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The Information Contents of VIX Index and Range-based Volatility on Volatility Forecasting Performance of S&P 500

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Abstract

In this paper, we investigate the information contents of S&P 500 VIX index and range-based volatilities by comparing their benefits on the GJR-based volatility forecasting performance. To reveal the statistical significance and ensure obtaining robust results, we employ Hansen's SPA test (2005) to examine the forecasting performances of GJR and GJR-X models for the S&P500 stock index. The results indicate that combining VIX and range-based volatilities into GARCH-type model can both enhance the one-step-ahead volatility forecasts while evaluating with different kinds of loss functions. Moreover, regardless of under-prediction, GJR-VIX model appears to be the most preferred, which implies that VIX index has better information content for improving volatility forecasting performance.

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1. Introduction

Volatility forecasting appears to be ongoing because of its broad applications in financial areas such as derivative products pricing, risk evaluation and hedging, portfolio allocation, and the derivation of value-at-risk measures. Among the literature about model-based volatility forecasting, GARCH-type models tend to be popular selections due to its success in capturing the dynamics nature of volatility. Even if some researches (Andersen et al., 2003; Koopman et al., 2005) showed that volatility forecasts generated by GARCH-type models are outperformed by using some time series methods based on realized volatility, we can still easily find that GARCH-type models are being implemented in empirical researches. Thus, it is meaningful to explore how to improve GARCH-based volatility forecasting.

A common manner to enhance forecasting ability of GARCH-based models is to add additional information by incorporating some weakly exogenous variables (e.g. implied volatility, realized volatility, range-based volatility[1] and trading volume etc.) in the variance equation. Blair et al. (2001) and Koopman et al. (2005) found that there is a considerable improvement in the volatility forecasting by incorporating realized volatility and VIX (implied volatility index) as an explanatory variable in the variance equation of a daily GARCH model. Similarly, Andersen et al. (1999) also observed a substantial improvement in the out-of-sample forecasting performance of the GARCH model. Martens (2001) then compared both GARCH-based methods for two exchanges rates. He found that the most accurate intraday GARCH model, which proved to be the model with highest sampling frequency, could not outperform the daily GARCH model extended with intraday volatility. These studies therefore indicate that intraday return series contain incremental information for longer-run volatility forecasts when used in combination with GARCH models. Moreover, the empirical result of Vipul and Jacob (2007) indicated that the performance of GJR-GARCH-based volatility forecasts can be improved by including range-based estimators.

In this paper, we investigate the information contents of S&P 500 VIX index and range-based volatilities by comparing their benefits on the GJR-based volatility forecasting performance. The range-based volatilities include volatility estimators of Parkinson (1980) (hereafter PK), Garman and Klass (1980) (hereafter GK) and Rogers and Satchell (1991) (hereafter RS). As indicated by previous studies, both range-based estimators and VIX can provide additional information for making one-day-ahead volatility prediction, and therefore lead to crucial improvements of forecasting performance. Not surprisingly, the derivative products (i.e. index options)

[1] Volatility estimators based on price range includes Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991), and Yang and Zhang (2000).

do not exist in every financial market. Thus VIX data are not always available for every stock index. For the range-based volatilities, they can be easily computed by using daily ranges data (open, high, low and close prices) that are effortlessly observed from the market. It should be worth to mention that these two variables have different features relative to one another. While range-based volatilities are calculated by taking all trade information into account, they might lead to an improvement of the volatility estimates rather than the return-based volatilities when incorporating into the GARCH-type models. The implied volatility index is calculated based on a highly liquid options market, and is a key measure of market expectations of near-term volatility conveyed by stock index option prices. Moreover, VIX has been considered by many to be the world's premier barometer of investor sentiment and market volatility.

