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Forecasting the volatility of crude oil futures: The role of oil investor attention and its regime switching characteristics under a high-frequency framework

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ABSTRACT

The purpose of this article is to investigate whether oil investor attention (OA), measured by Google search volume, contains incremental information content to predict crude oil futures volatility under high-frequency heterogeneous autoregressive (HAR) model specifications. Moreover, to account for possible structural breaks and nonlinearity in the relation between OA and crude oil volatility, this article extends HAR-type models with regime switching considerations. The results of parameter estimation and out-of-sample prediction show that the in-sample and out-of-sample performance of HAR-type and Markov switching (MS)-HAR-type models with OA is significantly better than that of their corresponding HAR-type and MS-HAR-type models without OA. Furthermore, our findings suggest that (i) HAR-type-OA models tend to produce better forecasts for the volatility of the crude oil market at short horizons (1-day) compared to HAR-type, MS-HAR-type and MS-HAR-type-OA models. (ii) MS-HAR-type-OA models have the best forecasting performance at relatively long prediction horizons (1-week and 1-month). Therefore, the result suggests that the OA and regime switching specifications have a significant positive impact on volatility predictions and can be useful for improving the performance of HAR-type models.

1. Introduction

Oil is a very important strategic resource and energy commodity, and it plays a vital role in the global economy. Oil price volatility exerts a considerable macro and micro economic impact on financial markets and the real economy [1–3]. Additionally, oil price volatility influences the oil risk management, derivative pricing, and other financial activities [4–7]. Therefore, accurate predictions of oil volatility are both essential and timely for academics, oil traders, and policy makers.

In this article, we attempt to study crude oil market volatility from the perspective of behavior in terms of the oil investor attention (OA), which has attracted considerable interest. A growing body of empirical evidence suggests that investor attention has a significant impact on oil prices [8–11]. Although the existing literature on investor attention has confirmed its significant impact on stock market volatility [12–15], research focusing on the role of the OA in explaining crude oil market volatility is, surprisingly, very limited [16–18]. For example, Ji and Guo [17] use the multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model to analyze the effect of four kinds of oil-related events on oil market volatility. However, the GARCH model is built for daily and even lower-frequency data; consequently, a large amount of intraday information may be lost. High-frequency data, however, have a considerable amount of information, which may enable market traders and investors to promptly make decisions. With the advancement of information science and computer technologies in recent years, high-frequency data and large data sets can be collected and stored, and research on oil market volatility has taken a new approach. Therefore, examining the role of investor attention in oil market volatility based on high-frequency data is urgently necessary and highly beneficial.

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A rich stream of empirical findings shows that the heterogeneous autoregressive (HAR) volatility model and its extensions are better than GARCH-type models and stochastic volatility models [19–23], providing an ideal test framework. Hence, in this article, we study the impact of OA on volatility based on the high-frequency HAR model and its extensions. The reasons for considering the extensions are as follows. On the one hand, the HAR model of realized volatility is linear, and the estimation coefficient of the model is constant. However, Granger and Ding [24] discover that the volatility persistence often becomes unstable over time. Previous studies have provided evidence of higher persistence at lower volatility, which suggests the presence of nonlinearity [25–27]. On the other hand, due to economic policies, major events, business cycles, and other factors, the statistical property of volatility will often experience structural breaks [28,29] or undergo regime shifts [30]. Hence, it is necessary to apply the regime switching approach to extend the traditional HAR model to describe volatility dynamics more precisely. This aspect has also been documented by Ma et al. [31], who find that considering regime switching can help increase forecasting performance. In recent research, Bissoondoyal-Bheenick et al. [32] use the adoption of regime switching in the HAR model to improve the volatility forecast of the wheat and corn markets across all prediction horizons. In addition, the HAR model with regime switching can enhance the performance of multistep volatility prediction in the soybean market. In line with these studies, we study the effect of OA on volatility based on the Markov switching (MS)-HAR model and its extensions.

In addition to the limitations mentioned above, the intrinsic characteristic of investor attention also calls for regime switching specifications. Notably, the dynamics of investor attention vary substantially with the economic cycle and financial conditions. Investors' concerns about the future more often than not seem overly pessimistic during economic recessions but become optimistic when the economy improves. Concerns may change frequently, and actual economic data often make these concerns seem confusing and unfounded. For example, news reports related to disasters, emergencies, government policies and wars explain most of the variations in investor attention [33,34].

Furthermore, some studies have shown that the effect of investor attention, represented by Google search volume, on asset returns will be immediately apparent in the short term [35,36]. Therefore, the timeliness and short-term effectiveness of investor attention should be considered. To that end, this paper uses high-frequency crude oil data to fully extract investor attention information to predict crude oil volatility, which is a characteristic that cannot be well considered by low-frequency data. Only a few existing studies have attempted to use high-frequency data to examine the effects of the OA on the oil market volatility. To the best of our knowledge, there is only one exception, Audrino et al. [37], whose research is closely related to our research. Audrino et al. [37] show that attention and sentiment variables can significantly improve the accuracy of HAR model volatility predictions. However, unlike this article, the previous paper does not address the decomposition between the jump (J) and continuous jump (CJ) parts. In addition, they do not consider how crude oil market volatility reacts when investor attention shifts. Considering these characteristics may lead to forecasts with improved accuracy.

The main tasks of this paper can be summarized as follows. First, we construct an OA index based on Google search volume and further evaluate whether investor attention contributes to the estimation and prediction of volatility by incorporating OA into the framework of HAR-type models. Although Campos et al. [38] study the impact of abnormal search volume from Google (ASVI) on oil VIX by using a simple HAR model, and their research has two main shortcomings. First of all, the HAR model based on daily VIX data cannot fully capture intraday volatility, and thus, this model cannot provide investors with instant and effective information. Second, the authors used the daily VIX data to build the HAR model, so they could not decompose daily oil VIX data into jump and continuous parts. In general, investors are highly sensitive to jumps, and their emotions are reflected in the volatility. Therefore, it is very important to consider the impact of investor attention and jump part on crude oil volatility. Second, taking into account possible structural breaks and nonlinearity in the relation between OA and crude oil volatility, this paper extends HAR-type models with regime switching considerations. Andrei and Hasler [12] indicate that when investors assign little attention to news, information is only gradually incorporated into prices because learning is gradual. Therefore, low attention results in a low return volatility. In contrast, attentive investors immediately incorporate new information into the prices, and thus high attention induces a high return volatility. These characteristics also prompt us to use the regime switching method in our research to explore the impact of the investor attention on the crude oil volatility. Third, we use these models to estimate and predict the oil market volatility at multiple horizons. Finally, to compare the prediction performance of the aforementioned models, this study applies three loss functions (i.e., MSE, HMSE and HMAE) and the model confidence set (MCS) developed by Hansen et al. [39].

