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Forecasting the volatility of crude oil futures using HAR-type models with structural breaks

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ABSTRACT

We introduce sixteen HAR-type volatility models with structural breaks and estimate their parameters by applying 5-min high-frequency transaction data for WTI crude oil futures. We find significant structural breaks in the volatility of crude oil futures. Additionally, the historical realized volatility, continuous sample path variation, negative realized semivariance, signed jump, signed semi-jump and leverage components contain substantial and salient information for forecasting the volatility of crude oil futures. Then, we use loss functions to assess the forecasting performance of these sixteen new models, and finally, rank these models using the PROMETHEE II method. Our results indicate that different models exhibit different predictive power in forecasting the 1-day, 1-week and 1-month volatility of crude oil futures. Of the new HAR-type models, the new HAR-RSV model performs best at forecasting the 1-day and 1-month volatilities, whereas the new HAR-CJ best forecasts the 1-week volatility.

1. Introduction

Oil is the lifeblood of industry and the main energy source for economic development; unsurprisingly, forecasts of most macroeconomic variables (such as inflation) depend heavily on changes in crude oil prices. Additionally, crude oil prices rely on the price of crude oil futures. However, the price of crude oil futures has been highly volatile in recent years. Therefore, forecasting the volatility of crude oil futures has attracted considerable attention from academics, governments and investors.

Most studies on forecasting the volatility of crude oil futures apply GARCH-type models that use low-frequency transaction data. Sadorsky (2006) conducts an empirical analysis of the forecasting of WTI crude oil futures volatility and finds that the GARCH model fits well and offers greater forecasting accuracy than the random walk model. Kang et al. (2009) demonstrate the superiority of the component GARCH and fractionally integrated GARCH models, which better capture the long memory of crude oil futures volatility than do the simple GARCH and integrated GARCH models. Wei et al. (2010) extend the work of Kang et al. (2009) and use a larger number of linear and nonlinear GARCH-type models to forecast the volatility of Brent and WTI crude oil markets and show that the nonlinear GARCH-type models, which capture the long-memory and/or asymmetry properties of volatility, have better predictive power than linear models. Kang and Yoon (2013) study the long-memory features of the front-month WTI crude oil futures contract volatility using several long-memory models (i.e., the ARIMA-GARCH, ARFIMA-GARCH, ARFIMA-IGARCH and ARFIMA-FIGARCH models). The out-of-sample analysis indicates that the simple ARIMA-GARCH model fits well in terms of forecasting the volatility of crude oil futures. In addition, other studies (such as Agnolucci, 2009; Arouri et al., 2012; Chang et al., 2010; Cheong, 2009; Chkili et al., 2014; Hou and Suardi, 2012; Narayan and Narayan, 2007; Nomikos and Pouliasis, 2011) also focus on evaluating the performance of GARCH models in forecasting the volatility of crude oil futures.

In addition to GARCH models, other models are applied to forecast the volatility of crude oil futures and use low-frequency transaction data. Sadorsky and McKenzie (2008) find that power autoregressive models are suitable for predicting the volatility of crude oil futures over short horizons. Askari and Krichene (2008) demonstrate that jump-diffusion models fit well with regard to Brent crude oil futures. In accordance with Askari and Krichene (2008), Baum and Zerilli (2016) and Larsson and Nossman (2011) propose a conditional

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moment estimator for stochastic volatility jump-diffusion models. These researchers find that jumps in the returns of crude oil futures add to the accuracy of volatility forecasts. Trolle and Schwartz (2009) develop a multifactor stochastic volatility model for forecasting volatility on light sweet crude oil futures trading on the NYMEX. Xu and Ouenniche (2012) use a data envelopment analysis framework to assess the relative performance of ARMA(1, 1), AR(1) and AR(5) models in forecasting the volatility of crude oil futures.

Although the above models have adequate forecasting power for crude oil futures volatility, they cannot describe the whole-day volatility information sufficiently well because they were established using low-frequency transaction data. Therefore, there are certain flaws in these models. In recent years, the wide application of computers has greatly reduced the cost of recording and storing high-frequency data, which has made high-frequency data an important tool in studying the volatility of the financial markets. Andersen and Bollerslev (1998) first used high-frequency data to propose a new method of measuring volatility, i.e., realized volatility (RV). Since then, the volatility models for high-frequency data applications have developed rapidly with a focus on forecasting financial markets. Andersen et al. (2003) propose the VAR-RV model and find that the model exhibits better performance than the traditional GARCH model in volatility forecasting. Koopman et al. (2005) show that the GARCH-RV, SV-RV and ARFIMA-RV models have better performance in forecasting volatility than traditional volatility models. In more recent work, Corsi (2009) proposes the heterogeneous autoregressive model of realized volatility (HAR-RV) and discovers that, in terms of forecasting performance, the HAR-RV model is markedly better than the GARCH model and the ARFIMA-RV model. Corsi (2009) has greatly elevated research on using volatility models to forecast the financial markets. In addition, many scholars have developed new volatility models based on the HAR-RV model (such as the HAR-RV-J, HAR-RV-CJ and HAR-RSV models) to further improve forecasting performance. Much research (such as Andersen et al., 2011; Çelik and Ergin, 2014; Chevallier and Sévi, 2011) has proven that HAR-type models offer better volatility forecasting performance than the GARCH-type, SV-type, VAR-RV and ARFIMA-RV models. However, a minimal number of studies (Haugom et al., 2014; Sévi, 2014) forecast the volatility of crude oil futures using HAR-type models. Therefore, HAR-type models will become an increasingly important tool to forecast the volatility of crude oil futures.

Additionally, Liao and Suen (2006) find significant changes in the crude oil futures market over the 1986–2004 period, supporting the evidence of a significant structural break taking place on November 12, 1999. Kang et al. (2011) also find significant structural breaks in the volatility of both the WTI and Brent crude oil futures using the iterated cumulative sums of squares (ICSS) algorithm. Similarly, Ewing and Malik (2013) show that there are some structural breaks in the volatility of WTI crude oil futures. Their results are consistent with widespread evidence that variance in asset returns contains structural changes (see Aggarwal et al., 1999; Starica and Granger, 2005; Gil-Alana et al., 2015). Mensi et al. (2014) show that the structural breaks reduce the degree of volatility persistence and enhance the understanding of this volatility in the oil markets. Mensi et al. (2015) find significant changes in the volatility of the petroleum markets, including the WTI, Europe Brent, kerosene, gasoline and propane markets. The above studies suggest that there are significant structural breaks in the volatility of crude oil futures and that it is thus important that HAR-type models control for structural breaks when forecasting the volatility of crude oil futures.