To reveal the statistical significance, the Superior Predictive Ability (SPA) test of Hansen (2005) is adopted to examine which variables can deliver better benefits to GARCH-based volatility forecasting. If GARCH-type models incorporated with daily range-based volatilities are not significantly outperformed by those with implied volatility, then there exists reasons for us to adopt range-based volatilities to improve GARCH-type-based volatility forecasts when implied volatility are not available. For the research objective, we employ several loss functions to empirically examine the one-step-ahead forecasting performances for the S&P500 stock index.

The remainder of this study is organized as follows. Section 2 outlines the methodology, including GJR-GARCH-based forecasting model and evaluation methods. Data description and main findings are reported in section 3. Finally, summary and conclusion are presented in the last section.

2. Methodology

2.1 GJR-GARCH model

Let p_t denote the stock index and the compounded daily stock return can be computed as $r_t = \log(p_t / p_{t-1}) \times 100$. The conditional mean equation[2] of GJR-GARCH models we adopt in this paper is formulated as follows:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = h_t^{0.5} z_t, \quad z_t \mid \Omega_{t-1} \overset{iid}{\sim} N(0,1) \tag{1}$$

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i \; I_{\{\varepsilon_{t-i} < 0\}}) \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{2}$$

[2] The empirical result of Awartani and Corradi (2005) indicated that the performance rankings of GARCH-type models will be consistent under different specifications of mean equation. While returns series are not auto-correlated, we do not make additional specification for mean equation.

where $\Omega_{t-1} = \{r_{t-1}, r_{t-2}, \ldots, r_1\}$ is the information set and ε_t denotes the innovation process, while N(0,1) is a density function with a mean of zero and a unit variance. Based on the rule of parsimonious principle, the lag length parameters of these conditional variance equation are set by p = 1 and q = 1 in our study. It is well known that GJR-GARCH model is a popular GARCH-type model, which is often employed to deal with the observed leverage effect. When γ_i takes a positive (negative) value, it is clear that from GJR-GARCH model that a negative ε_{t-i} value has a larger (smaller) impact on h_t.

This study examines the benefits of combining the range-based estimators and implied volatility index (VIX) with GARCH-type model on the lines of the approaches of Day and Lewis (1992). This is done by including the variance estimated by PK, GK, and RS estimators and also VIX as exogenous variables in the variance equation (2) of GJR-GARCH model (hereafter GJR-PK, GJR-GK, GJR-RS and GJR-VIX models, and we use GJR-X to denote this type of model), as follows:

$$\sigma_t^2 = \omega + (\alpha_1 + \gamma_1 \ I_{\{\varepsilon_{t-1}<0\}})\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \delta_1\hat{\sigma}_{X,t-1}^2 \tag{3}$$

where $\hat{\sigma}_{X,t-1}^2$ (X = PK, GK, RS and VIX) is respectively the mentioned-above volatility estimated for the trading period t-1. The significance of δ_1 would indicate if any of these variables, taken one at a time, contains some additional information for forecasting the conditional volatility. The likelihood ratio of the restricted model (2) to the unrestricted model (3) is used to test the significance of information content of the range-based estimators and implied volatility index.

In the following, we give a brief description of these range-based estimators. They are Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991). These three estimators are all developed under the assumption that the stock price follows a geometric Brownian motion, but with slight differences. Rogers and Satchell estimators allows a nonzero drift in the continuous path, but the drifts of Parkinson and Garman and Klass estimators assume a driftless price process. Parkinson (PK estimator) uses the scaled high-low range values for the variance and the PK estimator is given below:

$$\hat{\sigma}_{PK,t}^2 = \frac{(H_t - L_t)^2}{4\ln 2} \tag{4}$$

where H_t and L_t denote the log-transformed highest and lowest prices on the trading day t. Specially for less-liquid or non-continuous trading securities, the PK estimator calculated from observed high-low values at day t produces a downward bias.