This paper contributes to the literature in several ways. First, we find that OA can be utilized to significantly predict crude oil volatility under the high-frequency framework in both in-sample and out-of-sample analyses. Second, we document an immediate effect of OA on crude oil volatility, an effect indicated by the fact that HAR-type-OA models exhibit the highest predictive ability at the daily horizon. This result is in line with that of Stambaugh et al. [36], who immediately see the effect of investor attention. Third, we find that in most of the cases analyzed, the regime switching specification can fully extract information from investor attention, which in turn considerably influences the volatility forecast in the medium and long terms. To the authors' knowledge, this paper is the first to explicitly study the characteristics of shifts in investor attention under the high-frequency framework.

The paper is structured as follows. The related literature is introduced in Section 2. In Section 3, we introduce different volatility components. The data used in this study are described in Section 4. In Section 5, we describe four groups of volatility models. These models include HAR-type, HAR-type-OA, MS-HAR-type, and MS-HAR-type-OA models. Section 6 presents the in-sample estimation results. The out-of-sample forecast evaluation results are reported in Section 7, and the last section concludes.

2. Related literature

The literature on crude oil volatility predictions has evolved from the use of low-frequency data to high-frequency data. Hence, in the following sections, we review two major parts of the literature, namely, studies on forecasting the volatility of the oil price market and studies on forecasting volatility using realized volatility.

2.1. Forecasting the volatility of the oil price market

The modeling and forecasting of oil market volatility have been tested in many contributions, most of which contain daily data and GARCH specifications [40–45]. For example, Sadorsky [45] evaluates the out-of-sample predictions through prediction accuracy tests and finds that the GARCH model is suitable for unleaded gasoline and oil volatility, and the threshold GARCH (TGARCH) model is very applicable to heating oil volatility. Narayan and Narayan [44] employ the GARCH model to examine the role of market conditions and regimes in predicting the volatility of four oil markets. Cheong [41] finds that the standard GARCH model can predict the oil market volatility. Kang and Yoon [43] analyze the prediction capabilities of GARCH-type models using three different types of oil data. Arouri et al. [40] find that the predictive ability of the fractionally integrated GARCH (FIGARCH) model performs better than other GARCH-type models.

Another research branch of the literature focuses on the dynamic changes in volatility under different market conditions, which has been introduced by some scholars [46–49]. Fong and See [47] find that out-of-sample results suggest that regardless of the evaluation criteria, the MS-GARCH model is considerably superior to the non-switching GARCH model. Di Sanzo [46] shows that the Markov switching model can enhance the data description and that the prediction results are better than those obtained from the GARCH model regardless of the evaluation criteria. In recent years, Herrera et al. [48] have shown that the MS-GARCH model can often better predict the long-term volatility of oil prices than the simple or exponential GARCH (EGARCH) models. Lin et al. [49] find that the hidden Markov EGARCH model is superior to the competition models, that is, Markov switching models, GARCH-type models and other models with hidden Markov regimes. More recently, there have been many studies using the GARCH-mixed data sampling (MIDAS) model in predicting oil volatility [50,51]. For example, Liu et al. [50] develop the GARCH-MIDAS model by incorporating geopolitical risks to enhance the oil volatility forecasting. Pan et al. [51] find that MS-GARCH-MIDAS models perform better than their single-regime model in predicting oil volatility.

2.2. Forecasting volatility using realized volatility

In recent years, the availability of intraday data for investment purposes has led market participants and many researchers to take interest in these data and to use these new data for market applications and academic research. Among the many applications, volatility prediction is by far one of the most important fields.

The main empirical findings indicate that HAR-type modes yield results superior to those obtained using stochastic volatility (SV) and GARCH-type models in out-of-sample predictions. Andersen et al. [19] and Andersen et al. [20] demonstrate that in predicting volatility, the model with realized volatility (RV) is obviously better than GARCH-type models. Financial data are used by Corsi [52] to calculate volatility, and the HAR-RV is developed. Furthermore, some researchers have proposed extended HAR models based on the HAR-RV model to optimize the ability of the model to predict future volatility. Andersen et al. [53] propose the HAR-RV-J and HAR-CJ models by decomposing the RV of the HAR-RV model into continuous and discontinuous jump parts. Chen and Ghysels [54] decompose the RV of the HAR-RV model into positive and negative realized semivariance. To distinguish the effect of negative and positive signed jumps on volatility, Patton and Sheppard [55] present the HAR-RV-SJd model.

In further research, there is sufficient evidence to show that structural breaks in volatility have a significant impact on modeling and predicting the volatility of the oil market. Hence, taking into account the structural transmission of volatility in structural breaks or business cycles, some researchers have developed Markov switching models in financial data, which have proven to be more accurate than traditional HAR models in predicting volatility. Ma et al [31] develop MS-HAR-type models to predict oil price volatility. Duan et al. [56] show that realized volatility and economic policy uncertainty in the regime switching framework can substantially optimize the prediction performance of the HAR-RV model. Alizadeh et al. [57] demonstrate that the proposed MS-HAR-RV model allows variation in realized volatility with changes in market conditions.

The literature above reports that HAR-type models can effectively forecast the crude oil market volatility. However, there are few studies that employ HAR-type models with OA and regime switching specifications to predict the volatility of this market. Therefore, adding the OA index to HAR-type or MS-HAR-type models, this article proposes HAR-type or MS-HAR-type models with OA and examines the role of OA and its regime switching characteristics under a high-frequency framework in modeling and forecasting oil price volatility.

3. Volatility estimation and jump detection

3.1. Realized volatility

According to Andersen and Bollerslev [58], the RV is defined as the sum of squares of intraday returns. In our article, the RV measure is used and is written as follows:

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2, \tag{1}$$

where $r_{t,j}$ represents the j^{th}, $(j = 1, 2, \cdots, M)$ intraday return at day t.

Hence, when $M \to \infty$, RV converges uniformly in probability:

$$RV_t \xrightarrow{M\to\infty} \int_0^t \sigma_s{}^2 ds + \sum_{0<s<t} k_s{}^2, \tag{2}$$

where σ_s is a strictly positive SV process with a sample path that is right continuous and has well-defined left limits, and k_s refers to the size of the corresponding jumps.

To separate the jump part, following the work of Barndorff-Nielsen and Shephard [59], this paper uses the daily realized bipower variance (RBV) to estimate the daily continuous sample path variation $\int_0^t \sigma_s^2 ds$.

$$RBV_t = \mu_1^{-2}\left(\frac{M}{M-2}\right)\sum_{j=3}^{M} |r_{t,j-2}||r_{t,j}| \xrightarrow{M\to\infty} \int_0^t \sigma_s^2 ds, \tag{3}$$

where $\mu_1 = \sqrt{2/\pi}$. The RBV involves an additional stagger relative to the measure originally considered by Barndorff-Nielsen and Shephard [59], which renders it robust to certain types of market microstructure noise [53,60,61].

