money, computing the density using the corresponding Black & Scholes (1973) option prices. Finally, we parameterize the distributions of the left and right tails by separately fitting Generalized Extreme Value (GEV) distributions. Using the obtained distribution, we compute the risk-neutral Foster–Hart (FH) riskiness measure by solving the following equation:

$$\int_{S_T=0}^{\infty} \log\left(1 + \frac{S_T - S_0}{S_0} FH\right) f(S_T) dS_T = 0, \quad (16)$$

where S_T and S_0 are the stock prices at expiration and $t = 0$, respectively. $f(S_T)$ is the risk-neutral density at S_T . We numerically compute the integral using a trapezoidal rule and repeat this procedure on every trading day. Leiss & Nax (2018) remark that in some cases, Equation (16) does not have a solution, $FH \in (0, 1)$, in which case they set FH to 1 if the option-implied expected return $(\int_{S_T=0}^{\infty} \frac{S_T - S_0}{S_0} f(S_T) dS_T)$ is positive. If the option-implied return is negative and Equation (16) does not have a solution, we set FH to 0. FH may be interpreted as the fraction of wealth that can be invested in an asset so that no-bankruptcy is guaranteed. For this measure, we use data on traded option prices for all options on the S&P 500 for maturities between 10 and 50 days, each day picking the time to maturity

closest to 30 days.⁴ For the empirical tests, we follow [Leiss & Nax \(2018\)](#) and use a 21-day moving average of FH instead of the raw measure.

Generalized Measure of Riskiness Based on both [Foster & Hart \(2009\)](#) and [Aumann & Serrano \(2008\)](#), [Bali et al. \(2011\)](#) introduce a generalized measure of riskiness (GMR). We obtain GMR by solving the equation:

$$\int_{K=0}^S f_R(K)P(K)dK + \int_{K=S}^{\infty} f_R(K)C(K)dK - \frac{r\tau}{1+r\tau} \frac{1}{GMR} = 0, \quad (17)$$

with

$$f_R(K) = \frac{(1-\delta)}{S^2 GMR^2} \left(1 + \frac{K/S - 1}{GMR}\right)^{\delta-2}. \quad (18)$$

Following [Bali et al. \(2011\)](#), we set $\delta = -2$. All other variables are as previously defined. We compute the integrals for each trading day as described in the paragraph “Option-Implied Moments” using the standardized options with time to maturity of one month.

III. Main Results

Before discussing our main findings, it is instructive to look at the summary statistics reported in Table I. We can observe a positive market risk premium of around 6% p.a. The risk premium exhibits a standard deviation of around 16% p.a. We also notice that the sample moments of the VRP and the CRP are consistent with those reported in previous works ([Driessen et al., 2009, 2013](#)). In particular, we can see that although positive on average, the VRP is negatively skewed and prone to extreme movements as indicated by its high kurtosis, suggesting a sign-switching behavior. This observation could carry important

⁴For most measures in this study, we rely on the standardized options, provided by OptionMetrics. However, these are not suitable to obtain the entire risk-neutral density because they do not provide observations for deep out-of-the-money options which are necessary to accurately parametrize the GEV distributions.

implications for the predictive ability of this variable. We shall return to this point later.

The table also reports the AR(1) coefficient of each variable. We notice that the autoregressive coefficient of these variables is typically lower than that of the valuation ratios such as the (log) dividend to price ratio routinely analyzed in empirical works, e.g. [Goyal & Welch \(2003\)](#). This suggests that our analysis does not suffer from the statistical issues that affect these earlier works. We can also see that the AR(1) coefficient of the realized variance is much higher than that of the market risk premium, likely indicating that there might be a stronger evidence of predictability in the realized variance series than in the market excess returns.

Table II presents the sample correlation coefficients among all the predictive variables. While most variables are only weakly correlated, there is a high correlation between $SKEW^{BKM}$ and $EXKURT^{BKM}$ (-0.92). This suggests that these variables contain very similar information.

III.A Return Predictability

In-Sample Analysis We start by assessing the in-sample predictability of the equity risk premium. To do so, we estimate the standard regression model of the month-ahead excess return on a constant and the predictive variable(s):

$$ER_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_{t+1}, \tag{19}$$

where ER_{t+1} is the excess return on the market realized at the end of month $t + 1$. β_0 and β_1 are the intercept and slope parameters, respectively. X_t represents the forecasting variable(s) observed at the end of month t . Finally, ϵ_{t+1} is the regression error term at $t + 1$.

Table III summarizes the results for each predictive variable. The regression model enables us to ascertain whether the equity risk premium is time-varying or constant. Under

the null hypothesis that the future excess return cannot be predicted using X_t , we would expect that $\beta_1 = 0$. As a result, the expected market excess return would simply be constant. One implication of this is that the best estimate of the future excess return is simply its recursive mean. If there is evidence of predictability, we would expect to see that the slope loading is statistically significant. To avoid a small-sample bias (Stambaugh, 1999) and serial correlation in the error terms (Richardson & Stock, 1989), we base our statistical inference on the bootstrapped distribution obtained by implementing the framework of Rapach & Wohar (2006).⁵

We can see that the *CRP*, *GMR*, *SMIRK*, and *VRP* are statistically significant predictors in the univariate regressions. This is documented by their t -statistics of 2.76, 2.09, -2.06 , and 4.26, respectively. The positive and significant slope estimate related to the *VRP* confirms and updates, using a more recent sample period, the result of Bollerslev et al. (2009). It is also consistent with the authors' intuition that the *VRP* encodes information about time-variations in economic uncertainty. Note also that if, as argued by Driessen et al. (2013), *CRP* accounts for most of the *VRP*, then one would expect that *CRP* predicts future excess returns with a positive sign as we find in the data, since it has been documented that the *VRP* predicts the market excess return (Bollerslev et al., 2009).

The result that *CRP* predicts future returns is consistent with that in Driessen et al. (2009, 2013). There is a strong relationship between correlations and returns. It seems that correlations between stocks are time-varying and that correlations increase when returns are

⁵We estimate the process under the null hypothesis of no predictability, i.e. $ER_t = a_0 + \epsilon_{1,t}$ and $X_t = b_0 + b_1 X_{t-1} + \epsilon_{2,t}$, where a_0 , b_0 , and b_1 are the regression coefficients and $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are the error terms, respectively. We then form a series of error terms and set up our pseudo sample. For the pseudo sample, we compute the in-sample and out-of-sample statistics. Finally, we repeat this procedure 1,000 times. In the case of multiple regressions, we adjust the procedure by taking the multiple variables into account and, in-sample, by using the F -statistic rather than the individual t -statistic.

low.^{6,7} Moreover, the authors document a strong predictive power of IC for future returns, supported by a correlation of 0.24 between IC and VRP , shown in Table II.⁸ [Pollet & Wilson \(2010\)](#) provide evidence for the predictive power of (average) realized correlations for stock returns at a quarterly horizon.

The result of GMR for predicting future market returns confirms the findings of [Bali et al. \(2015\)](#). The authors find that GMR acts as a significant positive in-sample predictor of future aggregate market returns. The positive sign is consistent with the interpretation of GMR as a fundamental measure of risk: higher riskiness is associated with higher aggregate excess returns in the future.

The finding that $SMIRK$ predicts future returns with a negative sign extends the results of [Xing et al. \(2010\)](#) to the time series of the market excess return. The intuition behind this result is simple. An increase in $SMIRK$ implies a stronger demand for out-of-the-money put options. This increased demand signals that investors are actively purchasing insurance against expected declines in the stock index. The negative slope estimate of $SMIRK$ is consistent with this intuition.

It is also worth comparing the predictive power of individual variables. A cursory look at the in-sample R^2 reveals that VRP has the highest predictive power for future excess returns ($R^2 = 7.47\%$). The second most powerful predictor is the CRP , with an R^2 of 3.28%. While the slope estimate on the VRP is similar to that documented by [Bollerslev](#)

⁶They show that an increase in market correlations has two main effects. First, diversification possibilities are lower, thus, investors face limitations in their portfolio formations and suffering from a welfare reduction. Second, there is a rise in market volatility. One implication is that index options become relatively expensive compared to individual options. They represent a hedge against changes in market correlations, thus, also against losses due to diversification limitations.

⁷The use of CRP (and of IC and RC) can be theoretically motivated by the ICAPM of [Merton \(1973\)](#). It directly affects future investment opportunities, i.e. investors' future diversification benefits as well as the market variance. Moreover, [Driessen et al. \(2013\)](#) argue that CRP appears to drive the volatility of dividend growth, and also the volatility of dividend growth volatility, consistent with the argument of [Bollerslev et al. \(2009\)](#) for VRP . One implication is that CRP matters for both return as well as variance predictability.

⁸[Driessen et al. \(2009, 2013\)](#) document that IC strictly exceeds RC , indicating the existence of a large CRP . Our data support these findings. We observe a mean IC (RC) of 41.66 % (32.25 %), generating a mean CRP of 9.41 %.

et al. (2009), it is worth noticing that the predictive power we document at the monthly horizon is much higher, indicating that, if anything, the predictive ability of the *VRP* is much stronger in the more recent sample period.

It is worthwhile to analyze the performance of individual variables over time. Figure 1 plots the in-sample cumulative differences in squared forecast errors (CDSFE).⁹ We observe a similar (in-sample) performance in the case of the *CRP* and *VRP*, indicated by a sharp increase during the global financial crisis in 2008/2009, and a steady rise during the post crisis period. The findings suggest the outperformance of the unrestricted model to the restricted model, particularly in times of distress. It seems that investors can exploit the information content of both variables in times of high risk-aversion.

In the case of $EXKURT^{BKM}$ and $SKEW^{BKM}$, we find an increase in performance during the global financial crisis; however, afterwards there is a steady decline, suggesting the superior performance of the restricted model. Both variables appear to have substantial predictive power, particularly in crises. The CDFSE plot for *GMR* indicates that most of the predictive power stems from economic downturns.

SMIRK shows the strongest increase in the CDSFE plot during the global financial crisis, indicating that investors look for a hedge against a further market downturn, by buying put options. Finally, in the case of VAR^{BKM} , we see no strong fluctuations in its CDSFE, suggesting a similar performance of both the unrestricted and restricted model. Generally, we also find a strong increase in the performance after the dot-com bubble in 2001. This is true for all variables, except *SMIRK*.

To analyze the joint predictive ability of different variables, we perform three multiple regressions. Due to the high correlation between $SKEW^{BKM}$ and $EXKURT^{BKM}$, we run

⁹Please note that whenever there is a rise of the in-sample (or out-of-sample) performance, the unrestricted model outperforms the restricted model, and vice versa. In this case, a variable provides a better forecast than the benchmark model.

the regressions also once without the first and once without the second variable.¹⁰ In all cases we find that only *SMIRK* and *VRP* retain their statistical significance.¹¹ Overall, the adjusted R^2 increases to 8.81 %, 8.95 %, and 8.59 % in the first, second, and third case, respectively.

Out-of-Sample Results We now turn our focus to the out-of-sample evidence of return predictability. We use an initial training window of 5 years to first estimate the forecasting model presented in Equation (19). Equipped with the parameter estimates and the most recent observation of the forecasting variable in the training window, we are able to generate the first excess return forecast. The following month, we expand the training window by one observation month and re-estimate the forecasting model. With the new parameter estimates, we forecast the market excess return for the next month. We proceed analogously for all months, except the last month of our sample period.

In order to assess the out-of-sample performance of different models, we follow [Campbell & Thompson \(2008\)](#) and define the out-of-sample R^2 (R_{oos}^2) as follows:

$$R_{oos}^2 = 1 - \frac{MSE_u}{MSE_r}, \quad (20)$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted models, respectively. The unrestricted model is based on Equation (19). The restricted model imposes the null hypothesis that returns are unpredictable, i.e. $\beta_1 = 0$. Thus the R_{oos}^2 sheds light on the question: How large an improvement in forecast accuracy can one achieve by accounting for the predictive power of variable X_t ? The higher the R_{oos}^2 the better. A

¹⁰We present the results of the multiple regressions only for return predictability. In the case of realized variance predictability, we skip these regressions due to multicollinearity.