Garman and Klass (1980) improved the Parkinson's approach by using the opening and closing prices in addition to the high and low prices. They made the same assumptions as those of the PK estimator. Their estimator (GK estimator) is

$$\hat{\sigma}^2_{GK,t} = 0.511(H_t - L_t)^2 - 0.019\{(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)\}$$
$$-0.383(C_t - O_t)^2 \qquad (5)$$

where O_t and C_t are the log-transformed opening and closing prices of day t. It makes use of the squared range, which subtracted the squared open-to-close return, to adjust the drift. The process makes the GK estimator to become less biased.

Both of the Parkinson and the Garman and Klass estimator are proposed under the assumption that the drifts follow driftless processes. Rogers and Satchell (1991) release the restriction and develop an estimator that allows a nonzero drift term. Their estimator (RS estimator) is defined as

$$\hat{\sigma}^2_{RS,t} = (H_t - C_t)(H_t - O_t) + (L_t - C_t)(L_t - O_t) \qquad (6)$$

when the security price has a drift, the RS is claimed to be more efficient than PK and GK estimators.

2.2 Evaluation of volatility forecast performance

2.2.1 Symmetric Loss Function

The forecasting performance of competing models is evaluated using the mean squared error (MSE) and mean absolute error (MAE), defined as follows:

$$MSE = T^{-1}\sum_{t=1}^{T}\left(\hat{\sigma}^2_{true} - \hat{h}_{k,t}\right)^2 \qquad (7)$$

$$MAE = T^{-1}\sum_{t=1}^{T}\left|\hat{\sigma}^2_{true} - \hat{h}_{k,t}\right| \qquad (8)$$

where $\hat{\sigma}^2_{true}$ and $\hat{h}_{k,t}$ respectively denote the true volatility proxy[3] and the forecasted variance produced by model k at day t. The MSE criterion gives relatively more weight to forecast errors than MAE does. For the application of estimating market risk, such as value-at-risk, one who cares more about accurate forecasting of high volatility rather than low volatility may adopt MSE to reflect his (her) own concerns.

[3] In this paper we adopt daily PK estimator as the true volatility proxy, which is also used by Christoffersen (2003) and Sadorsky and Mckenzie (2008).

2.2.2 Asymmetric Loss Function

Following Pagan and Schwert (1990) and Brailsford and Faff (1996), the second research objective also utilizes mean mixed error statistics which account for potential asymmetry in the loss function. The mean mixed error statistics which penalize under-predictions (MME(U))[4] and over-predictions (MME(O)) of volatility more heavily are as follows:

$$\mathrm{MME(U)} = T^{-1}\left[\sum_{t=1}^{O}\left|\hat{\sigma}_t^2 - \hat{h}_{k,t}\right| + \sum_{t=1}^{U}\sqrt{\left|\hat{\sigma}_t^2 - \hat{h}_{k,t}\right|}\right] \tag{9}$$

$$\mathrm{MME(O)} = T^{-1}\left[\sum_{t=1}^{O}\sqrt{\left|\hat{\sigma}_t^2 - \hat{h}_{k,t}\right|} + \sum_{t=1}^{U}\left|\hat{\sigma}_t^2 - \hat{h}_{k,t}\right|\right] \tag{10}$$

where U (O) is the number of under-(over)-predictions, while T ($= U + O$) denotes the number of forecast data points. The aforesaid asymmetric loss functions are important for traders with long and short positions as well as option buyers and sellers. As mentioned by Brailsford and Faff (1996), an under-prediction of stock price volatility will lead to a downward bias to estimates of the call option price. As such, a seller will pay more attention to the under-estimate of the underlying volatility than a buyer, while the reverse is true of over-prediction cases. To the best of our knowledge, little previous studies employed asymmetric loss functions in evaluating out-of-sample volatility forecasting performance (McMillan et al., 2000; Balaban, 2004).