3.2. Jump detection

The discontinuous jump part J_t can be written as:

$$RV_t - RBV_t \xrightarrow{M\to\infty} J_t. \tag{4}$$

To choose statistically significant jumps from the discontinuous jump part, Huang and Tauchen [60] construct the statistic as follows:

$$Z_t = \frac{(RV_t - RBV_t)/RV_t}{\sqrt{\left(\left(\frac{\pi}{2}\right)^2 + \pi - 5\right)\frac{1}{M}\max\left(1, \frac{RQV_t}{RBV_t^2}\right)}} \to N(0,1), \tag{5}$$

where RQV_t is the estimator of the fourth power variation, which can be written as follows:

$$RQV_t = M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=5}^{M}|r_{t,j-4}|^{4/3}|r_{t,j-2}|^{4/3}|r_{t,j}|^{4/3}. \tag{6}$$

where $\mu_{4/3} = 2^{2/3}\Gamma(7/6)/\Gamma(1/2)$.

Hence, the daily jump variation can be expressed by:

$$J_t = I(Z_t > \Phi_\alpha)\cdot(RV_t - RBV_t), \tag{7}$$

where Φ_α indicates that the corresponding trigger value at the significance level of α is a standard normal distribution and $I(\cdot)$ is the indicator function. In our paper, we let $\alpha = 0.999$.

4. Data description

4.1. Construction of the OA index

The purpose of this section is to accurately measure investor attention to the oil markets. Hence, following the research of Da et al. [62] and Han et al. [8], we gather the daily search volume index (SVI) of a few keywords from Google Trends (http://www.google.com/trend/) to measure the OA. In addition to the SVI for the name of crude oil price, keywords are also downloaded that combine the name with the identifiers “oil,” “futures,” “economy,” and “WTI”. Therefore, from January 1, 2004, to December 25, 2016, a total of 1124 keywords can be collected in the form of weekly and daily data. To more precisely analyze the effect of the SVI on the oil market, this paper excludes keywords with insufficient data and noneconomic search terms from the 1124 keywords, and then selects 519 keywords. To reduce the outliers, this article classifies each series at the 5% level (2.5% at each tail) and calculates the changes for each search term.

$$\Delta SVI_{i,t} = \ln(SVI_{i,t}) - \ln(SVI_{i,t-1}). \tag{14}$$

Since the use of 519 keywords to check the interaction between investor attention and oil returns is inefficient, we perform backward regression to identify the typical search terms, as described by Da et al. [62]. We next sort the t-statistic of the SVI based on that regression. This paper selects the 50 most important terms and uses them to form the OA index. Finally, we select the top 83 terms because 83 is an acceptable number of observations that can diversify away idiosyncratic noise and avoid subjectivity bias [8,63]. Therefore, the OA at day t can be defined as follows:

$$OA_t = \sum_{i=1}^{83}\Delta SVI_{i,t}. \tag{15}$$

4.2. Oil prices

This paper uses the 5-min high-frequency Brent crude oil futures price data from Thompson Reuters Tick Historical Database (TRTH). Brent crude oil futures are traded on the London International Petroleum Exchange (IPE) in Europe, and the Brent crude oil futures contract refers to the front-month delivery of Brent crude oil futures on the IPE. When the current main contract is close to the delivery date, the trading data will be automatically linked to the next main contract to generate a continuous price series. The complete sampling period for our data is from December 30, 2003, to December 2, 2016. Our cleaning of the data follows [19,52]. To avoid explicitly modeling the seasonal behavior of trading activity induced by the weekend, we exclude all the realized volatility taking place from Friday 22:00 GMT to Sunday 22:00 GMT. After removing the shortened trading days, too few transactions and excessive jumps and matching the date with the OA, we obtain 3294 daily observations. To assess the prediction performance of various volatility models, the complete samples are divided into model estimation and out-of-sample prediction periods. The sample data in this paper are divided into two groups: 1) a group in which the estimation period is from January 2, 2004, to November 9, 2011, and 2) a group in which the out-of-sample forecast evaluation spans the period from November 10, 2011, to December 2, 2016.

5. Volatility model

In this section, we introduce the high-frequency volatility prediction model, which is based on the HAR model introduced by Corsi [52] and its extensions.

5.1. Original HAR-type and HAR-type-OA models

We employ the HAR model introduced by Corsi [52], which has been developed into a useful model for describing RV dynamics. The HAR-RV model is expressed as:

$$\overline{RV}_{t+H} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_{t-5,t} + \alpha_3 RV_{t-22,t} + \varepsilon_{t+H}, \tag{16}$$

where $\overline{RV}_{t+H} = (RV_{t+1} + RV_{t+2} + \cdots + RV_{t+H})/H, (H = 1, 5, 22)$ represent the 1-day, 1-week and 1-month future RV, respectively; RV_t is the daily RV, as defined in Eq. (1), where $RV_{t-i,t} = (RV_t + RV_{t-1} + \cdots + RV_{t-(i-1)})/i,\ (i = 5,\ 22)$ denotes the weekly and monthly RV.

Andersen et al. [53] found that the logarithmic HAR model exhibits a superior fitting ability compared to the traditional HAR model. In addition, the logarithmic transform of RV is used and exhibits better prediction performance [61,64,65]. Therefore, this paper uses the logarithmic form of HAR-type models to forecast crude oil market volatility. The corresponding HAR-RV model is written as follows:

$$\begin{aligned}\log\left(\overline{RV}_{t+H}\right) = {} & \alpha_0 + \alpha_1\log(RV_t) + \alpha_2\log(RV_{t-5,t}) \\ & + \alpha_3\log(RV_{t-22,t}) + \varepsilon_{t+H},\end{aligned} \tag{17}$$

To optimize the prediction performance of the HAR-RV model and assess whether the J part can be useful for predicting volatility, Andersen et al. [53] propose the HAR-RV-J model by incorporating the J part into the HAR-RV model:

$$\overline{RV}_{t+H} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_{t-5,t} + \alpha_3 RV_{t-22,t} + J_t + \varepsilon_{t+H}, \tag{18}$$

where J_t is the J part defined in Eq. (7).

Guided by this same idea, the corresponding HAR-RV-J model is defined as follows:

$$\begin{aligned}\log\left(\overline{RV}_{t+H}\right) = {} & \alpha_0 + \alpha_1\log(RV_t) + \alpha_2\log(RV_{t-5,t}) \\ & + \alpha_3\log(RV_{t-22,t}) + \beta_1\log(1 + J_t) + \varepsilon_{t+H},\end{aligned} \tag{19}$$

In this article, we employ logarithmic HAR-type models as our baseline model for forecasting realized volatility and then add the OA index to explore whether OA contains any incremental predictive information. Because changes in the OA index should capture new information that can be displayed to traders, we use OA in first differences. Similar to RV, we further consider the monthly and weekly averages of these variables. Therefore, we add the OA index to the HAR-type models (HAR-type-OA) as an additional variable.