¹¹The *CRP* does not retain its statistical significance in the multiple regressions. It seems that other variables, mainly the *VRP*, capture its information. In-sample multiple regressions have no explanatory power for out-of-sample predictability. For further details, we also refer to the forthcoming out-of-sample analysis.

variable has notable predictive power if it exhibits a positive and significant R_{oos}^2 , indicating an overall outperformance of the predictive variable.

In order to gauge whether the potential improvement is statistically significant, we compute the $MSE - F$ statistic of [McCracken \(2007\)](#):

$$MSE - F = H \times \left(\frac{MSE_r - MSE_u}{MSE_u} \right), \quad (21)$$

where H denotes the number of out-of-sample forecasts. All other variables are as previously defined. Briefly, the null hypothesis is that the restricted model performs at most as well as the unrestricted model, i.e. $MSE_r \leq MSE_u$. The alternative is that the unrestricted model provides smaller forecast errors than the restricted model. As can be seen from the last row of Table III, only *CRP* and *VRP* yield statistically significant improvements in the out-of-sample performance relative to the simple recursive mean. This result is noteworthy given that [Goyal & Welch \(2003\)](#) argue that the recursive mean is a tough benchmark to beat. Overall, these results suggest that the *CRP* and the *VRP* contain important information about next-month's market excess returns both in- and out-of-sample. In contrast, the multiple regressions do not improve the predictive power out-of-sample. In Figure 1, we observe a similar development of the out-of-sample performances as in-sample, except for VAR^{BKM} , showing a sharp drop during the global financial crisis, indicating a superior performance of the restricted model. It seems that investors have to rely on the historical mean rather than on VAR^{BKM} in times of distress.

III.B Variance Predictability

We now turn our attention to the predictability of the realized variance. In particular, we ask the question: Can any of the forecasting variables be used to predict next-month's realized variance?

In-Sample Using all the sample information, we estimate the following regression model:

$$RV_{t+1} = \gamma_0 + \gamma_1 X_t + \gamma_2 RV_t + \epsilon_{t+1}, \quad (22)$$

where γ_0 , γ_1 , and γ_2 are the intercept and slope parameters, respectively. All other variables are as previously defined. We include the lag of realized variance, because realized variance is a strongly persistent process, indicated by its AR(1) coefficient of 0.63, shown in Table I.¹² To account for the persistence, we use a fitted AR(1) process as naive benchmark rather than the historical mean variance.¹³

Table IV summarizes the results of the in-sample analysis. We notice that the variables have predictive power for future realized variance, as evidenced by their statistically significant R^2 s.¹⁴ This is true for all variables, except *FH* and *GMR*. The R^2 s range from 40.80% to 43.03%. These results are interesting for several reasons. First, they indicate that the predictability of realized variance is much stronger than that of excess returns. Second, they reveal that *CRP*, *SMIRK*, and *VRP* are able to predict (in-sample) not only next-month’s market excess return (see Table III) but also realized variance. Third, the risk-neutral variables of [Bakshi et al. \(2003\)](#) that do not predict future excess returns matter for realized variance forecasting. For instance, $EXKURT^{BKM}$ predicts next-month’s realized variance with a predictive power equal to 41.60%. *GMR* appears to predict only market returns, whereas *FH* predicts neither market returns nor realized variance. A likely cause for the rather poor performance of the two measures is that both variables exhibit clear breakpoints, especially around the financial crisis (see the time-series of these variables for example in Figure 1 of [Bali et al. \(2015\)](#) as well as Figure 1 of [Leiss & Nax \(2018\)](#)).

¹²Since realized variance is strongly persistent, future realized variance is primarily predictable by its current value. Ignoring the lag of realized variance allows the other lagged variables to partially capture this persistence. In particular VAR^{BKM} and RV are highly correlated. We refer to this point later in Table IV.

¹³In Section *V.C*, we use the historical mean variance as naive benchmark and show the results.

¹⁴Although *CRP* has a t -statistic of -1.59 , this variable generates a statistically significant improvement in the in-sample R^2 of 40.80%. We also refer to Section *V.C*.

An implication of this result is that when assessing the information content of a predictive variable, it is advisable to investigate whether it predicts not only excess returns but also realized variance. We observe that VAR^{BKM} and VRP have similar t -statistics and R^2_s , which is not surprising due to the construction of VRP and the used regression model in Equation (22).

Figure 2 shows the CDSFE for all individual variables predicting the next month's realized variance. There is a similar pattern for the variables. We observe a strong increase in their performance during the global financial crisis in 2008/2009, indicating the outperformance of the unrestricted model to the restricted model. It seems that investors can exploit the information content of the variables, particularly in times of high variance.

Out-of-Sample We use the first 5 years of observations to initially estimate the model parameters (see Equation (22)). Having done this, we then make a forecast for the following month. We expand the training window by one observation month and repeat all steps. This procedure mirrors that used for the return predictability analysis with the only difference that we assume a fitted AR(1) process as naive benchmark and that we forecast realized variance rather than the market excess return. The last row of Table IV shows the R^2_{oos} . All variables that predict realized variance in-sample are also good predictors out-of-sample. The R^2_{oos} s range from 2.40 % for $SKEW^{BKM}$ to 3.89 % for $SMIRK$. In Figure 2, we observe a similar pattern as in-sample. In particular in times of distress, investors should rely on the information content of the predictive variables rather than on the forecast of a fitted AR(1) model.

III.C Portfolio Choice Implications

We now study the portfolio choice implications of the predictability results reported earlier. To do this, we consider an investor with mean–variance preferences. The agent

allocates a fraction ω_t of her wealth to the risky portfolio and the remainder, i.e. $1 - \omega_t$, to the risk-free asset. The agent's objective function is:

$$\max_{\omega_t} E_t^{\mathbb{P}} \left(r_{p,t+1} - \frac{\gamma}{2} \sigma_{p,t+1}^2 \right), \quad (23)$$

where $E_t^{\mathbb{P}}(\cdot)$ is the physical expectation operator. $r_{p,t+1}$ is the next-period's (simple) return on the investor's portfolio. γ is the coefficient of relative risk-aversion. $\sigma_{p,t+1}^2$ is the conditional variance of the portfolio from t to $t + 1$. This return is the weighted average of the (simple) return on the risky stock and on the risk-free asset. Because our earlier analysis focuses on log-returns rather than simple returns, we use a second-order Taylor expansion to express the simple return as a function of the log-return and realized variance.¹⁵ Thus, we can express the objective function as follows:

$$\max_{\omega_t} E_t \left(R_{p,t+1} - \frac{\gamma - 1}{2} \sigma_{p,t+1}^2 \right), \quad (24)$$

where $R_{p,t+1}$ is the log-return on the portfolio and all other variables are as previously defined.

Using the first-order condition, it is straightforward to derive the optimal weight invested in the risky asset (Jordan et al., 2014):

$$\omega_t = \frac{E_t(ER_{t+1} + \frac{1}{2}RV_{t+1})}{\gamma E_t(RV_{t+1})} = \frac{E_t(ER_{t+1})}{\gamma E_t(RV_{t+1})} + \frac{1}{2\gamma}. \quad (25)$$

The expression above shows that the optimal allocation to the risky asset depends on the expected excess return, the risk-aversion parameter, and the expected realized variance. One implication of this expression is that, holding everything else constant, the allocation to the

¹⁵More precisely, the approximation yields the following relationship:

$$R_t \approx r_t - \frac{1}{2}RV_t,$$

where R_t , r_t , and RV_t are the log-return, simple return, and realized variance at time t , respectively.

risky stock rises with expected returns. In other words, if realized variance is unpredictable and a forecasting variable X_t positively (negatively) predicts excess returns, then the agent would invest more (less) in the risky stock as X_t increases. In contrast, if a variable X_t positively predicts future variance (and not returns), then the share of wealth invested in the risky stock decreases with the variable X_t .

Note that the preceding discussion focuses only on the predictability of either returns or variance and does not explore the case where both moments are predictable by the same variable. The share of the position in the stock will be determined by two (potentially offsetting) forces, one that increases with the expected excess return and the other that decreases with the expected realized variance.

In light of the preceding discussion, we find it interesting to distinguish between three cases. The first one deals with the case where only excess returns might be predictable. The second case allows for the predictability of realized variance alone. The third case deals with the possibility that both excess returns and realized variance are predictable by the same variable X_t .¹⁶

For a given case (ξ) and each calendar month of our out-of-sample window, we compute the weight ω_t and also the realized return of the portfolio. We impose the restriction that whenever the forecast of the market excess return or of the realized variance (or of both) in Equation (25) equals zero, we set the portfolio weight equal to $1/(2\gamma)$. Further, following [Campbell & Thompson \(2008\)](#) and [Jordan et al. \(2017\)](#), we impose the restriction that ω_t is bounded from below by 0 and from above by 1.5. Economically, the lower bound implies that the agent does not short-sell the risky asset. The upper bound prevents the agent from taking on excessive leverage. At the end of the sample period, we compute the certainty

¹⁶To be consistent with Section *III.B*, we predict realized variance by the variable X_t and the lag of realized variance.

equivalent return as follows:

$$CER^{(\xi)} = \bar{r}_p - \frac{\gamma}{2}\sigma_p^2, \quad (26)$$

where $CER^{(\xi)}$ is the certainty equivalent return associated with strategy ξ . This number is expressed in percent per annum. \bar{r}_p is the average (annualized) return on the portfolio. σ_p^2 is the variance of the portfolio returns.

Our approach consists in computing the utility gain ($\Delta CER^{(\xi)}$), the difference between $CER^{(\xi)}$ and the certainty equivalent return of the naive strategy that assumes that the first two moments are unpredictable, and thus relies on simple historical averages. We do this for each of the three scenarios.

We also compute the Sharpe Ratio (SR) of each strategy ξ :

$$SR^{(\xi)} = \frac{\bar{R}_p - rf}{\sigma_p}, \quad (27)$$

where \bar{R}_p is the average log-return on the portfolio. Similar to the certainty equivalent return analysis, we compute the improvement in SR by taking the difference between $SR^{(\xi)}$ and the SR linked to the naive strategy that assumes that the market excess return and realized variance are unpredictable. We use an approach suggested by [Jobson & Korkie \(1981\)](#), and after taking into account the correction suggested by [Mommel \(2003\)](#), we test whether the improvement is statistically significant.

Table V reports our results for different values of risk-aversion. We can see that statistical evidence of excess return predictability does not necessarily imply important economic gains. For instance, while the VRP predicts both excess returns and realized variance, a timing strategy relying on this variable would have underperformed the naive strategy. One possible explanation for this result is the following. Shortly before the crisis

period, the variance risk premium is high (since the historical variance is low). Because the *VRP* predicts future returns with a positive sign, this result implies that an agent should hold more (rather than less) stocks. As a result of this increased position, the strategy incurs more severe losses as the economy slides into recession. Similarly, as the economy recovers, the variance risk premium is low, implying that the agent should hold a small position in the stock. Because of this, the agent misses out on the rally in the market. Further, it seems that, though *VRP* predicts both returns and variance individually with a positive sign, the joint predictability is associated with large variance, thus generating negative certainty equivalent returns.¹⁷

In contrast, one can see that relative to an agent with risk-aversion $\gamma = 3$ who assumes that the market excess return and the realized variance are unpredictable, the agent who exploits the information content of the *CRP*, would improve her utility by 5.03% p.a. The finding is consistent with [Driessen et al. \(2009, 2013\)](#) who document that index options represent a hedge against changes in market correlations, and also against losses due to diversification limitations.

