Predicting the Equity Market with Option Implied Variables*

Marcel Prokopczuk[†,‡], Björn Tharann[†] and Chardin Wese Simen[‡]

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) emerges as a strong predictor of both excess returns and realized variance. This is true both in– and out–of–sample. A timing strategy based on the CRP leads to utility gains of more than 4.63 % per annum. In contrast, the variance risk premium (VRP), which strongly predicts excess returns, does not lead to economic gains.

JEL classification: G10, G11, G17

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

*We are grateful to Duygu Zirek (discussant) and seminar participants at the Financial Management Association (FMA) Annual Meeting 2017 in Boston (U.S.) for valuable comments. We thank Fabian Bätje and Fabian Hollstein for helpful comments and suggestions. Contact: prokopczuk@fmt.uni-hannover.de (M. Prokopczuk), tharann@fmt.uni-hannover.de (B. Tharann), and c.wese-simen@icmacentre.ac.uk (C. Wese Simen).

[†]Leibniz University Hannover, Koenigsworther Platz 1, D-30167 Hannover, Germany.

[‡]ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, UK.

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 the market excess returns? Do the variables that predict the market excess returns also forecast realized variance? Does the 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 recent literature on the option implied predictors. 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. Furthermore, we show that the CRP predicts not only the market excess returns but also its realized variance. We note also that most of the variables we study have strong predictive power 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 CRP would realize utility gains of 4.63 %. Relatedly, we find that a return timing strategy based on the VRP leads to lower utility than that afforded by the strategy based on the recursive mean, indicating that the statistical predictability of excess returns by the VRP does not always translate to economic gains. We conjecture that this result is likely due 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. 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 risk. Second, the variable needs to add economic value. Since the predictability, measured by R^2, is, in general, small in magnitude, the question arises whether it is economically meaningful. Brooks & Persand (2003) show that the choice of the loss function for performance evaluation might be decisive. Does an investor obtain an increase in portfolio return by taking the variable into account? This aspect is often ignored in the existing literature. Our results show that CRP emerges as the only predictor that passes both tests.

In addition, we analyze the predictability of different specifications of the VRP as robustness. 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 premium also pass both tests by providing evidence for significantly predicting excess returns and variance in–sample, and in adding economic value in 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 the 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 are the drivers of 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. 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 forecasting only explore the implication for a volatility timing strategy (Fleming et al., 2001). Unlike these studies, we jointly study the impact of return and volatility timing. This is important because in a mean–variance framework, the optimal portfolio weight invested in the risky asset depends on both the expected returns and the expected realized variance. If a forecasting variable predicts both the market excess returns 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 the 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 (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 data. Starting our sample in January 1996 allows us to guarantee the availability of data from all 3 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:

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

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]

[1] Throughout 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 $t+1$.

Following Goyal & Welch (2008), we use the 1–month T–bill rate to proxy for the riskless rate.

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:

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

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 variance (VAR^{BKM}), skewness ($SKEW^{BKM}$) and excess kurtosis

$(EXKURT^{BKM})$:

$$VAR^{BKM} = \frac{e^{r\tau}V - \mu^2}{\tau} \tag{3}$$

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

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

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:

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

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

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

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

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.

[2]We 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.

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 0.3 % 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 simply use a nearest neighborhood algorithm to extrapolate the implied volatilities (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. (2014) 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:

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

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:

$$VRP_t = VAR_t^{BKM} - RV_t \tag{11}$$

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:

$$IC_t = \frac{E_t^Q[\int_t^{t+\tau} \sigma_{I,s}^2 \, ds] - \sum_{i=1}^N \omega_i^2 \, E_t^Q[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds]}{\sum_{i=1}^N \sum_{j \neq i} \omega_i \omega_j \, E_t^Q[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds] \, E_t^Q[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds]} \tag{12}$$

where IC_t is the implied correlation at t. $E_t^Q[\int_t^{t+\tau} \sigma_{I,s}^2 \; ds]$ and $E_t^Q[\int_t^{t+\tau} \sigma_{i,s}^2 \; ds]$ are the risk–neutral expected variance of the index (I) and of the individual stock (i), respectively. As before, we proxy these expectations with the risk–neutral variance of Bakshi et al. (2003). w_i and w_j are the weights of stocks i and j in the market index I, respectively.

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

$$RC_t = \frac{E_t^P[\int_t^{t+\tau} \sigma_{I,s}^2 \, ds] - \sum_{i=1}^N \omega_i^2 \, E_t^P[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds]}{\sum_{i=1}^N \sum_{j \neq i} \omega_i \omega_j \, E_t^P[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds] \, E_t^P[\int_t^{t+\tau} \sigma_{i,s}^2 \, ds]} \tag{13}$$

where RC_t is the realized correlation at 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:

$$CRP_t = IC_t - RC_t \tag{14}$$

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. 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:

$$SMIRK_t = VOL_t^{OTMP} - VOL_t^{ATMC} \tag{15}$$

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 volatility of all out–of–the–money put options. VOL_t^{ATMC} refers to the volume–weighted average of all implied volatility of at–the–money calls at time t.