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_0+\alpha_1\log(RV_t)+\alpha_2\log(RV_{t-5,t})+\alpha_3\log(RV_{t-22,t}) +\lambda_1 OA_d+\lambda_2 OA_w+\lambda_3 OA_m+\varepsilon_{t+H}, \tag{26}$$

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_0+\alpha_1\log(RV_t)+\alpha_2\log(RV_{t-5,t}) +\alpha_3\log(RV_{t-22,t})+\beta_1\log(1+J_t) +\lambda_1 OA_d+\lambda_2 OA_w+\lambda_3 OA_m+\varepsilon_{t+H}, \tag{27}$$

where OA_d,OA_w, and OA_m represent the first difference of the daily, weekly, and monthly OA indexes.

$p_{11}=P(S_t=1|S_{t-1}=1)$,$p_{12}=1-p_{11}$,$p_{22}=P(S_t=2|S_{t-1}=2)$, and $p_{21}=1-p_{22}$.

By using the filtering program proposed by Hamilton [67] and then using the smoothing algorithm of Kim [68], MS-HAR-type models are estimated by the maximum likelihood function. The log-likelihood function of these models can be specified as follows:

$$f=\sum_{t=1}^{T}\log\left\{\sum_{s=1}^{2}\frac{1}{\sigma_{S_t=s}}\varphi\left(\frac{\varepsilon_t}{\sigma_{S_t=s}}\right)\left(\sum_{i=1}^{2}p_{is}\Pr(s_{t-1}=i|F_{t-1})\right)\right\} \tag{36}$$

where F_{t-1} represents the historical information available at time t-1 and φ(.) represents the normal probability density function.

Naturally, we will consider a combination of HAR-type-OA and HAR-type models with regime switching. Therefore, we present five new (MS-HAR-type-OA) models.

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_{0,S_t}+\alpha_{1,S_t}\log(RV_t)+\alpha_{2,S_t}\log(RV_{t-5,t})+\alpha_{3,S_t}\log(RV_{t-22,t}) +\lambda_{1,S_t}OA_d+\lambda_{2,S_t}OA_w+\lambda_{3,S_t}OA_m+\varepsilon_{t+H,S_t}, \tag{37}$$

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_{0,S_t}+\alpha_{1,S_t}\log(RV_t)+\alpha_{2,S_t}\log(RV_{t-5,t})+\alpha_{3,S_t}\log(RV_{t-22,t}) +\beta_{1,S_t}\log(1+J_t)+\lambda_{1,S_t}OA_d+\lambda_{2,S_t}OA_w+\lambda_{3,S_t}OA_m+\varepsilon_{t+H,S_t}, \tag{38}$$

5.2. MS-HAR-type and MS-HAR-type-OA models

High-frequency data often exhibit a business cycle pattern and structural breaks. Hence, it can be reasonably assumed that the parameters of the model change according to the stage of the economic cycle or according to the structural change. One possible solution to this data behavior is to use the Markov switching model of Hamilton [66], which has been widely used in the literature to model commodity prices and volatility. The parameters of this model depend on the structural change or current economic regime. For example, the parameters in the expansion and recession phases will be different. In our paper, we consider that Markov switching models have a fixed transition probability, and we incorporate regime-switching specifications into all variables in HAR-type models. The logarithmic MS-HAR-type models are defined as:

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_{0,S_t}+\alpha_{1,S_t}\log(RV_t)+\alpha_{2,S_t}\log(RV_{t-5,t}) +\alpha_{3,S_t}\log(RV_{t-22,t})+\varepsilon_{t+H,S_t}, \tag{31}$$

$$\log\left(\overline{RV}_{t+H}\right)=\alpha_{0,S_t}+\alpha_1\log(RV_t)+\alpha_{2,S_t}\log(RV_{t-5,t}) +\alpha_{3,S_t}\log(RV_{t-22,t}) +\beta_{1,S_t}\log(1+J_t)+\varepsilon_{t+H,S_t}, \tag{32}$$

where $\varepsilon_{t,t+H}\sim N(0,\Sigma_{S_t})$ and $S_t=\{1,2\}$ is an unobserved state dummy variable. Moreover, all parameters depend on the state. Additionally, the Markov process between two states depends on the transition probability matrix:

$$P=\begin{bmatrix}p_{11} & p_{12}\\ p_{21} & p_{22}\end{bmatrix},$$

where

where S_{t+H} is an unobserved state dummy variable and all parameters are now state dependent. Thus, we have 15 new models.

6. In-sample model performance

6.1. Parameter estimation for HAR-type/HAR-type-OA models

In the volatility prediction of the crude oil market, it is expected that OA will carry a considerable amount of important information. To test whether OA contains additional information on volatility forecasting, we use ordinary least squares (OLS) estimation throughout the sampling period to estimate the logarithmic HAR-type models and to estimate these models with the OA index.

Tables 1–2 display the estimation results of HAR models, and we observe that most parameters are obviously significant. Table 1 summarizes the parameter estimations for HAR-RV models when predicting oil market volatility at different horizons. The results of the volatility models suggest that all the coefficients of the weekly and monthly OA indexes (i.e., OA_w and OA_m) are positive and significant at the 5% level, indicating that weekly and monthly OA contain in-sample prediction information regarding oil market volatility at daily and weekly horizons. In particular, in Table 2, all the coefficients of the weekly OA index (OA_w) and monthly OA index (OA_m) are significantly positive at the one-week prediction horizon. Our findings show that investor attention will affect oil market volatility in the short and medium term. Finally, we observe that the logarithmic HAR-type-OA models generally have a higher R-squared than HAR-type models, indicating that HAR-type-OA models can explain and capture the dynamics of RV more precisely than HAR-type models for the oil market. In conclusion, by analyzing the coefficients of OA, we observe that most coefficients are significantly positive. Investor attention considerably influences short-term volatility and can increase volatility, but it has a relatively small impact on volatility in the long term. In summary, the empirical result shows that OA considerably influences oil market volatility, suggesting that OA will exacerbate market volatility and is a key factor in predicting RV.

6.2. Parameter estimation in MS-HAR-type/MS-HAR-type-OA models

Tables 3–4 exhibit the parameter estimation for the HAR models with regime switching. The importance of the estimated coefficients in the dynamics of the RV of the crude oil market under different regimes can be observed. Most coefficients of the RV models are significant in both regimes 1 and 2, while most of the coefficients of the OA index in the HAR-type models with regime switching for the one-day and one-week ahead volatilities are always significant at the 1% and 5% levels in both regimes 1 and 2. Hence, OA contains additional information in short-and medium-term predictions. Moreover, all the coefficients of the monthly OA index in the volatility models for the one-month ahead volatilities are always significant at the 1% level in regime 1. More notably, in the short- and medium-term volatility model estimations, high investor attention considerably impacts volatility, whereas in the long-term estimation, low investor attention exerts a more significant impact on the volatility. Thus, in a regime of low volatility, OA is more useful in predicting volatility. These results suggest that OA and regime switching specifications must be considered when modeling crude oil market volatility.