In this paper, we will assess the out-of-sample forecasting performance of HAR-type models with structural breaks that have different properties and determine which provides the best forecasting of crude oil futures volatility. However, Sadorsky (2005) applies RW, SMA, SES, AR, linear regression and SV models to forecast the volatility of crude oil futures and assesses the performance of these models based on various loss functions (i.e., MSE, MAE, MPE and MAPE) and statistical tests (DM test, modified DM test and regression tests for bias). The results are mixed with respect to which model outperforms the others because of the unidimensional nature of their rankings. Agnolucci (2009) applies a number of GARCH-class models and implied volatility models to forecast the volatility of crude oil futures and shows that the performance of these models is inconsistent regarding their use of myriad criteria (such as MAE or MSE). In addition, the results from Sadorsky (2006) and Marzo and Zagaglia (2010) are similar to those of Sadorsky (2005) and Agnolucci (2009), i.e., most methodologies used to assess the predictive power of competing volatility models are unidimensional in nature. Xu and Ouenniche (2012) also show that many performance criteria (e.g., MSE and ME) are generally restricted to ranking models by measure. To solve the problem that model performance is inconsistent under different loss functions, we employ an effective multi-criteria decision-making method (i.e., the PROMETHEE II method) based on the results of the loss functions to evaluate models' relative performance in forecasting the volatility of crude oil futures.

Our contribution mainly involves two aspects. On one hand, the HAR-type models in our paper control for structural breaks, which considerably enhances the predictive power of these models with regard to the volatility of the crude oil futures market. On the other hand, our paper applies the PROMETHEE II method to compare the predictive ability of different HAR-type models. We find that models of crude oil futures volatility present inconsistent forecasting performances in terms of loss functions (i.e., MAE, MAPE, RMSE and HRMSE), indicating that loss functions cannot provide a good comparison of the predictive performance of different HAR-type models. Fortunately, the PROMETHEE II method, which is based on the assessment results of loss functions, can solve the inconsistency of evaluation results. Moreover, we can find the best HAR-type models for forecasting the volatility of crude oil futures using the PROMETHEE II.

The remainder of this paper is organized as follows. In the next section, we introduce different volatility components. In Section 3, we present sixteen HAR-type models with structural breaks (i.e., the new HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models). These sixteen new models include the realized volatility, discontinuous jump variation, continuous variation sample path, realized semivariances, signed jump, and/or signed semi-jumps. Moreover, this model set consists of nearly all the existing HAR-type models. Section 4 includes a description of the data. Section 5 tests the structural breaks in the volatility of crude oil futures. In Section 6, we employ OLS with Newey–West standard errors to estimate the above models. Section 7 applies loss functions and the PROMETHEE II method to assess the out-of-sample forecasting power of models of crude oil futures volatility. Section 8 concludes.

2. Volatility components

2.1. Realized volatility

The daily realized volatility proposed by Andersen and Bollerslev (1998) can be computed as

$$RV_t^{d0} = \sum_{i=1}^{N} r_{t,i}^2 \tag{1}$$

where $r_{t,i}$ is the i^{th} intraday return ($i = 1, \cdots, N$) at day t, i.e., $r_{t,i} = 100(\ln P_{t,i} - \ln P_{t,i-1})$. N is the number of intervals in the trading day, and $P_{t,i}$ is the i^{th} intraday closing price at day t.

However, Eq. (1) does not consider the overnight return variance, (Andersen et al., 2011) and it does not involve the consistency estimation of integrated volatility. Therefore, according to Huang et al. (2013) and Gong et al. (2014), we obtain the new daily realized volatility

$$RV_t^d = RV_t^{d0} + r_{t,n}^2 = \sum_{j=1}^{M} r_{t,j}^2 \tag{2}$$

where $r_{t,n}$ is the overnight return, and $M = N + 1$.

2.2. Jump and continuous variations

We assume that the logarithmic price of crude oil futures ($p_t = \ln(P_t)$) within the trading day follows a standard jump-diffusion process

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t, 0 \le t \le T \tag{3}$$

where μ_t is the drift term with a continuous variation sample path, σ_t denotes a strictly positive stochastic volatility process, W_t denotes a standard Brownian motion and $\kappa_t dq_t$ is the pure jump component.

For the discrete price process, the log return volatility at time t includes the jump volatility and is not an unbiased estimator of integrated volatility. The log return from $t-1$ to t is a quadratic variation

$$QV_t = [\mathrm{r}, \mathrm{r}]_\mathrm{t} = \int_{t\text{-}1}^{t} \sigma_s^2 ds + \sum_{t\text{-}1<s\le t} \kappa_s^2 \tag{4}$$

where $\int_{t\text{-}1}^{t} \sigma_s^2 ds < \infty$ is an integrated variation and denotes the continuous component of the total variation. $\sum_{t\text{-}1<s\le t} \kappa_s^2$ is the cumulative jump variation in $[\mathrm{t}\text{-}1, \mathrm{t}]$.

Andersen and Bollerslev (1998) found that the quadratic variation, which cannot be observed directly, can be estimated using discrete data. When $M \to \infty$, the daily realized volatility RV_t^d can be used as a consistent estimator of QV_t.

$$RV_t^d \xrightarrow{M\to\infty} \int_{t\text{-}1}^{t} \sigma_s^2 ds + \sum_{t\text{-}1<s\le t} \kappa_s^2 \text{ or } RV_t^d \xrightarrow{M\to\infty} QV_t \tag{5}$$

Moreover, the integrated volatility IV_t can be estimated by the realized bipower variation RBV_t (Barndorff-Nielsen and Shephard, 2004, 2006). When $M \to \infty$, RBV_t can be used as a consistent estimator of the continuous sample path variation.