Our results are in line with those of [Fleming et al. \(2001\)](#), who show that volatility timing leads to notable utility gains for short-horizon investors. The positive economic value generated by the *CRP* is consistent with the work of [Buss et al. \(2018\)](#), who document a positive CER for the market timing strategy based on the *CRP*. Overall, our findings suggest that investors might earn larger utility gains when taking the predictability of both excess returns and realized variance into account.

Table A1 of the Online Appendix shows the portfolio choice implications taking into account turnover and transaction costs. Following [DeMiguel et al. \(2009\)](#), we define the

¹⁷We refer to Section *IV.B* for further details.

turnover for strategy ξ as the average sum of the absolute values of the trades, i.e.:

$$Turnover = \frac{1}{T - H} \sum_{t=1}^{T-H} \left(|\omega_{t+1}^{(\xi)} - \omega_{t^+}^{(\xi)}| \right), \quad (28)$$

where $T - H$ is the number of out-of-sample observations and $\omega_{t^+}^{(\xi)}$ is the portfolio weight before rebalancing at $t + 1$. All other variables are as previously defined. For the benchmark strategy, we observe an absolute value of the turnover ($Turnover_{abs}$) of 0.0448, which can be interpreted as the average percentage of wealth traded in each out-of-sample period. For our three strategies, we report the turnover ($Turnover_{rel}^{(\xi)}$) relative to the benchmark case. We notice that all strategies exhibit higher turnovers than the benchmark, indicated by values larger than one.

We follow [Balduzzi & Lynch \(1999\)](#) and include transaction costs of 50 basis points per transaction proportional to the asset's traded size $|\omega_{t+1}^{(\xi)} - \omega_{t^+}^{(\xi)}|$. Table A1 of the Online Appendix reports the corresponding utility gains and Sharpe Ratios. We observe that transaction costs have an impact on the results; however, the results are qualitatively similar. An agent who relies on the *CRP* would still improve her utility by 1.38 % p.a.

IV. Further Analyses

IV.A Sign Restriction

[Campbell & Thompson \(2008\)](#) propose imposing two economically motivated restrictions when studying the question of predictability. The authors suggest setting the slope estimate in the out-of-sample analysis equal to zero whenever its sign differs from that of the in-sample analysis. They also suggest setting the out-of-sample forecast equal to zero whenever its negative. Before discussing our findings, it is worth emphasizing that the first constraint is not implementable in real-time. This is because the implementation would

require the agent to know about the sign of the in-sample slope parameter, i.e. to have information about future data, thus, introducing a look-ahead bias.

The first set of results in Table VI reports the findings when imposing the first restriction. Panel A shows that the main results are similar: the *CRP* and *VRP* are the two best option-implied predictors for the market excess return. It is worth noticing that imposing the restriction has very little effect on the R_{oos}^2 related to the forecasting variables (see Table III for comparison). This suggests that the sign of the relationship between the forecasting variables *CRP* and *VRP* and future excess returns is relatively stable out-of-sample.

We also impose the restriction on the slope of the realized variance forecasting regression. In other words, we set the slope estimate equal to zero, if the sign of the recursively estimated parameter is different from that obtained in-sample.¹⁸ Overall, we can see from Panel B of Table VI that this restriction has very little impact on our main results.

The second set of results in Table VI reports the findings when imposing the second restriction. Finally, the last entries of each panel show the results when we jointly impose the restrictions (on the sign of the slope and the sign of the return/variance forecast). Summarized, in both cases our main results remain unchanged.¹⁹ We also repeat our economic value analysis using these economically motivated constraints. Tables VII to IX document that imposing the restriction(s) does (do) not affect our main conclusions on the economic value of the predictive power of both *CRP* and *VRP*.

¹⁸To be consistent with Section III.B, we impose the restriction for both the variable X_t and the lag of realized variance.

¹⁹Table A2 of the Online Appendix reports the absolute frequency of how often the restrictions are binding. Panel A shows the results for return predictability. We observe that the first restriction is not binding. This is true for all variables, except *FH*, *GMR*, and VAR^{BKM} , indicated by a frequency of 12, 8, and 35. The second restriction is binding more frequently, indicated by frequencies from 7 for *GMR* to 77 for *VRP*. It seems that the forecast restriction matters more for excess return predictability. Panel B of Table A2 shows the frequencies in the case of variance predictability. We find that the first (second) restriction is binding only for *CRP*, *FH*, and *GMR* ($EXKURT^{BKM}$) with a frequency of 75, 76, and 3 (3). Lagged realized variance appears to be not affected by the (first) restriction(s) at all, indicating the persistence of that variable. The findings reveal that the imposition of economically motivated restrictions matters more for return rather than variance predictability.

IV.B Forecast Combination

Rapach et al. (2010) suggest the use of forecast combinations. The pooled forecast is the weighted average of all G individual forecasts, where $g = 1, \dots, G$, i.e., $\widehat{ER}_{t+1}^{pool} = \sum_{g=1}^G x_{g,t} \widehat{ER}_{g,t+1}$ and $\widehat{RV}_{t+1}^{pool} = \sum_{g=1}^G x_{g,t} \widehat{RV}_{g,t+1}$, based on Equation (19) and (22), respectively. $x_{g,t}$ is the weight of the individual forecast in the pooled one.

Following the literature, we use three approaches. Table X shows the out-of-sample R^2 s of (i) the mean forecast combination, where the weight is simply $1/G$ for $g = 1, \dots, G$, (ii) the median forecast combination, where the pooled forecast is just the median of all individual forecasts, and (iii) the trimmed mean forecast combination, where $x_{g,t} = 0$ in the case of the individual forecasts with the smallest and largest value, respectively, and $x_{g,t} = 1/(G - 2)$ for the remaining forecasts.

The mean forecast combination exhibits superior performance in the case of return predictability ($R_{oos}^2 = 1.76\%$), whereas the median forecast combination works better in the case of variance predictability ($R_{oos}^2 = 4.12\%$).²⁰ The findings are interesting for several reasons. First, they support the results of Rapach & Zhou (2013), who argue that forecast combinations yield more stable forecasts and increase the forecasting performance. Second, the findings show a substantial increase in the magnitude of the R_{oos}^2 s. In the case of return predictability, the mean forecast combination generates an R_{oos}^2 which is substantially larger than for all individual variables, except for *VRP*.²¹ The median forecast combination outperforms all individual variables, predicting realized variance. Third, the findings support our previous conclusion. It seems that individual predictive variables generate notable

²⁰Since *FH* and *GMR* show an overall weak performance, we additionally compute the forecast combinations without these two variables. In that case, the mean forecast combination exhibits a superior performance, indicated by an R_{oos}^2 of 3.11%, whereas the median forecast combination generates an R_{oos}^2 of 4.83%.

²¹In detail, when using all predictive variables of our sample, the mean forecast combination generates an R_{oos}^2 which is similar to all individual variables, except for *VRP*. However, by excluding *FH* and *GMR*, the mean forecast combination generates an R_{oos}^2 which is substantially larger than for all individual variables, except for *VRP*.

variance when predicting excess returns and realized variance, respectively.

Table XI reports the economic value for different values of risk-aversion. Compared with our previous findings, all forecast combinations, in particular the median forecast combination, generate substantial certainty equivalent returns. For $\gamma = 3$, an annualized utility gain of 6.73% (relative to the naive strategy) may be achieved, when both return and variance are predicted by the combined forecast. It seems that forecast combinations rather than individual variables, generate more stable forecasts, thus, leading to significant positive utility gains.

IV.C Predictability of the Sharpe Ratio

After predicting excess returns and realized variance in isolation, we want to answer the question: What predictive power do the variables have, when predicting excess returns and realized variance jointly? In doing so, we estimate the following regression model:

$$\frac{ER_{t+1}}{\sqrt{RV_{t+1}}} = \varphi_0 + \varphi_1 X_t + \epsilon_{t+1}, \quad (29)$$

where $\frac{ER_{t+1}}{\sqrt{RV_{t+1}}}$ is the Sharpe Ratio, and φ_0 , and φ_1 are the intercept and slope parameters, respectively. All other variables are as previously defined.

Table XII documents the results for each predictive variable. The regression model (29) enables us to assess whether each variable has predictive power, when predicting excess returns and realized variance jointly. We find that *CRP*, *GMR*, *SKEW^{BKM}*, and *VRP* have predictive power for the future Sharpe Ratios, shown by their statistically significant *t*-statistics of 2.43, 1.77, -1.79, and 2.17. A look at the in-sample *R*²s reveals that *CRP* and *VRP* have the highest (in-sample) predictive power of 2.56% and 2.04%, respectively.

Further analysis reveals that *CRP* and *VRP* also contain important information about the future Sharpe Ratio out-of-sample, indicated by *R*²_{oos}s of 2.99% and 1.54%.

V. Additional Analysis

To use more information when estimating the realized variance, we follow [Corsi \(2009\)](#) and [Sévi \(2014\)](#) and use the heterogenous autoregressive (*HAR*) model. The *HAR*–*RV* model provides a conditional estimate for realized variance that accounts for different trading horizons. Further, in the previous analysis, we examine the total variance risk premium. However, [Andersen & Bondarenko \(2010\)](#), [Andersen et al. \(2015\)](#), and [Feunou et al. \(2015\)](#) show how to decompose the variance risk premium into downside and upside components. In the following section, we analyze the predictability of both components separately.

We follow [Andersen & Bondarenko \(2010\)](#) and [Andersen et al. \(2015\)](#) and use the downside and upside model-free implied variance. Following the arguments of [Feunou et al. \(2015\)](#), investors dislike increases in the volatility of the underlying, which is associated with an increase in the probability of severe losses. Investors hedge against these downward movements, thus, we expect that the downside variance risk premium is the main driver of the variance risk premium. Further, to get a better estimate for the physical expectation of variance, we analogously use the downside and upside realized variance.

V.A Variables

Variance Risk Premium based on HAR–RV Model We define the variance risk premium based on the *HAR*–*RV* model (VRP^{HAR}) as the difference between the risk-neutral variance (VAR^{BKM}) and the *RV*, estimated on the basis of the *HAR* model (RV^{HAR}):

$$VRP_t^{HAR} = VAR_t^{BKM} - RV_t^{HAR}, \quad (30)$$

where VAR_t^{BKM} is as previously defined. Analogously to Section II.B and using Equation (2), we follow Christoffersen (2012) and define

$$RV_{D,t+\frac{i}{N}} \equiv RV_{t+\frac{i}{N}}, \quad (31)$$

$$\begin{aligned} RV_{W,t+\frac{i}{N}} &\equiv RV_{(t+\frac{i}{N})-4,t+\frac{i}{N}} \\ &= \left[RV_{(t+\frac{i}{N})-4} + RV_{(t+\frac{i}{N})-3} + RV_{(t+\frac{i}{N})-2} + RV_{(t+\frac{i}{N})-1} + RV_{t+\frac{i}{N}} \right] / 5, \end{aligned} \quad (32)$$

$$RV_{M,t+\frac{i}{N}} \equiv RV_{(t+\frac{i}{N})-20,t+\frac{i}{N}} = \left[RV_{(t+\frac{i}{N})-20} + RV_{(t+\frac{i}{N})-19} + \dots + RV_{t+\frac{i}{N}} \right] / 21 \quad (33)$$

as the daily, weakly, and monthly realized variance on day $t + \frac{i}{N}$, respectively.²² Further, $RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}$ is the realized variance over the next 21 days, i.e.:

$$RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} = \left[RV_{(t+\frac{i}{N})+1} + RV_{(t+\frac{i}{N})+2} + \dots + RV_{(t+\frac{i}{N})+20} \right] / 21. \quad (34)$$

Finally, to compute RV_t^{HAR} , we run the following regression:

$$\begin{aligned} RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} &= \phi_0 + \phi_D RV_{D,t+\frac{i}{N}} + \phi_W RV_{W,t+\frac{i}{N}} \\ &\quad + \phi_M RV_{M,t+\frac{i}{N}} + \epsilon_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}, \end{aligned} \quad (35)$$

where ϕ_0 , ϕ_D , ϕ_W , and ϕ_M are the regression coefficients, and $\epsilon_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}$ is the error term over the next 21 days. The fitted values are the forecasted RV and represent RV_t^{HAR} .