7. Out-of-sample forecasting performance

7.1. Loss functions and the MCS

Compared with the results in the sample, policymakers and investors may be more concerned about the prediction performance because they may want to use the model to predict volatility in the future so that they can make further decisions. Therefore, below, we focus on whether adding OA to volatility models can optimize their ability to predict out-of-sample data. We apply three loss functions (i.e., MSE, HMSE and HMAE) to assess the prediction accuracy of the 20 models in the oil market. Here, we introduce the three loss functions that can quantitatively measure the accuracy of forecasting:

$$MSE = N^{-1}\sum_{t=1}^{N}(\sigma_t - RV_t)^2, \tag{42}$$

$$HMSE = N^{-1}\sum_{t=1}^{N}\left(1-\frac{RV_t}{\sigma_t}\right)^2, \tag{43}$$

$$HMAE = N^{-1}\sum_{t=1}^{N}\left|1-\frac{RV_t}{\sigma_t}\right|, \tag{44}$$

where RV_t represents the volatility prediction obtained from various HAR-type models, σ_t is the real value of the volatility, for which we apply RV to replace it, and N is the length of the prediction days.

This paper uses the MCS proposed by Hansen et al. [39] as a predictive evaluation method to compare the prediction performance of our proposed models. The MCS test has been widely used to assess the predictive performance of volatility models due to the advantages of not needing a prespecified benchmark model [69–71]. According to the above literature, the range-based (Range) and semiquadratic (SemiQ) statistics are selected as MCS statistics, and their p-values are obtained using a bootstrap program. In our research, every model has a p-value in an initial set of competition models, and a larger p-value corresponds to a higher predictive ability of the model. In this paper, we choose this model as a good prediction performance model based on the criterion that the p-value of the volatility model is greater than 0.10. The Range and SemiQ statistics are defined as:

$$T_R = \underset{u,v\in M}{MAX}\frac{\left|\overline{d}_{i,uv}\right|}{\sqrt{\mathrm{var}(d_{i,uv})}},\ T_{SQ} = \underset{u,v\in M}{MAX}\frac{\left(\overline{d}_{i,uv}\right)^2}{\mathrm{var}\left(\overline{d}_{i,uv}\right)},\ \overline{d}_{i,uv} = n^{-1}\sum_{t=1}^{n}d_{i,uv,t}, \tag{45}$$

where $\overline{d}_{i,uv}$ and $d_{i,uv}$ are relative sample loss statistics that measure the relative sample loss between the i^{th} and j^{th} models.

7.2. Forecast evaluation results

Given that Tables 1–4 show that HAR models and their extensions perform well in the sample, it is interesting to test whether incorporating the OA index into the model can help improve the accuracy of predictions. To answer these questions, in Tables 5–10, this paper reports the results of the MCS test. Table 5 shows the 1-day ahead RV prediction results. The result indicates that all HAR-type-OA models outperform other volatility models. All the p-values of the HAR-type-OA models are equal to 1, and the p-values of the other volatility models are greater than 0.10, indicating that all models exist in the model set. This result shows that OA contains a considerable amount of short-term incremental information about realized volatility. Therefore, OA can help optimize the prediction accuracy of traditional HAR models.

Table 6 reports the 1-week RV prediction results. At the horizon of 1 week, we observe that most MS-HAR models survive with p-values much larger than 0.10. In particular, all MS-HAR-type-OA models survive with p-values of 1 under the HMAE and HMSE functions. Upon closer inspection, we find that OA can greatly help to optimize the 1-week ahead forecasting accuracy of volatility models. Therefore, OA contains a considerable amount of useful information to predict oil price volatility, especially in MS-HAR-type models. Table 7 shows the 1-month RV prediction results. At the horizon of 1 month, we find that most MS-HAR-type-OA have the best forecasting performance, which implies that OA contains more additional information to predict oil price volatility. The result shows that in the process of introducing investor attention, a sudden and large increase in information may have a predictive effect on volatility in the short term but cannot effectively extract information for long-term prediction. With the regime switching method, the information of investor attention can be more fully extracted, and therefore, volatility forecasting is improved. In addition, we find that within the relatively long forecast horizons (1-week and 1-month) of the oil market, regime switching may be useful for RV forecasts.

As investors and policy makers, we are most concerned with which model can predict volatility most accurately. Therefore, below, we assess the prediction performance of all volatility models in this paper. To capture an overall picture of the relative forecasting power of the various volatility models, Table 8 displays the MCS test results used to compare the prediction performances of the HAR model and its extensions when predicting crude oil volatility at the short-term forecast horizons. In Table 8, the p-values of most MCS tests are greater than 0.1, showing that all volatility models survive at the short prediction horizons. However, we find that HAR-RV-OA models have the best forecasting performance, which implies that OA contains more additional information to predict crude oil volatility.

Table 9 summarizes the MCS test results used to compare the prediction performance of the HAR model and its extensions at the medium forecast horizons (1-week) to predict the RV of the oil market. At the horizon of 1 week, all p-values of the MS-HAR-RV-J-OA model are equal to 1 under the HMAE and HMSE functions. Moreover, the p-values of the MCS tests of all of the MS-HAR-RV-J models are greater than 0.1. This result indicates that the regime switching approach can significantly help to optimize the predictive ability of HAR models at the one-week horizon, in line with the MCS test results presented in Table 6. The result shows that the performance of the MS-HAR-RV-J-OA model is superior to that of other volatility models, which also suggests that OA and regime switching contain more incremental information.

Table 10 shows the 1-month all RV prediction results. At the horizon of 1 month, although the best volatility models are different under different loss functions, we find that the best model is a volatility model with regime switching specifications. Moreover, the p-values of the MCS tests of most of the MS-HAR-type and MS-HAR-type-OA models are greater than 0.1. This result indicates that regime switching specifications are useful for improving the predictive ability of HAR models at the one-month horizon, in line with the MCS test results presented in Table 7. Additionally, we find that adding OA to the benchmark model do not improve the volatility model, while adding OA and Markov switching methods at the same time can significantly improve the volatility prediction performance. Investor attention cannot effectively extract information for long-term forecasting. Through the regime switching specification, investor attention information can be more fully extracted, and therefore, volatility forecasting is improved.

Let us summarize the results thus far. First, we find that compared to HAR-type and MS-HAR models, HAR-type-OA models tend to produce better predictions of the volatility of the crude oil market over a short horizon. We also find that HAR-RV-OA and HAR-RV-J-OA models have better predictive ability than other RV models at the daily horizon. Second, we observe that the prediction performance of MS-HAR models is better than that of other models under weekly and monthly horizons. Moreover, regarding weekly volatility forecasts, our results show that MS-HAR-RV-J-OA models outperform other forecasting methods and that volatility models with regime switching perform relatively well. For monthly volatility forecasts, MS-HAR models outperform other forecasting methods, and volatility models with regime switching perform relatively well. To summarize, in the context of volatility forecasting, our findings suggest that OA and regime switching specifications can be utilized to improve volatility models.

