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RESEARCH ARTICLE

Volatility and jump risk in option returns

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Abstract
We examine the importance of volatility and jump risk in the time-series prediction of S&P 500 index option returns. The empirical analysis provides a different result between call and put option returns. Both volatility and jump risk are important predictors of put option returns. In contrast, only volatility risk is consistently significant in the prediction of call option returns over the sample period. The empirical results support the theory that there is option risk premium associated with volatility and jump risk, and reflect the asymmetry property of S&P 500 index distribution.

KEYWORDS
aggregate volatility, jump, option return, prediction

JEL CLASSIFICATION
G12; G14

1 | INTRODUCTION

The importance of time-varying volatility and jump risk in option pricing has been extensively documented in the literature. For example, D. S. Bates (2000), Duffie, Pan, and Singleton (2000), Pan (2002), Eraker (2004), and Santa-Clara and Yan (2010) propose no-arbitrage option pricing models to combine them into the standard Black–Scholes–Merton (BSM) option pricing model. Naik and Lee (1990), Broadie, Detemple, Ghysels, and Torrés (2000), and Branger, Schlag, and Schneider (2008) investigate the general equilibrium of options market with stochastic volatility or (and) jump. Recently, Christoffersen, Feunou, and Jeon (2015), Yang and Kanniainen (2017), and H.-L. Chang, Chang, Cheng, Peng, and Tseng (2019) introduce models allowing the underlying asset with volatility and jumps for option pricing. These models provide a rich option pricing framework in which both stochastic volatility and jump risk are considered. However, whether these two risks have predictive powers on option returns in the time series remains an unexplored question.

In this paper, we provide a comprehensive empirical study of the importance of volatility and jump risk in the time-series predictability of option returns. In particular, we investigate whether there is any difference between the results of the call and put option returns. Theoretically speaking, call option returns reflect the expectation of right-hand side distribution of underlying asset value, while put option returns reflect the expectation of left-hand side distribution. Any difference between call and put option indicates the asymmetry property of the underlying asset value distribution, which is of great importance for asset pricing and risk management.

Following numerous literatures on the predictability of asset returns,[1] we run several tests. We run in-sample regression to test the significance of aggregate volatility and jump risk predictors on predicting the call and put option returns. We follow the in-sample test by out-of-sample evaluation that investigates the statistical significance and economic value of out-of-sample forecast. Finally, we run several robustness tests to make sure our results are stable.

How to measure the aggregate volatility and jump risk is a critical question for our empirical analysis. We use variance risk premium (VRP) as a measure of aggregate volatility risk following Bollerslev, Tauchen, and Zhou (2009), and follow Cremers, Halling, and Weinbaum (2015) to construct two aggregate jump risk variables that they use in their robustness check. The two jump risk predictors are SMIRK,[2] the slope of the implied volatility proposed by Yan (2011), and TAIL[3] proposed by Du and Kapadia (2012). Since VRP is also affected by jump risk (Bollerslev & Todorov, 2011), we run the regression of VRP on SMIRK and TAIL and use the residuals (VRP-SMIRK and VRP-TAIL) as the alternative measures of aggregate volatility risk. We use these five variables in the empirical analysis and test their performance on the prediction of option returns. We also include the variables that are used in the stock return forecast literature and compare our results with the forecast using Coval and Shumay (CS, 2001). Coval and Shumway (2001) show that expected option return could be determined by the capital asset pricing model (CAPM) model under Geometric Brownian Motion (GBM) assumption. We are interested in whether there is additional improvement by aggregate volatility and jump risk predictors once the other predictors are controlled.

We employ both the standard predictive regression models and combination methods. The predictive regression model is a good way of testing the predictability when the number of predictors is limited. However, it loses power when the number of predictors is large. To address this concern, we follow Rapach et al. (2010) to use the combination forecast, and Lin et al. (2018) to use the regressed combination forecast. They show that these approaches are better ways of extracting useful information from a large set of predictors and provide a better forecast result than the predictive regression model that puts all variables into the multiple regression. We use two popular combination forecast, the mean combination (MC) forecast and J. M. Bates and Granger's (1969) weighted-mean combination (WC) forecast. These two forecasts are then regressed to obtain the regressed mean combination (RMC) forecast and the regressed weighted-mean combination (RWC) forecast, respectively.

Our empirical result shows that aggregate volatility risk is important for the prediction of both call and put option returns. The results are both statistically and economically significant. For example, using VRP as the predictor could generate an in-sample R^2 of 10.81% for the 30-day call option returns, and 14.16% for 30-day put option returns. The out-of-sample R^2's and utility gains are 9.54% and 5.38%, respectively, for 30-day call option returns, and 6.31% and 7.15%, respectively, for 30-day put option returns. Using the residuals of VRP provide similar results. The finding is also robust across different option series and forecast horizons. The results by grouped mean are also significant. These findings show the importance of volatility risk for both calls and puts.

In contrast, the results of jump risk show a different pattern between calls and puts. The jump risk is not significant in the prediction of call option returns. On the other hand, it is highly significant for the put option return. The different performances of jump risk predictors on the forecast of call and put option returns reflect the market's expectation about the asymmetry distribution of S&P 500 index. The forecast using CS (2001) is not significant for either calls or puts, which provides the evidence of rejection of the GBM assumption of S&P 500 index. The results show there is option risk premium associated with volatility and jump risk. Call and put options share similarities on the aggregate volatility risk component, while they are different on the jump risk component.

The combination forecast shows that aggregate volatility and risk predictors significantly improve the forecast performance once they are used in the combination forecast. For example, if only the predictors from stock return forecast literature are used, the out-of-sample R^2's of the 30-day call option and put option returns are only 3.74% and 2.84%, respectively, when MC forecast is used. However, they increase to 7.24% and 5.70% when the aggregate volatility and jump risk predictors are also utilized. Regressed combination forecast improves the forecast performance furthermore.

We also run several robustness tests. We evaluate the performance of other aggregate volatility risk predictors, including Volatility Index (VIX) that is a measure of the implied volatility of S&P 500 index options, Bernische Kantonal-Musikverband

[1]For example, Fama and Schwert (1977), Fama and French (1988), Campbell and Shiller (1988), Kothari and Shanken (1997), Pontiff and Schall (1998), Ang and Bekaert (2007), Rapach, Strauss, and Zhou (2010), Dangl and Halling (2012), Rapach, Strauss, and Zhou (2013), Pettenuzzo, Timmermann, and Valkanov (2014), and Huang, Jiang, Tu, and Zhou (2015) for predicting stock returns; Keim and Stambaugh (1986), Fama and French (1989), Greenwood and Hanson (2013), Lin, Wang, and Wu (2014), and Lin, Wu, and Zhou (2018) for predicting corporate bonds; and Fama and Bliss (1987), Campbell and Shiller (1991), Cochrane and Piazzesi (2005), Ludvigson and Ng (2009), Thornton and Valente (2012), Goh, Jiang, Tu, and Zhou (2012), Sarno, Schneider, and Wagner (2016), Gargano, Pettenuzzo, and Timmermann (2017), and Fulop, Li, and Wan (2017) for predicting Treasury bonds.

[2]SMIRK is defined as the difference in the implied volatilities of put and call options.

[3]TAIL is defined as the difference between the realized volatility and the annualized integrated volatility.

(BKMV) that is the aggregate volatility indicator following Bakshi, Kapadia, and Madan (2003)[4]; and volatility risk premium (VolP) that is calculated using the difference between model-free implied and realized standard deviation. We find that VIX and BKMV have different prediction performances for put and call option returns, while VolP keeps quite significant. This finding again suggests a different return dynamics between call and put option returns, and has interesting implication for stochastic volatility modeling. We also test the results using different option series and various forecast restrictions and find the results are robust.

Our subperiod analysis shows that aggregate volatility and jump risk predictors have better forecasting performance during the recent crisis. Both call and put option returns are more predictable between 2007 and 2011. This is consistent with the finding that asset returns are more predictable during recession periods (Henkel, Martin, & Nardari, 2011; Lin et al., 2018; Rapach et al., 2010).

This paper is related to Cremers et al. (2015) in that we both address the importance of aggregate volatility and jump risk and use similar measures. However, Cremers et al. (2015) investigate their impact on the cross-section of stock returns, while we examine their predictive power on the time series of option returns. Similarly, there are many other studies that construct volatility and jump risk measure from option market, see, for example, Ang, Hodrick, Xing, and Zhang (2006), Bollerslev and Todorov (2011), B. Y. Chang, Christoffersen, and Jacobs (2013), and others. However, they use the option-based measure to examine stock market while our focus is on the options market. This paper is also relevant to other studies that look at the predictability of asset returns, such as stock return and corporate bond returns. Our contribution lies in that we provide a first empirical study on the options market using several new predictors.

Our paper is about the time-series predictability of option returns, which is different from the cross-sectional predictability studied by others. Goyal and Saretto (2009) analyze the impact of volatility in the cross-section of options. They construct portfolios using straddles and delta-hedged calls and find a positive relation between stock returns and the difference between historical realized volatility and implied volatility. Cao and Han (2013) investigate the impact of idiosyncratic stock volatility on the cross-section of option returns. They find that delta-hedged option returns are negative for most stocks and decrease with total and idiosyncratic volatility. Bali and Murray (2013) document that the risk-neutral skewness could predict the cross-section of option portfolio returns. Hu and Jacobs (2019) analyze the relationship between the volatility of the underlying asset and expected option returns. Vasquez (2017) finds the slope of the implied volatility term structure is positively related to future equity option returns. These studies look at the cross-sectional predictability of option returns. While cross-sectional and time-series predictability are different questions, both sides of the research provide meaningful insights about the pricing in the options market.

Our research is also relevant to the literature that documents the difference between call and put returns. For example, Constantinides, Jackwerth, and Perrakis (2008) and Constantinides, Czerwonko, Carsten Jackwerth, and Perrakis (2011) showed that out-of-money (OTM) European calls on the S&P 500 index and OTM American calls on the S&P 500 index futures frequently violate stochastic dominance relationship, while this rarely happens for puts. Bondarenko (2014) argued that the historical returns of the equity index put options are puzzling and reported that average excess return is −39%/month for at-the-money (ATM) puts and is as low as −95%/month for deep OTM puts. Similarly, Driessen and Maenhout (2004) and Santa-Clara and Saretto (2009) find large certainty equivalent gains from selling put options. Broadie et al. (2000) explained this phenomenon by analyzing market-neutral portfolios and find that jump risk premiums and estimation risk can explain these portfolios. Our findings provide another explanation to this question that the different return characteristics of calls and puts could be due to their different risk components.

The rest of this paper is organized as follows. Section 2 introduces the methodology to construct the two main predictors, predictive regression models, and the statistical and economic significance measures we use in the out-of-sample evaluation. Section 3 describes our data to be used in the analysis. Section 4 presents the main empirical results. Finally, Section 5 concludes the paper.

2 | METHODOLOGY

2.1 | Aggregate volatility and risk predictor

Constantinides, Jackwerth, and Savov (2013) prove that, in the Black and Scholes (1973) and R. Merton (1973) model (BSM), the instantaneous expected return of a leverage-adjusted option equals the expected return of its underlying

[4]Cremers et al. (2015) use these two measures in their robustness test.

asset.[5] Numerous studies have shown since then that there are other priced factors besides the single factor in the BSM model, for example, the stochastic volatility factor in Heston (1993) and Britten-Jones and Neuberger (2000), the jump factor in R. C. Merton (1976), the combined stochastic volatility and jump factors in D. S. Bates (1996), and so forth. With the additional priced factors, the instantaneous expected return of an option becomes the expected return of its underlying asset plus premiums associated with each additional factor (Constantinides et al., 2013), which motivates us to construct those three aggregate predictors. We follow Bollerslev et al. (2009) to use variance risk premia representing aggregate volatility risk and follow Cremers et al. (2015) to use two aggregate jump predictors: SMIRK and TAIL. Next we introduce the three predictors one by one.