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 % per annum. The risk premium exhibits a volatility of around 16 % per annum. 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 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):

$$ER_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_{t+1} \qquad (16)$$

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 all our statistical inferences on the bootstrapped distribution obtained by implementing the framework of Rapach & Wohar (2006).[3]

We can see that the CRP, $SMIRK$ and VRP are statistically significant in the univariate regressions. This is illustrated by their $t-$statistics of 2.76, -2.06 and 4.26. The positive and significant slope estimate related to the VRP confirms and updates, using

[3] We estimate our process under the null hypothesis of no predictability via OLS, 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. Then, we form a series of error terms and set up our pseudo sample. For the pseudo sample, we calculate the in–sample and out–of–sample statistics. Finally, we repeat this procedure 1,000 times.

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 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 the 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 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 larger in the more recent sample period.

To analyze the joint predictive ability of different variables, we perform two multiple regressions. Due to the high correlation between $SKEW^{BKM}$ and $EXKURT^{BKM}$, we run the regressions once without the first and once without the second variable. In both cases we find that only $SMIRK$ and VRP retain their statistical significance. Overall, the adjusted

R^2 increases to 7.91 % and 8.13 % in the first and second cases, 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 (16). 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^2_{oos}) as follows:

$$R^2_{oos} = 1 - \frac{MSE_u}{MSE_r} \tag{17}$$

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 (16). The restricted model imposes the null hypothesis that returns are unpredictable, i.e. $\beta_1 = 0$. Thus the R^2_{oos} 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^2_{oos} the better. A variable has notable predictive power if it exhibits a positive and significant R^2_{oos}, 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):

$$MSE - F = N \times \left(\frac{MSE_r - MSE_u}{MSE_u} \right) \tag{18}$$

where N 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 least 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 set of results in Table III, CRP and VRP yield statistically significant improvements in 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 CRP and VRP contain important information about next–month's market excess returns both in– and out–of–sample. In contrast, both multiple regressions do not increase the predictive power out–of–sample.

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:

$$RV_{t+1} = \gamma_0 + \gamma_1 X_t + \epsilon_{t+1} \tag{19}$$

where γ_0 and γ_1 are the intercept and slope parameters, respectively. All other variables are as previously defined.

Table IV summarizes the results of the in–sample analysis. We notice that all variables have predictive power for future realized variance, as evidenced by their statistically significant $t-$statistics. The R^2 associated with these forecasting variables ranges from 3.19 % to 38.83 %. These results are interesting for several reasons. First, they indicate that the predictability of 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 returns (see Table III) but also realized variance. Third, some variables 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 9.24 %. 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.

While we analyze the joint predictive ability of different variables by performing two multiple regressions once without $SKEW^{BKM}$ and once without $EXKURT^{BKM}$ again, in both cases we find that all variables retain their statistical significance, except $SKEW^{BKM}$ and $EXKURT^{BKM}$. Overall, the adjusted R^2 increases to 45.47 % and 45.53 %, respectively.

Out–of–Sample We conduct our analysis out–of–sample in a similar way as before. Specifically, we use the first 5 years of observations to initially estimate the model parameters (see Equation (19)). 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 forecast realized variance rather than the market excess returns. The last row of Table IV shows the R^2_{oos}. Generally, the variables that predict realized variance in–sample are also predictors out–of–sample. This is true for all variables with the exception of VRP, which does not yield an improvement relative to the recursive mean. Further, in case of the two multiple regressions, there is an increase of the adjusted R^2_{oos} to 12.21 % and 12.20 %, respectively. However, the predictive power where using VAR^{BKM} individually is not achieved.

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

$$\max_{w_t} E_t^P \left(R_{p,t+1} - \frac{\gamma}{2} \sigma^2_{p,t+1} \right) \tag{20}$$

where $E_t^P(\cdot)$ is the physical expectation operator. $\sigma^2_{p,t+1}$ is the conditional variance of the portfolio at time $t+1$. γ is the coefficient of relative risk aversion. $R_{p,t+1}$ is the next–period's (simple) return on the investor's portfolio. 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.[4] Thus, we can express the objective function as follows:

$$\max_{w_t} E_t\left(w_t ER_{t+1} + rf_t + \frac{1}{2}w_t RV_{t+1} - \frac{\gamma}{2}w_t^2 RV_{t+1}^2\right) \tag{21}$$

where all 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):

$$\begin{aligned} \omega_t &= \frac{E_t(ER_{t+1} + \frac{1}{2}RV_{t+1})}{\gamma E_t(RV_{t+1})} \\ &= \frac{E_t(ER_{t+1})}{\gamma E_t(RV_{t+1})} + \frac{1}{2\gamma} \end{aligned} \tag{22}$$

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

[4] More 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.

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 returns 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.

For a given case i 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 (22) 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 equivalent return as follows:

$$CER^{(i)} = \bar{R}_p - \frac{\gamma}{2}\sigma_p^2 \tag{23}$$

where $CER^{(i)}$ is the certainty equivalent return associated with strategy i. 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 ($\Delta CER^{(i)}$), the difference between $CER^{(i)}$ 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 in turn.

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

$$SR^{(i)} = \frac{\bar{R}_p - \bar{R}_f}{\sigma_p^2} \tag{24}$$

Similar to the certainty equivalent return analysis, we compute the improvement in SR by taking the difference between $SR^{(i)}$ and the SR linked to the naive strategy that assumes that the market excess returns and realized variance are unpredictable. We follow Jobson & Korkie (1981) and take into account the correction suggested by Memmel (2003) to 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 excess returns, an investor 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 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.