8. Conclusion

In this research, we empirically investigate whether OA plays an important role in the predictability of crude oil market volatility by incorporating the OA index in the logarithmic HAR-type models and their extensions. Taking into account possible structural breaks and nonlinearity in the relation between OA and crude oil volatility, this article uses HAR-type models and HAR-type-OA models with regime switching specifications to estimate and predict the oil market volatility.

Our major empirical results can be summarized as follows. First, the in-sample results show that OA has a significant impact on the RV, as most coefficients of OA are significant. Second, the major result is that HAR-type-OA models exhibit the highest predictive ability at the daily horizon. We also find that HAR-RV-OA and HAR-RV-J-OA models have better predictive ability than other volatility models at the daily horizon. Hence, in the context of volatility prediction, the results suggest that OA can be utilized to optimize volatility models. Third, we find that in most of the cases analyzed, the prediction performance of MS-HAR-type and MS-HAR-type-OA models is better than that of other models under weekly and monthly horizons. Moreover, regarding weekly volatility forecasts, our results show that MS-HAR-RV-J-OA models outperform other forecasting methods and that volatility models with regime switching perform relatively well. For monthly volatility forecasts, MS-HAR models outperform other forecasting methods and that volatility models with regime switching perform relatively well. The MCS test, used to evaluate prediction performance, shows that MS-HAR-type and MS-HAR-type-OA models can obtain higher prediction accuracy in the medium and long term. Furthermore, the results show that in the medium and long term, forecasts based on HAR-type models with both OA and regime switching usually provide better results than forecasts based on benchmark models. In summary, the methods proposed and applied in our paper help to make better use of the informational content of OA and regime switching specifications. Hence, in many cases, they can obtain better predictions of the variables of interest.

The findings are of significance and complement the literature on forecasting volatility in commodity markets, especially in the crude oil market. Those results clarify that regime switching specifications contain additional ex ante information pertaining to the future volatility, particularly when forecasting mid- and long-term volatilities. In addition, the proposed MS-HAR-type-OA models exhibit a superior predictive ability for volatility in the crude oil market. Thus, the OA and regime switching specifications must be considered when modeling the crude oil volatility. Our findings contribute to the decision making of participants in the crude oil market, including financial traders, manufacturers, and policymakers. In particular, more accurate risk management plans can be prepared by the participants by using MS-HAR-type OA models.

Our findings contribute to the decision of all participants in the crude oil market, including policymakers, manufacturers, and investors. First, based on the high-frequency framework, policymakers can realize the real-time observation and supervision of crude oil volatility by considering the timeliness and short-term effectiveness of the investor attention. Second, due to economic policies, major events, business cycles, and other factors, the statistical property of volatility may often experience structural breaks or undergo regime shifts. Hence, policymakers can use the regime switching method to extend the traditional HAR model to more accurately capture crude oil volatility to realize policy adjustments. In particular, the participants can prepare more accurate risk management plans by using MS-HAR-type OA models. Specifically, investors in the crude oil market obtain higher profits by considering the impact of the OA, and policymakers and regulators can evade extreme risk and stabilize the operation of the crude oil market by tracing the dynamic impact of the OA on crude oil volatility.

Author statement

Yuanyuan Liu: Supervision, Conceptualization, Writing - review & editing. Zibo Niu: Data analysis, Writing - original draft, Writing - review & editing. Muhammad Tahir Suleman: Data curation, Writing - review & editing. Libo Yin: Conceptualization, Supervision, Methodology, Writing - review & editing. Hongwei Zhang: Conceptualization, Supervision, Methodology, Software, Writing - review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.121779.

Appendix

Table 1
HAR models estimates.

Models	Panel A: h = 1-day		Panel B: h = 1-week		Panel C: h = 1-month	
	HAR-RV	HAR-RV-OA	HAR-RV	HAR-RV-OA	HAR-RV	HAR-RV-OA
α_0	−0.0766***(0.0127)	−0.0802*** (0.0126)	0.0279*** (0.00912)	0.0259*** (0.00910)	0.0859*** (0.00818)	0.0849*** (0.00818)
α_1	0.163*** (0.0209)	0.146*** (0.0210)	0.124*** (0.0150)	0.114*** (0.0152)	0.0956*** (0.0135)	0.0907*** (0.0137)
α_2	0.357*** (0.0354)	0.355*** (0.0353)	0.324*** (0.0254)	0.326*** (0.0254)	0.198*** (0.0229)	0.198*** (0.0229)
α_3	0.434*** (0.0313)	0.453*** (0.0312)	0.491*** (0.0224)	0.501*** (0.0225)	0.613*** (0.0201)	0.618*** (0.0202)
λ_1		−0.0134 (0.0442)		−0.0176 (0.0319)		0.00214 (0.0288)
λ_2		0.387** (0.197)		0.420*** (0.143)		0.130 (0.129)
λ_3		2.754*** (0.600)		1.003** (0.432)		0.674* (0.389)
R^2	0.702	0.706	0.815	0.816	0.835	0.835

Note: The standard error of the coefficient is shown in parentheses. The asterisks *, ** and *** denote 10%, 5% and 1% levels of significance, respectively. Panels A, B, and C report the findings for the 1-step, 5-step and 22-step estimates, respectively, for realized volatility.

Table 2
HAR-RV-J models estimates.

Models	Panel A: h = 1-day		Panel B: h = 1-week		Panel C: h = 1-month	
	HAR-RV-J	HAR-RV-J-OA	HAR-RV-J	HAR-RV-J-OA	HAR-RV-J	HAR-RV-J-OA
α_0	−0.0731*** (0.0130)	−0.0775*** (0.0129)	0.0290*** (0.00933)	0.0264*** (0.00933)	0.0863*** (0.00838)	0.0851*** (0.00839)
α_1	0.172*** (0.0220)	0.153*** (0.0221)	0.127*** (0.0158)	0.115*** (0.0160)	0.0965*** (0.0142)	0.0911*** (0.0144)
α_2	0.356*** (0.0354)	0.354*** (0.0353)	0.324*** (0.0254)	0.326*** (0.0255)	0.197*** (0.0229)	0.198*** (0.0229)
α_3	0.433*** (0.0313)	0.452*** (0.0313)	0.491*** (0.0225)	0.501*** (0.0225)	0.613*** (0.0202)	0.618*** (0.0203)
β_1	−0.0219 (0.0173)	−0.0164 (0.0173)	−0.00681 (0.0125)	−0.00331 (0.0125)	−0.00228 (0.0112)	−0.000931 (0.0113)
λ_1		−0.0114 (0.0442)		−0.0172 (0.0320)		0.00225 (0.0288)
λ_2		0.380* (0.197)		0.419*** (0.143)		0.129 (0.129)
λ_3		2.735*** (0.600)		0.999** (0.432)		0.673* (0.390)
R^2	0.702	0.706	0.815	0.816	0.835	0.835

Note: The standard error of the coefficient is shown in parentheses. The asterisks *, ** and *** denote 10%, 5% and 1% levels of significance, respectively.