Our aggregate volatility risk predictor is the VRP, a measure of the difference between the model-free implied and realized variances. Bollerslev et al. (2009) find this variable is able to explain a fraction of the variation in stock market returns and dominates other commonly employed variables in the literature. We define it as VRP = IV − RV, where we use the square of the VIX index as a proxy for implied variance (IV) and estimate realized variance (RV) as

$$\mathrm{RV}_t = \sum_{n}^{j=1} [p_{t-1+j\Delta/n} - p_{t-1+(j-1)\Delta/n}]^2, \tag{1}$$

where p is the log price. We set Δ to be 5 min when calculating the RV. This high-frequency mode-free realized variance measure provides a more accurate observation of true return variation than other traditional sample variances based on daily data (Barndorff-Nielsen & Shephard, 2002; Meddahi, 2002).

We follow Yan (2011) to construct the aggregate jump predictor as the slope of the implied volatility SMIRK. In his model, the SMIRK is approximately proportional to the product of jump intensity and average stock jump size. So similar to Yan (2011), we estimate the aggregate jump predictor, SMIRK, as the difference between the implied volatility of an OTM put option ($\Delta = -20$) and an ATM call option ($\Delta = 50$).

To construct the second aggregate jump risk predictor, we first calculate Bakshi et al. (2003) measure of option-implied volatility (BKMV) by

$$\mathrm{BKMV}(0, T) = \left[\frac{1}{T}(e^{rT}V(0, T) - \mu(0, T)^2)\right]^{1/2} \tag{2}$$

with

$$V(0, T) = \int_{S(0)}^{\infty} \frac{2\left(1 - \ln\left[\frac{K}{S(0)}\right]\right)}{K^2} C(0, T, K)\,dK + \int_{0}^{S(0)} \frac{2\left(1 + \ln\left[\frac{S(0)}{K}\right]\right)}{K^2} P(0, T, K)\,dK, \tag{3}$$

$$\mu(0, T) = e^{rT} - 1, \tag{4}$$

where r is the risk-free rate, K is the strike price, S is the underlying asset price, and C and P are the associated call and option prices, respectively.

We then construct our second aggregate jump predictor, TAIL, as the difference of Bakshi et al. (2003) volatility measure in Equation (1) and the annualized integrated volatility estimated as follows:

$$\left[e^{rT}\frac{2}{T}\int_{S(0)}^{\infty} \frac{1}{K^2} C(0, T, K)\,dK + \int_{0}^{S(0)} \frac{1}{K^2} P(0, T, K)\,dK - e^{-rT}(e^{rT} - 1 - rT)\right]^{1/2}. \tag{5}$$

The construction of both volatilities requires continuous strike prices for a given maturity T. In this study, we use the interpolated implied volatility curve provided by the OptionMetrics and solve the integration over a range of zero to three times the underlying asset price. Similar to Cremers et al. (2015), we use 30-day options to be consistent with the VIX index.

[5] Coval and Shumway (2001) provide a similar study.

Bollerslev and Todorov (2011) show that compensation for rare events accounts for a large fraction of VRP. Besides VRP variable, we further decompose it into two components by regressing VRP on either SMIRK or TAIL variable and use the residuals for empirical analysis, naming it VRP-SMIRK or VRP-TAIL predictor.

2.2 | Predictive regression model

We forecast h-month option return with a standard predictive regression model

$$r_{t+h} = \alpha + \beta_1 x_{1,t} + \cdots + \beta_J x_{J,t} + \varepsilon_{t+h}, \tag{6}$$

where r_{t+h} is the S&P 500 option return, $x_{j,t}, j = 1, ..., T$ is the jth predictor, and ε_{t+h} is an error term. We run a regression of h-month option return on each predictor value to estimate the coefficients α and $\beta_j, j = 1, ..., T$, and adjust the in-sample standard errors by Newey and West (1987) estimator when the predictive horizon is beyond 1 month to account for the impact of data overlapping. In our empirical study, we focus on the predictability on 3-month horizon, and test the predictability on other horizons as a robustness check.

We then run the out-of-sample test. Suppose we have the option return data from 1 up to time T, and the out-of-sample forecast starts since m. At any time t between m and T, we use the information up to time m to estimate the coefficients, and then use the estimated coefficients and information at time m to forecast the h-month option return r_{t+h}. At time $t + h$, we could compare the forecasted and realized return to calculate the out-of-sample forecasting errors. This procedure is repeated from time m to $T - h$. As in other prediction studies (Rapach et al., 2010; Welch & Goyal, 2008), we generate forecasts using a recursive estimation window and choose the historical average of the option return as a benchmark forecasting model. Besides the univariate predictive regression, we consider the bivariate predictive regression by using aggregate volatility and jump risk predictors jointly.

When the number of predictors is large, the predictive regression model by putting all variables into the regression ("kitchen sink model") is generally poorly behaved and ends up with useless out-of-sample forecast. A possible solution is to use combination forecast. Researchers have shown that combination forecasts typically outperform individual forecasts both statistically and economically. For example, Rapach et al. (2010) find combination delivers consistent forecast gains for equity premium prediction. Lin et al. (2014) show that combining individual predictors improves the significance of out-of-sample forecasts and increases forecasting stability considerably. So we further combine the N individual forecasts as

$$\hat{r}_{c,t+h} = \sum_{k=1}^{N} w_{k,t} \hat{r}_{k,t+h}, \tag{7}$$

where $w_{k,t}$ is the weight of individual forecast in the combination forecast. We consider the MC forecast used in Rapach et al. (2010), and the WC forecast in J. M. Bates and Granger (1969), in which they give greater weights to those individual forecasts that contain the lower mean-squared errors and set the weights to be inversely proportional to the estimated residual variances.[6]

Lin et al. (2018) propose a regression-based combination approach and provide the evidence of its good predictability power on the corporate bond market. It is a very general method and is identical to another powerful procedure of forecast, the partial least squares (PLS) forecast method,[7] when the univariate prediction regression models are used in the MC forecast. It provides a powerful tool to extract useful information from a large set of predictors. In this paper, we also test its performance on the forecast of option returns. On the basis of any combination forecast, $r_{c,t+h}$, we first regress the return on it

$$r_{t+h} = \delta_0 + \delta(\hat{r}_{c,t+h} - \bar{r}_{t+h}) + u_{t+1}, \tag{8}$$

and use the predicted value $\delta_0 + \delta(\hat{r}_{c,t+h} - \bar{r}_{t+h})$ as the forecast. The motivation behind regressed combination forecast is similar to the portfolio choice under which an optimal portfolio will almost do better than investing in each asset individually. We also apply the regressed combination forecast out-of-sample using a recursive time window.

[6]Rapach et al. (2010) show that the combination forecast using simple mean performs as well as using complicated weighted schemes.

[7]Kelly and Pruitt (2013, 2015) show that the PLS provides a way of extracting information from a large set of predictors.

Depending on the choice of combination forecast used in the regression, we could obtain different regressed combination forecast results. In this paper, we consider the RMC forecast and the RWC forecast that are associated with the use of MC and WC forecast in the regression of Equation (8), respectively.

2.3 | Out-of-sample forecast evaluation

We conduct out-of-sample analysis in addition to in-sample analysis. To check the efficiency of the out-of-sample forecasts, we calculate the out-of-sample R^2 statistics, R^2_{OS}, of each predictor, given by

$$R^2_{\mathrm{OS}} = 1 - \frac{\sum_{j=m}^{T-h}(r_{j+h} - \hat{r}_{j+h})^2}{\sum_{j=m}^{T-h}(r_{j+h} - \bar{r}_{j+h})^2}, \tag{9}$$

where $\hat{r}$ and $\bar{r}$ are the return forecast of an option by a predictor j and by the benchmark model, respectively. The out-of-sample R^2 measures the improvement of the predictive regression model over the benchmark model in reducing the mean square prediction errors. A positive R^2_{OS} indicates the forecast model that outperforms the benchmark model.

We calculate the mean-squared prediction error (MSPE)-adjusted statistic to test the significance of R^2_{OS} following Clark and West (2007). Define

$$f_{t+h} = (r_{t+h} - \bar{r}_{t+h})^2 - [(r_{t+h} - \hat{r}_{t+h})^2 - (\hat{r}_{t+h} - \bar{r}_{t+h})^2]. \tag{10}$$

MSPE-adjusted statistic is obtained by regressing f_{t+h} on a constant. The p value for a one-sided test corresponding to the constant determines the significance of R^2_{OS}. We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping.

To examine whether the forecasts of the volatility and jump predictors bring additional information contents, we conduct an encompassing test. Considering a forecast $\hat{r}_{t+h}$ as a combination of two forecasts by predictor i and j:

$$\hat{r}_{t+h} = (1 - \lambda)\hat{r}_{i,t+h} + \lambda\hat{r}_{j,t+h}, \tag{11}$$

where $0 \le \lambda \le 1$. The forecasts by the predictor i encompass the forecasts by the predictor j if $\lambda = 0$ as the latter does not contain any useful information beyond that provided by the former. If $\lambda = 1$, the forecasts $\hat{r}_{t+h}$ are purely contributed by the predictor j and thus the predictor j encompasses the predictor i.

We estimate the Harvey, Leybourne, and Newbold (1998) MHLN statistics. Define $d_{t+h} = (\hat{\mu}_{i,t+h} - \hat{\mu}_{j,t+h})\hat{\mu}_{i,t+h}$, where $\hat{\mu}_{i,t+h} = \hat{r}_{t+h} - \hat{r}_{i,t+h}$, $\hat{\mu}_{j,t+h} = \hat{r}_{t+h} - \hat{r}_{j,t+h}$, $\bar{d} = [\frac{1}{T-h}]\sum_{t=1}^{T-h} d_{t+h}$, $\hat{V}(\bar{d}) = (T-h)^{-1}\hat{\phi}_0$, and $\hat{\phi}_0 = [\frac{1}{T-h}]\sum_{t=1}^{T-h}(d_{t+h} - \bar{d})^2$, the MHLN statistic is

$$\mathrm{MHLN} = \left[\frac{T-h-1}{T-h}\right](\hat{V}(\bar{d})^{-0.5})\bar{d} \tag{12}$$

with a t-distribution of $T - h - 1$ degree of freedom. We can then examine the information content added by the volatility and jump predictors by testing the null hypotheses that $\lambda = 0$ compared with other predictors.

Following Welch and Goyal (2008), Rapach et al. (2010), and many others, we calculate realized utility gains for a mean–variance investor to gauge the economic significance of our predictors. Suppose an investor chooses to allocate her portfolio between options and risk-free bills based on the benchmark forecasts, at the end of period t, the weight of her portfolio to options in $t + 1$ is

$$w_{0,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\bar{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{13}$$

where γ is the risk aversion parameter and $\hat{\sigma}^2_{t+1}$ is the rolling-window estimate of the variance of option returns. The investor achieves an average utility over the out-of-sample period:

$$\hat{\upsilon}_0 = \hat{u}_0 - \frac{1}{2}\gamma\hat{\sigma}_0^2, \tag{14}$$

where $\hat{u}_0$ and $\hat{\sigma}_0^2$ are, respectively, the sample mean and variance of the portfolio returns of the investor using the benchmark forecasts.

We then compute that the utility of the investor can realize if she allocates her portfolio utilizing a predictor j, the weight to options in $t + 1$ becomes

$$w_{j,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{15}$$

and her utility is

$$\hat{\upsilon}_j = \hat{u}_j - \frac{1}{2}\gamma\hat{\sigma}_j^2, \tag{16}$$

where $\hat{u}_j$ and $\hat{\sigma}_j^2$ are, respectively, the sample mean and variance of the portfolio returns of the investor using the predictor j.

We measure the utility gain as the difference between $\hat{\upsilon}_j$ and $\hat{\upsilon}_0$, which can be interpreted as the portfolio management fee that the investor is willing to pay for obtaining additional information brought by the predictor j (Rapach et al., 2010).