Downside and Upside Variance Risk Premium We define the downside and upside variance risk premium (VRP^{DOWN} and VRP^{UP}) as the difference between the downside and upside model-free implied variance ($(\sigma_t^{Q-})^2$ and $(\sigma_t^{Q+})^2$) and the downside and upside

²²Since we now work with daily rather than intraday data, we follow the common approach and define one month as 21 trading days.

realized variance (RV^{DOWN} and RV^{UP}), respectively:

$$VRP_t^{DOWN} = \left(\sigma_t^{\mathbb{Q}^-}\right)^2 - RV_t^{DOWN}, \quad (36)$$

$$VRP_t^{UP} = \left(\sigma_t^{\mathbb{Q}^+}\right)^2 - RV_t^{UP}. \quad (37)$$

To obtain $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$, we follow [Andersen & Bondarenko \(2010\)](#) and [Andersen et al. \(2015\)](#) and use their corridor implied volatility method to decompose the model-free implied variance into different parts, and define the model-free implied variance ($(\sigma_t^{\mathbb{Q}})^2$) as:

$$\left(\sigma_t^{\mathbb{Q}}\right)^2 = 2 \int_0^\infty \frac{M(K)}{K^2} dK = (\sigma_t^{\mathbb{Q}^-})^2 + (\sigma_t^{\mathbb{Q}^+})^2, \quad (38)$$

where $M(K) = \min(P(K), C(K))$ is the minimum price of the put and call with maturity of 1 month and strike K . Consistently, we also compute the grid of 1,000 equidistant interpolated moneyness levels of out-of-the money option prices, as described above. Finally, to compute $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$, we assume the threshold Se^θ with $\theta = 0$:

$$\left(\sigma_t^{\mathbb{Q}^-}\right)^2 = 2 \int_0^{Se^\theta} \frac{M(K)}{K^2} dK, \quad (39)$$

$$\left(\sigma_t^{\mathbb{Q}^+}\right)^2 = 2 \int_{Se^\theta}^\infty \frac{M(K)}{K^2} dK. \quad (40)$$

We then use the trapezoidal rule to approximate the integrals, as outlined above.

Following [Barndorff-Nielsen et al. \(2010\)](#), we decompose the realized variance into the upside and downside realized variance for a given threshold κ . Imposing $\kappa = 0$, we compute RV_t^{DOWN} (RV_t^{UP}) on the basis of Equation (2), however, using only log-returns that are at most (least) equal to κ .

Downside and Upside Variance Risk Premium based on HAR–RV Model We define the downside and upside variance risk premium based on the *HAR–RV* model

($VRP^{DOWN,HAR}$ and $VRP^{UP,HAR}$) as the difference between the downside and upside model-free implied variance ($(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$) and the downside and upside realized variance, estimated on the basis of the *HAR* model ($RV^{DOWN,HAR}$ and $RV^{UP,HAR}$), respectively:

$$VRP_t^{DOWN,HAR} = \left(\sigma_t^{\mathbb{Q}^-}\right)^2 - RV_t^{DOWN,HAR}, \quad (41)$$

$$VRP_t^{UP,HAR} = \left(\sigma_t^{\mathbb{Q}^+}\right)^2 - RV_t^{UP,HAR}, \quad (42)$$

where $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$ are as previously defined. To compute $RV_t^{DOWN,HAR}$ ($RV_t^{UP,HAR}$), we follow the steps described above, however, using RV^{DOWN} (RV^{UP}) instead of RV .

V.B Results

Table A3 of the Online Appendix reports the regression results for the different specifications predicting the next month's excess return and realized variance, respectively. In Panel A, we observe that all specifications exhibit an inferior performance in predicting excess returns compared to the *VRP* as proposed by [Bollerslev et al. \(2009\)](#). However, we notice that VRP^{UP} , VRP^{DOWN} , and $VRP^{UP,HAR}$ have still (in-sample) significant predictive power, indicated by *t*-statistics between 2.47 and 2.17, and in-sample R^2 s from 2.65 % to 2.05 %.

In Panel B of Table A3 of the Online Appendix, we find that all specifications have a similar (insignificant) in-sample predictive power for *RV* as *VRP*. We observe noteworthy significant out-of-sample predictability for VRP^{HAR} ($R_{oos}^2 = 3.40$ %), VRP^{DOWN} ($R_{oos}^2 = 4.34$ %), and $VRP^{UP,HAR}$ ($R_{oos}^2 = 4.63$ %).

We now turn our attention to the portfolio choice implications. Table A4 of the Online Appendix reports the results of the economic value. For an agent with risk-aversion of $\gamma = 3$, we observe that VRP^{UP} (VRP^{DOWN}) provides substantial improvements in the utility gain

of 6.74 % p.a. (6.31 % p.a.) and in the Sharpe Ratio of 0.71 (0.59).

Overall, the results confirm our previous findings in providing evidence for a stronger variance than return predictability. We also observe that VRP^{DOWN} , VRP^{UP} , and $VRP^{UP,HAR}$ predict in-sample both returns and realized variance. In addition, we notice that VRP^{HAR} , VRP^{DOWN} , and $VRP^{UP,HAR}$ strongly predict realized variance out-of-sample. Finally, the results reveal that VRP^{UP} and VRP^{DOWN} provide evidence for generating statistically significant economic value.

V.C Alternative Approach of Variance Predictability

In our main analysis, we included lagged realized variance as an additional predictor when predicting realized variance, as it is well known that variance is a persistent process. To see whether our results are driven by this choice, we repeat the analysis without including lagged realized variance. We now estimate the following regression model for realized variance:

$$RV_{t+1} = \gamma_0 + \gamma_1 X_t + \epsilon_{t+1}, \quad (43)$$

where all variables are as previously defined. Under the null hypothesis of no predictability, the variable X_t has no predictive power for future realized variance. In this case, we expect that $\gamma_1 = 0$, and that the best estimate for future realized variance would be its mean. Accordingly, the historical mean variance serves as benchmark model. Using this specification, we are able to analyze the individual predictive power of variables subject to the standard approach in extant literature. Tables A5 and A6 of the Online Appendix summarize the results of the predictability and economic value analysis.

In Table A5, we find that all variables, except FH , have in-sample predictive power for future realized variance. CRP turns out to have significant predictive ability, indicated by a t -statistic of -3.72 . We notice that the in-sample R^2 s are smaller compared with our

previous results. They range from 3.19 % for $SKEW^{BKM}$ to 38.83 % for VAR^{BKM} .

In the out-of-sample analysis, we observe that in general the variables that predict realized variance in-sample are also predictors out-of-sample. All variables, with the exception of FH , GMR , and VRP , yield an improvement relative to the recursive mean. The reason for the poor behavior of these three variables is likely twofold: FH and GMR perform poorly in general and the VRP exhibits a sign-switching behavior as discussed previously. The R_{oos}^2 s range from 1.88 % for CRP to 34.65 % for VAR^{BKM} . It seems that, using the standard methodology, the predictive power of some variables increases, compared to our previous results.

In the economic value analysis, shown in Table A6, we find similar results as before. It seems that statistical evidence of predictability does not necessarily imply important economic gains. One can see that relative to an agent with risk-aversion $\gamma = 3$ who assumes that the market excess return and the realized variance are unpredictable, the agent who exploits the information content of CRP would improve her utility by 4.63 % p.a. Overall, the results confirm our previous findings.

VI. Conclusion

This paper comprehensively studies the predictive power of option-implied variables for future excess returns and realized variance. A variable is considered to have predictive power if it exhibits statistically significant forecasting power and also adds economic value. We find that the correlation risk premium and the variance risk premium emerge as statistically significant predictors of both the market excess return and the realized variance. This is true both in- and out-of-sample.

We then investigate the economic value of the documented predictability. Our results highlight an important contrast between the two variables. Relative to a naive strategy that

assumes that excess returns and realized variance are unpredictable, the agent who relies on the correlation risk premium as a timing signal realizes utility gains of 5.03% p.a. In contrast, the timing strategy that uses the variance risk premium as timing signal yields lower certainty equivalent returns than a naive strategy that assumes constant excess returns and realized variance. Thus, our analysis shows that statistical evidence of predictability does not necessarily translate into economic value. Moreover, we find that forecast combinations generate stable forecasts for both excess returns and realized variance, and that they add substantial economic value.

We further decompose the total variance risk premium into the downside and upside components, and analyze the predictability of different versions of the variance risk premium. We show that the upside and downside variance risk premia have noteworthy (in-sample) predictive power for excess returns and realized variance. Further, a timing strategy provides substantial utility gains.

Future research could analyze the predictive power of option-implied variables for specific industry returns as well as different asset classes. Furthermore, we believe that it would be interesting to study whether the *CRP* performs similarly well in predicting equity returns in further developed and emerging markets. Finally, it could be interesting to test whether forward-looking option-implied information drives out the predictive power of U.S. returns for developed and emerging countries, as documented by [Rapach et al. \(2013\)](#).

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Figure 1: Return Predictability

This figure plots the in- and out-of-sample performances of individual variables. We regress monthly excess returns on a constant and the lagged predictive variable. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return and the cumulative squared regression residual, and the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. All data are sampled at the monthly frequency and relate to the S&P 500 index.

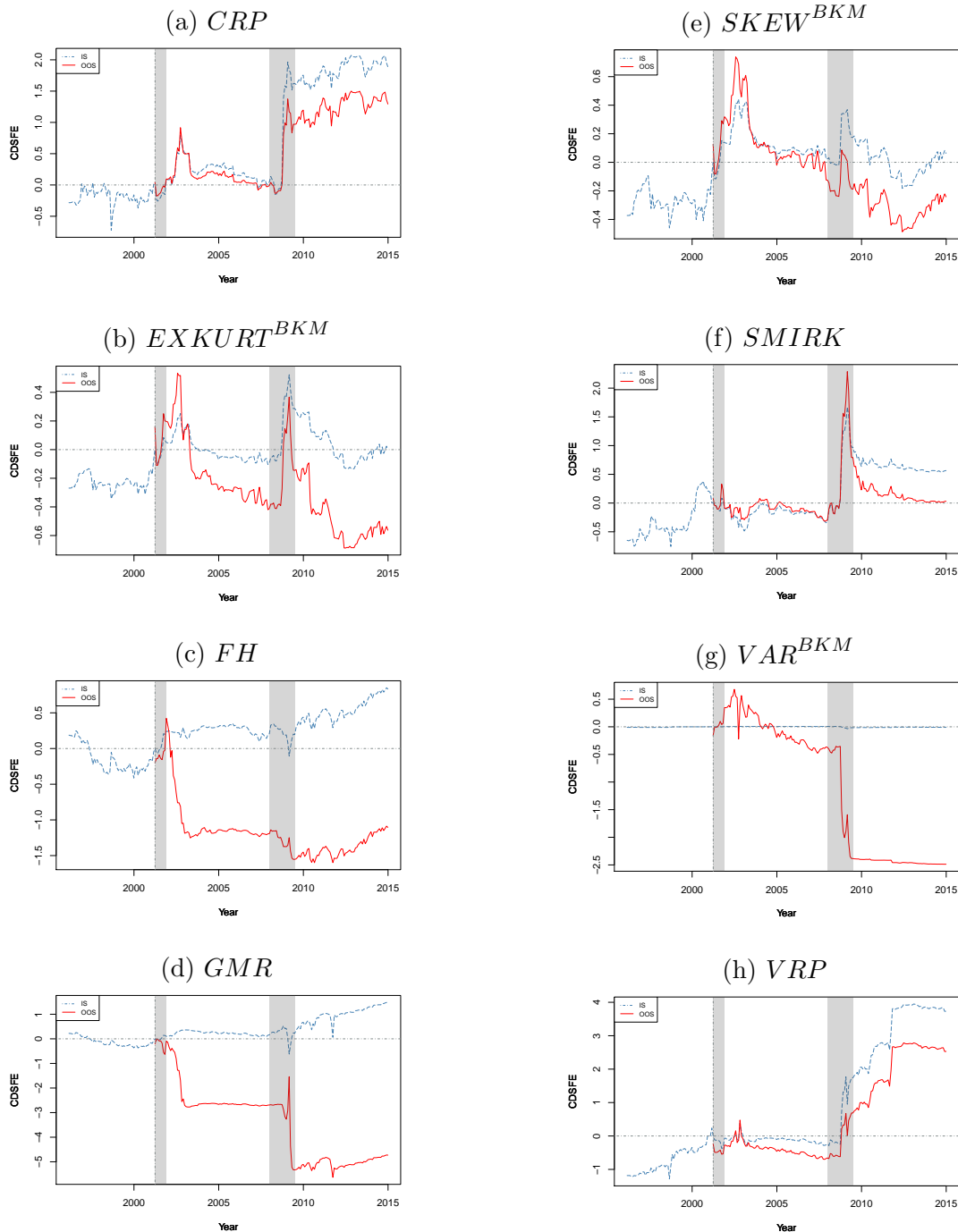


Figure 2: Variance Predictability

This figure plots the in- and out-of-sample performances of individual variables. We regress monthly realized variance on a constant, the lagged predictive variable, and the lagged realized variance. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return and the cumulative squared regression residual, and the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. All data are sampled at the monthly frequency and relate to the S&P 500 index.