In contrast, one can see that relative to an agent with risk aversion $\gamma = 3$, who assumes that the market excess returns and the realized variance are unpredictable, the agent who exploits the information content of CRP would improve her utility by 4.63 %.

Table A1 in the online appendix shows the portfolio choice implications taking turnover and transaction costs into account. Following DeMiguel et al. (2009), we define the turnover for strategy i as the average sum of the absolute values of the trades, i.e.:

$$Turnover = \frac{1}{T-M} \sum_{t=1}^{T-M} \left(|\omega_{t+1}^{(i)} - \omega_{t^+}^{(i)}| \right) \tag{25}$$

where $T - M$ is the training window over which the moments are estimated and $\omega_{t^+}^{(i)}$ 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 ($Turnover_{rel}^{(i)}$) relative to the benchmark case. We notice that all strategies exhibit higher turnovers than the benchmark, indicated by values large than one.

To achieve a practical point of view, we follow Balduzzi & Lynch (1999) and include transaction costs of 50 basis points per transaction proportional to the asset's traded size $|\omega_{t+1}^{(i)} - \omega_{t^+}^{(i)}|$. Table A1 reports the corresponding utility gains and Sharpe Ratios. We observe that transaction costs have an systematic impact on the results. Although the patterns are qualitatively similar, we notice a noteworthy reduction in the utility gains and Sharpe Ratios.

E.g., CRP yields a utility gain of 1.78 %, assuming both that excess returns and variance are predictable by that variable. The improvement in the Sharpe Ratio amounts to 0.15.

IV. Further Analyses

IV.A Sign Restriction

Campbell & Thompson (2008) propose to impose economically–motivated restrictions when studying the question of predictability. The authors suggest to set the slope estimate in the out–of–sample analysis equal to zero whenever its sign differs from that of the in–sample analysis.

Panel A of Table VI shows that the main results hold: the CRP and VRP are the two main option implied predictors of the market excess returns. It is worth noticing that imposing this restriction has very little effect on the R^2_{oos} related to the forecasting variable (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 a similar 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. Overall, we can see from Panel B of Table VI that this restriction has very little impact on our main results.

Pursuing our analysis, we impose the restriction that we set the forecast equal to zero, whenever its negative. The second set of results in Table VI reports these findings. Finally, the last entries of each panel of Table VI show the results when we jointly impose the restrictions (on the sign of the slope and the sign of the return/variance forecast).

We also repeat our economic value analysis using these economically–motivated constraints. Before discussing the findings, it is worth emphasizing that the timing strategies are 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. Tables VII–IX document that imposing the restriction(s) does not affect our main conclusions on the economic value of the predictive power of both CRP and VRP.

IV.B Forecast Combination

Rapach et al. (2010) suggest the use of forecast combinations. The pooled forecast is the weighted average of all N individual forecasts, i.e. $\widehat{ER}_{t+1}^{pool} = \sum_{i=1}^{N} x_{i,t}\widehat{ER}_{i,t+1}$ and $\widehat{RV}_{t+1}^{pool} = \sum_{i=1}^{N} x_{i,t}\widehat{RV}_{i,t+1}$, based on Equation (16) and (19), respectively. $x_{i,t}$ 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^2s of (i) the mean forecast combination, where the weight is simply $1/N$ for $i = 1, ..., N$, (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 $x_{i,t} = 0$ in case of the individual forecasts with the smallest and largest value, respectively, and $x_{i,t} = 1/(N-2)$ for the remaining forecasts.

The mean forecast combination exhibits superior performance in both cases, the return

($R^2_{oos} = 3.11\,\%$) as well as variance predictability ($R^2_{oos} = 16.01\,\%$).

Table XI reports the economic value for different values of risk aversion. Compared to the previous findings, the median forecast combination now exhibits superior performance. For $\gamma = 3$, an annualized utility gain of $3.98\,\%$ (relative to the naive strategy) may be achieved, assuming both return and variance can be predicted by the forecasting variables.

Note, according to our understanding a variable has predictive power if it satisfies two tests, i.e. a variable has predictive power if and only if it exhibits statistical as well as economic significance at once. Therefore, in contrast to the literature, we focus our analysis on both aspects. In our case, only the CRP fulfills both conditions.

V. Additional Analysis

To use more information in estimating the RV, we follow Corsi (2009) and Sévi (2014) and use the heterogeneous auto–regressive (HAR) model. The HAR–RV model provides a conditional estimate for RV that accounts for different trading horizons. Second, 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 VRP 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 VRP. Further, to get a better estimate for the physical expectation of variance, we analogously use the downside and upside RV.

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}):

$$VRP_t^{HAR} = VAR_t^{BKM} - RV_t^{HAR} \tag{26}$$

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

$$RV_{D,t+\frac{i}{N}} \equiv RV_{t+\frac{i}{N}} \tag{27}$$

$$\begin{aligned} RV_{W,t+\frac{i}{N}} &\equiv RV_{(t+\frac{i}{N})-4,t+\frac{i}{N}} \\ &= \left[RV_{(t+\frac{i}{N})-4} + RV_{(t+\frac{i}{N})-3} + RV_{(t+\frac{i}{N})-2} + RV_{(t+\frac{i}{N})-1} + RV_{t+\frac{i}{N}}\right] / \ 5 \end{aligned} \tag{28}$$

$$RV_{M,t+\frac{i}{N}} \equiv RV_{(t+\frac{i}{N})-20,t+\frac{i}{N}} = \left[RV_{(t+\frac{i}{N})-20} + RV_{(t+\frac{i}{N})-19} + ... + RV_{t+\frac{i}{N}}\right] / \ 21 \tag{29}$$

as the daily, weakly, and monthly RV on day $t + \frac{i}{N}$, respectively.[5] Further,

[5]We follow the common approach and define one month as 21 trading days.

$RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}$ is the RV over the next 21 days, i.e.:

$$RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} = \left[RV_{(t+\frac{i}{N})+1} + RV_{(t+\frac{i}{N})+2} + ... + RV_{(t+\frac{i}{N})+20}\right] / \, 21 \quad (30)$$

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

$$\begin{aligned} RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} = \phi_0 + \phi_D RV_{D,t+\frac{i}{N}} + \phi_W RV_{W,t+\frac{i}{N}} \\ + \phi_M RV_{M,t+\frac{i}{N}} + \epsilon_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} \end{aligned} \quad (31)$$

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 forecast 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 ($(\sigma_t^{\mathbb{Q}-})^2$ and $(\sigma_t^{\mathbb{Q}+})^2$) and the downside and upside RV (RV^{DOWN} and RV^{UP}), respectively:

$$VRP_t^{DOWN} = \left(\sigma_t^{\mathbb{Q}-}\right)^2 - RV_t^{DOWN} \quad (32)$$

$$VRP_t^{UP} = \left(\sigma_t^{\mathbb{Q}+}\right)^2 - RV_t^{UP} \quad (33)$$

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:

$$\left(\sigma_t^{\mathbb{Q}}\right)^2 = 2\int_0^{\infty} \frac{M(K)}{K^2}\,dK = (\sigma_t^{\mathbb{Q}-})^2 + (\sigma_t^{\mathbb{Q}+})^2 \tag{34}$$

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 $\theta = 0$:

$$\left(\sigma_t^{\mathbb{Q}-}\right)^2 = 2\int_0^{Se^{\theta}} \frac{M(K)}{K^2}\,dK \tag{35}$$

$$\left(\sigma_t^{\mathbb{Q}+}\right)^2 = 2\int_{Se^{\theta}}^{\infty} \frac{M(K)}{K^2}\,dK \tag{36}$$

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

Following Barndorff-Nielsen et al. (2010), we decompose the RV 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 RV estimated on the basis of the HAR model ($RV^{DOWN,HAR}$ and $RV^{UP,HAR}$), respectively:

$$VRP_t^{DOWN,HAR} = \left(\sigma_t^{\mathbb{Q}-}\right)^2 - RV_t^{DOWN,HAR} \quad (37)$$

$$VRP_t^{UP,HAR} = \left(\sigma_t^{\mathbb{Q}+}\right)^2 - RV_t^{UP,HAR} \quad (38)$$

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 A2 in the online appendix shows the regressions results for the different specifications predicting the next month's excess return and RV, 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^2s from 2.65 % to 2.05 %.

In contrast, Panel B of Table A2 demonstrates that all specifications outperform the VRP in predicting RV in–sample. We observe significant R^2s ($t-$statistics) ranging between 39.16 % (−12.04) for VRP^{UP} and 12.46 % (5.66) for $VRP^{UP,HAR}$. Further, we observe noteworthy significant out–of–sample predictability for VRP^{HAR} ($R^2_{oos} = 34.24$ %), $VRP^{DOWN,HAR}$ ($R^2_{oos} = 24.79$ %) and $VRP^{UP,HAR}$ ($R^2_{oos} = 10.45$ %).

We now turn our attention to the portfolio choice implications. Table A3 in 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 6.25 % (5.26 %) and in the Sharpe Ratio of 0.55 (0.44).

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

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 emerges as a strong predictor of both the market excess returns and the realized variance. This is true both in– and out–of–sample. Relatedly, we show that the variance risk premium predicts the market excess returns in– and out–of–sample. However, its predictive power for realized variance is only evident in–sample and does not extend 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 4.63 %. 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 to 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 premium have noteworthy (in–sample) predictive power for excess returns and variance. Further, a timing strategy provides a utility gain of 6.25 % and 5.26 %, respectively.

Bibliography

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, *71*(2), 579–625.

Andersen, T. G., & Bondarenko, O. (2010). Dissecting the pricing of equity index volatility. *Working Paper*.

Andersen, T. G., Bondarenko, O., & Gonzalez-Perez, M. T. (2015). Exploring return dynamics via corridor implied volatility. *Review of Financial Studies*, *28*(10), 2902–2945.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies*, *16*(1), 101–143.

Balduzzi, P., & Lynch, A. W. (1999). Transaction costs and predictability: Some utility cost calculations. *Journal of Financial Economics*, *52*(1), 47–78.

Bali, T. G., & Hovakimian, A. (2009). Volatility spreads and expected stock returns. *Management Science*, *55*(11), 1797–1812.

Bali, T. G., Hu, J., & Murray, S. (2014). Option implied volatility, skewness, and kurtosis and the cross-section of expected stock returns. *Working Paper*.

Barndorff-Nielsen, O. E., Kinnebrock, S., & Shephard, N. (2010). *Volatility and time series econometrics: Essays in honor of Robert Engle*. Oxford University Press.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654.