$$RBV_t = z_1^{-2} \frac{M}{M-2} \sum_{j-3}^{M} |r_{t,j-2}||r_{t,j}| \tag{6}$$

where $z_1 = E(Z_t) = \sqrt{\pi/2}$, and Z_t is a random variable that follows a standard normal distribution. $M/(M\text{-}2)$ denotes an adjustment for the sample size. Following Barndorff-Nielsen and Shephard (2004, 2006) and Huang and Auchen (2005), we use Z-statistics to identify the discontinuous jump variation

$$Z_t = \frac{(RV_t - RBV_t) RV_t^{-1}}{\sqrt{(\mu_1^{-4} + 2\mu_1^{-2} - 5) \frac{1}{M} \max\left(1, \frac{RTQ_t}{RBV_t^2}\right)}} \to N(0, 1) \tag{7}$$

where $\mu_1 = \sqrt{2/\pi}$, and RTQ_t is a realized tri-power quarticity, $RTQ_t = M\mu_{4/3}^{-3} \left(\frac{M}{M-4}\right) \sum_{j=4}^{M} |\mathrm{r}_{\mathrm{t,j\text{-}4}}|^{4/3} |\mathrm{r}_{\mathrm{t,j\text{-}2}}|^{4/3} |\mathrm{r}_{\mathrm{t,j}}|^{4/3}$, where $(\mu_{4/3} = E(|Z_T|^{4/3}) = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1})$.

The daily discontinuous jump variation J_t^d can be defined by

$$J_t^d = I(Z_t > \phi_\alpha)(RV_t - RBV_t) \tag{8}$$

Additionally, the daily continuous sample path variation C_t^d can be measured by

$$C_t^d = I(Z_t \le \phi_\alpha) RV_t + I(Z_t > \phi_\alpha) RBV_t \tag{9}$$

where $I(\cdot)$ is an indicator function, and α equals 0.99 (Andersen et al., 2007, 2011).

2.3. Realized semivariances

Barndorff-Nielsen et al. (2010) propose the daily realized semivariance, which can capture the variation solely from negative or positive returns. The daily positive realized semivariance estimator is written as

$$RSV_t^{d+} = \sum_{j=1}^{M} I\{r_{t,j} \ge 0\} r_{t,j}^2 \tag{10}$$

Similarly, the daily negative realized semivariance estimator is defined as

$$RSV_t^{d-} = \sum_{j=1}^{M} I\{r_{t,j} < 0\} r_{t,j}^2 \tag{11}$$

2.4. Signed jump

Patton and Sheppard (2011) define the daily signed jump as the difference between positive and negative realized semivariances:

$$SJ_t^d = RSV_t^{d+} - RSV_t^{d-} \tag{12}$$

2.5. Signed semi-jumps

In this paper, we further decompose the daily signed jump (Eq. (12)) into the daily positive and negative signed semi-jumps, and these are computed, respectively, as

$$SSJ_t^{d+} = I\left\{SJ_t^d \ge 0\right\} SJ_t^d \tag{13}$$

$$SSJ_t^{d-} = I\left\{SJ_t^d < 0\right\} SJ_t^d \tag{14}$$

3. Models

3.1. HAR-RV model

Based on the heterogeneous market hypothesis proposed by Muller et al. (1993), Corsi (2009) proposes the HAR-RV model:

$$\overline{RV}_{t+H}^d = c + \alpha_1 RV_t^d + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \varepsilon_{t+H} \tag{15}$$

where $\overline{RV}_{t+H}^d$ is the average realized volatility between time t and $t+H$; $\overline{RV}_{t+1}^d$ represents the 1-day future realized volatility; $\overline{RV}_{t+5}^d$ represents the 1-week future realized volatility; $\overline{RV}_{t+22}^d$ represents the 1-month future realized volatility; RV_t^d is the daily realized volatility, as defined in Eq. (2); $RV_t^w = (RV_t^d + RV_{t-1}^d + \cdots + RV_{t-4}^d)/5$ is the weekly realized volatility; and $RV_t^m = (RV_t^d + RV_{t-1}^d + \cdots + RV_{t-21}^d)/22$ is the monthly realized volatility.

This model reveals that volatility is complex and includes various components, including the total transactions of short-term, medium-term and long-term traders. Furthermore, we use dummy variables to control for the structural breaks in volatility. We thus obtain a new

HAR-RV model:

$$\overline{RV}^d_{t+H} = c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H} \quad (16)$$

where D_i are dummy variables that are determined by the structural breaks in volatility. P is the number of structural breaks in volatility during the sample period.

3.2. HAR-RV-J model

To improve the forecasting performance of volatility models and evaluate whether the jump component can help forecast volatility, Andersen et al. (2007) develop the HAR-RV-J model by adding daily discontinuous jump variation to the HAR-RV model. We obtain a new HAR-RV-J model by controlling for the structural breaks in volatility:

$$\overline{RV}^d_{t+H} = c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \beta_1 J^d_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H} \quad (17)$$

where J^d_t is the daily discontinuous jump variation defined in Eq. (8).

3.3. HAR-CJ model

Andersen et al. (2007) develop the HAR-RV-CJ model on the basis of the HAR-RV model by decomposing realized volatility into continuous sample path variation and discontinuous jump variation. This model can assess the role of these different volatility components (the continuous sample path variation and discontinuous jump variation) in forecasting volatility. Controlling for the structural breaks in volatility, we propose a new form of the HAR-RV-CJ model.

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 C^d_t + \alpha_2 C^w_t + \alpha_3 C^m_t + \beta_1 J^d_t + \beta_2 J^w_t + \beta_3 J^m_t \\ &\quad + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (18)$$

where C^d_t is the daily continuous sample path variation as measured in Eq. (9); $C^w_t = (C^d_t + C^d_{t-1} + \cdots + C^d_{t-4})/5$ is the weekly continuous sample path variation; $C^m_t = (C^d_t + C^d_{t-1} + \cdots + C^d_{t-21})/22$ is the monthly continuous sample path variation; $J^w_t = (J^d_t + J^d_{t-1} + \cdots + J^d_{t-4})/5$ is the weekly discontinuous jump variation; and $J^m_t = (J^d_t + J^d_{t-1} + \cdots + J^d_{t-21})/22$ is the monthly discontinuous jump variation.

3.4. HAR-RSV model

The HAR-RSV model uses the heterogeneous structure of the genuine HAR over positive and negative realized semivariances (RSV, Patton and Sheppard, 2011). This model assumes that positive and negative realized semivariances can have different predictive abilities for the short, medium and long terms. Then, introducing a dummy variable for the structural breaks in volatility, we propose a new HAR-RSV model.

