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Leverage effect, economic policy uncertainty and realized volatility with regime switching

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HIGHLIGHTS

- Investigate the impacts of leverage effect and EPU on future volatility with regime switching.
- The leverage effect and EPU with regimes can achieve higher forecast accuracy.
- Our proposed models outperform HAR-RV-type and GARCH-class models in forecasting volatility.
- Our findings are robust.

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ABSTRACT

In this study, we first investigate the impacts of leverage effect and economic policy uncertainty (EPU) on future volatility in the framework of regime switching. Out-of-sample results show that the HAR-RV including the leverage effect and economic policy uncertainty with regimes can achieve higher forecast accuracy than RV-type and GARCH-class models. Our robustness results further imply that these factors in the framework of regime switching can substantially improve the HAR-RV's forecast performance.

1. Introduction

Volatility plays a central role in asset pricing, hedging, asset allocation and risk measurement. Using the intraday data to model and forecast volatility is always a hot topic in academia and practice fields. Many scholars have found that the high-frequency volatility models outperform GARCH-class models [1–3]. Corsi [4] proposes a simple heterogeneous autoregressive RV (HAR-RV), which can powerfully capture "stylized facts" in financial market volatility such as long memory and multi-scaling behavior. For this reason, it has received much attention in financial econometrics (see, e.g., [5–11]). Considered the above advantages of this model, and inspired by Corsi and Renò [12], Liu and Zhang [13], Liu et al. [14]

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and Ma et al. [15,16], we use the HAR-RV model as our benchmark model to investigate the impacts of leverage effect and economic policy uncertainty (EPU) on future volatility and further combine the switching regime model to explore whether those improvements can increase the models forecasting performance.

To the best of our knowledge, some studies [12–14] have related to our research, but those works are all based on the framework of the linear models. Goldman et al. [17], Raggi and Bordignon [18], Ma et al. [15,16] and Wang et al. [19] have evidenced that high level of persistence when volatility is low, implying the presence of nonlinearities. Moreover, due to many factors such as business cycle, major events and economic policy, the statistical property of volatility (e.g., volatility persistence) always undergoes structural breaks or switches between different regimes. Therefore, in this study, we fill the gap to first investigate the effects of leverage effect and EPU on future realized volatility in the framework of the regime switching.

Out-of-sample results show that the HAR-RV model including the leverage effect and EPU and combining the regimes significantly outperform other RV-type and GARCH-class models. Furthermore, we use the RK to replace RV as the dependent variable and find that add the leverage effect and EPU to HAR-RK model with regime switching also have better performance than other RK-type and GARCH-class models'. Our findings are very helpful to the researchers, market participants, and policymakers to make their decisions.

The remainder of the paper is organized as follows. The next section introduces the volatility models, for example, HAR-RV and extended models. Section 3 describes the empirical data. In-sample estimation, out-of-sample evaluation, and robustness check are discussed in Section 4. Section 5 provides the conclusions.

2. Methodology

2.1. Realized volatility

In this study, we use the intraday returns of the S&P 500 and construct the daily realized variance (RV). RV is proposed by Andersen and Bollerslev [20]. For a given day t, we divide the time interval [0, 1] into n subintervals of length, where $M = 1/\Delta$ and Δ is the sampling frequency. Consequently, the realized volatility or variance[1] (RV) can be defined as the sum of all available intraday high-frequency squared returns and defined as:

$$\mathrm{RV}_t = \sum_{j=1}^{1/\Delta} r_{t,j}^2. \tag{1}$$

where $r_{t,j}$ represents the day t of jth intraday return. Based on the theory of Barndorff-Nielsen and Shephard [21], RV can be satisfied as when $\Delta \to 0$:

$$\mathrm{RV}_t \to \int_0^t \sigma^2(s)ds + \sum_{0<s\leq t} \kappa^2(s). \tag{2}$$

where $\int_0^t \sigma^2(s)ds$ is the continuous component. When $\Delta \to 0$, this part is approximately equal to the realized bi-power variation (BPV). BPV can be calculated by:

$$\mathrm{BPV}_t = u_1^{-2} \sum_{j=2}^{1/\Delta} \left|r_{t,j}\right| \left|r_{t,j-1}\right|. \tag{3}$$

where $u_1 \sim 0.7979$. $\sum_{0<s\leq t} \kappa^2(s)$ is the discontinuous part of the quadratic variation process, which is the jump component.