Bollerslev, T., Marrone, J., Xu, L., & Zhou, H. (2014). Stock return predictability and variance risk premia: Statistical inference and international evidence. *Journal of Financial and Quantitative Analysis*, *49*(3), 633–661.

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. *Review of Financial Studies*, *22*(11), 4463–4492.

Brooks, C., & Persand, G. (2003). Volatility forecasting for risk management. *Journal of Forecasting*, *22*(1), 1–22.

Çakmaklı, C., & van Dijk, D. (2016). Getting the most out of macroeconomic information for predicting excess stock returns. *International Journal of Forecasting*, *32*(3), 650–668.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*(4), 1509–1531.

Chang, B.-Y., Christoffersen, P., Jacobs, K., & Vainberg, G. (2012). Option-implied measures of equity risk. *Review of Finance*, *16*, 385–428.

Christoffersen, P. F. (2012). *Elements of financial risk management*. 2nd Edition. Academic Press.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 174–196.

Cosemans, M. (2011). The pricing of long and short run variance and correlation risk in stock returns. *Working Paper*.

Cremers, M., & Weinbaum, D. (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Finance*, *45*(2), 335–367.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953.

Drechsler, I., & Yaron, A. (2011). What's vol got to do with it. *Review of Financial Studies*, *24*(1), 1–45.

Driessen, J., Maenhout, P. J., & Vilkov, G. (2009). The price of correlation risk: Evidence from equity options. *Journal of Finance*, *64*(3), 1377–1406.

Driessen, J., Maenhout, P. J., & Vilkov, G. (2013). Option-implied correlations and the price of correlation risk. *Working Paper*.

Du, J., & Kapadia, N. (2012). The tail in the volatility index. *Working Paper*.

Feunou, B., Jahan-Parvar, M. R., & Okou, C. (2015). Downside variance risk premium. *Working Paper*.

Fleming, J., Kirby, C., & Ostdiek, B. (2001). The economic value of volatility timing. *Journal of Finance*, *56*(1), 329–352.

Goyal, A., & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*(5), 639–654.

Goyal, A., & Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*(4), 1455–1508.

Jiang, G. J., & Tian, Y. S. (2005). The model-free implied volatility and its information content. *Review of Financial Studies*, *18*(4), 1305–1342.

Jobson, J. D., & Korkie, B. M. (1981). Performance hypothesis testing with the Sharpe and Treynor measures. *Journal of Finance*, *36*(4), 889–908.

Jordan, S. J., Vivian, A., & Wohar, M. E. (2017). Forecasting market returns: Bagging or combining? *International Journal of Forecasting*, *33*(1), 102–120.

Jordan, S. J., Vivian, A. J., & Wohar, M. E. (2014). Forecasting returns: New European evidence. *Journal of Empirical Finance*, *26*, 76–95.

Kourtis, A., Markellos, R. N., & Symeonidis, L. (2016). An international comparison of implied, realized, and GARCH volatility forecasts. *Journal of Futures Markets*, *36*(12), 1164–1193.

McCracken, M. W. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, *140*(2), 719–752.

McGee, R. J., & McGroarty, F. (2017). The risk premium that never was: A fair value explanation of the volatility spread. *European Journal of Operational Research*, *262*(1), 370–380.

Memmel, C. (2003). Performance hypothesis testing with the sharpe ratio. *Finance Letters*, *1*(1).

Prokopczuk, M., & Wese Simen, C. (2014). The importance of the volatility risk premium for volatility forecasting. *Journal of Banking & Finance*, *40*, 303–320.

Pyun, S. (2016). Variance risk in aggregate stock returns and time-varying return predictability. *Working Paper*.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies*, *23*(2), 821–862.

Rapach, D. E., & Wohar, M. E. (2006). In-sample vs. out-of-sample tests of stock return predictability in the context of data mining. *Journal of Empirical Finance*, *13*(2), 231–247.

Rehman, Z., & Vilkov, G. (2012). Risk-neutral skewness: Return predictability and its sources. *Working Paper*.

Richardson, M., & Stock, J. H. (1989). Drawing inferences from statistics based on multiyear asset returns. *Journal of Financial Economics*, *25*(2), 323–348.

Sévi, B. (2014). Forecasting the volatility of crude oil futures using intraday data. *European Journal of Operational Research*, *235*(3), 643–659.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, *54*(3), 375–421.

Stilger, P. S., Kostakis, A., & Poon, S.-H. (2016). What does risk-neutral skewness tell us about future stock returns? *Management Science*, *63*(6), 1814–1834.

Xing, Y., Zhang, X., & Zhao, R. (2010). What does the individual option volatility smirk tell us about future equity returns? *Journal of Financial and Quantitative Analysis*, *45*(3), 641–662.

Zhou, H. (2013). On the predictive power of the implied correlation index. *Working Paper*.