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 RSV^{d+}_t + \alpha_2 RSV^{w+}_t + \alpha_3 RSV^{m+}_t + \beta_1 RSV^{d-}_t \\ &\quad + \beta_2 RSV^{w-}_t + \beta_3 RSV^{m-}_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (19)$$

where RSV^{d+}_t represents the daily positive realized semivariance, as defined in Eq. (10); $RSV^{w+}_t = (RSV^{d+}_t + RSV^{d+}_{t-1} + \cdots + RSV^{d+}_{t-4})/5$ represents the weekly positive realized semivariance; $RSV^{m+}_t = (RSV_t{}^{d} + + RSV^{d+}_{t-1} + \cdots + RSV^{d+}_{t-21})/22$ represents the monthly positive realized semivariance; RSV^{d-}_t represents the daily negative realized semivariance, as defined in Eq. (11); $RSV^{w-}_t = (RSV^{d-}_t + RSV^{d-}_{t-1} + \cdots + RSV^{d-}_{t-4})/5$ represents the weekly negative realized semivariance; and $RSV^{m-}_t = (RSV^{d-}_t + RSV^{d-}_{t-1} + \cdots + RSV^{d-}_{t-21})/22$ represents the monthly negative realized semivariance.

3.5. HAR-RSV-J model

As a benchmark for their study based on nonparametric estimators, Chen and Ghysels (2011) propose the HAR-RSV-J model, which is a version of the HAR-RSV model that includes the lagged daily discontinuous jump variation. The HAR-RSV-J model with structural breaks is written as

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 RSV^{d+}_t + \alpha_2 RSV^{w+}_t + \alpha_3 RSV^{m+}_t + \beta_1 RSV^{d-}_t + \beta_2 RSV^{w-}_t \\ &\quad + \beta_3 RSV^{m-}_t + \phi_1 J^d_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (20)$$

3.6. HAR-RV-SJ model

The HAR-RV-SJ model introduces the notion of the signed jump that is defined in Eq. (12). This model is similar to the new HAR-RV-J model (i.e., Eq. (17)), except that the lagged daily discontinuous jump variation is replaced with the lagged daily signed jump.

$$\overline{RV}^d_{t+H} = c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \beta_1 SJ^d_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H} \quad (21)$$

where SJ^d_t is the daily signed jump, as defined in Eq. (12).

3.7. HAR-RV-SSJ (I) model

The HAR-RV- SSJ (I) model is based on the new HAR-RV model (i.e., Eq. (16)) and introduces the lagged daily positive and negative signed semi-jumps.

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \beta_1 SJ^{d+}_t \\ &\quad + \phi_1 SJ^{d-}_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (22)$$

where SJ^{d+}_t and SJ^{d-}_t represent the daily positive and negative signed semi-jumps, respectively, as defined in Eqs. (13) and (14).

3.8. HAR-RV-SSJ (II) model

The HAR-RV-SSJ (II) model introduces the lagged weekly positive and negative signed semi-jumps and monthly positive and negative signed semi-jumps on the basis of the HAR-RV-SSJ (I) model.

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \beta_1 SJ^{d+}_t + \beta_2 SJ^{w+}_t + \beta_3 SJ^{m+}_t \\ &\quad + \phi_1 SJ^{d-}_t + \phi_2 SJ^{w-}_t + \phi_3 SJ^{m-}_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (23)$$

where SJ^{w+}_t is the weekly positive signed semi-jump, $SJ^{w+}_t = (SJ^{d+}_t + SJ^{d+}_{t-1} + \cdots + SJ^{d+}_{t-4})/5$; SJ^{m+}_t is the monthly positive signed semi-jump, $SJ^{m+}_t = (SJ^{d+}_t + SJ^{d+}_{t-1} + \cdots + SJ^{d+}_{t-21})/22$; SJ^{w+}_t is the weekly negative signed semi-jump, $SJ^{w-}_t = (SJ^{d-}_t + SJ^{d-}_{t-1} + \cdots + SJ^{d-}_{t-4})/5$; and SJ^{m-}_t is the monthly negative signed semi-jump, $SJ^{m-}_t = (SJ^{d-}_t + SJ^{d-}_{t-1} + \cdots + SJ^{d-}_{t-21})/22$.

3.9. LHAR-RV model

Asai et al. (2012) propose the LHAR-RV model, which is based on the HAR-RV model and introduces the notion of leverage effects, as advocated in Corsi and Renò (2012). Furthermore, by adding the structural breaks to the LHAR-RV model, we obtain a new LHAR-RV model:

$$\begin{aligned}\overline{RV}^d_{t+H} &= c + \alpha_1 RV^d_t + \alpha_2 RV^w_t + \alpha_3 RV^m_t + \lambda_1 r^{d-}_t \\ &\quad + \lambda_2 r^{w-}_t + \lambda_3 r^{m-}_t + \sum\nolimits_1^P (\theta_i D_i) + \varepsilon_{t+H}\end{aligned} \quad (24)$$

where r^{d-}_t denotes the daily negative returns, i.e., $r^{d-}_t = r_t I\{r_t < 0\}$; r^{w-}_t denotes the weekly negative returns, i.e., $r^{w-}_t = \frac{1}{5}(r_t + r_{t-1} + \cdots +$

$r_{t-4})I\{(r_t + r_{t-1} + \cdots + r_{t-4}) < 0\}$; and r_t^{m-} denotes the monthly negative returns, i.e., $r_t^{m-} = \frac{1}{22}(r_t + r_{t-1} + \cdots + r_{t-21})I\{(r_t + r_{t-1} + \cdots + r_{t-21}) < 0\}$.