2.2. HAR-RV and its extended models

In this research, we use an attractive high-frequency model to predict volatility, the heterogeneous autoregressive model of realized volatility (HAR-RV) proposed by Corsi [4]. The standard HAR-RV model contains only three independent variables: the one-day (RV_t), one-week (RVW_t) and one-month (RVM_t) lagged averaged realized variances. The model is,

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \varepsilon_{t+1}. \tag{4}$$

We consider another popular extended model, which include the "leverage effect" that volatility is correlated with lagged negative returns, named the LHAR-RV,

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_d r_t^- + \gamma_w rw_t^- + \gamma_m rm_t^- + \varepsilon_{t+1}. \tag{5}$$

which $r_t^- = r_t I(r_t < 0)$, rw_t^- and rm_t^- are the average weekly and monthly negative daily returns, respectively.

[1] We will use the terms realized volatility and realized variation (variance) interchangeably, which is similar to the work of Andersen et al. [5].

Table 1
Typology of the empirical specifications used in the paper.

Model number	Model name	Reference	Eq. number in this paper
M0	HAR-RV	Corsi [4] Eq. (6)	Eq. (4)
M1	LHAR-RV		Eq. (5)
M2	HAR-RV-EPU		Eq. (6)
M3	LHAR-RV-EPU		Eq. (7)
M4	MS-HAR-RV-J		Eq. (9)
M5	MS-LHAR-RV	New specification in this paper	Eq. (9)
M6	MS-HAR-RV-EPU		Eq. (10)
M7	MS-LHAR-RV-EPU		Eq. (11)

To investigate the impact of the EPU on future volatility, we add the EPU as an additional explanatory variable to the HAR-RV and LHAR-RV and construct two new models, HAR-RV-EPU and LHAR-RV-EPU,

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + +\gamma EPU_t + \varepsilon_{t+1}. \tag{6}$$

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_d r_t^- + \gamma_w rw_t^- + \gamma_m rm_t^- + \gamma EPU_t + \varepsilon_{t+1}. \tag{7}$$

2.3. Regime switching models

Furthermore, we extend these abovementioned models by considering regime changes in parameters due to government policy and structural breaks. We consider the two high and low regimes, following by Goldman et al. [17], Ma et al. [15] and Wang et al. [19]. To save space, we only take the HAR-RV model as an example, constructing the MS-HAR-RV, which formulation is as below,

$$RV_{t+1} = c_{s_t} + \beta_{d,s_t} RV_t + \beta_w RVW_t + \beta_m RVM_t + \omega_{t+1}, \;\; \omega_{t+1} \sim (0, \sigma_{s_{t+1}}) \tag{8}$$

where the S_{t+1} is an unobserved state dummy variable. When S_t is equal to 0, which indicate a low volatility regime with small conditional variance, meaning that the market is the stable and normal volatility state. Whereas, label 1 indicates high and fluctuating volatility. The unobserved state variable, S_t, is assumed to follow a two-state Markov process with a transition probability matrix given by,

$$P = \begin{bmatrix} p^{00} & 1 - p^{00} \\ 1 - p^{11} & p^{11} \end{bmatrix}, \tag{9}$$

where,

$$p^{00} = p(s_t = 0 | s_{t-1} = 0), \tag{10}$$

$$p^{11} = p(s_t = 1 | s_{t-1} = 1). \tag{11}$$

The MS-HAR-RRV model can be estimated by maximum likelihood using the filtering procedure of Hamilton [22] followed by the smoothing algorithm of Kim [23].[2] The log likelihood of this model is given by:

$$\ln L = \sum_{t=1}^{T} \ln\left(\frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \exp\left(-\frac{RV_{t+1} - c_{s_t} - \beta_{d,s_t} RV_t - \beta_w RVW_t - \beta_m RVM_t}{2\sigma_{s_t}^2}\right)\right). \tag{12}$$