Table I: **Summary Statistics**

This table summarizes key statistics about several variables. CRP denotes the correlation risk premium. ER refers to the (annualized) excess return on the stock index. $EXKURT^{BKM}$ is the risk–neutral kurtosis of Bakshi et al. (2003). RV is the (annualized) realized variance computed using intraday data sampled at the 5–min frequency. $SKEW^{BKM}$ is the risk–neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the (annualized) risk–neutral variance of Bakshi et al. (2003). Finally, VRP is the (annualized) variance risk premium computed as the difference between the most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003). "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	0.09	0.10	0.14	3.30	0.25	228
ER	0.06	0.16	-0.83	4.43	0.09	228
$EXKURT^{BKM}$	0.76	0.28	0.49	3.04	0.72	228
RV	0.03	0.05	7.31	75.23	0.63	228
$SKEW^{BKM}$	-0.87	0.20	0.26	3.03	0.65	228
$SMIRK$	0.13	0.25	0.16	3.48	0.33	228
VAR^{BKM}	0.05	0.04	3.31	18.05	0.79	228
VRP	0.02	0.03	-5.06	61.75	0.13	228

Table II: **Correlation Matrix**

This table reports the correlation among all predictive variables. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk–neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ 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 most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003). All data are sampled at the monthly frequency and relate to the S&P 500 index.

	CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
CRP						
$EXKURT^{BKM}$	0.20					
$SKEW^{BKM}$	-0.22	-0.92				
$SMIRK$	-0.06	-0.02	-0.10			
VAR^{BKM}	-0.04	-0.38	0.17	0.35		
VRP	0.40	-0.03	0.02	-0.14	-0.02	

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. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk–neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ 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 most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003). R^2 and R^2_{oos} 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	-0.035	-0.136	0.096**	0.056	-0.023	-0.193	-0.284*
	(-0.67)	(-0.34)	(-0.84)	(2.40)	(1.05)	(-0.59)	(-1.49)	(-1.65)
CRP	0.957***						0.341	0.321
	(2.76)						(0.90)	(0.84)
$EXKURT^{BKM}$		0.123					0.175	
		(0.96)					(1.26)	
$SKEW^{BKM}$			-0.224					-0.272
			(-1.22)					(-1.46)
$SMIRK$				-0.290**			-0.279*	-0.293**
				(-2.06)			(-1.88)	(-1.96)
VAR^{BKM}					0.028		1.147	0.945
					(0.03)		(1.22)	(1.07)
VRP						5.176***	4.438***	4.422***
						(4.26)	(3.31)	(3.31)
R^2	3.28***	0.41	0.66	1.84**	0.00	7.47***	7.91***	8.13***
R^2_{oos}	2.81***	-1.22	-0.53	0.07	-5.41	5.50***	-2.86**	-2.67**

Table IV: **Variance Predictability**

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. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk–neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ 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 most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003). R^2 and R^2_{oos} 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***	0.074***	0.073***	0.022***	-0.004	0.038***	0.017*	0.023*
	(9.49)	(7.84)	(4.71)	(6.09)	(-1.00)	(9.88)	(1.82)	(1.79)
CRP	-0.123***						-0.072***	-0.071***
	(-3.72)						(-2.56)	(-2.53)
$EXKURT^{BKM}$		-0.057***					-0.013	
		(-4.78)					(-1.26)	
$SKEW^{BKM}$			0.047***					0.019
			(2.72)					(1.34)
$SMIRK$				0.071***			0.026***	0.027***
				(5.53)			(2.38)	(2.43)
VAR^{BKM}					0.756***		0.658***	0.675***
					(11.95)		(9.44)	(10.33)
VRP						-0.399***	-0.245***	-0.243***
						(-3.36)	(-2.47)	(-2.45)
R^2	5.80***	9.24***	3.19***	11.97***	38.83***	4.79***	45.47***	45.53***
R^2_{oos}	1.88***	8.04***	2.65***	8.61***	34.65***	-2.92	12.21***	12.20***

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] 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]. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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**

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). $SKEW^{BKM}$ 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 most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003). "(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^2_{oos} 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	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)	R^2_{oos}	2.81***	-1.22	-0.53	0.07	-3.84	5.50***
		(4.83)	(-2.02)	(-0.87)	(0.12)	(-6.18)	(9.73)
(II)	R^2_{oos}	2.69**	0.37	0.56	0.93	-3.39	4.43***
		(4.61)	(0.62)	(0.95)	(1.57)	(-5.48)	(7.74)
(I+II)	R^2_{oos}	2.69**	0.37	0.56	0.93	-2.95	4.43***
		(4.61)	(0.62)	(0.95)	(1.57)	(-4.79)	(7.74)

Panel B: Variance Predictability

		CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)	R^2_{oos}	1.88***	8.04***	2.65***	8.61***	34.65***	-1.81
		(3.20)	(14.60)	(4.54)	(15.73)	(88.54)	(-2.97)
(II)	R^2_{oos}	1.93***	8.77***	2.65***	8.61***	34.65***	-2.68
		(3.29)	(16.06)	(4.54)	(15.73)	(88.54)	(-4.35)
(I+II)	R^2_{oos}	1.93***	8.77***	2.65***	8.61***	34.65***	-1.57
		(3.29)	(16.06)	(4.54)	(15.73)	(88.54)	(-2.58)

Table VII: **Economic Value: Restriction I**

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 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]. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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***
$SKEW^{BKM}$	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}	-8.81	7.19	-1.66	-0.48***	0.50***	-0.09
VRP	-6.10	-1.58	-5.93	-0.41*	-0.12	-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	1.50	2.86	0.45**	0.14*	0.43*
$EXKURT^{BKM}$	3.92	3.05	4.83	0.63***	0.40***	0.70***
$SKEW^{BKM}$	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}	-11.50	5.67	-0.45	-0.63***	0.70***	0.02
VRP	-8.49	-0.95	-7.20	-0.60***	-0.10	-0.58***