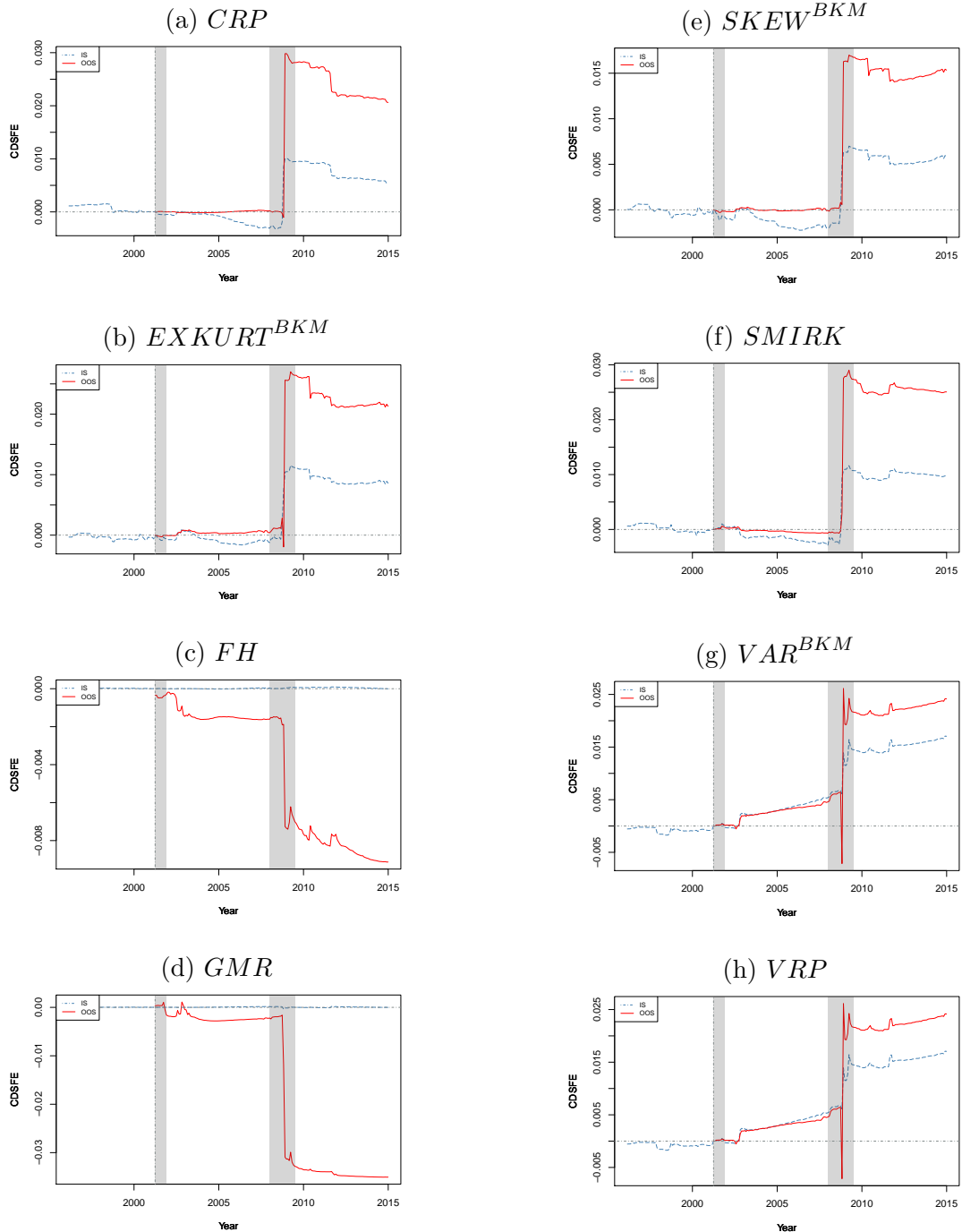


Table I: Summary Statistics

This table summarizes key statistics about several variables. CRP denotes the correlation risk premium. IC is the implied correlation. RC is the realized correlation. ER is the market excess return. $EXKURT^{BKM}$ is the risk-neutral kurtosis of [Bakshi et al. \(2003\)](#). FH is the risk-neutral riskiness measure of [Leiss & Nax \(2018\)](#). GMR is the generalized measure of riskiness of [Bali et al. \(2011\)](#). RV is the realized variance. $SKEW^{BKM}$ is the risk-neutral skewness of [Bakshi et al. \(2003\)](#). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of [Bakshi et al. \(2003\)](#). VRP is the variance risk premium computed as the difference between the risk-neutral variance of [Bakshi et al. \(2003\)](#) and the most recent observation of the realized variance. VRP^{HAR} denotes the variance risk premium based on the HAR-RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR-RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR-RV model. “Mean”, “Std Dev”, “Skew”, and “Kurt” denote the mean, standard deviation, skewness, and kurtosis, respectively. The last two columns show the AR(1) coefficient and the number of observations, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

	Mean	Std Dev	Skew	Kurt	AR(1)	Nobs
CRP	0.0941	0.1019	0.1409	3.2970	0.2496	228
IC	0.4166	0.1403	0.5092	3.1725	0.7621	228
RC	0.3225	0.1398	0.8731	3.5571	0.5854	228
ER	0.0591	0.1555	-0.8294	4.4268	0.0900	228
$EXKURT^{BKM}$	0.7571	0.2840	0.4887	3.0378	0.7522	228
FH	0.4302	0.3250	0.0241	1.4467	0.9250	228
GMR	9.0972	12.5814	2.3413	11.0123	0.8818	228
RV	0.0317	0.0519	7.3129	75.2277	0.6333	228
$SKEW^{BKM}$	-0.8698	0.1978	0.2588	3.0325	0.6611	228
$SMIRK$	0.1326	0.2522	0.1584	3.4828	0.3299	228
VAR^{BKM}	0.0474	0.0427	3.3066	18.0518	0.7880	228
VRP	0.0157	0.0284	-5.0586	61.7528	0.1340	228
VRP^{HAR}	0.0459	0.0414	3.2330	17.3103	0.7887	228
VRP^{DOWN}	-0.0136	0.0249	-7.5246	79.4665	0.5899	228
VRP^{UP}	-0.0143	0.0244	-7.5439	78.4141	0.6219	228
$VRP^{DOWN,HAR}$	0.0016	0.0015	2.7589	13.2030	0.7708	228
$VRP^{UP,HAR}$	0.0007	0.0007	1.7649	7.6611	0.5894	228

Table II: Correlation Matrix

This table reports the correlations among all predictive variables. CRP denotes the correlation risk premium. IC is the implied correlation. RC is the realized correlation. ER is the market excess return. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Naz (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). RV is the realized variance. $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. VRP^{HAR} denotes the variance risk premium based on the HAR-RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR-RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR-RV model. All data are sampled at the monthly frequency and relate to the S&P 500 index.

	CRP	IC	RC	$EXKURT^{BKM}$	FH	GMR	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
CRP	0.37														
IC	-0.36	0.74													
RC	0.20	0.06	-0.09												
$EXKURT^{BKM}$	-0.10	-0.48	-0.40	-0.17											
FH	0.09	0.66	0.59	0.07	-0.68										
GMR	-0.22	-0.24	-0.08	-0.92	0.20	-0.19									
$SKEW^{BKM}$	-0.06	0.31	0.35	-0.02	-0.22	0.36	-0.10								
$SMIRK$	-0.04	0.54	0.57	-0.38	-0.12	0.43	0.17	0.35							
VAR^{BKM}	0.40	0.24	-0.05	-0.03	-0.01	0.11	0.02	-0.14	-0.02						
VRP	-0.04	0.54	0.57	-0.38	-0.12	0.43	0.17	0.35	1.00	-0.01					
VRP^{HAR}	0.26	-0.30	-0.49	0.29	0.09	-0.29	-0.12	-0.36	-0.82	0.59	-0.81				
VRP^{DOWN}	0.27	-0.29	-0.48	0.28	0.09	-0.26	-0.13	-0.36	-0.81	0.60	-0.80	0.98			
VRP^{UP}	0.06	0.62	0.58	-0.31	-0.18	0.51	0.09	0.33	0.97	0.17	0.97	-0.68	-0.67		
$VRP^{DOWN,HAR}$	0.18	0.44	0.31	-0.46	0.01	0.29	0.32	0.13	0.71	0.60	0.72	-0.24	-0.21	0.79	
$VRP^{UP,HAR}$															

Table III: Return Predictability

This table reports the regression results of monthly excess returns on a constant, which we denote by β_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. The historical mean serves as naïve benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Naz (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

β_0	-0.032 (-0.67)	-0.035 (-0.34)	0.129** (2.16)	0.004 (0.10)	-0.136 (-0.84)	0.096** (2.40)	0.056 (1.05)	-0.023 (-0.59)	-0.119 (-0.77)	-0.186 (-0.97)	-0.219 (-1.03)
CRP	0.957*** (2.76)								0.321 (0.85)	0.301 (0.79)	0.306 (0.80)
$EXKURT^{BKM}$		0.123 (0.96)							0.104 (0.73)		-0.138 (-0.36)
FH			-0.164 (-1.49)						-0.037 (-0.25)	-0.040 (-0.27)	-0.044 (-0.29)
GMR				0.006** (2.09)					0.006 (1.34)	0.006 (1.28)	0.006 (1.27)
$SKEW^{BKM}$					-0.224 (-1.22)				-0.179 (-0.93)	-0.179 (-0.68)	-0.351 (-0.68)
$SMIRK$						-0.290** (-2.06)			-0.357** (-2.34)	-0.365** (-2.38)	-0.370** (-2.40)
VAR^{BKM}							0.028 (0.03)		0.327 (0.31)	0.249 (0.25)	0.048 (0.04)
VRP								5.176*** (4.26)	4.015*** (2.94)	4.032*** (2.96)	3.991*** (2.92)
R^2	3.28***	0.41	0.97	1.90*	0.66	1.84**	0.00	7.47***	8.81***	8.95***	8.59***
R_{oos}^2	2.81***	-1.22	-2.40	-10.29	-0.53	0.07	-5.41	5.50***	-23.14	-23.68	-25.42

Table IV: Variance Predictability

This table reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , the lagged predictive variable, and the lagged realized variance RV . We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. The forecast of a fitted $AR(1)$ model serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Nax (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