In line with the MS-HAR-RV model, we have three new models, labeled as MS-LHAR-RV, MS-HAR-RV-EPU and MS-LHAR-RV-EPU, respectively, and the specifications of those models can be seen as:

$$RV_{t+1} = c_{s_t} + \beta_{d,s_t} RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_{d,s_t} r_t^- + \gamma_w rw_t^- + \gamma_m rm_t^- + \varepsilon_{t+1}. \tag{13}$$

$$RV_{t+1} = c_{s_t} + \beta_{d,s_t} RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_{s_t} EPU_t + \varepsilon_{t+1}. \tag{14}$$

$$RV_{t+1} = c_{s_t} + \beta_{d,s_t} RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_{d,s_t} r_t^- + \gamma_w rw_t^- + \gamma_m rm_t^- + \gamma EPU_t + \varepsilon_{t+1}. \tag{15}$$

Thus, in this research, we have eight models to forecast the realized volatility and compare the predictive ability. More importantly, we will consider and compare the eight popular GARCH-class models with our proposed in forecasting the future volatility.

Table 1 provides a typology of the eight models that are analyzed in the present study.

[2] Please see more details on estimation the Markov model in [15,16].

Table 2
Descriptive statistics of realized measures.

	r_t^-	r_t^-	rw_t^-	rm_t^-	RV_t	RVW_t	RVM_t	EPU_t
Mean	8.49×10^{-5}	-4.19×10^{-3}	-1.78×10^{-3}	-7.98×10^{-4}	−9.6762	−9.5731	−9.4964	4.3989
Std.	1.26×10^{-2}	8.03×10^{-3}	3.42×10^{-3}	1.60×10^{-3}	1.0571	0.9612	0.8931	0.6621
Min.	-9.79×10^{-2}	-9.79×10^{-2}	-3.89×10^{-2}	-1.62×10^{-2}	−12.7049	−11.9467	−11.3572	1.2000
Max.	0.1071	0.0000	0.0000	0.0000	−4.8880	−5.7033	−6.1811	6.5780
Skew.	−0.1119***	−3.4816***	−3.6335***	−3.3507***	0.4969***	0.6634***	0.7755***	−0.2163***
Kur.	7.4304***	18.7336***	21.3045***	15.6199***	0.4182***	0.4868***	0.4385***	0.2887***
J–B	9.24×10^{3}***	6.68×10^{4}***	8.46×10^{4}***	4.81×10^{4}***	1.94×10^{2}***	3.34×10^{2}***	4.32×10^{2}***	45.2319***
BDS	28.7118***	10.6720***	53.1311***	86.4415***	1.72×10^{2}***	4.43×10^{2}***	5.78×10^{2}***	87.1174***
ADF	−48.9940***	−9.7506***	−12.8173***	−11.2219***	−6.3343***	−5.7693***	−5.0914***	−6.9070***
Q (5)	35.456***	3.44×10^{2}***	4.16×10^{3}***	1.42×10^{4}***	1.11×10^{4}***	1.69×10^{4}***	1.94×10^{4}***	5.83×10^{3}***
Q (22)	74.384***	1.38×10^{3}**	*5.10×10^{3}**	*2.69×10^{4}***	3.60×10^{4}***	5.25×10^{4}***	7.06×10^{4}***	2.04×10^{4}***

Notes: Kurtosis is excess kurtosis. The Jarque–Bera statistic tests for the null hypothesis of normality for the distribution of the series. ADF is the Augmented Dickey–Fuller statistic. criterion. $Q(n)$ is the Ljung–Box statistic for up to 5th and 22th order serial correlation. Asterisk *** denote rejections of null hypothesis at 1% significance levels.

3. Data and preliminary analysis

We use intraday price data from the S&P 500 index for the January 4, 2000 to April 29, 2016. The data are for the trading time of each business day between 9:30:00 and 16:00:00. After removing days with shortened trading sessions or too few transactions, we obtain high-frequency data for 4014 business days. All of the price data are taken from the Thomson Reuters Tick History Database.