3.10. LHAR-RV-J model

The LHAR-RV-J model is developed by adding leverage effects to the new HAR-RV-J model.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RV_t^d + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \beta_1 J_t^d + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{25}$$

3.11. LHAR-CJ model

Corsi and Renò (2012) add leverage effects to the new HAR-CJ model to develop the LHAR-CJ model.

$$\overline{RV}_{t+H}^d = c + \alpha_1 C_t^d + \alpha_2 C_t^w + \alpha_3 C_t^m + \beta_1 J_t^d + \beta_2 J_t^w + \beta_3 J_t^m + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{26}$$

3.12. LHAR-RSV model

The LHAR-RSV model adds leverage effects to the new HAR-RSV model.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RSV_t^{d+} + \alpha_2 RSV_t^{w+} + \alpha_3 RSV_t^{m+} + \beta_1 RSV_t^{d-} + \beta_2 RSV_t^{w-} + \beta_3 RSV_t^{m-} + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{27}$$

3.13. LHAR-RSV-J model

The LHAR-RSV-J model is based on the new HAR-RSV-J model and introduces leverage effects.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RSV_t^{d+} + \alpha_2 RSV_t^{w+} + \alpha_3 RSV_t^{m+} + \beta_1 RSV_t^{d-} + \beta_2 RSV_t^{w-} + \beta_3 RSV_t^{m-} + \phi_1 J_t^d + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{28}$$

3.14. LHAR-RV-SJ model

The LHAR-RV-SJ model is developed by adding leverage effects to the HAR-RV-SJ model.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RV_t^d + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \beta_1 SJ_t^d + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{29}$$

3.15. LHAR-RV-SSJ (I) model

The LHAR-RV-SSJ (I) model is based on the HAR-RV-SSJ (I) model and introduces leverage effects.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RV_t^d + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \beta_1 SJ_t^{d+} + \beta_2 SJ_t^{d-} + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{30}$$

3.16. LHAR-RV-SSJ (II) model

The LHAR-RV-SSJ (II) model is obtained by adding leverage effects to the HAR-RV-SSJ (II) model.

$$\overline{RV}_{t+H}^d = c + \alpha_1 RV_t^d + \alpha_2 RV_t^w + \alpha_3 RV_t^m + \beta_1 SJ_t^{d+} + \beta_2 SJ_t^{w+} + \beta_3 SJ_t^{m+} + \phi_1 SJ_t^{d-} + \phi_2 SJ_t^{w-} + \phi_3 SJ_t^{m-} + \lambda_1 r_t^{d-} + \lambda_2 r_t^{w-} + \lambda_3 r_t^{m-} + \sum_1^P (\theta_i D_i) + \varepsilon_{t+H} \tag{31}$$

4. Data description

This paper uses 5-min, high-frequency transaction data from the NYMEX-CME for the front-month WTI crude oil futures contract. The full sample period is from January 2, 1998 to May 9, 2014. After removing days with shortened trading sessions or excessively few transactions, we obtain 4800 daily observations.

The resulting summary statistics are reported in Table 1. This table shows that the means of daily, weekly and monthly variables are approximately equal. According to the Ljung–Box *Q*-statistics reported in the table, we find that all variables, except for the daily jump J_t^d and the daily signed jump SJ_t^d, reveal significant dynamic dependencies. In addition, the augmented Dickey–Fuller test statistic reported in the table shows that the null hypothesis of a unit root is rejected for all variables.

5. Structural breaks test

The Inclán and Tiao (1994) ICSS algorithm calculates the standard deviations between the change points to determine the number of structural breaks. Fig. 1 plots of the crude oil futures returns with break points and ± 3 standard deviations. Table 2 reports the number and time periods of structural breaks in volatility that are identified by the ICSS algorithm.

Crude oil returns exhibit eleven break points. With regard to Fig. 1 and Table 2, there are substantial differences in standard deviations in different time periods. The most volatile period for the crude oil futures markets is from September 15, 2008 to March 17, 2009. This period corresponds to the financial crisis that occurred in September 2008. However, the least volatile period is from November 20, 2012 to May 9, 2014, which is mainly because the price of crude oil entered a stationary phase after the financial crisis and European debt crisis.

6. Parameter estimation

To explain the possible presence of serial correlation in the data, we employ OLS with Newey–West standard errors to estimate the HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models that control for the structural breaks.

Tables 3–5 report the estimation results of sixteen new HAR-type models for forecasting volatilities at three horizons (i.e., 1-day, 1-week and 1-month). From the *t*-statistic values of the coefficients of the HAR-type models with RV (i.e., the HAR-RV, HAR-RV-J, HAR-RV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models), it is clear that the weekly realized volatility is not significant when these models forecast the 1-day or 1-month future volatility, which shows that weekly realized volatility does not have predictive power for the 1-day or 1-month future volatility of crude oil futures. However, the daily and monthly realized volatilities at these three different horizons are significant, and the weekly realized volatility is significant when these models forecast the 1-week future volatility. This result indicates that the volatility of crude oil futures has a long memory and that investor heterogeneity

Table 1
Summary statistics for all variables.

	Mean	Std. Dev.	Skewness	Kurtosis	Q(5)	Q(10)	Q(15)	ADF test
RV_t^d	4.8363	8.1155	18.067	651.45	2431.8***	4452.1***	6325.6***	−4.6407***
RV_t^w	4.8379	5.5392	6.1399	69.789	15,640***	24,790***	33,008***	−4.1579***
RV_t^m	4.8453	4.6542	3.9461	24.058	23,070***	44,424***	63,810***	−3.8476***
C_t^d	4.1915	5.0670	4.4023	30.816	7007.5***	13,390***	19,509***	−4.4309***
C_t^w	4.1931	4.0644	3.5664	18.978	19,710***	34,837***	49,049***	−3.5066***
C_t^m	4.1971	3.7341	3.4739	17.841	23,472***	45,791***	66,629***	−3.5451***
J_t^d	0.6448	5.6572	38.352	1962.6	2.1052	5.1906	5.8270	−8.9618***
J_t^w	0.6448	2.5633	16.301	361.87	6049.8***	6077.8***	6107.3***	−7.9433***
J_t^m	0.6482	1.2918	6.8301	67.595	18,855***	32,019***	40,836***	−6.6792***
RSV_t^{d+}	2.4015	6.0032	35.485	1805.4	622.73***	1179.4***	1769.2***	−4.6440***
RSV_t^{w+}	2.4020	3.4659	11.661	218.37	11,772***	16,761***	21,577***	−4.6412***
RSV_t^{m+}	2.4061	2.6368	5.3810	42.84	22,484***	42,802***	60,957***	−4.2818***
RSV_t^{d-}	2.4349	3.9110	8.6078	134.04	2151.9***	3863.1***	5382.7***	−6.7831***
RSV_t^{w-}	2.4359	2.6338	3.8372	23.285	14,991***	23,123***	30,436***	−4.3757***
RSV_t^{m-}	2.4392	2.1732	2.8963	13.2340	22,973***	43,893***	62,485***	−3.7047***
SJ_t^d	0.0334	6.0670	−28.120	1475.8	4.2194	10.584	15.239	−10.263***
SSJ_t^{d+}	0.6880	2.8990	15.901	350.50	69.029***	130.26***	162.89***	−35.780***
SSJ_t^{w+}	0.6887	1.4395	7.2460	75.353	7597.5***	8302.5***	8884.4***	−7.3847***
SSJ_t^{m+}	0.6897	0.8619	3.1306	15.335	20,651***	36,138***	47,002***	−4.8175***
SSJ_t^{d-}	−0.6546	5.2443	−45.943	2585.0	7.6161	16.843*	30.164**	−8.1743***
SSJ_t^{w-}	−0.6548	2.4227	−19.699	483.99	6345.9***	6516.2***	6749.6***	−7.4857***
SSJ_t^{m-}	−0.6566	1.3037	−8.6472	97.754	19,493.	33,871***	44,259***	−6.4818***
r_t^{d-}	−0.7412	1.3270	−3.2523	20.175	92.512	150.00***	232.90***	−26.096***
r_t^{w-}	−0.3248	0.5838	−2.9761	16.287	5183.0	5207.5***	5476.4***	−16.299***
r_t^{m-}	−0.7423	0.4191	−1.7509	7.3252	21,054	37,455***	49,777***	−5.0105***