γ_0	0.016*** (3.80)	0.031*** (3.57)	0.012** (2.43)	0.011*** (3.28)	0.035*** (2.78)	0.010*** (2.98)	0.002 (0.49)	0.002 (0.49)
RV	0.612*** (11.51)	0.596*** (11.14)	0.633*** (12.20)	0.631*** (11.66)	0.621*** (12.01)	0.585*** (10.67)	0.374*** (4.06)	0.750*** (12.26)
CRP	-0.043 (-1.59)							
$EXKURT^{BKM}$		-0.024** (-2.37)						
FH			0.000 (-0.05)					
GMR				0.000 (0.15)				
$SKEW^{BKM}$					0.026* (1.91)			
$SMIRK$						0.027** (2.40)		
VAR^{BKM}							0.376*** (3.37)	
VRP								0.376*** (3.37)
R^2	40.80**	41.60**	40.13	40.14	41.09**	41.64**	43.03**	43.03**
R_{oos}^2	3.18***	3.34***	-1.41	-5.42	2.40***	3.89***	3.78***	3.78***

Table V: Economic Value

This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row], and in the latter case, by both the forecasting variable [name in row] and the lagged realized variance. The historical mean return, and the forecast of a fitted $AR(1)$ model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a naive strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	-0.01	5.03	0.46**	0.13	0.39*
EXKURT ^{BKM}	5.39	2.83	6.39	0.51***	0.29*	0.50**
FH	1.99	1.50	4.03	0.18	0.12*	0.30**
GMR	-3.77	4.67	2.63	-0.12	0.25***	0.22*
SKEW ^{BKM}	1.86	2.32	3.84	0.16	0.24*	0.30*
SMIRK	2.96	2.33	3.21	0.30	0.25**	0.27
VAR ^{BKM}	-7.28	6.39	-4.24	-0.42***	0.38***	-0.19
VRP	-6.10	7.80	-2.60	-0.41*	0.51***	-0.09

Panel C: $\gamma = 9$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	-5.26	0.96	0.40*	-0.07	0.42*
EXKURT ^{BKM}	2.82	2.11	3.34	0.67***	0.40***	0.63**
FH	-0.03	-1.87	-2.55	0.16	0.00	0.14
GMR	-6.87	1.97	-3.71	-0.36**	0.18***	0.03
SKEW ^{BKM}	0.58	0.87	0.74	0.20	0.24**	0.39*
SMIRK	1.40	0.50	1.69	0.38*	0.18*	0.40*
VAR ^{BKM}	-10.28	3.76	-4.09	-0.63***	0.49***	-0.25
VRP	-8.15	3.72	-7.67	-0.63***	0.63***	-0.42*

Panel B: $\gamma = 6$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	-4.27	2.29	0.45**	-0.04	0.40*
EXKURT ^{BKM}	3.92	2.42	4.90	0.63***	0.38**	0.62***
FH	-0.05	-1.38	0.47	0.13	0.02	0.29*
GMR	-8.82	3.00	-2.66	-0.35**	0.21***	0.11
SKEW ^{BKM}	1.20	1.17	2.48	0.22	0.25**	0.41**
SMIRK	2.07	0.80	2.26	0.38*	0.22*	0.36
VAR ^{BKM}	-10.70	5.53	-5.54	-0.60***	0.49***	-0.24
VRP	-8.49	5.46	-8.16	-0.60***	0.59***	-0.36

Panel D: $\gamma = 12$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	-5.88	-0.14	0.40*	-0.10	0.41
EXKURT ^{BKM}	2.11	1.75	2.29	0.67***	0.40***	0.64**
FH	-0.05	-2.15	-3.87	0.16	-0.03	0.05
GMR	-5.59	1.47	-2.95	-0.37**	0.18***	0.03
SKEW ^{BKM}	0.44	0.50	-0.14	0.20	0.21**	0.38
SMIRK	1.05	0.36	1.21	0.38*	0.17*	0.40*
VAR ^{BKM}	-8.37	2.80	-3.12	-0.63***	0.49***	-0.25
VRP	-6.18	2.30	-6.73	-0.63***	0.60***	-0.44*

Table VI: **Out-of-Sample Analysis: Restriction**

This table reports the results of the out-of-sample analysis after imposing economically motivated restrictions. We report the MSE-F statistics in parenthesis. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Nax (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. The historical mean return, and the forecast of a fitted $AR(1)$ model for realized variance serve as naive benchmarks. “(I)” denotes the imposition of the first restriction, where we set the slope estimate in the out-of-sample analysis equal to zero, whenever its sign differs from that of the in-sample analysis. “(II)” denotes the imposition of the second restriction, where we set the forecast equal to zero, whenever it is negative. “(I+II)” denotes the joint imposition of both restrictions. R_{oos}^2 is the out-of-sample R^2 . *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

		CRP	$EXKURT^{BKM}$	FH	GMR	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)	R_{oos}^2	2.81*** (4.83)	-1.22 (-2.02)	-2.70 (-4.39)	-3.27 (-5.30)	-0.53 (-0.87)	0.07 (0.12)	-3.84 (-6.18)	5.50*** (9.73)
(II)	R_{oos}^2	2.69** (4.61)	0.37 (0.62)	-1.40 (-2.31)	-3.69 (-5.94)	0.56 (0.95)	0.93 (1.57)	-3.39 (-5.48)	4.43*** (7.74)
(I+II)	R_{oos}^2	2.69** (4.61)	0.37 (0.62)	-1.38 (-2.27)	-3.27 (-5.30)	0.56 (0.95)	0.93 (1.57)	-2.95 (-4.79)	4.43*** (7.74)

Panel B: Variance Predictability

		CRP	$EXKURT^{BKM}$	FH	GMR	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)	R_{oos}^2	3.28*** (5.67)	3.34*** (5.77)	-1.82 (-2.98)	-11.23 (-16.87)	2.40** (4.10)	3.89*** (6.76)	3.78*** (6.57)	3.78*** (6.57)
(II)	R_{oos}^2	3.18** (5.48)	3.44*** (5.95)	-1.41 (-2.32)	-5.42 (-8.58)	2.40** (4.10)	3.89*** (6.76)	3.78*** (6.57)	3.78** (6.57)
(I+II)	R_{oos}^2	3.28** (5.67)	3.44** (5.95)	-1.82 (-2.98)	-11.23 (-16.87)	2.40** (4.10)	3.89*** (6.76)	3.78** (6.57)	3.78** (6.57)

Table VII: Economic Value: Restriction I

This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing the first economically motivated restriction following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance and relate to the S&P 500 index. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	6.12	6.87	0.46**	0.54***	0.60***
EXKURT ^{BKM}	5.39	6.35	8.01	0.51***	0.61***	0.76***
FH	2.08	4.27	6.72	0.18	0.30***	0.52***
GMR	-5.94	5.55	3.84	-0.21	0.32***	0.30**
SKEW ^{BKM}	1.86	6.26	6.88	0.16	0.57***	0.63***
SMIRK	2.96	5.00	4.88	0.30	0.55***	0.52***
VAR ^{BKM}	-8.81	6.96	-1.53	-0.48***	0.52***	-0.10
VRP	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*

Panel C: $\gamma = 9$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	2.61	3.33	0.40*	0.35***	0.64**
EXKURT ^{BKM}	2.82	3.11	5.17	0.67***	0.52***	0.94***
FH	0.00	0.36	1.07	0.16	0.10	0.34
GMR	-7.61	2.23	0.14	-0.42***	0.29***	0.16
SKEW ^{BKM}	0.58	2.84	4.03	0.20	0.47***	0.80***
SMIRK	1.40	1.96	2.17	0.38*	0.49***	0.58***
VAR ^{BKM}	-10.81	3.26	-0.58	-0.66***	0.66***	-0.08
VRP	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*

Panel B: $\gamma = 6$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	3.91	5.11	0.45**	0.44***	0.69***
EXKURT ^{BKM}	3.92	4.58	6.46	0.63***	0.59***	0.90***
FH	0.00	1.64	3.46	0.13	0.19	0.49**
GMR	-9.93	3.32	0.30	-0.41***	0.29***	0.16
SKEW ^{BKM}	1.20	4.11	5.60	0.22	0.53***	0.80***
SMIRK	2.07	2.91	3.14	0.38*	0.51***	0.57**
VAR ^{BKM}	-11.50	4.88	-0.85	-0.63***	0.66***	-0.08
VRP	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*

Panel D: $\gamma = 12$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	1.96	2.62	0.40*	0.30***	0.66**
EXKURT ^{BKM}	2.11	2.35	4.05	0.67***	0.47***	0.93***
FH	-0.03	0.22	-0.15	0.16	0.07	0.26
GMR	-6.15	1.68	0.08	-0.42***	0.29***	0.16
SKEW ^{BKM}	0.44	2.17	3.14	0.20	0.44***	0.80***
SMIRK	1.05	1.47	1.63	0.38*	0.49***	0.58***
VAR ^{BKM}	-8.77	2.44	-0.44	-0.66***	0.66***	-0.08
VRP	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

Table VIII: Economic Value: Restriction II

This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing the second economically motivated restriction following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance and relate to the S&P 500 index. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	6.22	6.88	0.46**	0.55***	0.61***
EXKURT ^{BKM}	5.39	6.35	8.01	0.51***	0.61***	0.76***
FH	1.99	4.68	7.11	0.18	0.32***	0.56***
GMR	-3.77	5.55	4.32	-0.12	0.32***	0.33**
SKEW ^{BKM}	1.86	6.26	6.88	0.16	0.57***	0.63***
SMIRK	2.96	5.00	4.88	0.30	0.55***	0.52***
VAR ^{BKM}	-7.28	6.96	-1.48	-0.42***	0.53***	-0.10
VRP	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*

Panel C: $\gamma = 9$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	2.54	3.23	0.40*	0.34***	0.63**
EXKURT ^{BKM}	2.82	3.11	5.17	0.67***	0.52***	0.94***
FH	-0.03	1.82	2.42	0.16	0.23***	0.51**
GMR	-6.87	2.23	0.31	-0.36**	0.29***	0.18
SKEW ^{BKM}	0.58	2.84	4.03	0.20	0.47***	0.80***
SMIRK	1.40	1.96	2.17	0.38*	0.49***	0.58***
VAR ^{BKM}	-10.28	3.26	-0.57	-0.63***	0.67***	-0.07
VRP	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*

Panel B: $\gamma = 6$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	3.81	5.02	0.45**	0.43***	0.69***
EXKURT ^{BKM}	3.92	4.58	6.46	0.63***	0.59***	0.90***
FH	-0.05	2.71	3.75	0.13	0.25***	0.52**
GMR	-8.82	3.32	0.54	-0.35**	0.29***	0.18
SKEW ^{BKM}	1.20	4.11	5.60	0.22	0.53***	0.80***
SMIRK	2.07	2.91	3.14	0.38*	0.51***	0.57**
VAR ^{BKM}	-10.70	4.88	-0.82	-0.60***	0.67***	-0.07
VRP	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*

Panel D: $\gamma = 12$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	1.91	2.55	0.40*	0.29***	0.65**
EXKURT ^{BKM}	2.11	2.35	4.05	0.67***	0.47***	0.93***
FH	-0.05	1.37	1.76	0.16	0.21***	0.51**
GMR	-5.59	1.68	0.21	-0.37**	0.29***	0.18
SKEW ^{BKM}	0.44	2.17	3.14	0.20	0.44***	0.80***
SMIRK	1.05	1.47	1.63	0.38*	0.49***	0.58***
VAR ^{BKM}	-8.37	2.44	-0.43	-0.63***	0.67***	-0.07
VRP	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