Table 2 exhibits the descriptive statistics about the important variables, such as return, realized volatility and EPU. For all series discussed in Table 2, the results of Jarque–Bera statistic test show that the null hypothesis of normality is rejected at the 1% significance level, and this feature can be found by the high degree of excess kurtosis and skewness. The Ljung–Box statistic for serial correlation shows that the null hypothesis of no autocorrelation up to the 20th order is rejected, thus confirming serial correlation in the volatility and jump series. The Augmented Dickey–Fuller test supports the rejection of the null hypothesis of a unit root at the 1% significance level, implying that all of the series are stationary and can be modeled directly without further transformation.

4. Empirical results

4.1. In-sample estimation results

The in-sample estimation results are reported in Table 3. We find that the estimated parameters of daily (β_d), weekly (β_w) and monthly (β_m) RV in each model are significant at the 1% significance level, suggesting strong persistence in the realized volatility dynamics. The EPU has statistically significantly positive impact on the future volatility in all models discussed in this article, implying that the higher EPU can produce higher future volatility. Moreover, we find that the negative returns have significantly negative effects on future volatility, and the aggregate weekly and monthly returns have also negative influence on future volatility. We use the Wald test to test whether the daily realized volatility, negative return and EPU during the high and low volatility have significant difference, because the p-values are all close to zero.

4.2. Out-of-sample forecast evaluations

Compared with the in-sample performance, the out-of-sample performance of a model (i.e., its predictive ability) is more important to market participants, because they are more concerned about the model's ability to improve their future performance than its ability to analyze past patterns [19]. To evaluate the models' forecasting performance, we use the four popular loss functions, which are calculate by as below,

$$HMSE = M^{-1}\sum_{m=1}^{M}(1-\hat{\sigma}_m^2/\mathrm{RV}_m)^2 \tag{16}$$

$$HMAE = M^{-1}\sum_{m=1}^{M}|1-\hat{\sigma}_m^2/\mathrm{RV}_m| \tag{17}$$

$$QLIKE = M^{-1}\sum_{m=1}^{M}(\ln(\hat{\sigma}_m^2)+\mathrm{RV}_m/\hat{\sigma}_m^2) \tag{18}$$

$$R^2LOG = M^{-1}\sum_{m=1}^{M}(\ln(\mathrm{RV}_m)/\hat{\sigma}_m^2)^2 \tag{19}$$

Table 3
The in-sample estimation results of benchmark and its extended models over the in-sample period.

Models	c	$\beta_d/\beta_{d,s_t}$	β_w	β_m	γ
HAR-RV	−0.6601***	0.3458***	0.3997***	0.1943***	
HAR-RV-EPU	−0.9631***	0.3452***	0.3961***	0.1858***	0.0412***
MS-HAR-RV		0.3077***			
$p_{00}=0.9863$***	−0.6217***	0.3122***	0.4343***	0.2000***	
$p_{01}=0.0130$					
MS-HAR-RV-EPU		0.3127***			0.0732***
$p_{00}=0.9941$***	−1.1195***	0.3056***	0.4307***	0.1786***	0.0424**
$p_{01}=0.0054$					

Models	c	$\gamma_d/\gamma_{d,s_t}$	γ_w	γ_m	$\beta_d/\beta_{d,s_t}$	β_w	β_m	γ
LHAR-RV	−1.7414***	−10.857	−31.378***	−24.350***	0.2414***	0.3565***	0.2431***	
LHAR-RV-EPU	−2.0335***	−10.940	−31.265***	−23.950***	0.2408***	0.3536***	0.2345***	0.0401***
MS-LHAR-RV		−5.6491			0.1863***			
$p_{00}=0.9938$***	−1.6962***	−20.516***	−30.755***	−26.814***	0.1992***	0.3840***	0.2704***	
$p_{01}=0.0062$								
MS- LHAR-RV-EPU	−1.9412***	−10.559***			0.2272***			0.0122
$p_{00}=0.8688$***		−23.599**	−31.320***	−23.948***	0.2875***	0.3648***	0.2378***	0.2125***
$p_{01}=0.9998$***								

Notes: Asterisk *** denotes the rejection of null hypothesis at 1% significance level.

where $\hat{\sigma}_t^2$ is the volatility forecast and generated by the rolling window method, M is the number of forecasting data points (M =1000). RV_m is the proxy for actual market volatility in out-of-sample period.