Table 3
MS-HAR-RV models estimates.

Models	Panel A: h = 1-day		Panel B: h = 1-week		Panel C: h = 1-month	
	MS-HAR-RV	MS-HAR-RV-OA	MS-HAR-RV	MS-HAR-RV-OA	MS-HAR-RV	MS-HAR-RV-OA
$\alpha_{0,1}$	−0.122*** (0.0156)	−0.130*** (0.0155)	−0.136*** (0.0113)	−0.138*** (0.0110)	−0.120*** (0.00739)	−0.118*** (0.00683)
$\alpha_{1,1}$	0.256*** (0.0338)	0.252*** (0.0329)	0.0563*** (0.0129)	0.0511*** (0.0129)	0.0465*** (0.0101)	0.0421*** (0.0101)
$\alpha_{2,1}$	0.350*** (0.0471)	0.351*** (0.0459)	0.243*** (0.0217)	0.246*** (0.0216)	0.0712*** (0.0168)	0.0677*** (0.0167)
$\alpha_{3,1}$	0.358*** (0.0379)	0.362*** (0.0367)	0.581*** (0.0207)	0.584*** (0.0206)	0.712*** (0.0157)	0.717*** (0.0155)
$\lambda_{1,1}$		0.0674 (0.0476)		−0.0375 (0.0266)		−0.0238 (0.0206)
$\lambda_{2,1}$		0.0851 (0.253)		0.292** (0.123)		0.141 (0.0946)
$\lambda_{3,1}$		1.392** (0.667)		1.261*** (0.383)		1.283*** (0.304)
$\alpha_{0,2}$	0.0769 (0.0505)	0.110** (0.0531)	0.525*** (0.0329)	0.517*** (0.0320)	0.461*** (0.0136)	0.463*** (0.0129)
$\alpha_{1,2}$	0.0222 (0.0717)	−0.0422 (0.0725)	0.01000 (0.0238)	−0.0106 (0.0242)	0.00703 (0.0153)	0.00284 (0.0155)
$\alpha_{2,2}$	0.251 (0.156)	0.203 (0.168)	0.0557 (0.0553)	0.0763 (0.0575)	0.213*** (0.0290)	0.210*** (0.0292)
$\alpha_{3,2}$	0.658*** (0.137)	0.759*** (0.148)	0.795*** (0.0569)	0.798*** (0.0594)	0.630*** (0.0257)	0.635*** (0.0259)
$\lambda_{1,2}$		−0.243 (0.165)		−0.0445 (0.0484)		−0.00176 (0.0324)
$\lambda_{2,2}$		1.393* (0.763)		0.592*** (0.224)		0.105 (0.146)
$\lambda_{3,2}$		7.920*** (2.505)		1.634** (0.703)		0.869* (0.472)
Σ_1	0.3974 (0.0144)	0.3965 (0.0142)	0.2614 (0.0047)	0.2594 (0.0046)	0.1966 (0.0037)	0.1958 (0.0036)
Σ_2	0.8105 (0.0368)	0.7920 (0.0346)	0.3152 (0.0081)	0.3124 (0.0082)	0.2396 (0.0050)	0.2392 (0.0050)
p_{11}	0.8415	0.8440	0.9531	0.9520	0.9758	0.9765
p_{21}	0.4299	0.4383	0.1064	0.1087	0.0339	0.0333
SBIC	1.5991	1.5974	0.5883	0.5932	−0.0492	−0.0437

Note: The standard error of the coefficient is shown in parentheses. The asterisks *, ** and *** denote 10%, 5% and 1% levels of significance, respectively. SBIC is the Schwarz Bayesian Information Criterion.

Table 4
MS-HAR-RV-J models estimates.

Models	Panel A: h = 1-day		Panel B: h = 1-week		Panel C: h = 1-month	
	MS-HAR-RV-J	MS-HAR-RV-J -OA	MS-HAR-RV-J	MS-HAR-RV-J -OA	MS-HAR-RV-J	MS-HAR-RV-J -OA
$\alpha_{0,1}$	−0.119*** (0.0158)	−0.127*** (0.0158)	−0.131*** (0.0116)	−0.133*** (0.0111)	−0.113*** (0.00788)	−0.112*** (0.00717)
$\alpha_{1,1}$	0.277*** (0.0358)	0.277*** (0.0349)	0.0684*** (0.0136)	0.0621*** (0.0136)	0.0568*** (0.0107)	0.0515*** (0.0107)
$\alpha_{2,1}$	0.333*** (0.0479)	0.330*** (0.0468)	0.244*** (0.0216)	0.247*** (0.0215)	0.0721*** (0.0167)	0.0684*** (0.0167)
$\alpha_{3,1}$	0.364*** (0.0384)	0.368*** (0.0373)	0.580*** (0.0207)	0.582*** (0.0207)	0.705*** (0.0158)	0.710*** (0.0156)
$\beta_{1,1}$	−0.0528** (0.0260)	−0.0536** (0.0258)	−0.0364*** (0.0127)	−0.0335*** (0.0127)	−0.0303*** (0.0105)	−0.0283*** (0.0106)
$\lambda_{1,1}$		0.0700 (0.0480)		−0.0351 (0.0266)		−0.0206 (0.0206)
$\lambda_{2,1}$		−0.00645 (0.257)		0.280** (0.123)		0.138 (0.0948)
$\lambda_{3,1}$		1.402** (0.669)		1.242*** (0.383)		1.252*** (0.306)
$\alpha_{0,2}$	0.0699 (0.0480)	0.0932* (0.0500)	0.520*** (0.0327)	0.515*** (0.0317)	0.465*** (0.0141)	0.467*** (0.0130)
$\alpha_{1,2}$	0.0177 (0.0732)	−0.0594 (0.0737)	0.0102 (0.0250)	−0.0134 (0.0255)	0.0186 (0.0161)	0.0141 (0.0164)
$\alpha_{2,2}$	0.302** (0.149)	0.279* (0.159)	0.0579 (0.0554)	0.0826 (0.0575)	0.205*** (0.0290)	0.203*** (0.0293)
$\alpha_{3,2}$	0.619*** (0.129)	0.699*** (0.139)	0.797*** (0.0567)	0.794*** (0.0590)	0.634*** (0.0257)	0.639*** (0.0259)
$\beta_{1,2}$	0.0102 (0.0517)	0.0331 (0.0509)	−0.000595 (0.0166)	0.00516 (0.0162)	−0.0246** (0.0110)	−0.0229** (0.0110)
$\lambda_{1,2}$		−0.210 (0.153)		−0.0452 (0.0483)		−0.000404 (0.0324)
$\lambda_{2,2}$		1.454** (0.697)		0.589*** (0.225)		0.0686 (0.146)
$\lambda_{3,2}$		7.292*** (2.277)		1.686** (0.705)		0.912* (0.471)
Σ_1	0.3888 (0.0152)	0.3868 (0.0151)	0.2607 (0.0047)	0.2589 (0.0046)	0.1964 (0.0037)	0.1954 (0.0036)
Σ_2	0.7956 (0.0355)	0.7761 (0.0333)	0.3151 (0.0080)	0.3121 (0.0081)	0.2392 (0.0050)	0.2391 (0.0050)
p_{11}	0.8246	0.8246	0.9529	0.9518	0.9761	0.9767
p_{21}	0.4278	0.4348	0.1069	0.1091	0.0336	0.0331
SBIC	1.6025	1.6010	0.5908	0.5959	−0.0479	−0.0419

Note: The standard error of the coefficient is shown in parentheses. The asterisks *, ** and *** denote 10%, 5% and 1% levels of significance, respectively. SBIC is the Schwarz Bayesian Information Criterion.