Note: Asterisks indicate statistical significance at the 1% (***), 5% (**) or 10% (*) levels. The last column is the augmented Dickey–Fuller test statistic.

is salient in the crude oil futures market. The results again provide further verification of the "heterogeneous market hypothesis" (Muller et al., 1993). According to the results of the HAR-RV-J, HAR-CJ, LHAR-RV-J and LHAR-CJ models, we find that the historical continuous sample path variation contains more forecast information for future volatility than the historical discontinuous jump variation. Similarly, the estimation results of the HAR-RSV, HAR-RSV-J, LHAR-RSV and LHAR-RSV-J models show that the predictive information offered by negative realized semivariance is greater than that of positive realized semivariance. Additionally, the results also indicate that weekly negative realized semivariance and positive realized semivariance perform poorly at forecasting the volatility of crude oil futures. Then, the estimates of the HAR-RV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models demonstrate that the signed jump and signed semi-jumps can predict the volatility of crude oil futures. Moreover, the weekly negative signed semi-jump is non-significant in forecasting the 1-day or 1-month volatility of crude oil futures. According to the above analysis, we find that the daily and monthly volatility components exhibit better predictive ability than the weekly volatility components. This finding shows that the volatility of crude oil futures is substantially affected by short- and long-term information but is little affected by medium-term information. In the eight new HAR-type models with leverage effects, a number of leverage components are highly significant, which indicates that volatility in the crude oil futures market exhibits the leverage effect.

7. Forecasting volatility and forecast evaluation

7.1. Forecast methodology

We choose the rolling window prediction method to analyze the out-of-sample forecasting performance of sixteen HAR-type models with structural breaks (i.e., the new HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models). The prediction method can be expressed as follows.

First, we divide the total sample ($t = 1, 2,\ldots, N$) into the "estimation sample" and the "prediction sample". The estimation sample includes 1000 data points (i.e., rolling window $a = 1000$), and the prediction sample contains the last 3800 data points (i.e., $t = a + 1, a + 2,\ldots, a + h$, where $h = 3800$).

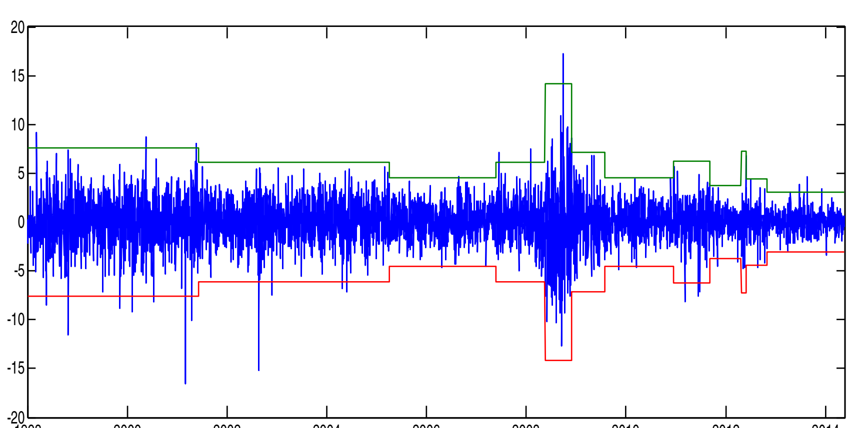

Fig. 1. Daily return dynamics of the crude oil markets and the ±3 standard deviation bands around the structural break points.

Table 2
Structural breaks in the volatility of crude oil futures as detected by the ICSS algorithm.

Break points	Time period	Standard deviation
11	January 2, 1998–January 16, 2002	2.5384
	January 17, 2002–September 28, 2005	2.0441
	September 29, 2005–October 14, 2007	1.5258
	October 15, 2007–September 14, 2008	2.0314
	September 15, 2008–March 17, 2009	4.7142
	March 18, 2009–October 31, 2009	2.3771
	November 1, 2009–February 16, 2011	1.4887
	February 17, 2011–October 24, 2011	2.1006
	October 25, 2011–May 29, 2012	1.2204
	May 30, 2012–July 3, 2012	2.5182
	July 4, 2012–November 20, 2012	1.4506
	November 20, 2012–May 9, 2014	1.0133

Second, we choose the data from the 1st to the 1000th as the 1st estimation sample and test the structural breaks of the 1000 data using the ICSS algorithm. Then, we use this sample to estimate the HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models with structural breaks. In addition, we use the recursion method to obtain the predicted values of the 1-day, 1-week and 1-month volatilities. The predicted values are written as $\hat{\sigma}^d_{a+1}$, $\hat{\sigma}^w_{a+1}$ and $\hat{\sigma}^m_{a+1}$, respectively.