When a particular loss function for model A is smaller than model B, it can be concluded that the forecasting performance of the former is superior to that of the latter. Such a conclusion cannot be made on the basis of a single loss function and a single sample. Recent work has focused on the testing framework that can determine whether one particular model is outperformed by another [24–26].

However, the SPA test is designed to address whether a particular benchmark is significantly outperformed by any of the alternatives used in the comparison. Recently, Hansen et al. [27] proposed a new test method to compare the volatility models, which is named as Model Confidence Set (MCS). Compared with an SPA test, the MCS test has many attractive features. Firstly, the MCS test does not require a benchmark to be specified, which is very useful in application without an obvious benchmark. Secondly, the MCS test acknowledges the limitations of the data. Thirdly, the MCS procedure allows the possibility of more than one "best" model. To save space, this paper includes no further technical details of the MCS test, but more in-depth discussions can be found in the study of Hansen et al. [27].

Table 4 reports the loss functions of the 15 volatility models. It can be seen that using the four comparison criteria functions, the HAR-RV model including the leverage effect, EPU and regime switching achieves the smallest value, which implies that MS-LHAR-RV model outperforms other models. To evaluate the statistical significance of differences between HAR-RV and its various extensions, we use the novel forecasting evaluation—model confidence set (MCS) proposed by Hansen et al. [27]. Following Martens et al. [28], Hansen et al. [27] and Laurent et al. [29], we choose the confidence level α of 0.25. If the p-value is smaller than 0.25, which imply that the forecasting performance of this model is significantly worse than other models. The empirical results of Table 5 show that the only the MS-LHAR-RV survives in MCS test, which tell us that this model has the 'best' model in forecasting. From the MCS test results, we further find that the leverage effect, EPU and regime switching can significantly improve the HAR-RV model's forecasting performance. To the best of our knowledge, there are few works to investigate the impact of leverage effect and EPU on future volatility in the framework of the Markov regime switching, which can prove some new insights to forecast the volatility of the stock market and other markets.

4.3. Robustness check

It has been well documented that market microstructure noise plays an important part. Barndorff-Nielsen et al. [30] point out that realized kernel (RK) is robust to noise, so we use the RK to replace RV in HAR-RV and its various extensions models. Table 6 shows the MCS test results. Under the four loss functions, we find that the MS-LHAR-RK-EPU model achieves higher forecast accuracy than other RV-type and GARCH-class models, further implying that combined the leverage effect and EPU with regime switching can help in forecasting.

5. Conclusions remark

With the increasing availability of intraday high-frequency financial data, modeling and forecasting the realized volatility (RV) have received wide attentions since the seminal work of Andersen and Bollerslev [20]. In this study, we first investigate the effects of the leverage effect and EPU on future volatility in the framework of the regime switching. Out-of-sample results show that the HAR-RV model including the leverage effect and EPU and combining the regimes significantly outperform other RV-type and GARCH-class models. Furthermore, we use the RK to replace RV as the dependent variable and find that add the leverage effect and EPU to HAR-RK model with regime switching have also better performance that other RK-type and GARCH-class models'.

Table 4
Out-of-sample forecasting accuracy with four loss functions.

	QLIKE	HMSE	HMAE	R^2LOG
HAR-RV	−7.6649	2.9575	1.1469	1.2291
HAR-RV-EPU	−8.4277	1.6722	0.8052	0.6637
LHAR-RV	−8.3960	2.7246	0.8978	0.7214
LHAR-RV-EPU	−8.5618	1.2966	0.7138	0.5155
MS-HAR-RV	−8.6239	0.6860	0.5379	0.3739
MS-HAR-RV-EPU	−8.6249	0.6654	0.5352	0.3718
MS-LHAR-RV	−8.6500	0.6353	0.5204	0.3472
MS-LHAR-RV-EPU	**−8.6514**	**0.6091**	**0.5168**	**0.3447**
APARCH	−8.6171	2.5762	1.0076	0.5852
EGARCH	−8.5309	5.6901	1.4438	0.8658
FIEGARCH	−8.5360	5.3871	1.3247	0.8061
FIGARCH	−8.5500	3.6055	1.1505	0.7019
GARCH	−8.5769	3.7257	1.1778	0.6991
GJR	−8.6177	2.6704	1.0220	0.5904
HYGARCH	−8.5602	3.4867	1.1360	0.6902

Notes: The minimum numbers are indicated in bold.