Running out-of-sample forecast sometimes provides a result that is too extreme to be reasonable. A restriction is normally imposed to make it within an interval in the literature. For example, Campbell and Thompson (2008) impose the economic constraint that out-of-sample stock return forecast should be nonnegative and show that such constraint significantly improves the out-of-sample performance.[8] Option return premium could be negative due to the impact of negative VolP. We impose the restriction that the quarterly option return must be between −7% and 10%.[9] If a model gives an out-of-sample forecast that is out of this interval, we replace that with the historical average for the predictive regression model and combination forecast. For the two regression-based combination results, we replace those extreme forecasts with the simpler mean or WC forecasts, respectively. The restriction minimizes the impact of volatile out-of-sample forecasts when a regression is estimated over a short sample period or when the data suffers structural break. We demonstrate the robustness of our results over different restriction intervals in the robustness test. For utility gains, we restrict the weight to be between −100% and 150% and $\gamma = 3$ to be practical.[10]

3 | DATA DESCRIPTION

Constantinides et al. (2013) show that the returns of index options are highly volatile, skewed, and nonlinear that impose a difficulty on the linear models. Having a highly skewed dependent variable may make the standard ordinary least squares (OLS) regression rather inappropriate. OLS regression models the mean that usually is not a good measure of central tendency in a highly skewed distribution. Moreover, high skew tends to significantly inflate variance and possibly push it towards infinity, which makes the conditions of Gauss–Markov theorem not being reasonably satisfied.

To address this concern, they construct a panel of leveraged-adjusted option portfolios that have targeted market beta of one and also maintain targeted maturity and moneyness. An option's 1-day return is converted to a leveraged-adjusted return by a hypothetical portfolio with ψ^{-1}_{BSM} dollars invested in the option and $1 - \psi^{-1}_{\mathrm{BSM}}$ dollars invested in the risk-free asset, where ψ^{-1}_{BSM} is the BSM elasticity based on the implied volatility of the option, and equals

[8] Rapach et al. (2010) and Pettenuzzo et al. (2014) also use similar constraint.

[9] This is equivalent to an annual return between −28% and 40% for a portfolio with unit beta, which is a large interval.

[10] Rapach et al. (2010) restrict the weight between 0% and 300%, and Thornton and Valente (2012) require the weight between −100% and 200%.

$(\partial C_{\text{BSM}}/\partial S) \times (S/C_{\text{BSM}}) > 1$ for a call and $(\partial P_{\text{BSM}}/\partial S) \times (S/P_{\text{BSM}}) < -1$ for a put. As a result, a leverage-adjusted call option portfolio consists a long position in both call and risk-free asset, while a leverage-adjusted put includes a short position in a put and more than 100% position in the risk-free asset. The leverage-adjusted option returns are then combined into daily portfolio returns, which are then compounded into monthly returns. Constantinides et al. (2013) show that these adjustments are necessary to guarantee the monthly portfolio returns to have low skewness and are close to normal, which allows us to investigate the predictability of linear forecasting models.[11]

We use the adjusted option returns in Constantinides et al. (2013) in our empirical analysis. Data are downloaded from Alexi Savov's website. Their data start from 1986. Since our aggregate jump risk predictors are constructed using OptionMetrics data set that only contains end-of-day quotes from 1996, we only use their data from 1996 to match the time period of the predictors. Our sample includes month-end S&P 500 index option portfolio returns from January 1996 to December 2011. We focus on the ATM options and test the options with different moneyness for robustness.

We use the standardized volatility surfaces, taken from the Ivy DB OptionMetrics database, to calculate the Bakshi et al. (2003) volatility measure and Du and Kapadia (2012) jump index. Since not all moneyness options are traded on each end of month, OptionMetrics interpolates the surface to obtain the missing data. We further obtain the VIX data from the Chicago Board Options Exchange (CBOE) and the 1-year constant Treasury yield for risk-free rate from the Federal Reserve Bank. The 5-min high-frequency data of S&P 500 index used to calculate the realized variance are from SIRCA Thomson Reuters Tick History.

The underlying asset of S&P 500 option is S&P 500 index. It is highly possible that the variables used to forecast equity returns are also useful in predicting the option market returns. Besides the aggregate volatility and jump risk measure, we also use the predictors in Welch and Goyal (2008) and Rapach et al. (2010) in their stock return forecast.[12] These variables include:

1. Book-to-market ratio, B/M: Ratio of book value to market value for firms included in the Dow Jones Industrial Average.
2. Treasury bill rate, TBL: Interest rate on a 3-month Treasury bill (secondary market).
3. Long-term yield, LTY: Long-term government bond yield.
4. Net equity expansion, NTIS: Ratio of the 12-month moving sum of net issues by New York Stock Exchange (NYSE)-listed stocks to total end-of-year market capitalization of NYSE stocks.
5. Long-term return, LTR: Return on long-term government bonds.
6. Stock return variance, SVAR: Sum of squared daily returns on the S&P 500 index in a month.
7. Inflation, INFL: Calculated from the CPI (all urban consumers). Since inflation rate data are released in the following month, following Welch and Goyal (2008), we use the 1-month lag inflation data.
8. Dividend–price ratio (log), D/P: Difference between the log of dividends paid on the S&P 500 index and the log of stock prices (S&P 500 index), where dividends are measured using a 1-year moving sum.
9. Dividend yields (log), D/Y: Difference between the log of dividends and the log of lagged stock prices.
10. Dividend–payout ratio (log), D/E: Difference between the log of dividends and the log of earnings.
11. Earnings–price ratio (log), E/P: Difference between the log of earnings on the S&P 500 index and the log of stock prices, where earnings are measured using a 1-year moving sum.
12. Term spread, TMS: Difference between the long-term yield and the Treasury bill rate.
13. Default yield spread, DFY: Difference between BAA- and AAA-rated corporate bond yields.
14. Default return spread, DFR: Difference between long-term corporate bond and long-term government bond returns.

Table 1 summarizes the statistics of monthly option portfolio returns of different maturities and moneyness. The return distributions of ATM calls are close to normal with skewness near zero for all 30-, 60-, and 90-day options (−0.02, 0.00, and 0.00) and moderate excess kurtosis (0.65, 0.64, and 0.57); the ATM puts also have the skewness of about −0.71 and excess kurtosis around 3.25 for all maturities. The first-order autoregressive coefficients are all small with a maximum of 0.12 for 30-day puts. The OTM calls and in-the-money (ITM) puts are more right skewed and the ITM calls and OTM puts are more left skewed, nevertheless, all skewness and excess kurtosis indicate that the option portfolio return distributions are temperately deviated from normality. This feature is desirable for our linear predictive regression. The ITM calls and OTM puts have higher average returns than the OTM calls and ITM puts. The last two rows

[11]In their concluding remark, Constantinides et al. (2013) argue that the construction of delevered monthly returns of option portfolios lowers the skewness of monthly portfolio returns and renders them close to normal thereby allowing the future exploration of linear factor models, as well as linear forecasting models.

[12]Data were downloaded from Amit Goyal's website.

TABLE 1 Summary statistics of option returns

	Mean	Std.	Min.	Max.	Skewness	Kurtosis	ρ (1)
K/S = 100							
30-Day call (%)	−0.02	4.26	−12.93	13.35	−0.02	0.65	−0.02
60-Day call (%)	0.05	4.30	−12.13	13.96	0.00	0.64	0.01
90-Day call (%)	0.11	4.30	−12.24	14.24	0.00	0.57	0.02
30-Day put (%)	0.65	5.65	−27.02	19.53	−0.72	3.54	0.12
60-Day put (%)	0.58	5.56	−26.27	19.31	−0.71	3.25	0.10
90-Day put (%)	0.52	5.53	−26.33	18.32	−0.71	3.25	0.10
K/S = 90							
30-Day call (%)	0.18	4.44	−13.09	12.97	−0.22	0.48	0.02
60-Day call (%)	0.17	4.40	−12.83	13.20	−0.18	0.46	0.03
90-Day call (%)	0.18	4.39	−12.57	13.34	−0.16	0.44	0.03
30-Day put (%)	1.72	7.06	−33.30	28.38	−1.25	5.59	0.17
60-Day put (%)	1.12	6.59	−32.74	25.72	−1.06	4.90	0.15
90-Day put (%)	0.88	6.28	−32.19	24.10	−0.95	4.75	0.14
K/S = 95							
30-Day call (%)	0.12	4.37	−13.14	13.42	−0.16	0.51	0.02
60-Day call (%)	0.13	4.35	−12.60	13.87	−0.11	0.57	0.02
90-Day call (%)	0.15	4.33	−11.95	13.81	−0.09	0.44	0.02
30-Day put (%)	1.17	6.29	−28.74	24.24	−0.92	3.95	0.12
60-Day put (%)	0.83	6.00	−28.79	23.31	−0.81	3.96	0.12
90-Day put (%)	0.71	5.90	−29.57	21.54	−0.81	4.14	0.12
K/S = 105							
30-Day call (%)	−0.14	4.28	−13.32	18.06	0.45	1.92	−0.01
60-Day call (%)	0.00	4.29	−11.80	15.39	0.24	1.02	0.01
90-Day call (%)	0.08	4.29	−12.89	14.68	0.16	0.90	0.01
30-Day put (%)	0.43	5.09	−23.47	16.12	−0.56	2.64	0.09
60-Day put (%)	0.43	5.17	−23.97	16.28	−0.60	2.71	0.09
90-Day put (%)	0.43	5.23	−24.35	16.68	−0.60	2.85	0.09
K/S = 110							
30-Day call (%)	−0.10	4.12	−13.38	23.58	1.20	6.00	−0.02
60-Day call (%)	−0.01	4.23	−11.78	20.07	0.77	2.93	0.02
90-Day call (%)	0.05	4.28	−12.67	15.46	0.34	1.34	0.02
30-Day put (%)	0.37	4.85	−20.93	14.64	−0.44	1.86	0.06
60-Day put (%)	0.36	4.94	−22.06	14.77	−0.50	2.15	0.07
90-Day put (%)	0.37	5.03	−22.82	15.61	−0.53	2.36	0.07
Stock							
S&P 500 (%)	0.50	4.70	−16.94	10.77	−0.59	0.65	0.10

Notes: This table reports the summary statistics of the option returns. Option return data include call and put option of 30-, 60-, and 90-day maturities. We report the results of option returns with different moneyness, including K/S = 100, 95, 90, 105, and 110, respectively. ρ (1) is the autoregressive coefficients at lag 1-month interval. The t value in the last row is to test correlation coefficient being different from one. K/S is the ratio of the strike price to the underlying stock price.

report the return statistics of the S&P 500 index as a comparison. The returns of ATM puts are closer to the S&P 500 index than that of ATM calls. Figure 1 plots the time series of the 30-, 60-, and 90-day options, returns are more volatile during the 1998–1999 Asian crisis and the 2008–2009 financial crisis and are relatively stable during other periods. There are several spikes of option returns during the 1998–1999 Asian crisis and the 2008–2009 financial crisis, which reflects the impact of crisis on option market. Put returns have a larger fluctuation than the corresponding call returns, consistent with the standard deviation values in Table 1.

An option is a derivative whose value largely depends on the underlying asset. It is therefore possible that the correlation between option and stock index return is close to one, and it is not worthwhile to investigate the forecast option return separately. We test whether the correlation between S&P 500 index return and the ATM option returns is significantly different from one. The t values for the six option series are −3.49, −3.27, −3.21, −3.15, −3.02, and −2.98, respectively. All are highly significant. The rejection of the test suggests that the information content between these return series may not be the same.