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***
$SKEW^{BKM}$	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}	-10.81	3.94	-0.19	-0.66***	0.73***	0.05
VRP	-8.15	-0.64	-7.53	-0.63***	-0.09	-0.62***

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***
$SKEW^{BKM}$	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}	-8.77	2.95	-0.15	-0.66***	0.73***	0.05
VRP	-6.18	-0.48	-6.84	-0.63***	-0.09	-0.63***

Table VIII: **Economic Value: Restriction II**

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 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]. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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 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***
$SKEW^{BKM}$	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**

Table IX: **Economic Value: Restrictions I and II**

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 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]. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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***
$SKEW^{BKM}$	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}	-8.81	7.19	-1.66	-0.48***	0.50***	-0.09
VRP	-6.10	-1.58	-5.93	-0.41*	-0.12	-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	1.50	2.86	0.45**	0.14*	0.43*
$EXKURT^{BKM}$	3.92	3.05	4.83	0.63***	0.40***	0.70***
$SKEW^{BKM}$	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}	-11.50	5.67	-0.45	-0.63***	0.70***	0.02
VRP	-8.49	-0.95	-7.20	-0.60***	-0.10	-0.58***

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***
$SKEW^{BKM}$	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}	-10.81	3.94	-0.19	-0.66***	0.73***	0.05
VRP	-8.15	-0.64	-7.53	-0.63***	-0.09	-0.62***

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***
$SKEW^{BKM}$	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}	-8.77	2.95	-0.15	-0.66***	0.73***	0.05
VRP	-6.18	-0.48	-6.84	-0.63***	-0.09	-0.63***

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. 6 forecasting variables are used. CRP *denotes the correlation risk premium.* $EXKURT^{BKM}$ *is the risk–neutral kurtosis of Bakshi et al. (2003).* $SKEW^{BKM}$ *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 most recent observation of the realized variance and the risk–neutral variance of Bakshi et al. (2003).* R^2_{oos} *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^2_{oos}	3.11***	1.72***	2.36***
	(5.37)	(2.91)	(4.03)

Panel B: Variance Predictability

	$MeanFC$	$MedianFC$	$TrMeanFC$
R^2_{oos}	16.01***	10.16***	7.44***
	(31.84)	(18.89)	(13.42)

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. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.08	2.84	3.05	0.09	0.28***	0.30
$\gamma = 6$	0.96	1.77	2.03	0.14	0.30***	0.36*
$\gamma = 9$	0.65	1.20	1.37	0.14	0.30***	0.36*
$\gamma = 12$	0.49	0.91	1.03	0.14	0.30***	0.36*

Panel B: Median Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	2.85	2.32	3.98	0.28*	0.26**	0.43***
$\gamma = 6$	1.21	1.54	2.44	0.19	0.29**	0.47***
$\gamma = 9$	0.82	1.04	1.64	0.19	0.29**	0.47***
$\gamma = 12$	0.62	0.79	1.24	0.19	0.29**	0.47***

Panel C: Trimmed Mean Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.59	2.52	3.16	0.14	0.26***	0.32*
$\gamma = 6$	0.96	1.61	2.00	0.15	0.29**	0.36**
$\gamma = 9$	0.65	1.09	1.35	0.15	0.29**	0.36**
$\gamma = 12$	0.49	0.82	1.02	0.15	0.29**	0.36**

Predicting the Equity Market with Option Implied Variables

Online Appendix

JEL classification: G10, G11, G17

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

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] 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 column]. $Turnover_{abs}$ *is the is 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.* $*, **, ***$ *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	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
$Turnover_{abs}$	0.0448	0.0448	0.0448	0.0448	0.0448	0.0448
$Turnover_{rel}^{(1)}$	12.1906	5.4513	5.5545	8.9341	2.2193	9.6821
$Turnover_{rel}^{(2)}$	4.5800	5.0967	2.1663	2.1896	3.3301	2.6606
$Turnover_{rel}^{(3)}$	11.6951	8.0804	6.3212	8.8524	3.4276	8.8747
$\Delta CER^{(1)}$	2.48	4.19	0.64	0.85	-7.62	-8.46
$\Delta CER^{(2)}$	0.69	2.61	1.47	1.15	6.57	-2.04
$\Delta CER^{(3)}$	1.78	4.34	1.86	0.82	-2.30	-7.58
$\Delta SR^{(1)}$	0.21	0.39**	0.06	0.05	-0.43***	-0.57***
$\Delta SR^{(2)}$	0.03	0.23**	0.10	0.10	0.46***	-0.16
$\Delta SR^{(3)}$	0.15	0.40*	0.16	0.05	-0.13	-0.56**