2.2.3 VaR-based Loss function

To analyze the improving degree of forecasting performance from risk management perspective, we employ VaR (Value-at-Risk) application as an alternative loss function. Following González-Rivera et al. (2004), the VaR-based error (VaRE) measurement

$$\mathrm{VaRE} = T^{-1}\sum_{t=1}^{T}\left(\alpha - m_\delta(r_{t+1}, \mathrm{VaR}_{t+1}^{\alpha})\right)\left(r_{t+1} - \mathrm{VaR}_{t+1}^{\alpha}\right) \tag{11}$$

where $\mathrm{VaR}_{t+1}^{\alpha} = \mu_{t+1} + \Phi^{-1}(\alpha)\sigma_{t+1}$ and $m_\delta(a,b) = \{1 + \exp[\delta(a-b)]\}^{-1}$. Note that $\Phi(\cdot)$ is the cumulative distribution (in this paper we consider normal case and the case of $\alpha = 95\%$ confidence level) of standardized return. $m_\delta(a,b) = 1 - m_\delta(b,a)$, and the parameter $\delta > 0$ controls the smoothness. We consider many values of δ and only report the result for $\delta = 25$.

[4] Notably, as the absolute values of forecast errors are less than unity, taking their square root will place a heavier weighting on the under-predictions. If the absolute value of all forecast errors were greater than unity, the MME(U) would need to square the errors in order to achieve the desired penalty (Brailsford and Faff, 1996).

2.2.4 Superior Predictive Ability Test

Recent work has focused on a testing framework for determining whether a particular model is outperformed by another model. A further development of the White's reality check test (White, 2000) is known as the superior predictive ability (SPA) test and is proposed by Hansen (2005) where it is also shown that SPA has good power properties and is robust.

Consider l+1 different models M_k for k = 0,1,…,l and which are discussed in previous section. M_0 is the benchmark model and the null hypothesis is that none of the models k = 1,2,…,l outperforms the benchmark in terms of the specific loss function chosen. For each model M_k, we generate n volatility forecast $\hat{h}_{k,t}$ for t = 1,2,…,n. For every forecast, we generate the loss function $L_{k,t}$ describing as follows. Let $L_{k,t} \equiv L(\hat{\sigma}_t^2, \hat{h}_{k,t})$ denote the loss if one makes the prediction $\hat{h}_{k,t}$ with k-th model when the true volatility turns out to be $\hat{\sigma}_t^2$. The performance of model k relative to the benchmark model (at time t), can be defined as:

$$f_{k,t} = L_{0,t} - L_{k,t} \quad \text{for } k = 1,2,\ldots,l\ ;\ t = 1,2,\ldots,n \tag{12}$$

Assuming stationarity for $f_{k,t}$, we can define the expected relative performance of model k relative to the benchmark as $\mu_k = E[f_{k,t}]$ for k=1,2,…,l. If model w outperforms the benchmark, then the value of μ_w will be positive. Therefore, we can analyze whether any of the competing models significantly outperform the benchmark, testing the null hypothesis that $\mu_k \le 0$, for k=1,2,…,l. Consequently, the null hypothesis that none of models is better than the benchmark (i.e. no predictive superiority over the benchmark itself) can be formulated as:

$$H_0:\ \mu_{max} \equiv \max_{k=1,\cdots,l} \mu_k \le 0 \tag{13}$$

The associate test statistic proposed by Hansen (2005) is given by

$$T = \max_{k=1,\ldots,l} \frac{\sqrt{n}\,\bar{f}_k}{\hat{\omega}_{kk}} \tag{14}$$

with $\hat{\omega}_{kk}^2$ as a consistent estimate of ω_{kk}^2, and where $\bar{f}_k = n^{-1}\sum_{t=1}^{n} f_{k,t}$, $\omega_{kk}^2 = \lim_{N\to\infty} \text{var}(\sqrt{n}\,\bar{f}_k)$. A consistent estimator of ω_{kk} and *p*-value of test statistic T can be obtained via a stationary bootstrap procedure of Politis and Romano (1994). More details of this procedure are detailed in Hansen (2005) and Hansen and Lunde (2005).