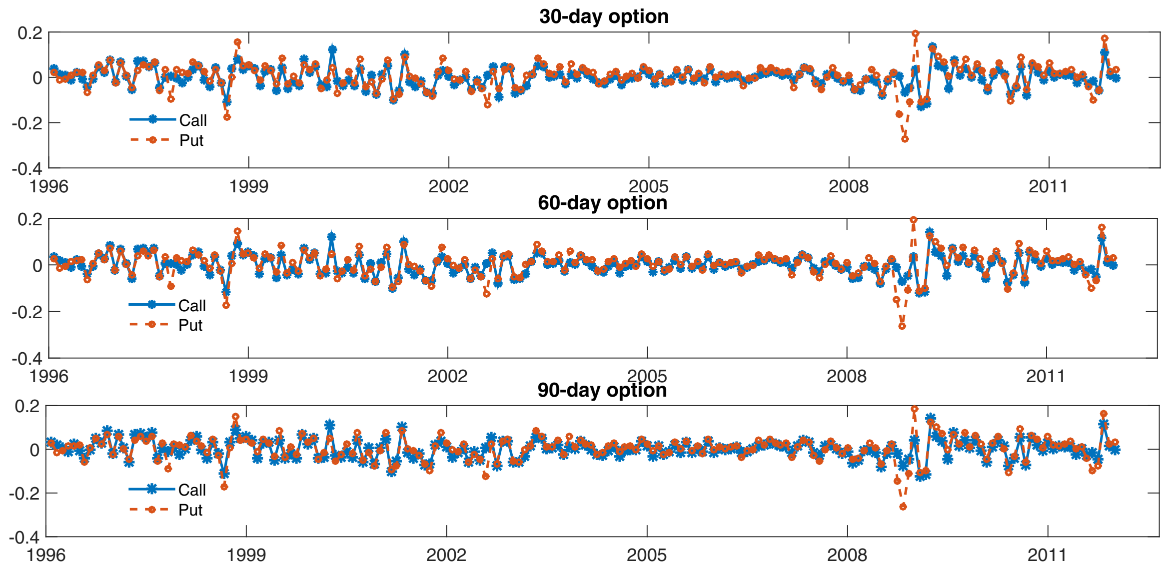

FIGURE 1 Option returns. *Note*: This graph plots the time series of call and put option returns from 1996 to 2011 [Color figure can be viewed at wileyonlinelibrary.com]

Table 2 reports the statistics of those predictors we use. The VRP has a mean of 0.03 and a standard deviation of 0.03. It is also slightly right skewed with skewness being 1.19 and has an excess kurtosis of 9.69. The TAIL predictor is more right skewed and has higher peakedness. Figure 2 illustrates the movements of these three predictors: They have spikes in late 1998 and 2008 due to the impact of Long-Term Capital Management (LTCM) and Lehman Brother's bankruptcy.

4 | EMPIRICAL RESULTS

In this section we present our empirical results. First, we run univariate regression for each predictor to test both its in-sample and out-of-sample performances starting from January 2002 to December 2011. Then we investigate the performance of bivariate regression of the three volatility and jump predictors and the combination and regressed combination forecasts, followed by robustness tests.

4.1 | Univariate and bivariate predictive regressions

Table 3 presents the regression results for the ATM option returns. The performance of the volatility and jump predictors for the 30-day options is shown in the first panel. The in-sample test shows that the volatility risk predictors have significant coefficients for calls at the 1% level while none of the jump risk indicators is significant, with the largest in-sample R^2 11.76% for the VRP-TAIL. In contrast, all of the in-sample results for puts are significant at the 1% level except those for the TAIL, with the largest 14.16% in-sample R^2. The bivariate regression is consistent with the univariate regression and slightly improves the in-sample performance. All significant coefficients are positive suggesting that the higher the volatility or jump risk, the larger the option return.

The second and third panel of Table 3 also shows the results for 60- and 90-day options. They are very close to those of 30-day options. To compare the results of predictive regression models between option returns and stock index return, we also run the predictive regressions for S&P 500 index. The results are very close to those of call option returns. The predictive coefficients of stock returns are larger than option returns, suggesting that stock returns are more sensitive to these risk predictors. The VRP predictor has good predictability on index returns, in line with the findings in Bollerslev et al. (2009). None of the jump risk predictors is significant in-sample. The predictability of call option return is closer to stock index return. In contrast, there is significant difference between the predictability of put option return and stock index return, indicating the differences of forecasting stock and option returns, especially put option returns.

TABLE 2 Summary statistics of predictors

	Mean	Std.	Min.	Max.	Skewness	Kurtosis	ρ (1)
VRP	0.03	0.03	−0.09	0.14	1.08	9.69	0.35
SMIRK	0.05	0.02	−0.02	0.16	1.19	2.45	0.57
TAIL (×100)	0.21	0.18	−0.06	1.40	3.48	17.04	0.72
BM	0.25	0.07	0.12	0.44	0.22	−0.76	0.95
TBL	0.03	0.02	0.00	0.06	−0.11	−1.59	0.99
LTY	0.05	0.01	0.02	0.07	−0.09	−0.23	0.95
NTIS	0.01	0.02	−0.06	0.03	−1.34	1.42	0.96
LTR	0.01	0.03	−0.11	0.14	0.00	2.72	−0.01
SVAR	0.00	0.01	0.00	0.06	5.72	43.03	0.69
INFL	0.00	0.00	−0.02	0.01	−1.12	5.52	0.47
D/P	−4.06	0.23	−4.52	−3.28	0.42	0.76	0.97
D/Y	−4.05	0.23	−4.53	−3.29	0.32	0.60	0.97
D/E	−0.84	0.50	−1.24	1.38	2.83	8.34	0.98
E/P	−3.21	0.42	−4.84	−2.57	−1.71	3.77	0.97
TMS	0.02	0.01	0.00	0.05	−0.06	−1.35	0.97
DFY	0.01	0.00	0.01	0.03	2.83	9.34	0.96
DFR	0.00	0.02	−0.10	0.07	−0.44	6.50	0.04

Notes: This table reports the summary statistics of the predictors. The predictors used in the analysis are variance risk premium (VRP) following Bollerslev et al. (2009), the implied volatility SMIRK measure following Yan (2011; SMIRK), and the tail index defined in Du and Kapadia (2012; TAIL), and other predictors used in Welch and Goyal (2008) and Rapach et al. (2010) for stock return forecast, including the book-to-market ratio (B/M), Treasury bill rate (TBL), long-term yield (LTY), net equity expansion (NTIS), long-term return (LTR), stock variance (SVAR), inflation rate (INFL), the dividend–price ratio (D/P), dividend yields (D/Y), the dividend–payout ratio (D/E), the earnings–price ratio (E/P), term spread (TMS), default yield spread (DFY), and default return spread (DFR). ρ (1) is the autoregressive coefficients at lag 1-month interval.

Turning now to the out-of-sample performance reported in Table 4, consistent with the in-sample results, the volatility predictors have significant R^2_{OS} for both calls and puts, while the jump predictors are only significant for puts. Between the two jump risk predictors, the prediction power of SMIRK is stronger than that of TAIL. The utility gains for puts are all positive and mostly larger than the corresponding calls. The aggregate volatility and jump risk are both

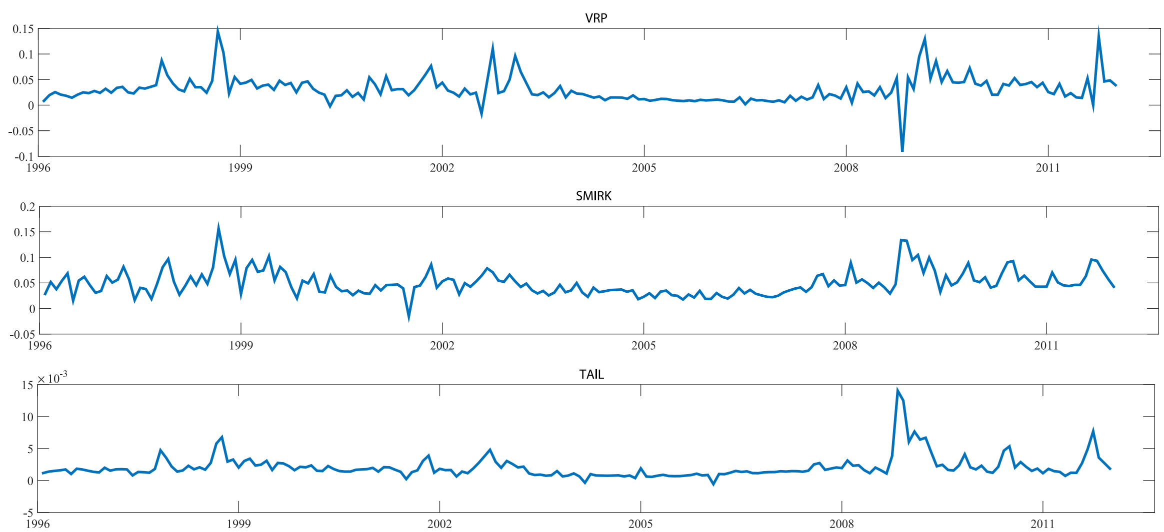

FIGURE 2 Aggregate volatility and jump risk predictor. *Note*: This graph plots the time series of variance risk premium (VRP) measure and aggregate jump risk measure (SMIRK and TAIL) from 1996 to 2011. VRP is the variance risk premium following Bollerslev et al. (2009), and SMIRK is the slope of the implied volatility SMIRK proposed in Yan (2011). TAIL is the tail index following Du and Kapadia (2012) [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 In-sample predictive regression: aggregate jump and volatility risk predictors

Variable	β_1	t Value	β_2	t Value	R^2 (%)	β_1	t Value	β_2	t Value	R^2 (%)
	30-Day call					*30-Day put*				
VRP	0.90*	4.84			10.81	1.34*	5.27			14.16
SMIRK	0.29	0.77			0.51	1.02*	3.15			7.08
TAIL	1.21	0.17			−0.44	11.84	1.54			5.03
VRP-SMIRK	0.99*	4.60			10.18	1.14*	2.90			7.68
VRP-TAIL	1.01*	5.13			11.76	1.20*	2.95			9.54
VRP-SMIRK + SMIRK	0.99*	4.98	0.29	1.07	10.75	1.14*	4.66	1.02*	4.13	14.86
VRP-TAIL + TAIL	1.01*	5.45	1.24	0.37	11.39	1.20*	6.39	11.88*	3.31	14.68
	60-Day call					*60-Day put*				
VRP	0.95*	4.79			11.31	1.31*	5.34			14.03
SMIRK	0.36	0.93			1.01	0.98*	3.02			6.71
TAIL	2.10	0.29			−0.25	11.14	1.47			4.57
VRP-SMIRK	1.01*	4.37			9.95	1.13*	2.99			7.78
VRP-TAIL	1.04*	4.82			11.69	1.19*	3.03			9.68
VRP-SMIRK + SMIRK	1.01*	4.91	0.36	1.29	11.03	1.13*	4.75	0.98*	3.97	14.58
VRP-TAIL + TAIL	1.04*	5.37	2.14	0.59	11.51	1.19*	6.41	11.18*	3.13	14.36
	90-Day call					*90-Day put*				
VRP	0.96*	4.84			11.30	1.33*	5.32			14.35
SMIRK	0.39	1.01			1.22	0.98*	3.02			6.81
TAIL	2.47	0.34			−0.15	11.20	1.47			4.63
VRP-SMIRK	1.01*	4.27			9.66	1.14*	3.00			7.99
VRP-TAIL	1.04*	4.73			11.44	1.20*	3.05			9.94
VRP-SMIRK + SMIRK	1.01*	4.83	0.39	1.41	10.95	1.14*	4.76	0.99*	3.98	14.90
VRP-TAIL + TAIL	1.04*	5.37	2.50	0.69	11.36	1.20*	6.44	11.23*	3.15	14.68
	Stock									
VRP	1.23*	6.94			13.45					
SMIRK	0.55	1.25			2.01					
TAIL	2.70	0.30			−0.21					
VRP-SMIRK	1.26*	5.44			10.94					
VRP-TAIL	1.35*	6.19			13.92					
VRP-SMIRK + SMIRK	1.27*	6.72	0.55	1.60	13.03					
VRP-TAIL + TAIL	1.35*	7.56	2.75	0.64	13.80					

Notes: In this table, we report the results of in-sample univariate predictive regressions of option returns using different aggregate jump and volatility risk predictors. The prediction horizon is one quarter. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.
Abbreviation: VRP, variance risk premium.

statistically and economically important for the forecast of put option returns. On the other hand, only aggregate volatility risk plays a role in the prediction of call option returns. The different performances of aggregate volatility and jump risk on call and put option predictability reflect the asymmetry property of S&P 500 index distribution, indicating that the jump risk is a more important factor of option return for puts than for calls.

Besides those volatility and jump predictors, we show the performance of a naive predictor called grouped average (GA), which simply sorts the option return series into three groups using their implied volatility levels at time $t-1$ and calculate the mean of option returns in each group. At time t, we first determine the group that the current volatility level belongs to, then use the mean of that group as the forecast. GA thus naively takes into consideration of option returns under different stochastic volatility environments. Interestingly this naive predictor has good out-of-sample performance, especially for puts, achieving the largest utility gain at 10.32%. They are significant for both puts and calls, suggesting that stochastic volatility is an important factor for option returns.