Panel B: $\gamma = 6$

	CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
$Turnover_{abs}$	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
$Turnover_{rel}^{(1)}$	15.9051	7.0084	7.0350	9.3238	4.2300	12.5610
$Turnover_{rel}^{(2)}$	5.5783	7.9003	2.1338	1.9366	5.5947	2.7470
$Turnover_{rel}^{(3)}$	16.6921	13.2556	9.1192	9.8982	4.7116	10.7379
$\Delta CER^{(1)}$	0.88	3.03	0.30	0.85	-11.25	-10.32
$\Delta CER^{(2)}$	0.86	2.04	1.14	0.97	5.01	-1.26
$\Delta CER^{(3)}$	0.60	3.03	1.15	0.83	-0.98	-7.70
$\Delta SR^{(1)}$	0.18	0.49***	0.10	0.10	-0.61***	-0.73***
$\Delta SR^{(2)}$	0.07	0.26**	0.12*	0.11	0.63***	-0.13
$\Delta SR^{(3)}$	0.16	0.46*	0.20	0.11	-0.04	-0.66***

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

Panel C: $\gamma = 9$

	CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
$Turnover_{abs}$	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151
$Turnover_{rel}^{(1)}$	18.4886	8.8266	9.2375	10.2124	5.7328	15.0938
$Turnover_{rel}^{(2)}$	6.2895	11.1201	2.3148	2.1032	6.6482	2.9964
$Turnover_{rel}^{(3)}$	22.6290	18.7570	11.4928	10.9996	5.6936	13.6412
$\Delta CER^{(1)}$	0.15	2.11	-0.18	0.57	-10.81	-9.58
$\Delta CER^{(2)}$	0.59	1.38	0.77	0.66	3.46	-0.85
$\Delta CER^{(3)}$	-0.34	2.16	0.82	0.58	-0.59	-7.54
$\Delta SR^{(1)}$	0.13	0.50***	0.07	0.10	-0.65***	-0.74***
$\Delta SR^{(2)}$	0.06	0.25**	0.11*	0.11	0.65***	-0.11
$\Delta SR^{(3)}$	0.10	0.48*	0.22	0.11	-0.02	-0.69***

Panel D: $\gamma = 12$

	CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
$Turnover_{abs}$	0.0108	0.0108	0.0108	0.0108	0.0108	0.0108
$Turnover_{rel}^{(1)}$	19.5157	9.1852	10.0488	10.6805	6.4946	15.8094
$Turnover_{rel}^{(2)}$	6.5802	13.6314	2.4100	2.1901	6.9049	3.1283
$Turnover_{rel}^{(3)}$	27.5858	22.9493	12.4248	11.4994	5.9533	15.4444
$\Delta CER^{(1)}$	0.07	1.58	-0.17	0.43	-8.86	-7.25
$\Delta CER^{(2)}$	0.44	1.03	0.58	0.50	2.59	-0.64
$\Delta CER^{(3)}$	-0.80	1.54	0.62	0.43	-0.46	-6.96
$\Delta SR^{(1)}$	0.12	0.50***	0.07	0.10	-0.65***	-0.75***
$\Delta SR^{(2)}$	0.05	0.25*	0.11*	0.11	0.65***	-0.10
$\Delta SR^{(3)}$	0.07	0.47*	0.22	0.11	-0.02	-0.69***

Table A2: **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, and the lagged predictive variable. Statistical inferences are based on a bootstrapped distribution. 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^2_{oos} 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^2_{oos}	-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	38.24***	38.73***	39.16***	26.82***	12.46***
R^2_{oos}	34.24***	-8.93	-11.63	24.79***	10.45***
$t-stat$	(11.80)	(-11.93)	(-12.04)	(9.08)	(5.66)

Table A3: **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] 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 column]. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$ *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.* $*$, $**$, $***$ *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
$\Delta CER^{(2)}$	7.13	5.70	3.97	5.64	4.99
$\Delta CER^{(3)}$	-1.78	5.26	6.25	-5.11	-7.18
$\Delta SR^{(1)}$	-0.43***	0.04	0.19**	-0.55***	-0.58***
$\Delta SR^{(2)}$	0.50***	0.44***	0.33***	0.41***	0.41***
$\Delta SR^{(3)}$	-0.10	0.44***	0.55***	-0.37**	-0.59***

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
$\Delta CER^{(2)}$	5.62	3.24	2.33	3.47	3.11
$\Delta CER^{(3)}$	-0.60	3.36	3.64	-3.33	-4.92
$\Delta SR^{(1)}$	-0.60***	-0.12	0.17*	-0.64***	-0.69***
$\Delta SR^{(2)}$	0.70***	0.47***	0.35***	0.43***	0.39***
$\Delta SR^{(3)}$	0.00	0.54***	0.61***	-0.38**	-0.58***

Table A3: **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
$\Delta CER^{(2)}$	3.91	2.17	1.57	2.32	2.10
$\Delta CER^{(3)}$	-0.31	2.24	2.43	-2.24	-3.31
$\Delta SR^{(1)}$	-0.62***	-0.21	0.17*	-0.65***	-0.73***
$\Delta SR^{(2)}$	0.73***	0.47***	0.35***	0.43***	0.39***
$\Delta SR^{(3)}$	0.03	0.54***	0.61***	-0.38**	-0.58***

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
$\Delta CER^{(2)}$	2.93	1.63	1.18	1.74	1.57
$\Delta CER^{(3)}$	-0.24	1.68	1.82	-1.69	-2.49
$\Delta SR^{(1)}$	-0.63***	-0.23*	0.17*	-0.62***	-0.72***
$\Delta SR^{(2)}$	0.73***	0.47***	0.35***	0.43***	0.39***
$\Delta SR^{(3)}$	0.03	0.54***	0.61***	-0.38**	-0.58***