Table 5
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-day forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	**0.4436**	**0.3493**	**0.6099**	**0.4976**	**0.3177**	**0.1418**
HAR-RV-OA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
MS-HAR-RV	**0.3900**	**0.1595**	**0.1250**	**0.4976**	**0.2387**	**0.1233**
MS-HAR-RV-OA	**0.4436**	**0.4199**	**0.6099**	**0.4976**	**0.4199**	**0.5476**
HAR-RV-J	**0.4853**	**0.2929**	**0.6090**	**0.5291**	**0.3004**	**0.2418**
HAR-RV-J-OA	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
MS-HAR-RV-J	**0.4274**	**0.1638**	**0.1248**	**0.5291**	**0.2209**	**0.1248**
MS-HAR-RV-J-OA	**0.4853**	**0.4915**	**0.6090**	**0.5291**	**0.4915**	**0.5701**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

Table 6
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-week forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	0.0000	0.0587	**0.1481**	0.0000	0.0679	**0.1499**
HAR-RV-OA	0.0000	0.0530	**0.1481**	0.0000	0.0600	**0.1483**
MS-HAR-RV	**1.0000**	**0.3490**	**0.5744**	**1.0000**	**0.3490**	**0.5744**
MS-HAR-RV-OA	0.0066	**1.0000**	**1.0000**	0.0066	**1.0000**	**1.0000**
HAR-RV-J	0.0000	0.0618	**0.1484**	0.0000	0.0785	**0.1524**
HAR-RV-J-OA	0.0000	0.0565	**0.1474**	0.0000	0.0665	**0.1494**
MS-HAR-RV-J	**1.0000**	**0.4814**	**0.5982**	**1.0000**	**0.4814**	**0.5982**
MS-HAR-RV-J-OA	0.0113	**1.0000**	**1.0000**	0.0113	**1.0000**	**1.0000**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

Table 7
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-month forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	0.0000	0.0749	0.0994	0.0000	0.0882	**0.4773**
HAR-RV-OA	0.0000	0.0715	0.0994	0.0000	0.0786	**0.4773**
MS-HAR-RV	**1.0000**	**0.1962**	**0.7093**	**1.0000**	**0.1962**	**0.7093**
MS-HAR-RV-OA	0.0000	**1.0000**	**1.0000**	0.0000	**1.0000**	**1.0000**
HAR-RV-J	0.0000	0.0741	0.0999	0.0000	0.0890	**0.4807**
HAR-RV-J-OA	0.0000	0.0709	0.0996	0.0000	0.0837	**0.4807**
MS-HAR-RV-J	**1.0000**	**0.1971**	**0.6882**	**1.0000**	**0.1971**	**0.6882**
MS-HAR-RV-J-OA	0.0000	**1.0000**	**1.0000**	0.0000	**1.0000**	**1.0000**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

Table 8
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-day forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	**0.4620**	**0.5223**	**0.5948**	**0.4959**	**0.3168**	**0.1278**
HAR-RV-OA	**0.6299**	**1.0000**	**1.0000**	**0.5274**	**1.0000**	**1.0000**
MS-HAR-RV	**0.4620**	**0.5223**	**0.5948**	**0.4688**	**0.1901**	**0.1237**
MS-HAR-RV-OA	**0.6299**	**0.5223**	**0.5948**	**0.5274**	**0.3331**	**0.1278**
HAR-RV-J	**0.6299**	**0.5223**	**0.5948**	**0.5274**	**0.2056**	**0.1278**
HAR-RV-J-OA	**1.0000**	**0.5223**	**0.5948**	**1.0000**	**0.3331**	**0.1278**
MS-HAR-RV-J	**0.6299**	**0.5223**	**0.5948**	**0.5274**	**0.2182**	**0.1278**
MS-HAR-RV-J-OA	**0.6299**	**0.5223**	**0.5948**	**0.5274**	**0.3331**	**0.1278**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

Table 9
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-week forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	0.0000	0.0631	**0.1501**	0.0000	0.0838	**0.1535**
HAR-RV-OA	0.0000	0.0564	**0.1501**	0.0000	0.0670	**0.1500**
MS-HAR-RV	0.0118	**0.4413**	**0.5889**	0.0008	**0.5974**	**0.6107**
MS-HAR-RV-OA	0.0009	**0.8980**	**0.6281**	0.0001	**0.8980**	**0.6281**
HAR-RV-J	0.0000	**0.4413**	**0.5889**	0.0000	**0.1166**	**0.1789**
HAR-RV-J-OA	0.0000	0.0631	**0.1501**	0.0000	0.0735	**0.1510**
MS-HAR-RV-J	**1.0000**	**0.4413**	**0.5889**	**1.0000**	**0.4912**	**0.5924**
MS-HAR-RV-J-OA	0.0118	**1.0000**	**1.0000**	0.0008	**1.0000**	**1.0000**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

Table 10
MCS test results are used to compare the prediction performances of HAR models and their extensions at 1-month forecast horizon.

Volatility models	Range			SemiQ		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
HAR-RV	0.0000	0.0821	0.0995	0.0000	0.0962	**0.4909**
HAR-RV-OA	0.0000	0.0815	0.0994	0.0000	0.0787	**0.2734**
MS-HAR-RV	0.0000	**0.2392**	**0.7045**	0.0000	**0.2481**	**0.7226**
MS-HAR-RV-OA	0.0000	**1.0000**	**0.9113**	0.0000	**1.0000**	**0.9113**
HAR-RV-J	0.0000	**0.2392**	**0.6912**	0.0000	**0.1211**	**0.4983**
HAR-RV-J-OA	0.0000	0.0821	0.0995	0.0000	0.0845	**0.3488**
MS-HAR-RV-J	**1.0000**	**0.2392**	**0.7045**	**1.0000**	**0.2666**	**0.7799**
MS-HAR-RV-J-OA	0.0000	**0.4184**	**1.0000**	0.0000	**0.4184**	**1.0000**

Notes: MCS p-values are calculated based on the test statistics T_R and T_{SQ}. Models with $p > 0.10$ are indicated in bold.

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