3. Empirical results

3.1 Data description

The data for this study consists of S&P500 stock index daily opening, closing, high and low prices during the period from January 2, 2001 to December 31, 2007, which constitutes a total of 1758 observations. The daily data is retrieved from the database of Yahoo Finance website (http://finance.yahoo.com/). The VIX[5] data used in this paper are downloaded from the CBOE (Chicago Board Option Exchange) one-line database. For the research objective, the whole data period is divided into estimation and forecasted periods. The observations of estimation period are 1250, and the forecasting performance of GJR-X models for the last 500 days of the data set is the focus of our out-of-sample evaluation and comparison.

Preliminary analysis of daily returns of S&P500 for the whole sample period is reported in Table 1. From panel A, the average daily returns are positive and very small compared with the variable’s standard deviation. The returns series is skewed towards the right, while the returns series is characterized by a distribution with tails that are significantly thicker than for a normal distribution. J-B test statistic further confirms that the daily return is non-normal distributed. Moreover, the Q^2 and LM-test statistics display linear dependence of squared returns and strong ARCH effects. Accordingly, these preliminary analyses of the data encourage the adoption of a sophisticated distribution, which embody fat-tailed features, and of conditional models to allow for time-varying volatility. Panel B of Table 1 reports the Phillips and Perron (1988) (PP) unit root tests and KPSS (Kwiatkowski et al., 1992) unit root tests. The test results indicate no evidence of non-stationarity in the S&P500 returns serie. Finally, the test statistic of Engle and Ng (1993) indicates that returns volatility exhibits asymmetric behavior which supports us to adopt GJR-GARCH specification for capturing the dynamics of volatility process.

Table 1 Preliminary analysis of S&P 500 daily returns

Panel A. Summary statistics

Mean %	Std. Dev.	Skewness	Kurtosis	J-B	$Q^2(12)$	LM(12)
0.007	1.066	0.082	5.714*	539.155*	1070.010*	364.090*

Panel B. Unit root tests

PP	Bandwidth	KPSS	Bandwidth
-44.015*	0	0.054	0

[5] We choose new methodology for VIX data, and the calculation procedure of VIX can be referred to the CBOE website.

Panel C. Engle & Ng test for asymmetric volatility	
Test statistic (~ χ^2 (3))	26.937*

Notes: 1. * denotes significantly at the 1% level. 2. J-B represents the statistics of Jarque amd Bera (1987)'s normal distribution test. 3. $Q^2(12)$ denotes the Ljung-Box Q test for 12th order serial correlation of the squared returns. 4. LM test also examines for autocorrelation of the squared returns. 5. PP and KPSS are the test statistics for stationarity of return series. The PP-test rejects the null hypothesis of non-stationarity if the test statistic is negative and the absolute value of the test statistic exceeds the critical value of the respective significance level: 1%: -3.969; 5%: -3.415; 10%: -3.130. The KPSS-test rejects the null hypothesis of stationarity if the test statistic exceeds the critical value of the respective significance level: 1%: 0.739; 5%: 0.463; 10%: 0.347.

3.2 Model Estimates

In this study, the parameters are estimated by quasi maximum likelihood estimation (QMLE) in terms of the BFGS optimization algorithm using the econometric package of WinRATS 7.1 model estimates and diagnostic tests for S&P500 returns during the in-sample period are provided in Table 2.

As shown in Table 2, the parameters in the conditional variance equation of GJR model are all positive and found to be highly significant. The coefficients δ_1 of all models are significant and indicate that these exogenous variables are helpful to explain the conditional variance. As indicated by Akaike information criterion (AIC), the in-sample fit of GJR-PK is highest among these models. Diagnostics of the standardized residuals of these GJR and GJR-X models confirm that the GJR(1,1) specification is sufficient to correct the serial correlation of the S&P500 return series in the conditional variance equation.