Table 5
Out-of-sample forecasting results with MCS test.

	QLIKE		HMSE		HMAE		R^2LOG	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
HAR-RV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HAR-RV-EPU	0.0000	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
LHAR-RV	0.0000	0.0000	0.0037	0.0023	0.0000	0.0000	0.0000	0.0000
LHAR-RV-EPU	0.0000	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
MS-HAR-RV	0.0218	0.0212	0.0271	0.0087	0.0002	0.0003	0.0000	0.0000
MS-HAR-RV-EPU	0.0218	0.0229	0.0433	0.0167	0.0008	0.0009	0.0000	0.0000
MS-LHAR-RV	0.2340	0.2340	0.0433	0.0167	0.0556	0.0556	0.1036	0.1036
MS-LHAR-RV-EPU	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
APARCH	0.0218	0.0028	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
EGARCH	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
FIEGARCH	0.0000	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
FIGARCH	0.0218	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GJR	0.0218	0.0057	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
HYGARCH	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The numbers with p-values larger than 0.25 are indicated in bold. The actual volatility is RV. The length of estimation window is 1000 day.

Table 6
Out-of-sample forecasting results with MCS test (RK).

	QLIKE		HMSE		HMAE		R^2LOG	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
HAR-RK	0.0071	0.0077	**0.8645**	**0.8597**	0.1002	0.0573	0.0000	0.0000
HAR-RK-EPU	0.0087	0.0147	**1.0000**	**1.0000**	0.1002	0.0573	0.0000	0.0000
LHAR-RK	0.2466	0.1043	**0.7129**	**0.5187**	0.1002	0.0573	0.0989	0.0660
LHAR-RK-EPU	**0.3193**	**0.3193**	**0.8376**	**0.7791**	0.1002	0.0573	0.1365	0.1365
MS-HAR-RK	0.0087	0.0083	**0.8376**	**0.7563**	0.1002	0.0503	0.0000	0.0000
MS-HAR-RK-EPU	0.0083	0.0077	**0.8645**	**0.8597**	0.1002	0.0573	0.0000	0.0000
MS-LHAR-RK	0.2466	0.1043	**0.7129**	**0.3192**	0.1002	0.0573	0.0989	0.0239
MS-LHAR-RK-EPU	**1.0000**	**1.0000**	**0.8645**	**0.8597**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
APARCH	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EGARCH	0.0000	0.0000	0.0197	0.0000	0.0000	0.0000	0.0000	0.0000
FIEGARCH	0.0009	0.0000	0.1241	0.0000	0.0000	0.0000	0.0000	0.0000
FIGARCH	0.0071	0.0002	0.0042	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GJR	0.0071	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HYGARCH	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The numbers with p-values larger than 0.25 are indicated in bold. The actual volatility is RK. The length of estimation window is 1000 day.