Coval and Shumway (2001) examine expected option returns in the context of asset pricing theory and show that under GBM assumption, expected option returns vary linearly with option betas. Since the leverage-adjusted option portfolios used in our empirical analysis have targeted market beta of one, their expected return could be approximated by the expected return of stock market portfolio. Following this, we first forecast the stock market return and use it as a forecast of option returns. We follow Rapach et al. (2010) and use the mean of 14 individual forecasts as the forecast of stock returns. The last row of each panel in Table 4 reports R^2_{OS} of this approach. The forecast is not significant for either calls or puts. This provides the evidence of rejection of GBM assumption for S&P 500 index.

The empirical results in Table 4 show that option returns are associate with GBM, volatility, and jump risk components. Volatility risk is important for both puts and calls, while jump risk is only significant for the puts. Call and put option returns share both similarities and difference in their predictability. The different performances of jump risk predictors on the prediction of call and put option returns reflect the asymmetry property of S&P 500 index distribution. This is consistent with Constantinides et al. (2008), Constantinides et al. (2011), and Constantinides and Lian (2015) about the different patterns of call and put option returns.

Figure 3 plots the time series of option return forecasts by the VRP and SMIRK predictors against the benchmark historical average forecasts. Clearly the forecasts by the two predictors are more volatile and capture the dynamics of actual returns better for puts than for calls, and the historical average forecasts are too stable to predict returns timely.

Table 5 shows the results for other predictors that are widely applied for stock. For brevity, we only report the results of 30-day option returns.[13] The results show that NTIS and D/Y have significant in-sample coefficients for the call returns, and B/M, D/P, D/Y, and D/E have significant in-sample coefficients for the put returns. The out-of-sample results also suggest that there are some variables that could be used to forecast option returns. For example, R^2_{OS} of TBL and DFY of call returns are significantly positive, while R^2_{OS} of LTY, NITS, INFL, D/Y, and DFY of put returns is significantly positive. This means the variables used in the stock return forecast are also helpful on the forecast of option returns.

Next we conduct an encompassing test to examine whether the forecasts by the volatility and jump predictors bring additional information content. Table 6 reports the p values corresponding to a test of the null hypothesis that the forecast given in the column heading encompasses the forecast given in the row heading against the alternative hypothesis that the forecast given in the column heading does not encompass the forecast given in the row heading. Panel A reports the results of 30-day calls while Panel B reports the results of 30-day puts. For example, the result of intersection of column (8) and row (1) is 0.00. This means the probability that the forecast of call option returns by BM encompasses the forecast by VRP is 0.00.

Most of the numbers in the up-right part of matrix in Panels A and B are <0.10. This indicates that the forecasts by other predictors largely do not encompass the forecasts by the volatility and jump predictors. These results suggest that the volatility and jump predictors contain information that is not captured by those predictors widely used for stock returns. VRP encompasses most of the other three predictors. This implies that VRP has most information content among the predictors.

4.2 | Other option series and forecast horizon

So far we focus on the quarterly returns of 30-, 60-, and 90-day ATM options. To show the robustness of our results, we test our predictive regression on option returns with different moneyness and forecasting horizon.

Panel A of Table 7 reports the results of 30-day options with different moneyness, including K/S = 0.90, K/S = 0.95, K/S = 1.00, and K/S = 1.05. The results are similar to those of ATM options. The coefficients of predictive regression gradually decrease with the increase of K/S. This suggests the returns of deep OTM call option and deep ITM put options are more sensitive to these risk predictors.

Panel B of Table 7 reports the results of longer horizon, including two quarters, three quarters, and 1 year. The results are even stronger than those of quarterly return forecast. For example, using the best-performing predictor, VRP, in the forecast of 30-day put option returns gives an R^2_{OS} of 7.15% at the quarterly horizon as reported in Table 3, and provides an R^2_{OS} of 10.61% at the yearly horizon. There is also some evidence of predictability of call option return at longer horizon. For example, the jump risk predictors are significantly positive in-sample at the yearly horizon, and all of R^2_{OS} are significantly positive.

Overall, the results of other option series and forecast horizon show that the predictability of put option return by volatility and jump risk predictors and the predictability of call option return by volatility risk predictors are robust. The predictability of option returns is more significant at a longer forecast horizon.

[13] The results of 60- and 90-day option returns are similar and available upon request.

TABLE 4 Out-of-sample forecast of option returns: aggregate jump and volatility risk predictors

Variable	Call		Put	
	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)
Panel A: 30-day				
VRP	9.54*	5.38	6.31*	7.15
SMIRK	−7.73	−1.29	2.92*	4.79
TAIL	−6.90	−0.04	0.66**	3.93
VRP-SMIRK	15.04*	6.80	7.51*	5.18
VRP-TAIL	13.20*	7.38	7.70*	6.35
VRP-SMIRK + SMIRK	9.78*	4.62	7.50*	7.06
VRP-TAIL + TAIL	9.07*	5.74	2.04*	6.19
Grouped average (GA)	2.00**	1.29	3.40*	10.32
Coval and Shumway (CS, 2001)	−11.73	−8.62	0.89	4.38
Panel B: 60-day				
VRP	9.65*	5.45	6.55*	7.02
SMIRK	−7.49	−0.68	1.39*	4.04
TAIL	−7.69	−0.51	−0.21	3.51
VRP-SMIRK	14.59*	6.88	8.08*	5.55
VRP-TAIL	13.92*	7.52	10.21*	6.82
VRP-SMIRK + SMIRK	9.41*	4.72	7.60*	6.57
VRP-TAIL + TAIL	7.86*	5.52	2.56*	5.97
Grouped average (GA)	1.01**	1.42	4.28*	9.65
Coval and Shumway (CS, 2001)	−9.06	−7.06	0.78	2.93
Panel C: 90-day				
VRP	10.24*	5.38	6.46a	6.90
SMIRK	−7.00	−0.21	1.15a	3.75
TAIL	−7.24	−0.54	−0.57	3.14
VRP-SMIRK	14.51*	6.75	10.24*	5.91
VRP-TAIL	14.20*	7.51	10.32*	6.92
VRP-SMIRK + SMIRK	9.63*	4.80	7.60*	6.41
VRP-TAIL + TAIL	7.57*	5.27	2.31*	5.74
Grouped average (GA)	0.25**	1.62	4.87*	9.05
Coval and Shumway (CS, 2001)	−7.53	−6.00	0.67	1.91

Notes: In this table, we report the out-of-sample forecast of option returns using different aggregate jump and risk predictors. The prediction horizon is one quarter. The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, ** , and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviations: MSPE, mean-squared prediction error; VRP, variance risk premium.

4.3 | Combination forecast and regressed combination forecast

Given the different performances of the volatility and jump predictors and their additional information content, in this section we investigate the option return forecast using combination forecast and regressed combination forecast. For the combination forecast, we report the results of using other predictors only and using all the predictors, including the volatility and jump risk and GA predictors.

The up panel of Table 8 reports the results of 30-day ATM options. All combinations of the forecasts yield significant out-of-sample R^2_{OS} at the 5% level, in line with these approaches' good performance for stock returns in Rapach et al. (2010) and corporate bond returns in Lin et al. (2014). Introducing volatility and jump risk variables into the combination forecast improves the out-of-sample forecast performance of both the call and put option returns. For example, R^2_{OS} of MC forecast using other variables for 30-day call option and 30-day put option returns are 3.74% and 2.84%, respectively, while they significantly increase to 7.24% and 5.80%, respectively, when all variables are used. This improvement shows the importance of aggregate volatility and jump risk predictors on forecasting option returns after

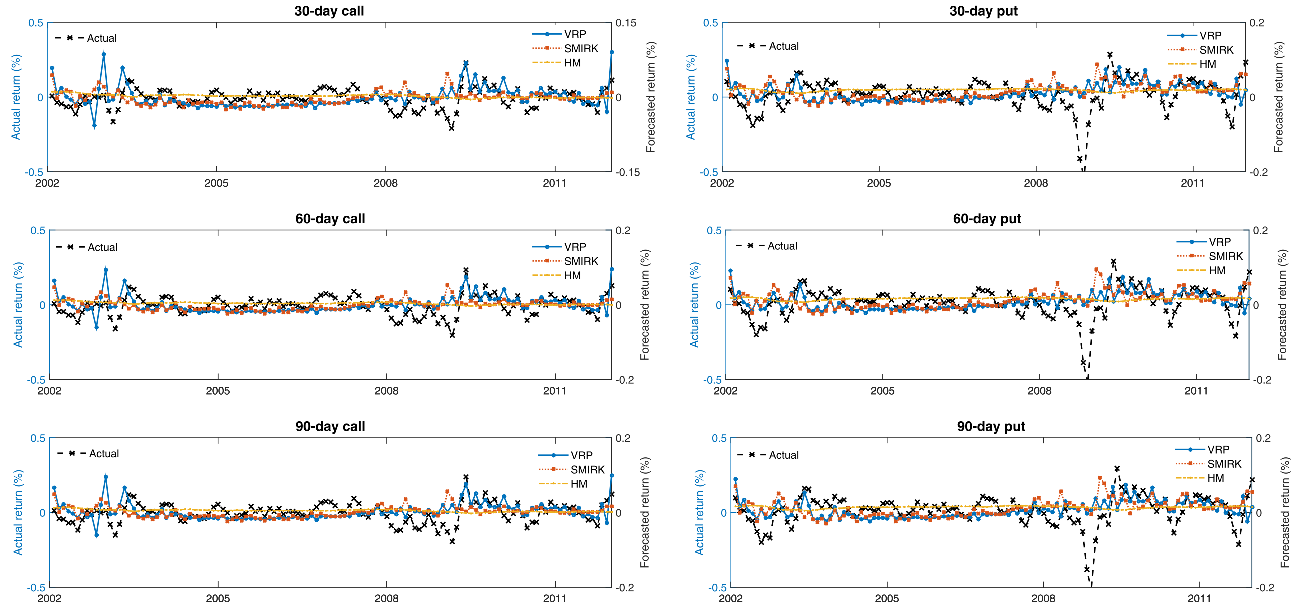

FIGURE 3 Option return forecast by aggregate volatility and jump risk measure. *Notes*: This graph plots the time series of option return forecast by VRP and SMIRK. We also plot the forecast using the historical mean (HM) that is used as the benchmark model. VRP, variance risk premium [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Forecast of option returns by other variables

	Call					Put				
	In-sample			Out-of-sample		In-sample			Out-of-sample	
Variable	Beta	*t* Value	R^2 (%)	R^2_{OS} (%)	ΔU (%)	Beta	*t* Value	R^2 (%)	R^2_{OS} (%)	ΔU (%)
BM	0.09	0.96	0.46	−19.61	−4.54	0.20***	1.69	2.12	−3.99	−3.74
TBL	0.42	1.18	1.00	2.22*	6.17	−0.30	−0.66	−0.06	−0.73	2.94
LTY	0.67	0.81	0.36	−3.50	6.15	−0.95	−0.96	0.52	1.37*	2.85
NTIS	0.84**	2.18	5.50	−10.41	0.38	0.76	1.31	2.37	4.77*	4.23
LTR	−0.03	−0.12	−0.52	−1.15	−0.63	0.00	0.01	−0.53	0.37	0.87
SVAR	−1.86	−1.69	2.08	−3.25	−0.49	0.27	0.18	−0.50	−2.51	−1.22
INFL	0.63	0.38	−0.42	−1.61	−0.19	−1.98	−0.95	0.15	1.38*	5.55
D/P	0.06	1.50	3.06	−10.53	−7.57	0.10**	2.26	5.82	0.00	−2.41
D/Y	0.06c	1.66	3.08	−7.83	−7.65	0.10*	2.51	6.18	1.44*	−1.80
D/E	0.01	0.71	0.06	3.03	2.44	0.03***	1.72	2.26	0.80	6.89
E/P	0.00	0.10	−0.52	−2.58	0.07	−0.01	−0.49	−0.16	−2.77	5.50
TMS	−0.52	−1.18	0.69	−0.85	1.76	0.17	0.28	−0.45	−1.20	1.80
DFY	−1.28	−0.58	0.28	6.20**	3.57	1.16	0.50	−0.14	6.87*	8.90
DFR	0.03	0.09	−0.53	−2.45	−0.78	0.39	0.76	0.09	−0.47	0.86

Notes: In this table, we report the results of 30-day option return forecast by the variables used in the stock return forecast literature. The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviations: BM, book-to-market ratio; D/E, dividend–payout ratio; D/P, dividend–price ratio; D/Y, dividend yields; DFR, default return spread; DFY, default yield spread; E/P, earnings–price ratio; INFL, inflation rate; LTR, long-term return; LTY, long-term yield; MSPE, mean-squared prediction error; NTIS, net equity expansion; SVAR, stock variance; TBL, Treasury bill rate; TMS, term spread.