Table 2 Estimates of GJR and GJR-X models with alternative exogenous variables

Parameter	GJR	GJR-VIX	GJR-PK	GJR-GK	GJR-RS
μ	-0.040 ^{a}	-0.022	-0.017	-0.024	-0.020
	[0.021]	[0.023]	[0.023]	[0.022]	[0.020]
ω	0.101 ^{c}	-0.190 ^{c}	0.010	0.011 ^{c}	0.013 ^{b}
	[0.002]	[0.006]	[0.006]	[0.003]	[0.006]
α_1	0.035 ^{c}	-0.028	-0.163 ^{c}	-0.166 ^{c}	-0.070 ^{c}
	[0.007]	[0.017]	[0.005]	[0.005]	[0.015]
β_1	0.772 ^{c}	0.716 ^{c}	0.828 ^{c}	0.829 ^{c}	0.802 ^{c}
	[0.007]	[0.013]	[0.018]	[0.005]	[0.032]
γ_1	0.234 ^{c}	0.192 ^{c}	0.122 ^{c}	0.122 ^{c}	0.131 ^{c}
	[0.020]	[0.031]	[0.024]	[0.014]	[0.031]
δ_1		0.021 ^{c}	0.357 ^{c}	0.360 ^{c}	0.300 ^{c}
		[0.000]	[0.007]	[0.007]	[0.042]
Q(12)	11.607	11.218	15.613	14.589	14.635
$Q^2(12)$	14.824	18.491	17.810	17.542	15.486
LL	-1794.903	-1732.871	-1724.974	-1735.516	-1729.919
AIC	3599.806	3475.742	3466.418	3481.032	3469.838

Notes: 1. Standard errors for the estimators are included in parentheses. 2. a, b and c indicate significantly at the 10%, 5% and 1% level, respectively. 3. Q(12) and $Q^2(12)$ are the Ljung-Box Q test for serial correlation in the standardized residuals and squared standardized residuals with 12 lags. 5. LL refers to the log-likelihood value. 6. The Akaike information criterion (AIC) is calculated as -2LL+2p where p is the number of coefficients that is estimated.

3.3 SPA test results of alternative loss functions

The volatility forecasting results of alternative loss function values and the *p-values* of SPA test for GJR and GJR-X models are presented in Table 3. As can be seen, the GJR-VIX model has lowest function values for symmetric (MSE and MAE), asymmetric (MME(O)[6]) and also VaR-based loss functions, which indicate that GJR model incorporated with implied volatility index (VIX) can better improve volatility forecasts while evaluating with these loss functions. In other words, implied volatility index provides more information than range-based estimators in volatility forecasting.

However, when a particular loss function is smaller for model A than for model B, we can not clearly conclude that the forecasting performance of model A is superior to that of model B. Such a conclusion cannot be made on the basis of just one criterion and just one sample. For this reason, we present a multiple comparison of the benchmark model with all of the remaining models by employing SPA test of Hansen (2005). The *p-values* of SPA test are computed by using the stationary bootstrap of Politics and Romano (1994) generating 10000 bootstrap re-samples with smoothing parameter q = 0.5. The null hypothesis is that the best of the competing models is no better than the benchmark. As reported in Table 3, the GJR model is dominated by competing models (GJR-X models) for most loss functions, which means that the range-based estimators and VIX can both significantly improve GARCH-type models in one-step-ahead volatility forecasts. This is consistent with the findings of Day and Lewis (1992), Blair et al. (2001), Koopman et al. (2005) and Vipul and Jacob (2007).