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References

[1] M. Martens, J. Zein, Predicting financial volatility: High-frequency time-series forecasts vis-à-vis implied volatility, J. Future Markets 24 (11) (2004) 1005–1028.
[2] S.J. Koopman, B. Jungbacker, E. Hol, Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements, J. Empir. Financ. 12 (3) (2005) 445–475.
[3] Y. Wei, Forecasting volatility of fuel oil futures in China: GARCH-type, SV or realized volatility models?, Physica A 391 (22) (2012) 5546–5556.
[4] F. Corsi, A simple approximate long-memory model of realized volatility, J. Financ. Econom. 7 (2009) 174–196.
[5] T.G. Andersen, T. Bollerslev, F.X. Diebold, Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility, Rev. Econ. Stat. 89 (2007) 701–720.
[6] F. Corsi, D. Pirino, R. Reno, Threshold bipower variation and the impact of jumps on volatility forecasting, J. Econometrics 159 (2010) 276–288.
[7] T. Busch, B.J. Christensen, M.Ø, . Nielsen, The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets, J. Econometrics 160 (2011) 48–57.
[8] F. Ma, Y. Wei, D. Huang, Y. Chen, Which is the better forecasting model? A comparison between HAR-RV and multifractality volatility, Physica A 405 (2014) 171–180.
[9] F. Wen, X. Gong, S. Cai, Forecasting the volatility of crude oil futures using HAR-type models with structural breaks, Energy Econ. 59 (2016) 400–413.
[10] D. Mei, J. Liu, F. Ma, W. Chen, Forecasting stock market volatility: Do realized skewness and kurtosis help?, Physica A 481 (2017) 153–159.
[11] X. Gong, F. Wen, X.H. Xia, J. Huang, B. Pan, Investigating the risk-return trade-off for crude oil futures using high-frequency data, Appl. Energy 196 (2017) 152–161.
[12] F. Corsi, R. Renò, Discrete-time volatility forecasting with persistent leverage effect and the link with continuous-time volatility modeling, J. Bus. Econom. Statist. 30 (3) (2012) 368–380.
[13] L. Liu, T. Zhang, Economic policy uncertainty and stock market volatility, Finance Res. Lett. 15 (2015) 99–105.
[14] Z. Liu, Y. Ye, F. Ma, J. Liu, Can economic policy uncertainty help to forecast the volatility: A multifractal perspective, Physica A 482 (2017) 181–188.
[15] F. Ma, L. Liu, Z. Liu, Y. Wei, Forecasting realized range volatility: A regime-switching approach, Appl. Econom. Lett. 22 (2015) 1361–1365.
[16] F. Ma, M.I.M. Wahab, D. Huang, W. Xu, Forecasting the realized volatility of the oil futures market: A regime switching approach, Energy Econ. 67 (2017) 136–145.
[17] E. Goldman, J. Nam, H. Tsurumi, J. Wang, Regimes and long memory in realized volatility, Stud. Nonlinear Dynam. Econom. 17 (5) (2013) 521–549.
[18] D. Raggi, S. Bordignon, Long memory and nonlinearities in realized volatility: A markov switching approach, Comput. Statist. Data Anal. 56 (2012) 3730–3742.
[19] Y. Wang, F. Ma, Y. Wei, C. Wu, Forecasting realized volatility in a changing world: A dynamic model averaging approach, J. Bank. Financ. 64 (2016) 136–149.
[20] T.G. Andersen, T. Bollerslev, Answering the skeptics: Yes, standard volatility models do provide accurate forecasts, Internat. Econom. Rev. 39 (1998) 885–905.
[21] O.E. Barndorff-Nielsen, N. Shephard, Power and bipower variation with stochastic volatility and jumps, J. Financ. Econom. 2 (1) (2004) 1–37.
[22] J.D. Hamilton, Analysis of time series subject to changes in regime, J. Econometrics 45 (1990) 39–70.
[23] C.J. Kim, Dynamic linear models with Markov-switching, J. Econometrics 60 (1994) 1–22.
[24] F.X. Diebold, R.S. Mariano, Comparing predictive accuracy, J. Bus. Econom. Statist. 13 (1995) 253–263.
[25] K.D. West, Asymptotic inference about predictive ability, Econometrica 64 (1996) 1067–1084.
[26] H. White, A reality check for data snooping, Econometrica 68 (2000) 1097–1126.
[27] P.R. Hansen, A. Lunde, J.M. Nason, The model confidence set, Econometrica 79 (2) (2011) 453–497.
[28] M. Martens, D.D. Van, P.M. De, Forecasting S&P 500 volatility: Long memory, level shifts, leverage effects, day-of-the-week seasonality, and macroeconomic announcements, Int. J. Forecast. 25 (2009) 282–303.
[29] S. Laurent, J.V. Rombouts, F. Violante, On the forecasting accuracy of multivariate GARCH models, J. Appl. Econometrics 27 (2012) 934–955.
[30] O.E. Barndorff-Nielsen, P.R. Hansen, A. Lunde, N. Shephard, Designing realized kernels to measure the ex post variation of equity prices in the presence of noise, Econometrica 76 (2008) 1481–1536.