TABLE 6 MHLN test

	VRP (1)	SMIRK (2)	TAIL (3)	VRP-SMIRK (4)	VRP-TAIL (5)	GA (6)	CS (7)	BM (8)	TBL (9)	LTY (10)	NTIS (11)	LTR (12)	SVAR (13)	INFL (14)	D/P (15)	D/Y (16)	D/E (17)	E/P (18)	TMS (19)	DFY (20)	DFR (21)
Panel A: 30-day call option																					
VRP (1)		0.00	0.01	0.80	0.75	0.02	0.00	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.00
SMIRK (2)	0.90		0.31	0.97	0.93	0.26	0.00	0.00	0.33	0.17	0.02	0.72	0.42	0.62	0.00	0.02	0.59	0.00	0.43	0.26	0.50
TAIL (3)	0.80	0.22		0.93	0.88	0.11	0.00	0.00	0.24	0.07	0.00	0.38	0.21	0.26	0.00	0.01	0.34	0.00	0.23	0.08	0.26
VRP-SMIRK (4)	0.01	0.00	0.00		0.05	0.02	0.00	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00
VRP-TAIL (5)	0.13	0.00	0.00	0.64		0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GA (6)	0.06	0.01	0.00	0.40	0.20		0.00	0.00	0.04	0.00	0.00	0.08	0.01	0.04	0.01	0.01	0.18	0.00	0.02	0.04	0.03
CS (7)	0.34	0.02	0.00	0.91	0.64	0.54		0.01	0.15	0.02	0.00	0.73	0.41	0.74	0.28	0.49	0.87	0.16	0.49	0.12	0.56
BM (8)	0.38	0.07	0.05	0.86	0.58	0.24	0.23		0.07	0.03	0.01	0.60	0.49	0.48	0.41	0.48	0.37	0.09	0.21	0.05	0.52
TBL (9)	0.06	0.01	0.00	0.27	0.13	0.02	0.00	0.00		0.00	0.00	0.07	0.01	0.04	0.00	0.00	0.14	0.00	0.06	0.22	0.03
LTY (10)	0.15	0.05	0.02	0.49	0.32	0.05	0.00	0.00	0.90		0.00	0.15	0.06	0.13	0.00	0.01	0.24	0.00	0.14	0.43	0.08
NTIS (11)	0.31	0.09	0.07	0.56	0.49	0.06	0.00	0.00	0.10	0.09		0.18	0.17	0.16	0.01	0.01	0.18	0.00	0.08	0.23	0.11
LTR (12)	0.43	0.02	0.01	0.90	0.69	0.24	0.00	0.00	0.19	0.05	0.00		0.15	0.28	0.00	0.01	0.52	0.00	0.24	0.12	0.23
SVAR (13)	0.38	0.05	0.01	0.90	0.69	0.28	0.00	0.00	0.23	0.06	0.00	0.47		0.43	0.02	0.03	0.59	0.00	0.27	0.13	0.27
INFL (14)	0.40	0.01	0.00	0.93	0.72	0.26	0.00	0.00	0.22	0.05	0.00	0.39	0.13		0.01	0.02	0.66	0.00	0.28	0.10	0.17
D/P (15)	0.56	0.04	0.06	0.93	0.72	0.30	0.14	0.03	0.13	0.03	0.00	0.59	0.34	0.51		0.90	0.48	0.12	0.30	0.07	0.49
D/Y (16)	0.48	0.02	0.03	0.91	0.68	0.27	0.05	0.01	0.12	0.03	0.00	0.48	0.25	0.42	0.03		0.46	0.08	0.26	0.06	0.34
D/E (17)	0.09	0.01	0.00	0.58	0.31	0.11	0.00	0.00	0.09	0.00	0.00	0.04	0.01	0.02	0.00	0.01		0.00	0.03	0.03	0.02
E/P (18)	0.00	0.00	0.00	0.07	0.01	0.04	0.00	0.01	0.02	0.00	0.00	0.02	0.00	0.01	0.00	0.01	0.06		0.01	0.05	0.00
TMS (19)	0.21	0.03	0.00	0.72	0.45	0.18	0.00	0.00	0.32	0.01	0.00	0.22	0.04	0.17	0.01	0.02	0.71	0.00		0.08	0.08
DFY (20)	0.01	0.00	0.00	0.08	0.03	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00		0.00
DFR (21)	0.39	0.04	0.01	0.88	0.66	0.20	0.00	0.00	0.18	0.04	0.00	0.44	0.16	0.30	0.02	0.04	0.43	0.00	0.22	0.07	
Panel B: 30-day put option																					
VRP (1)		0.03	0.00	0.26	0.55	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.11	0.00
SMIRK (2)	0.52		0.03	0.38	0.50	0.01	0.01	0.00	0.00	0.01	0.22	0.01	0.01	0.03	0.02	0.04	0.03	0.00	0.00	0.22	0.01
TAIL (3)	0.61	0.45		0.48	0.58	0.01	0.05	0.00	0.01	0.03	0.25	0.05	0.02	0.07	0.03	0.04	0.06	0.00	0.01	0.22	0.04
VRP-SMIRK (4)	0.10	0.01	0.00		0.17	0.02	0.01	0.00	0.00	0.01	0.14	0.00	0.00	0.01	0.00	0.00	0.05	0.00	0.00	0.15	0.00
VRP-TAIL (5)	0.19	0.01	0.00	0.09		0.01	0.00	0.00	0.00	0.01	0.12	0.00	0.00	0.01	0.00	0.00	0.04	0.00	0.00	0.15	0.00
GA (6)	0.01	0.00	0.00	0.07	0.05		0.04	0.01	0.03	0.06	0.02	0.03	0.01	0.02	0.03	0.04	0.01	0.01	0.03	0.12	0.02
CS (7)	0.30	0.11	0.03	0.73	0.63	0.14		0.03	0.05	0.45	0.51	0.30	0.03	0.38	0.17	0.24	0.22	0.02	0.04	0.66	0.13
BM (8)	0.23	0.17	0.05	0.66	0.43	0.17	0.50		0.11	0.56	0.45	0.46	0.14	0.46	0.56	0.66	0.27	0.16	0.13	0.41	0.35
TBL (9)	0.42	0.15	0.03	0.64	0.71	0.23	0.36	0.02		0.63	0.43	0.30	0.04	0.37	0.10	0.16	0.31	0.01	0.21	0.83	0.14
LTY (10)	0.22	0.07	0.02	0.58	0.53	0.16	0.25	0.02	0.02		0.41	0.13	0.01	0.27	0.13	0.20	0.22	0.02	0.01	0.65	0.08
NTIS (11)	0.18	0.10	0.06	0.33	0.30	0.00	0.11	0.02	0.05	0.12		0.13	0.09	0.12	0.08	0.10	0.03	0.00	0.06	0.19	0.09

TABLE 6 (Continued)

	VRP (1)	SMIRK (2)	TAIL (3)	VRP-SMIRK (4)	VRP-TAIL (5)	GA (6)	CS (7)	BM (8)	TBL (9)	LTY (10)	NTIS (11)	LTR (12)	SVAR (13)	INFL (14)	D/P (15)	D/Y (16)	D/E (17)	E/P (18)	TMS (19)	DFY (20)	DFR (21)
LTR (12)	0.54	0.23	0.06	0.88	0.82	0.15	0.53	0.02	0.09	0.57	0.52		0.03	0.54	0.17	0.27	0.29	0.03	0.06	0.63	0.17
SVAR (13)	0.88	0.62	0.35	0.97	0.95	0.15	0.80	0.06	0.21	0.75	0.67	0.83		0.73	0.29	0.41	0.39	0.04	0.25	0.63	0.52
INFL (14)	0.39	0.16	0.03	0.71	0.63	0.07	0.18	0.02	0.03	0.23	0.40	0.21	0.01		0.16	0.23	0.15	0.01	0.03	0.54	0.10
D/P (15)	0.25	0.17	0.05	0.56	0.38	0.12	0.26	0.08	0.07	0.28	0.24	0.22	0.05	0.30		0.94	0.21	0.09	0.08	0.30	0.18
D/Y (16)	0.18	0.11	0.03	0.45	0.30	0.10	0.19	0.04	0.05	0.20	0.21	0.14	0.03	0.23	0.02		0.17	0.06	0.05	0.27	0.12
D/E (17)	0.23	0.08	0.03	0.46	0.43	0.11	0.22	0.02	0.11	0.27	0.29	0.21	0.07	0.21	0.14	0.19		0.01	0.12	0.61	0.15
E/P (18)	0.03	0.02	0.01	0.27	0.14	0.29	0.35	0.12	0.07	0.39	0.25	0.20	0.04	0.18	0.21	0.25	0.20		0.08	0.59	0.14
TMS (19)	0.58	0.27	0.06	0.81	0.83	0.24	0.59	0.02	0.57	0.83	0.52	0.54	0.07	0.58	0.15	0.24	0.40	0.02		0.81	0.23
DFY (20)	0.08	0.02	0.01	0.15	0.16	0.01	0.05	0.01	0.04	0.08	0.05	0.06	0.02	0.05	0.04	0.06	0.01	0.00	0.04		0.04
DFR (21)	0.62	0.29	0.11	0.87	0.84	0.14	0.55	0.03	0.10	0.55	0.51	0.51	0.10	0.56	0.22	0.32	0.35	0.02	0.10	0.66	

Notes: This table reports *p* values for the Harvey, Leybourne, and Newbold (1998) MHLN statistic. The statistic corresponds to a test of the null hypothesis that the forecast given in the column heading encompasses the forecast given in the row heading against the alternative hypothesis that the forecast given in the column heading does not encompass the forecast given in the row heading. The prediction horizon is quarterly. Abbreviations: BM, book-to-market ratio; CS, Coval and Shumay; D/E, dividend–payout ratio; D/P, dividend–price ratio; D/Y, dividend yields; DFR, default return spread; DFY, default yield spread; E/P, earnings–price ratio; GA, grouped average; INFL, inflation rate; INFL, inflation; LTR, long-term return; LTY, long-term yield; MSPE, mean-squared prediction error; NTIS, net equity expansion; SVAR, stock variance; TBL, Treasury bill rate; TMS, term spread; VRP, variance risk premium.