Table IX: Economic Value: Restrictions I and II

This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing both economically motivated restrictions following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	6.12	6.87	0.46**	0.54***	0.60***
EXKURT ^{BKM}	5.39	6.35	8.01	0.51***	0.61***	0.76***
FH	2.08	4.27	6.72	0.18	0.30***	0.52***
GMR	-5.94	5.55	3.84	-0.21	0.32***	0.30**
SKEW ^{BKM}	1.86	6.26	6.88	0.16	0.57***	0.63***
SMIRK	2.96	5.00	4.88	0.30	0.55***	0.52***
VAR ^{BKM}	-8.81	6.96	-1.53	-0.48***	0.52***	-0.10
VRP	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*

Panel C: $\gamma = 9$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	2.61	3.33	0.40*	0.35***	0.64**
EXKURT ^{BKM}	2.82	3.11	5.17	0.67***	0.52***	0.94***
FH	0.00	0.36	1.07	0.16	0.10	0.34
GMR	-7.61	2.23	0.14	-0.42***	0.29***	0.16
SKEW ^{BKM}	0.58	2.84	4.03	0.20	0.47***	0.80***
SMIRK	1.40	1.96	2.17	0.38*	0.49***	0.58***
VAR ^{BKM}	-10.81	3.26	-0.58	-0.66***	0.66***	-0.08
VRP	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*

Panel B: $\gamma = 6$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	3.91	5.11	0.45**	0.44***	0.69***
EXKURT ^{BKM}	3.92	4.58	6.46	0.63***	0.59***	0.90***
FH	0.00	1.64	3.46	0.13	0.19	0.49**
GMR	-9.93	3.32	0.30	-0.41***	0.29***	0.16
SKEW ^{BKM}	1.20	4.11	5.60	0.22	0.53***	0.80***
SMIRK	2.07	2.91	3.14	0.38*	0.51***	0.57**
VAR ^{BKM}	-11.50	4.88	-0.85	-0.63***	0.66***	-0.08
VRP	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*

Panel D: $\gamma = 12$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	1.96	2.62	0.40*	0.30***	0.66**
EXKURT ^{BKM}	2.11	2.35	4.05	0.67***	0.47***	0.93***
FH	-0.03	0.22	-0.15	0.16	0.07	0.26
GMR	-6.15	1.68	0.08	-0.42***	0.29***	0.16
SKEW ^{BKM}	0.44	2.17	3.14	0.20	0.44***	0.80***
SMIRK	1.05	1.47	1.63	0.38*	0.49***	0.58***
VAR ^{BKM}	-8.77	2.44	-0.44	-0.66***	0.66***	-0.08
VRP	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

Table X: **Out-of-Sample Analysis: Forecast Combinations**

This table reports the results of the out-of-sample analysis after the use of forecast combinations. The mean forecast combination [MeanFC], the median forecast combination [MedianFC], and the trimmed mean forecast combination [TrMeanFC] are used as alternative specifications. We report the MSE-F statistics in parenthesis. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. Six forecasting variables are used. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Nax (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R_{oos}^2 is the out-of-sample R^2 . *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

	MeanFC	MedianFC	TrMeanFC
R_{oos}^2	1.76*** (2.99)	0.91** (1.54)	1.36*** (2.31)

Panel B: Variance Predictability

	MeanFC	MedianFC	TrMeanFC
R_{oos}^2	2.50*** (4.28)	4.12*** (7.18)	3.06*** (5.27)

Table XI: **Economic Value: Forecast Combinations**

*This table reports utility gains and Sharpe Ratios for each of the three scenarios based on forecast combinations. Scenario 1 assumes that realized variance is unpredictable and that the forecast combination only predicts excess returns. Scenario 2 assumes that excess returns are unpredictable but that the forecast combination predicts the variance of market returns. Scenario 3 implicitly assumes that excess returns and variance can be predicted by the forecast combination. The historical mean return and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: Mean Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.21	6.07	5.80	0.11	0.50***	0.50***
$\gamma = 6$	0.83	3.76	3.76	0.14	0.55***	0.60***
$\gamma = 9$	0.55	2.52	2.59	0.14	0.54***	0.62***
$\gamma = 12$	0.41	1.89	1.94	0.14	0.54***	0.62***

Panel B: Median Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	2.00	6.08	6.22	0.18	0.54***	0.57***
$\gamma = 6$	0.57	3.68	3.85	0.10	0.58***	0.64***
$\gamma = 9$	0.38	2.46	2.62	0.10	0.57***	0.65***
$\gamma = 12$	0.28	1.85	1.96	0.10	0.57***	0.65***

Panel C: Trimmed Mean Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.63	6.05	5.94	0.14	0.52***	0.52***
$\gamma = 6$	0.69	3.69	3.80	0.12	0.56***	0.62***
$\gamma = 9$	0.46	2.47	2.56	0.12	0.56***	0.62***
$\gamma = 12$	0.34	1.86	1.92	0.12	0.56***	0.62***

Table XII: Predictability of the Sharpe Ratio

This table reports the regression results of monthly Sharpe Ratios on a constant, which we denote by φ_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. A fitted $AR(1)$ model serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of $Bakshi$ et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Nar (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{0os}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10%, 5%, and 1% significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

φ_0	0.445 (1.53)	0.076 (0.12)	1.381*** (3.87)	0.650** (2.46)	-0.776 (-0.80)	1.092*** (4.50)	1.005*** (3.12)	0.669*** (2.74)	0.040 (0.04)	-0.563 (-0.47)	-0.972 (-0.74)
CRP	5.084** (2.43)								2.983 (1.27)	2.772 (1.18)	2.829 (1.20)
$EXKURT^{BKM}$		1.125 (1.46)							0.742 (0.84)		-1.711 (-0.73)
FH			-1.059 (-1.60)						-0.319 (-0.34)	-0.344 (-0.37)	-0.392 (-0.42)
GMR				0.030* (1.77)					0.032 (1.17)	0.030 (1.08)	0.029 (1.07)
$SKEW^{BKM}$					-1.958* (-1.79)					-1.424 (-1.20)	-3.556 (-1.12)
$SMIRK$						-1.262 (-1.48)			-1.708* (-1.81)	-1.781* (-1.88)	-1.846* (-1.94)
VAR^{BKM}							-1.710 (-0.34)		-0.268 (-0.04)	-0.609 (-0.10)	-3.091 (-0.44)
VRP								16.265** (2.17)	8.439 (1.00)	8.703 (1.03)	8.198 (0.97)
R^2	2.56**	0.94	1.13	1.38*	1.40*	0.97	0.05	2.04**	3.30*	3.63**	3.42*
R_{0os}^2	2.99**	-0.50	-0.11	-1.84	0.96	0.24	-0.45	1.54*	-14.01	-12.82	-14.81

Predicting the Equity Market with Option-Implied Variables

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Online Appendix

JEL classification: G10, G11, G17

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Predictability, Timing Strategies

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Table A1: Economic Value with Turnover and Transaction Costs

This table reports the turnover, the utility gains, and the Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in column] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in column] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in column], and in the latter case, by the forecasting variable [name in column] and the lagged realized variance. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $Turnover_{abs}$ is the monthly absolute value of the turnover for the naive strategy. $Turnover_{rel}^{(i)}$ represents the monthly relative turnover of strategy i related to the benchmark. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	CRP	EXKURT ^{BKM}	FH	GMR	SKEW ^{BKM}	SMIRK	VAR ^{BKM}	VRP
$Turnover_{abs}$	0.0448	0.0448	0.0448	0.0448	0.0448	0.0448	0.0448	0.0448
$Turnover_{rel}^{(1)}$	12.1906	5.4513	4.5365	3.0830	5.5545	8.9341	2.2193	9.6821
$Turnover_{rel}^{(2)}$	4.8831	5.5580	1.2842	2.0465	2.9157	2.7424	2.7127	3.9283
$Turnover_{rel}^{(3)}$	14.6331	8.2202	4.1985	2.0576	6.6146	10.9321	3.4473	11.5826
$\Delta CER^{(1)}$	2.48	4.19	1.03	-4.31	0.64	0.85	-7.62	-8.46
$\Delta CER^{(2)}$	-1.03	1.60	1.43	4.39	1.81	1.87	5.94	7.04
$\Delta CER^{(3)}$	1.38	4.46	3.17	2.36	2.33	0.55	-4.91	-5.47
$\Delta SR^{(1)}$	0.21	0.39**	0.12	-0.14	0.06	0.05	-0.43***	-0.57***
$\Delta SR^{(2)}$	0.06	0.20	0.12*	0.24***	0.21	0.21**	0.36***	0.47***
$\Delta SR^{(3)}$	0.13	0.36*	0.26**	0.22*	0.20	0.06	-0.22	-0.25

Panel B: $\gamma = 6$

	CRP	EXKURT ^{BKM}	FH	GMR	SKEW ^{BKM}	SMIRK	VAR ^{BKM}	VRP
$Turnover_{abs}$	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
$Turnover_{rel}^{(1)}$	15.9051	7.0084	5.7696	5.5303	7.0350	9.3238	4.2300	12.5610
$Turnover_{rel}^{(2)}$	10.6311	10.8603	2.2327	2.5870	6.8986	4.7041	5.8114	9.8254
$Turnover_{rel}^{(3)}$	25.8225	16.2198	8.4137	5.2987	13.7024	18.2632	5.2006	18.7912
$\Delta CER^{(1)}$	0.88	3.03	-0.79	-9.52	0.30	0.85	-11.25	-10.32
$\Delta CER^{(2)}$	-5.70	0.95	-1.58	2.76	0.29	0.26	4.83	4.18
$\Delta CER^{(3)}$	-1.36	2.62	-0.68	-3.30	0.64	-0.28	-6.18	-10.91
$\Delta SR^{(1)}$	0.18	0.49***	0.07	-0.38***	0.10	0.10	-0.61***	-0.73***
$\Delta SR^{(2)}$	-0.14	0.25	0.02	0.21***	0.20*	0.16	0.44***	0.49***
$\Delta SR^{(3)}$	0.12	0.41*	0.22	0.08	0.27	0.06	-0.28	-0.54**

Table A1: **Economic Value with Turnover and Transaction Costs**
(continued)

Panel C: $\gamma = 9$

	<i>CRP</i>	<i>EXKURT</i> ^{BKM}	<i>FH</i>	<i>GMR</i>	<i>SKEW</i> ^{BKM}	<i>SMIRK</i>	<i>VAR</i> ^{BKM}	<i>VRP</i>
<i>Turnover</i> _{abs}	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151
<i>Turnover</i> _{rel} ⁽¹⁾	18.4886	8.8266	7.1716	6.7321	9.2375	10.2124	5.7328	15.0938
<i>Turnover</i> _{rel} ⁽²⁾	15.6516	16.8364	3.4586	2.6537	10.1848	5.1486	6.6592	17.8674
<i>Turnover</i> _{rel} ⁽³⁾	36.6566	26.1824	11.1854	7.8807	20.6825	24.7431	5.7841	22.0822
ΔCER ⁽¹⁾	0.15	2.11	-0.62	-7.43	-0.18	0.57	-10.81	-9.58
ΔCER ⁽²⁾	-6.59	0.70	-2.11	1.82	0.03	0.13	3.25	2.20
ΔCER ⁽³⁾	-2.17	1.01	-3.55	-4.35	-1.03	-0.41	-4.53	-9.70
ΔSR ⁽¹⁾	0.13	0.50***	0.08	-0.40***	0.07	0.10	-0.65***	-0.74***
ΔSR ⁽²⁾	-0.18	0.25*	-0.01	0.18***	0.18*	0.14	0.44***	0.49***
ΔSR ⁽³⁾	0.14	0.39	0.07	-0.01	0.22	0.10	-0.29	-0.59***