Except for the asymmetric loss function MME(U), we find that the GJR-VIX model has largest Hansen's *p-values* (SPA_c and SPA_l) and seems to be the most preferred. Based on the results, we can conclude that GARCH-type model incorporated with VIX can provide significant improvement in the bias and efficiency of one-step-ahead volatility forecasts while evaluating with MAE and MSE criteria. Also, the inference holds from the risk management perspective. To consider the possible effects of over- and under-predictions for different volatility applications, such as buyers and sellers of call and put options, we adopt mean mixed error (MME) to investigate this issue. For the over-prediction case (MME(O)), the conclusion remains the same as MAE, MSE and VaRE. For the under-prediction case (MME(U)), surprisingly, GJR-GK model takes the place of GJR-VIX model and turns out to be the most preferred model though the difference of their function value is small. The result implies that, for a seller, GJR-GK model should be used to calculate the call or

[6] For the sake of achieving the desired penalty, the forecasted volatilities and the true volatility proxy are both divided by 10 to make the forecast errors less than unity.

put options so as to generate reasonable profit.

Table 3 SPA test results of alternative loss functions

Panel A. Performance based on mean squared error (MSE)						
Benchmark (M_0)	MSE	Rank	SPA_c	Rank	SPA_l	Rank
GJR	0.378	3	0.058	5	0.050	5
GJR-VIX	0.351	1	0.989	1	0.778	1
GJR-PK	0.383	4	0.115	4	0.101	4
GJR-GK	0.374	2	0.184	2	0.108	3
GJR-RS	0.387	5	0.126	3	0.126	2
Panel B. Performance based on mean absolute error (MAE)						
Benchmark	MAE	Rank	SPA_c	Rank	SPA_l	Rank
GJR	0.396	5	0.000	5	0.000	5
GJR-VIX	0.369	1	0.867	1	0.571	1
GJR-PK	0.379	3	0.302	4	0.270	4
GJR-GK	0.374	2	0.552	2	0.345	2
GJR-RS	0.379	3	0.329	3	0.295	3
Panel C. Performance based on mean mixed error (MME)						
Benchmark	MME(O)	Rank	SPA_c	Rank	SPA_l	Rank
GJR	0.142	5	0.000	5	0.000	5
GJR-VIX	0.133	1	0.962	1	0.600	1
GJR-PK	0.137	2	0.197	4	0.173	3
GJR-GK	0.137	2	0.206	3	0.173	3
GJR-RS	0.137	2	0.210	2	0.177	2
	MME(U)	Rank	SPA_c	Rank	SPA_l	Rank
GJR	0.074	5	0.052	5	0.052	5
GJR-VIX	0.072	2	0.490	2	0.350	2
GJR-PK	0.072	2	0.195	4	0.166	4
GJR-GK	0.071	1	0.950	1	0.686	1
GJR-RS	0.072	2	0.350	3	0.267	3
Panel D. Performance based on VaR-based error (VaRE)						
Benchmark	VaRE(O)	Rank	SPA_c	Rank	SPA_l	Rank
GJR	0.157	3	0.082	4	0.065	5
GJR-VIX	0.154	1	0.971	1	0.607	1
GJR-PK	0.158	5	0.068	5	0.068	4
GJR-GK	0.157	3	0.153	3	0.119	3
GJR-RS	0.156	2	0.302	2	0.155	2

4. Conclusions

In this paper, we investigate the information contents of S&P 500 VIX index and range-based volatilities by comparing their benefits on the GJR-based volatility forecasting performance. To extend previous study and widen the implication of volatility forecasts, we not only adopt the symmetric loss functions to evaluate the bias and efficiency problems, but also address the issues for risk management and over-and under-predictions by using VaR-based and asymmetric loss functions. Moreover, to reveal the statistical significance and ensure obtaining robust results, we employ Hansen's SPA test (2005) to empirically examine the one-step-ahead forecasting performances of GJR and GJR-X models for the S&P500 stock index for the last 500 observations of our research period.

The results indicate that combining VIX and range-based estimators into GARCH-type model can both enhance the one-step-ahead volatility forecasts for all considered loss functions, which is consistent with previous studies. Overall, GJR-VIX model appears to be the most preferred, which implies that VIX index has better information content for improving volatility forecasting performance.

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