TABLE 7 Results of predictive regressions: robustness test

	Call					Put				
	In-sample		Out-of-sample			In-sample		Out-of-sample		
Variable	Beta	t Value	R^2 (%)	R^2_{OS} (%)	ΔU (%)	Beta	t Value	R^2 (%)	R^2_{OS} (%)	ΔU (%)
Panel A: other moneyness										
90% K/S										
VRP	1.00*	5.66	11.59	8.04*	5.36	1.63*	4.82	13.10	3.57*	2.66
SMIRK	0.40	1.03	1.17	−5.78	−0.54	1.52*	5.09	10.23	2.20*	2.68
TAIL	2.14	0.28	−0.27	−7.74	−1.10	19.17*	2.54	8.71	−0.04	0.22
VRP-SMIRK	1.06*	4.77	10.03	14.28*	7.22	1.21**	2.19	5.35	2.83*	1.73
VRP-TAIL	1.10*	5.31	12.04	14.26*	8.00	1.30**	2.19	6.99	3.58*	2.80
95% K/S										
VRP	0.97*	5.23	11.36	10.24*	5.53	1.45*	5.12	13.55	4.88*	7.29
SMIRK	0.36	0.93	0.96	−7.09	−1.03	1.21*	4.00	8.28	4.28*	5.96
TAIL	1.71	0.23	−0.36	−8.30	−1.03	14.73**	1.97	6.51	−0.49	3.73
VRP-SMIRK	1.04*	4.66	10.07	14.68*	7.13	1.17*	2.57	6.55	5.73*	5.02
VRP-TAIL	1.08*	5.21	12.07	14.33*	7.80	1.24*	2.57	8.27	6.27*	5.93
105% K/S										
VRP	0.84*	4.27	9.64	8.28*	5.38	1.17*	5.19	13.52	10.90*	7.15
SMIRK	0.35	0.93	1.03	−8.74	−1.29	0.84*	2.69	5.89	1.10*	4.79
TAIL	1.93	0.27	−0.28	−4.78	−0.04	9.42	1.35	3.87	−0.21	3.93
VRP-SMIRK	0.88*	3.95	8.15	12.90*	6.80	1.03*	3.05	7.82	10.06*	5.18
VRP-TAIL	0.92*	4.61	9.93	11.31*	7.38	1.08*	3.11	9.63	11.26*	6.35
110% K/S										
VRP	0.71*	3.93	7.05	6.87*	2.87	1.11*	5.19	13.16	10.95*	6.68
SMIRK	0.25	0.75	0.27	−4.93	0.33	0.74**	2.31	4.87	−0.13	2.84
TAIL	0.41	0.07	−0.52	0.06	1.69	7.84	1.14	2.80	−1.46	2.60
VRP-SMIRK	0.78*	3.66	6.45	10.07*	3.63	1.00*	3.25	8.16	10.92*	5.90
VRP-TAIL	0.82*	4.45	8.03	11.16*	4.89	1.05*	3.33	10.02	12.12*	7.15
Panel B: other horizon										
Two quarters										
VRP	1.02*	2.93	6.10	9.39*	3.72	1.80*	3.46	9.17	7.86*	5.36
SMIRK	0.60	1.54	1.65	0.09	1.05	1.73*	4.56	8.13	2.94*	3.39
TAIL	7.25	1.10	1.14	−0.06	1.40	25.37*	3.11	9.23	3.34*	4.77
VRP-SMIRK	0.95**	2.32	3.89	10.60*	3.16	1.25	1.58	3.08	8.11*	5.04
VRP-TAIL	0.93**	2.36	4.35	6.95*	3.12	1.25	1.57	3.60	7.30*	5.07
Three quarters										
VRP	0.97**	2.09	3.20	13.71*	3.69	1.87*	2.69	6.43	7.82*	4.78
SMIRK	0.89*	2.17	2.50	6.91*	2.74	1.91*	3.29	6.48	6.13*	3.63
TAIL	11.64***	1.72	2.19	11.97*	3.72	32.07*	3.80	9.80	4.88*	3.40
VRP-SMIRK	0.70	1.29	0.95	11.52*	3.05	1.23	1.16	1.77	9.95*	5.02
VRP-TAIL	0.73	1.43	1.36	11.61*	3.38	1.12	1.09	1.68	8.25*	4.78
One year										
VRP	0.87***	1.81	1.61	18.66*	4.78	2.06**	2.44	5.66	10.61*	5.80
SMIRK	1.04**	2.37	2.40	13.22*	4.27	2.40*	3.57	7.56	7.59*	3.99
TAIL	13.41**	2.42	2.01	18.84*	5.13	38.75*	4.71	10.57	8.23*	4.57
VRP-SMIRK	0.48	0.80	−0.05	16.25*	4.16	1.17	0.90	0.99	11.67*	5.94
VRP-TAIL	0.57	1.01	0.26	17.30*	4.52	1.13	0.88	1.09	11.52*	6.17

Notes: This table reports the results of several robustness tests. Panel A reports the results of other moneyness option, while Panel B reports the results of other forecast horizon.The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviations: MSPE, mean-squared prediction error; VRP, variance risk premium.

TABLE 8 Forecast of option returns: combination forecast and regressed combination forecast

Model	Variables	Call R^2_{IS} (%)	Call R^2_{OS} (%)	Call ΔU (%)	Put R^2_{IS} (%)	Put R^2_{OS} (%)	Put ΔU (%)
30-Day option							
Combination forecast	Other predictors: mean	2.47	3.74**	2.03	1.89	2.84**	4.75
	Other predictors: weighted mean	2.54	3.69**	1.97	1.96	2.87**	4.81
	All predictors: mean	6.89	7.24*	4.47	6.89	5.70*	7.43
	All: weighted mean	7.20	7.38*	4.52	7.25	5.80*	7.50
Regressed	Mean	22.83	20.38*	9.39	20.56	16.67*	13.42
combination forecast	Weighted mean	20.76	17.97*	9.20	18.25	16.01*	13.31
60-Day option							
Combination forecast	Other predictors: mean	2.52	3.41**	1.78	1.95	3.12*	4.57
	Other predictors: weighted mean	2.57	3.35**	1.69	2.01	3.16*	4.62
	All predictors: mean	7.00	7.04*	4.27	7.04	6.07*	7.21
	All: weighted mean	7.30	7.17*	4.30	7.38	6.17*	7.28
Regressed	Mean	23.12	14.36*	8.26	21.38	18.11*	13.39
combination forecast	Weighted mean	21.96	16.37*	8.04	19.62	17.41*	13.18
90-Day option							
Combination forecast	Other predictors: mean	2.57	3.87**	2.08	1.91	3.23*	4.41
	Other predictors: weighted mean	2.61	3.78**	1.97	1.96	3.27*	4.45
	All predictors: mean	6.98	7.37*	4.44	7.16	6.26*	7.10
	All: weighted mean	7.26	7.49*	4.44	7.52	6.37*	7.17
Regressed	Mean	22.98	16.87*	10.16	21.69	18.33*	13.08
combination forecast	Weighted mean	21.93	16.85*	9.87	20.32	17.63*	12.83

Notes: In this table, we report the results of option return forecast using bivariate regression, combination forecast, and regressed combination forecast. The prediction horizon is one quarter. For the combination forecast, we report the results of using other predictors only and using all the predictors, including aggregate volatility and jump risk predictors. We use mean and weighted mean to calculate the combination forecast. We use all variables in the regressed combination forecast. The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviation: MSPE, mean-squared prediction error.

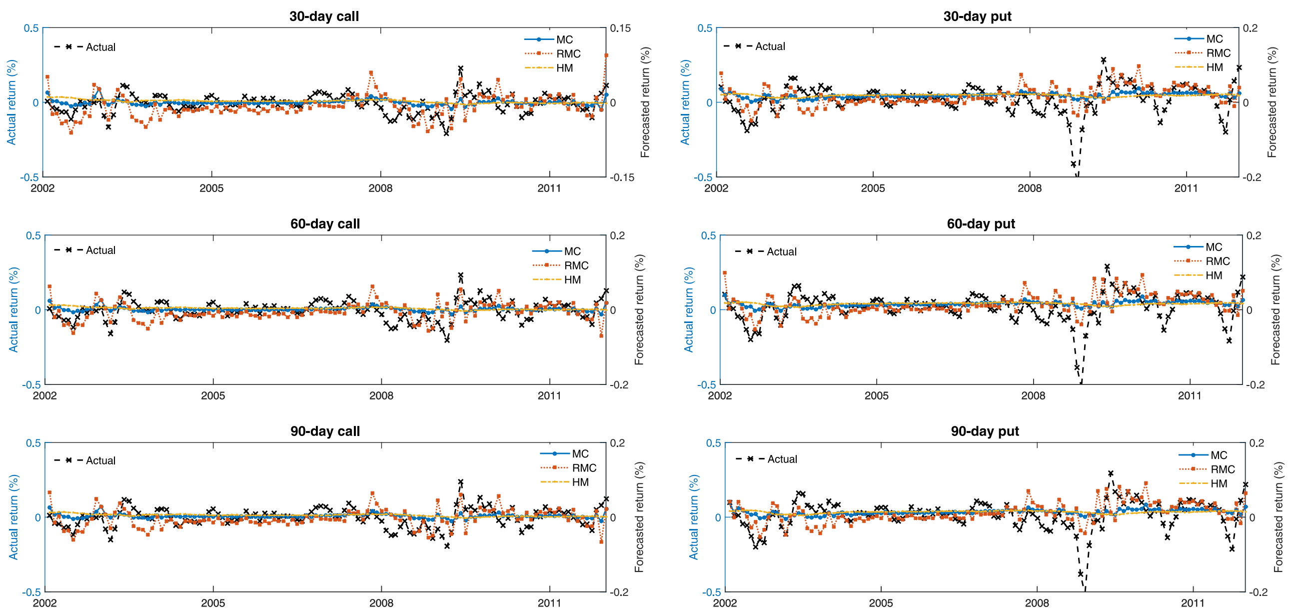

FIGURE 4 Option return forecast by mean combination and regressed mean combination. *Notes:* This graph plots the time series of option return forecast by mean combination (MC) and regressed mean combination (RMC). We also plot the forecast using the historical mean (HM) that is used as the benchmark model [Color figure can be viewed at wileyonlinelibrary.com]

the other variables are controlled for. Combining the volatility and jump predictors with other predictors generally have larger utility gains for puts than for calls. For example, using all the predictors increases the out-of-sample utility gain from 2.03% to 4.47% for calls, and they increase from 4.75% to 7.43%, when the MC approach is used.

Consistent with Lin et al. (2018), regressed combination forecast significantly improves both the in-sample R^2, the out-of-sample R^2, and utility gains for both calls and puts. R^2_{OS} of regressed combination forecast is around 20% that is much higher than the other forecasts. They are also of high economic value. For the 30-day puts, the utility gain using regressed combination forecast could reach more than 13%, which are much higher than those of combination forecast and bivariate predictive regressions. The results of 60- and 90-day options are similar. This shows that regressed combination forecast provides a superior forecast performance for the option returns.

Figure 4 plots the time series of option return forecast by MC and RMC. As expected, the forecast by MC is quite stable across the time. On the other hand, the forecast by RMC is much more volatile, especially during the recent financial crisis, but better captures the dynamics of option returns.

4.4 | Other test

In this section, we run several other tests. First we test whether the forecast performance is robust to different volatility predictors. Then we test the performance of these predictors during subperiods. Finally investigate whether adding different return constraints yields similar forecast performance.

We consider three alternative predictors of volatility risk, VIX, BKMV, and VolP. Under the stochastic volatility framework, such as Heston (1993), D. S. Bates (2000), and Pan (2002), volatility follows a mean-reverting process. The market price of volatility risk is a linear function of volatility level. The current level of volatility is therefore an effective measure of volatility risk and a useful predictor of option return. Du and Kapadia (2012) show that when there exist price discontinuities, the VIX index is a biased estimator of market volatility, while the volatility measure of Bakshi et al. (2003) is much less biased. Cremers et al. (2015) also use VIX and BKMV as the measure of volatility risk in their

TABLE 9 Forecast of option returns: other aggregate jump and volatility risk predictors

	Call			Put		
Variable	**In-sample R^2**	**R^2_{OS} (%)**	**ΔU (%)**	**In-sample R^2**	**R^2_{OS} (%)**	**ΔU (%)**
30-Day option						
VIX	−0.31	−4.84	0.35	4.57	0.72*	0.91
BKMV	−0.47	−4.09	0.47	3.98	0.69*	0.01
VolP	5.11	10.52**	3.77	1.92	3.82**	5.30
VolP-SMIRK	7.01	10.82*	4.43	5.20	7.44*	8.97
VolP-TAIL	7.08	14.09*	5.26	7.41	12.30*	10.81
60-Day option						
VIX	−0.12	−5.17	0.16	4.12	0.46*	0.99
BKMV	−0.35	−4.40	0.33	3.55	0.36*	−0.01
VolP	4.89	10.86**	4.25	2.08	4.05**	4.98
VolP-SMIRK	7.09	11.71*	5.06	5.36	9.60*	9.00
VolP-TAIL	7.37	15.11*	5.96	7.47	12.33*	10.07
90-Day option						
VIX	0.00	−4.68	0.19	4.03	0.09**	0.92
BKMV	−0.27	−4.01	0.28	3.46	−0.02	−0.17
VolP	4.54	10.40*	4.33	2.36	4.35**	4.98
VolP-SMIRK	6.78	11.50*	5.20	5.82	10.14*	8.88
VolP-TAIL	7.12	14.92*	6.14	8.04	13.01*	9.94

Notes: In this table, we report the out-of-sample forecast of option returns using different aggregate jump and risk predictors. The prediction horizon is one quarter. The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviations: BKMV, Bernische Kantonal-Musikverband; MSPE, mean-squared prediction error; VIX, Volatility Index; VolP, volatility risk premium.