Panel D: $\gamma = 12$

	<i>CRP</i>	<i>EXKURT</i> ^{BKM}	<i>FH</i>	<i>GMR</i>	<i>SKEW</i> ^{BKM}	<i>SMIRK</i>	<i>VAR</i> ^{BKM}	<i>VRP</i>
<i>Turnover</i> _{abs}	0.0108	0.0108	0.0108	0.0108	0.0108	0.0108	0.0108	0.0108
<i>Turnover</i> _{rel} ⁽¹⁾	19.5157	9.1852	7.4131	7.4079	10.0488	10.6805	6.4946	15.8094
<i>Turnover</i> _{rel} ⁽²⁾	18.2998	21.0369	4.5438	2.6821	12.2949	5.3345	6.8723	24.3221
<i>Turnover</i> _{rel} ⁽³⁾	45.3856	34.0648	12.6527	9.0251	25.9198	27.6275	6.0582	23.5223
ΔCER ⁽¹⁾	0.07	1.58	-0.49	-6.05	-0.17	0.43	-8.86	-7.25
ΔCER ⁽²⁾	-7.04	0.49	-2.40	1.36	-0.24	0.08	2.43	0.77
ΔCER ⁽³⁾	-2.90	0.09	-4.75	-3.49	-1.78	-0.48	-3.45	-8.30
ΔSR ⁽¹⁾	0.12	0.50***	0.08	-0.41***	0.07	0.10	-0.65***	-0.75***
ΔSR ⁽²⁾	-0.21	0.25*	-0.04	0.18***	0.14	0.13	0.44***	0.43**
ΔSR ⁽³⁾	0.11	0.38	-0.01	-0.01	0.21	0.09	-0.29	-0.59***

Table A2: **Out-of-Sample Analysis: Restriction – Frequencies**

This table reports the absolute frequency of how often the economically motivated restrictions imposed are binding in the out-of-sample analysis, shown in Table VI. Panel A shows the frequency for each individual variable, predicting the next month’s excess return. Panel B shows the frequency for each individual variable as well as lagged realized variance, predicting the next month’s realized variance. *CRP* denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). *FH* is the risk-neutral riskiness measure of Leiss & Nax (2018). *GMR* is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). *SMIRK* is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, *VRP* is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. “(I)” denotes the imposition of the first restriction, where we set the slope estimate in the out-of-sample analysis equal to zero, whenever its sign differs from that of the in-sample analysis. “(II)” denotes the imposition of the second restriction, where we set the forecast equal to zero, whenever it is negative. “(I+II)” denotes the joint imposition of both restrictions. “(I+II) (I)” (“(I+II) (II)”) refers to the frequency of the first (second) restriction in the case of the joint imposition of both restrictions. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

		<i>CRP</i>	$EXKURT^{BKM}$	<i>FH</i>	<i>GMR</i>	$SKEW^{BKM}$	<i>SMIRK</i>	VAR^{BKM}	<i>VRP</i>
(I)		0	0	12	8	0	0	35	0
(II)		53	32	8	7	29	62	56	77
(I+II)	(I)	0	0	12	8	0	0	35	0
(I+II)	(II)	53	32	9	0	29	62	50	77

Panel B: Variance Predictability

		<i>CRP</i>	$EXKURT^{BKM}$	<i>FH</i>	<i>GMR</i>	$SKEW^{BKM}$	<i>SMIRK</i>	VAR^{BKM}	<i>VRP</i>
(I)		75	0	76	3	0	0	0	0
(II)		0	3	0	0	0	0	0	0
(I+II)	(I)	75	0	76	3	0	0	0	0
(I+II)	(II)	0	3	0	0	0	0	0	0
Lagged Realized Variance									
(I)		0	0	0	0	0	0	0	0
(II)		-	-	-	-	-	-	-	-
(I+II)	(I)	0	0	0	0	0	0	0	0
(I+II)	(II)	-	-	-	-	-	-	-	-

Table A3: Return and Variance Predictability of *VRP* Specifications

Panel A of this table reports the regression results of monthly excess returns on a constant, which we denote by β_0 , and the lagged predictive variable. Panel B reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , the lagged predictive variable, and the lagged realized variance. Statistical inferences are based on a bootstrapped distribution. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. VRP^{HAR} denotes the variance risk premium based on the HAR–RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR–RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR–RV model. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. We report the t -statistics in parentheses. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
R^2	0.00	2.23**	2.65**	0.38	2.05**
R_{oos}^2	-5.37	-1.13	-2.38	-4.10	-1.25
$t - stat$	(0.10)	(2.26)	(2.47)	(0.93)	(2.17)

Panel B: Variance Predictability

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
R^2	42.95	41.03	40.34	41.19	43.94
R_{oos}^2	3.40***	4.34***	-3.46	-4.05	4.63***
$t - stat$	(3.32)	(1.85)	(0.89)	(2.01)	(3.90)

Table A4: **Economic Value of VRP Specifications**

This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in column] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in column] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in column], and in the latter case, by the forecasting variable [name in column] and the lagged realized variance. The historical mean return, and the forecast of a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-7.41	0.24	2.25	-9.33	-9.25
$\Delta CER^{(2)}$	6.29	7.40	6.73	5.17	5.11
$\Delta CER^{(3)}$	-4.36	6.31	6.74	-4.99	-8.24
$\Delta SR^{(1)}$	-0.43***	0.04	0.19**	-0.55***	-0.58***
$\Delta SR^{(2)}$	0.38***	0.69***	0.71***	0.37***	0.40***
$\Delta SR^{(3)}$	-0.20	0.59***	0.71***	-0.29*	-0.51**

Panel B: $\gamma = 6$

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-10.71	-1.91	0.96	-11.09	-10.73
$\Delta CER^{(2)}$	5.47	5.94	5.12	3.70	4.81
$\Delta CER^{(3)}$	-6.36	4.47	6.13	-6.32	-8.17
$\Delta SR^{(1)}$	-0.60***	-0.12	0.17*	-0.64***	-0.69***
$\Delta SR^{(2)}$	0.46***	0.74***	0.60***	0.40***	0.62***
$\Delta SR^{(3)}$	-0.27	0.61**	0.79***	-0.37**	-0.59***

Table A4: Economic Value of *VRP* Specifications (continued)

Panel C: $\gamma = 9$					
	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-10.65	-2.43	0.63	-10.89	-9.83
$\Delta CER^{(2)}$	3.72	4.24	3.21	2.49	4.36
$\Delta CER^{(3)}$	-4.72	3.39	4.63	-5.68	-6.97
$\Delta SR^{(1)}$	-0.62***	-0.21	0.17*	-0.65***	-0.73***
$\Delta SR^{(2)}$	0.47***	0.67***	0.45**	0.36***	0.76***
$\Delta SR^{(3)}$	-0.29	0.64**	0.80***	-0.40**	-0.60***

Panel D: $\gamma = 12$					
	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-8.65	-2.20	0.47	-10.35	-7.82
$\Delta CER^{(2)}$	2.78	3.15	2.25	1.85	3.43
$\Delta CER^{(3)}$	-3.60	2.53	3.25	-4.61	-5.49
$\Delta SR^{(1)}$	-0.63***	-0.23*	0.17*	-0.62***	-0.72***
$\Delta SR^{(2)}$	0.47***	0.61***	0.43*	0.34***	0.80***
$\Delta SR^{(3)}$	-0.29	0.65**	0.76**	-0.40**	-0.59***

Table A5: Variance Predictability: Alternative Approach

This table reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. The historical mean serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). FH is the risk-neutral riskiness measure of Leiss & Nae (2018). GMR is the generalized measure of riskiness of Bali et al. (2011). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{cos}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10%, 5%, and 1% significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

γ_0	0.043*** (9.49)	0.074*** (7.84)	0.036*** (6.28)	0.025*** (5.87)	0.073*** (4.71)	0.022*** (6.09)	-0.004 (-1.00)	0.038*** (9.88)	0.021* (1.84)	0.025* (1.75)	0.025 (1.56)
CRP	-0.123*** (-3.72)								-0.074*** (-2.61)	-0.073*** (-2.59)	-0.073*** (-2.58)
$EXKURT^{BKM}$		-0.057*** (-4.78)							-0.010 (-0.91)		-0.001 (-0.05)
FH			-0.010 (-0.93)						-0.012 (-1.04)	-0.011 (-1.02)	-0.011 (-1.02)
GMR				0.001*** (2.98)					-0.001* (-1.69)	-0.001* (-1.66)	-0.001* (-1.65)
$SKEW^{BKM}$					0.047*** (2.72)				0.014 (0.96)	0.014 (0.96)	0.012 (0.32)
$SMIRK$						0.071*** (5.53)			0.030*** (2.62)	0.030*** (2.66)	0.030*** (2.64)
VAR^{BKM}							0.756*** (11.95)		0.720*** (9.15)	0.731*** (9.94)	0.729*** (8.63)
VRP								-0.399*** (-3.36)	-0.209** (-2.06)	-0.208** (-2.05)	-0.208** (-2.05)
R^2	5.80***	9.24***	0.38	3.79***	3.19***	11.97***	38.83***	4.79***	45.69***	45.71***	45.47***
R_{cos}^2	1.88***	8.04***	-0.75	-7.12	2.65***	8.61***	34.65***	-2.92	5.18***	4.25***	0.55***

Table A6: Economic Value: Alternative Approach

This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean serves as naive benchmark for both return and variance predictability. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a naive strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	1.63	4.63	0.46**	0.11	0.40*
EXKURT ^{BKM}	5.39	3.69	6.24	0.51***	0.34***	0.58***
FH	1.99	0.01	1.30	0.18	-0.04	0.12
GMR	-3.77	2.46	-0.96	-0.12	0.13***	-0.05
SKEW ^{BKM}	1.86	1.78	3.28	0.16	0.13***	0.29
SMIRK	2.96	1.47	2.91	0.30	0.14	0.30
VAR ^{BKM}	-7.28	7.19	-1.65	-0.42***	0.50***	-0.09
VRP	-6.10	-1.57	-5.43	-0.41*	-0.13	-0.41*

Panel C: $\gamma = 9$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	1.04	1.56	0.40*	0.12*	0.38
EXKURT ^{BKM}	2.82	2.27	3.74	0.67***	0.40***	0.74***
FH	-0.03	0.26	-0.20	0.16	-0.02	0.07
GMR	-6.87	1.10	-0.93	-0.36**	0.13***	-0.10
SKEW ^{BKM}	0.58	0.88	1.76	0.20	0.13***	0.41**
SMIRK	1.40	0.75	1.47	0.38*	0.14	0.38*
VAR ^{BKM}	-10.28	3.94	-0.18	-0.63***	0.73***	0.05
VRP	-8.15	-0.65	-6.22	-0.63***	-0.10	-0.58**

Panel B: $\gamma = 6$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	1.50	2.86	0.45**	0.14*	0.43*
EXKURT ^{BKM}	3.92	3.05	4.83	0.63***	0.40***	0.70***
FH	-0.05	0.36	-0.35	0.13	-0.01	0.03
GMR	-8.82	1.62	-1.35	-0.35**	0.13***	-0.10
SKEW ^{BKM}	1.20	1.30	2.36	0.22	0.14**	0.37**
SMIRK	2.07	1.10	2.13	0.38*	0.14	0.37*
VAR ^{BKM}	-10.70	5.67	-0.45	-0.60***	0.71***	0.02
VRP	-8.49	-0.98	-6.14	-0.60***	-0.12	-0.53**

Panel D: $\gamma = 12$

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	0.78	0.87	0.40*	0.10*	0.36
EXKURT ^{BKM}	2.11	1.80	2.93	0.67***	0.40***	0.74***
FH	-0.05	0.20	-0.19	0.16	-0.02	0.08
GMR	-5.59	0.83	-0.71	-0.37**	0.13***	-0.10
SKEW ^{BKM}	0.44	0.66	1.35	0.20	0.13***	0.42**
SMIRK	1.05	0.57	1.10	0.38*	0.14	0.38*
VAR ^{BKM}	-8.37	2.95	-0.15	-0.63***	0.73***	0.05
VRP	-6.18	-0.49	-5.82	-0.63***	-0.10	-0.59**