Third, retaining the rolling window length ($a = 1000$), we move the window forward 1 day. In other words, we choose the data from the 2nd to the 1001th as the 2nd estimation sample and test the structural breaks of the 1000 data; we also use the sample to estimate the HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models with structural breaks. Then, we obtain the three new predicted values of $\hat{\sigma}^d_{a+2}$, $\hat{\sigma}^w_{a+2}$ and $\hat{\sigma}^m_{a+2}$.

Finally, we repeat the above three steps and obtain 3800 predicted values for 1-day, 1-week and 1-month volatility. These volatilities can be expressed as $\hat{\sigma}^d_{a+3}$, $\hat{\sigma}^w_{a+3}$ and $\hat{\sigma}^m_{a+3}$; $\hat{\sigma}^d_{a+4}$, $\hat{\sigma}^w_{a+4}$ and $\hat{\sigma}^m_{a+4}$; $\cdots$; $\hat{\sigma}^d_{a+h}$, $\hat{\sigma}^w_{a+h}$ and $\hat{\sigma}^m_{a+h}$.

7.2. Forecast evaluation

7.2.1. Loss functions

7.2.1.1. Methodology. In this paper, we choose four loss functions to evaluate the forecasting power of the HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models for the volatility of WTI crude oil futures. These four loss functions are the mean absolute error (MAE), the heteroskedasticity-adjusted mean absolute percentage error (HMAE), the root mean squared error (RMSE) and the heteroskedasticity-adjusted root mean squared error (HRMSE). The smaller the values of these four loss functions, the better their forecasting performance. MAE, MAPE, RMSE and HRMSE are defined as

$$MAE = \frac{1}{h}\sum_{t=a+1}^{a+h}\left|\sigma_t^2 - \hat{\sigma}_t^2\right| \tag{32}$$

$$HMAE = \frac{1}{h}\sum_{t=a+1}^{a+h}\left|\left(\sigma_t^2 - \hat{\sigma}_t^2\right)/\sigma_t^2\right| \tag{33}$$

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=a+1}^{a+h}\left(\sigma_t^2 - \hat{\sigma}_t^2\right)^2} \tag{34}$$

$$HRMSE = \sqrt{\frac{1}{h}\sum_{t=a+1}^{a+h}\left[\left(\sigma_t^2 - \hat{\sigma}_t^2\right)/\sigma_t^2\right]^2} \tag{35}$$

where σ_t^2 is the real volatility, and $\hat{\sigma}_t^2$ is the predicted volatility.

7.2.1.2. Results. The results of the loss functions (MAE, MAPE, RMSE and HRMSE) are illustrated in Tables A.1, A.2 and A.3 of Appendix A. The results of the Diebold and Mariano test (Diebold and Mariano, 1995) under different loss functions are reported in Tables A.4, A.5, A.6, A.7, A.8, A.9, A.10, A.11, A.12, A.13, A.14 and A.15 of Appendix A. These results show that the performance of the models varies with each loss function by comparing their loss functions and the Diebold and Mariano test. Thus, the loss functions cannot provide a good comparison of the predictive performance of these models. We therefore use another methodology to further analyze the forecasting power of these models.

7.2.2. PROMETHEE II method

7.2.2.1. Methodology. The Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) is an effective multi-criteria decision-making tool often applied to address complex rank ordering among different alternatives. This tool was developed by Brans (1982) and further extended by Vincke and Brans (1985). Furthermore, Behzadian et al. (2010), Gulmans (2013) and Macharis et al. (2004) demonstrate the merits of the PROMETHEE method in decision support systems.

Currently, the PROMETHEE I and PROMETHEE II methods are widely used in the economics and management fields (Chatzimouratidis and Pilavachi, 2012; Ghafghazi et al., 2010; Ghazinoory et al., 2009; Kilic et al., 2015; Sola et al., 2011). The PROMETHEE I method can derive the partial ordering of decision alternatives. However, the PROMETHEE II method can provide the full ranking of decision alternatives. In this paper, the PROMETHEE II method is employed to obtain the full ranking of the alternative models for forecasting the volatility of WTI crude oil futures.

The procedural steps involved in the PROMETHEE II method are as follows.

Step I: Normalize the decision matrix.

Range transformation is also known as the standard 0–1 transformation. According to a certain criterion, the worst criterion value of each scheme transforms to 0, and the optimal criterion will transform to 1. If C_k is a benefit criterion, r_i can be written as

$$r_i = \frac{a_i - a^{\min}}{a^{\max} - a^{\min}} \tag{36}$$

Additionally, if C_k is a cost criterion, r_i can be written as

$$r_i = \frac{a^{\max} - a_i}{a^{\max} - a^{\min}} \tag{37}$$

Step II: Calculate the preference function.

$$P_k(a_i, a_j) = \varphi_k(d), \quad \text{where } d = r_i - r_j \tag{38}$$

The six most common preference functions are listed in Table 6.

Step III: Define the multi-criteria preference outranking index.

In PROMETHEE II, each criterion is derived from one general preference function or self-defined preference function of the decision-maker.

Table 3
The estimation results of HAR-type volatility models for forecasting 1-day volatility.