TABLE 10 Forecast of option returns: subperiod analysis

	Call				Put			
	Jan. 1999–Jun. 2007		Jul. 2007–Dec. 2011		Jan. 1999–Jun. 2007		Jul. 2007–Dec. 2011	
Model	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)
30-Day option								
VRP	−7.83	4.61	17.90*	6.32	−2.21	0.49	8.84*	15.12
SMIRK	−8.57	2.11	−7.33	−5.40	−12.60	−2.42	7.53*	13.48
TAIL	−10.71	3.17	−5.06	−3.88	−18.88	−1.60	6.47***	10.49
VRP-SMIRK	2.20**	2.89	21.22*	11.83	8.20**	2.71	7.31*	7.97
VRP-TAIL	−6.07	4.00	22.46*	11.69	1.58*	1.03	9.52*	12.67
VRP-SMIRK + SMIRK	−10.81	3.51	19.69*	6.01	−11.02	−1.16	13.00*	17.04
VRP-TAIL + TAIL	−11.54	3.70	18.98*	8.30	−17.40	−1.50	7.82**	15.45
GA	6.01**	1.24	0.07	1.32	20.78*	10.56	−1.77	9.93
CS (2001)	−9.74	−3.50	−12.69	−14.68	4.59*	2.23	−0.21	7.11
RMC	15.00*	8.59	22.97*	10.37	13.63*	5.51	17.57*	23.08
60-Day option								
VRP	−10.17	4.42	19.05*	6.71	−2.44	1.01	9.39*	14.26
SMIRK	−9.36	1.94	−6.60	−3.86	−12.99	−2.22	5.93*	11.63
TAIL	−13.17	3.02	−5.09	−4.72	−16.75	−0.93	5.00***	8.78
VRP-SMIRK	1.30**	2.85	20.90*	12.04	7.79*	3.07	8.17*	8.39
VRP-TAIL	−4.30	3.79	22.56*	12.25	1.33*	1.51	13.01*	13.20
VRP-SMIRK + SMIRK	−12.70	3.34	19.90*	6.43	−11.70	−0.66	13.69*	15.41
VRP-TAIL + TAIL	−14.08	3.53	18.27*	7.98	−15.60	−0.82	8.29**	14.19
GA	5.04**	1.34	−0.89	1.47	23.19*	11.23	−1.69	7.63
CS (2001)	−7.15	−2.60	−9.96	−12.36	5.23*	2.50	−0.62	3.60
RMC	12.82*	8.20	15.09*	8.29	14.67*	6.15	19.20*	22.32
90-Day option								
VRP	−9.49	4.32	19.49*	6.66	−3.20	1.22	9.54*	13.78
SMIRK	−8.66	2.00	−6.22	−2.91	−14.31	−2.23	6.08*	11.04
TAIL	−12.37	3.11	−4.84	−4.89	−18.34	−0.84	5.09***	7.87
VRP-SMIRK	1.48**	2.72	20.62*	11.85	7.39*	3.26	11.15*	9.00
VRP-TAIL	−3.36	3.69	22.42*	12.31	0.85*	1.76	13.34*	13.19
VRP-SMIRK + SMIRK	−11.86	3.29	19.70*	6.66	−12.62	−0.37	14.04*	14.76
VRP-TAIL + TAIL	−13.27	3.51	17.34*	7.42	−17.24	−0.72	8.54**	13.62
GA	4.02**	1.41	−1.52	1.83	25.02*	11.63	−1.56	5.83
CS (2001)	−5.59	−2.03	−8.43	−10.70	5.62*	2.55	−0.91	1.28
RMC	12.70*	7.94	18.82*	12.89	11.46*	5.91	20.52*	22.03

Notes: In this table, we report the results of option return forecast before and after the financial crisis. We follow Dick-Nielsen et al. (2012) and Subrahmanyam et al. (2012) to use July 2007 as the starting point of financial crisis. The prediction horizon is one quarter. We report the results of univariate predictive regression, bivariate predictive regression, and regressed combination forecast. For regressed combination forecast, we report the results of regressed mean combination (RMC) using all predictors. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.
Abbreviations: CS, Coval and Shumay; GA, grouped average; VRP, variance risk premium.

empirical test. VolP is the difference between 30-day realized volatility and 30-day ATM implied volatility. The realized volatility is measured by the square root of realized variance, while 30-day ATM implied volatility is measured by VIX. Goyal and Saretto (2009) find that the returns of stock portfolios constructed using this measure are both economically and statistically significant. Similarly, we also run the regression of VolP on SMIRK and TAIL and use their residuals in the forecast.

Table 9 reports the results when we use the VIX, BKMV, VolP, and its regression residuals on SMIRK or TAIL variables as a proxy for the aggregate volatility risk. We find that both the VolP and its residual have similar performances to VRP. They are both statistically and economically significant for the prediction of call and put option returns.

The VIX and BKMV, nevertheless, are only significant for put option returns. They do not provide useful information for the prediction of call option returns. The different performances of VIX and BKMV on the prediction of call and put option returns again show the different patterns of calls and puts. Since the use of VIX or BKMV as a measure of volatility risk is based on the assumption of linear relationship between VolP and volatility level, this finding also suggests that these linear stochastic volatility models might be misspecified in the pricing of call options. These models could be extended by considering a time-varying risk price, or a nonlinear function form of VolP as discussed in Pan (2002), to better capture the call option return dynamics.

The behavior of option return is quite different between crisis and noncrisis period. An interesting question is to test the performance of these predictors during these two periods. We follow Dick-Nielsen, Feldhütter, and Lando (2012) and Subrahmanyam, Jankowitsch, and Friewald (2012) to use July 2007 as the starting point of financial crisis. We separate data sample into two periods: from January 2002 to June 2007 and from July 2007 to December 2011.

Table 10 reports the results of option return forecast during these two subperiods. The up, middle, and down panels report the results of 30-, 60-, and 90-day ATM options, respectively. We find that the aggregate volatility and jump risk predictors have better forecasting performance during the second subperiod that includes the financial crisis period. For example, using VRP as the predictor to forecast 30-day call option returns generates an out-of-sample R^2 of 17.90% and a utility gain of 6.32% during the second subperiod, while they are only −7.83% and 4.61%, respectively, during the first subperiod. VRP-SMIRK and VRP-TAIL provide similar results. SMIRK and TAIL keep insignificant during both subperiods for calls, suggesting that they do not help call option returns under both economic conditions. It is also interesting to observe that jump risk predictors are only significant for puts during the second subperiod, which suggests that jump risk is a more important component of option risk premium when the market is turbulent (Table 11).

On the other hand, the forecast by GA performs better during the first subperiod than the second subperiod. When the crisis comes, the historical grouped mean does not contain much useful information any longer because of structure break. The results by RMC also show that option returns are more predictable during the second subperiod. Overall, the higher predictability of option returns during the second subperiod is consistent with the literature that asset returns are more predictable during the recession periods.

We next investigate the impact of forecast constraint on the forecast performance. We use $[-7\%, 10\%]$ to constrain the forecast in the above empirical analysis. It is a concern that forecast performance might be sensitive to the choice of

TABLE 11 Robustness check of regressed combination forecast using different forecast constraints

		$[-6\%, 9\%]$		$[-6\%, 10\%]$		$[-7\%, 9\%]$		$[-8\%, 8\%]$	
Option	**Model**	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)	R^2_{OS} (%)	ΔU (%)
30-Day option									
Call	RMC	16.97*	9.10	18.73*	9.18	18.61*	9.32	16.24*	9.32
	RWC	20.03*	9.20	20.03*	9.20	17.97*	9.20	16.33*	9.15
Put	RMC	16.85*	13.40	16.67*	13.42	16.85*	13.40	16.21*	13.30
	RWC	16.17*	13.29	16.01*	13.31	16.17*	13.29	15.57*	13.20
60-Day option									
Call	RMC	15.19*	8.05	15.19*	8.05	14.36*	8.26	14.36*	8.26
	RWC	16.63*	8.04	18.55*	8.04	14.44*	8.04	14.44*	8.04
Put	RMC	18.00*	13.36	18.11*	13.39	18.00*	13.36	17.23*	13.17
	RWC	17.14*	13.18	17.41*	13.18	17.14*	13.18	17.94*	13.20
90-Day option									
Call	RMC	19.29*	10.23	19.29*	10.23	16.87*	10.16	16.87*	10.16
	RWC	18.96*	9.93	18.96*	9.93	16.85*	9.87	16.85*	9.87
Put	RMC	18.50*	13.04	18.33*	13.08	18.50*	13.04	17.74*	12.89
	RWC	17.63*	12.83	17.63*	12.83	17.63*	12.83	17.77*	12.80

Notes: In this table, we report the robust results of regressed combination forecast using different forecast constraints. If the regressed combination forecast is not within this interval, then it is replaced with the combination forecast. We use all variables in the forecast, and then use mean and weighted mean to calculate the combination forecast. They are further used to calculate the regressed mean combination forecast (RMC) and regressed weighted-mean combination forecast (RWC), respectively. The out-of-sample forecast starts from 2002. The significance of R^2_{OS} is calculated from MSPE-adjusted statistic following Clark and West (2007). We use Hodrick (1992) to calculate the standard errors that are robust for the data overlapping. *, **, and *** denote the significance level of 1%, 5%, and 10%, respectively.

Abbreviation: MSPE, mean-squared prediction error.

forecast constraint. Table 10 reports the results of regressed combination forecast using different constraints.[14] If the regressed combination forecast is not within this interval then it is replaced with the combination forecast. We use all variables in the forecast, and then use mean and weighted mean to calculate the combination forecast. They are further used to calculate the RMC forecast and RWC forecast, respectively. The results clearly indicate that the performance of regressed combination forecast is robust to the choice of forecast constraint.

5 | CONCLUSION

In this paper, we conduct a comprehensive study on the time-series predictability of option returns by volatility and risk predictors. We consider one measure of aggregate volatility risk, VRP, and two measures of aggregate jump risk predictors, SMIRK, and TAIL. We find a different result between call and put option returns. The measure of volatility risk, VRP, provides an important role in the forecast of both call and put option returns. In contrast, the aggregate jump risk predictor is only significant for puts. The results are robust across option series, forecast horizon, and model specification. The different performances of aggregate jump predictor on the prediction of call and put option returns reflect the asymmetry property of S&P 500 index.

The empirical results suggest that there is option risk premium associated with volatility and jump risk. Call and put options share similarity on their volatility risk component, while they are different on jump risk component. Separate risk component between calls and puts might help explain the different patterns of call and put options documented in the literature.

We find that the combination and the regressed combination forecast also provide stable and significant results for options. The aggregate volatility and jump risk predictors have information contents that are not included in the other predictors used in the stock return forecast. Subperiod analysis suggests that option returns are more predictable during the crisis period.

We also find that the volatility risk predictors of VIX and BKMV have different performances on the prediction of call and put option returns. They keep significant in the put option return forecast, while they lose predictive power for calls.

Our empirical results have interesting implications for future research. The asymmetry property of underlying assets suggests that different models might be necessary when we price calls and puts. Varying performance of VIX and BKMV on calls and puts implies that the linear relationship between VolP and volatility level might be misspecified for the call option pricing. Possibly extension include the consideration of a time-varying risk price or a nonlinear relationship. It will be of great interest to explore these issues in future research.

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DATA AVAILABILITY STATEMENT

The index option data are from the OptionMetrics, and the 5-min high-frequency data of S&P 500 index are from the SIRCA Thomson Reuters Tick History and are available with their permission. Restrictions apply to the availability of these data, which were used under license for this study. Other data that support the findings of this study are openly available.

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[14]The results of other forecast are similar and available upon request.

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