Volatility models		c	α_1	α_2	α_3	β_1	β_2	β_3	ϕ_1	ϕ_2	ϕ_3	λ_1	λ_2	λ_3	Structural breaks	Adj.R^2
Without leverage effect	HAR-RV	3.549***	0.104***	0.130	0.239**										Yes	0.278
		(5.676)	(3.856)	(0.987)	(2.108)											
	HAR-RV-J	2.961***	0.400**	0.103	0.145*	-0.415**									Yes	0.300
		(5.751)	(2.385)	(0.826)	(1.690)	(−2.443)										
	HAR-CJ	2.198***	0.323**	0.229*	0.446***	0.012	0.053	-0.606**							Yes	0.311
		(3.667)	(2.205)	(1.728)	(2.588)	(0.722)	(0.686)	(−2.309)								
	HAR-RSV	2.638***	0.027	0.050	-0.109	0.279***	0.235**	0.676***							Yes	0.294
		(5.256)	(1.499)	(0.417)	(−0.637)	(2.759)	(1.961)	(3.026)								
	HAR-RSV-J	2.423***	0.302*	0.059	-0.143	0.421***	0.171	0.562***	-0.331**						Yes	0.306
		(4.568)	(1.814)	(0.549)	(−0.919)	(2.760)	(1.323)	(3.099)	(−2.134)							
	HAR-RV-SJ	3.193***	0.172***	0.120	0.226**	0.165***									Yes	0.290
		(5.999)	(2.585)	(0.875)	(2.173)	(2.839)										
	HAR-RV-SSJ(I)	3.043***	0.376*	0.105	0.178**	-0.170			0.411**						Yes	0.297
		(5.938)	(1.939)	(0.789)	(1.977)	(−0.936)			(2.165)							
	HAR-RV-SSJ(II)	2.551***	0.305*	0.088	0.719***	-0.113	0.179	-0.985***	0.313*	0.018	1.264***				Yes	0.306
		(5.061)	(1.677)	(0.493)	(4.119)	(−0.644)	(0.815)	(−3.413)	(1.719)	(0.111)	(3.870)					
With leverage effect	LHAR-RV	2.261***	0.079***	0.088	0.219*							-0.497***	-0.926*	-1.051**	Yes	0.295
		(4.899)	(3.414)	(0.672)	(1.795)							(−3.790)	(−1.657)	(−2.176)		
	LHAR-RV-J	2.086***	0.335**	0.076	0.149	-0.353**						-0.425***	-0.697	-0.704	Yes	0.310
		(4.279)	(2.153)	(0.606)	(1.501)	(−2.320)						(−3.953)	(−1.634)	(−1.580)		
	LHAR-CJ	1.794***	0.265*	0.187	0.533**	0.005	0.043	-0.584**				-0.473***	-0.783*	0.337***	Yes	0.320
		(3.236)	(1.905)	(1.207)	(2.520)	(0.331)	(0.595)	(−2.279)				(−4.484)	(−1.814)	(0.613)		
	LHAR-RSV	2.265***	0.038**	0.076	-0.051	0.197*	0.115	0.661**				-0.340***	-0.776	-0.187	Yes	0.300
		(4.795)	(2.373)	(0.638)	(−0.278)	(1.884)	(0.665)	(2.232)				(−2.961)	(−1.417)	(−0.335)		
	LHAR-RSV-J	2.123***	0.325**	0.080	-0.098	0.325**	0.074	0.592**	-0.341**			-0.433***	-0.673	0.100	Yes	0.312
		(4.409)	(1.971)	(0.764)	(−0.593)	(2.189)	(0.397)	(2.319)	(−2.156)			(−3.719)	(−1.333)	(0.169)		
	LHAR-RV-SJ	2.239***	0.128**	0.085	0.205*	0.099*						-0.295**	-0.840*	-1.051**	Yes	0.298
		(4.711)	(2.195)	(0.643)	(1.755)	(1.774)						(−2.297)	(−1.654)	(−2.204)		
	LHAR-RV-SSJ(I)	2.144***	0.339*	0.078	0.163	-0.284			0.352***			-0.480***	-0.655	-0.829*	Yes	0.306
		(4.393)	(1.872)	(0.602)	(1.602)	(−1.422)			(1.952)			(−3.200)	(−1.615)	(−1.849)		
	LHAR-RV-SSJ(II)	2.066***	0.282	0.070	0.720***	-0.218	0.078	-1.044***	0.279	-0.011	1.207***	-0.497***	-0.650	-0.264	Yes	0.314
		(4.256)	(1.607)	(0.388)	(3.772)	(−1.160)	(0.363)	(−3.869)	(1.558)	(−0.062)	(3.556)	(−3.642)	(−1.394)	(−0.444)		

Note: Asterisks indicate statistical significance at the 1% (***), 5% (**) or 10% (*) level.

Table 4
The estimation results of HAR-type volatility models for forecasting 1-week volatility.

Volatility models		c	α_1	α_2	α_3	β_1	β_2	β_3	ϕ_1	ϕ_2	ϕ_3	λ_1	λ_2	λ_3	Structural breaks	Adj.R^2
Without leverage effect	HAR-RV	3.739***	0.021	0.163**	0.261**										Yes	0.576
		(6.127)	(0.777)	(2.204)	(2.441)											
	HAR-RV-J	3.467***	0.158***	0.151**	0.218**	-0.192***									Yes	0.586
		(6.144)	(3.043)	(2.182)	(2.219)	(−3.243)										
	HAR-CJ	2.720***	0.063	0.401***	0.390***	0.001	0.023	-0.391**							Yes	0.609
		(4.694)	(1.332)	(3.955)	(3.406)	(0.076)	(0.334)	(−2.033)								
	HAR-RSV	3.109***	-0.007	0.080	0.006	0.078**	0.295**	0.584***							Yes	0.589
		(5.438)	(−0.507)	(0.890)	(0.030)	(2.124)	(2.494)	(3.273)								
	HAR-RSV-J	3.019***	0.110**	0.084	-0.009	0.138***	0.268**	0.537***	-0.140***						Yes	0.594
		(5.368)	(2.205)	(0.965)	(−0.048)	(2.631)	(2.253)	(3.131)	(−2.699)							
	HAR-RV-SJ	3.567***	0.054**	0.158**	0.255**	0.080***									Yes	0.582
		(6.031)	(2.542)	(2.101)	(2.455)	(3.115)										
	HAR-RV-SSJ(I)	3.507***	0.136**	0.153**	0.236**	-0.055			0.178***						Yes	0.584
		(6.063)	(2.442)	(2.099)	(2.333)	(−0.856)			(2.990)							
	HAR-RV-SSJ(II)	3.041***	0.022	0.380***	0.664***	0.078	-0.202	-1.021***	0.027	0.352**	1.080***				Yes	0.611
		(5.609)	(0.437)	(3.399)	(4.040)	(1.417)	(−1.172)	(−2.869)	(0.474)	(2.383)	(3.716)					
With leverage effect	LHAR-RV	3.035***	0.008	0.115*	0.291**							-0.159***	-1.364**	-0.197	Yes	0.600
		(6.292)	(0.355)	(1.647)	(2.122)							(−2.623)	(−2.090)	(−0.329)		
	LHAR-RV-J	2.967***	0.108**	0.110*	0.264**	-0.138***						-0.131**	-1.274**	-0.062	Yes	0.605
		(6.264)	(2.386)	(1.647)	(1.977)	(−2.798)						(−2.026)	(−2.012)	(−0.104)		
	LHAR-CJ	2.693***	0.021	0.329***	0.549***	0.001	0.014	-0.370*				-0.194***	-1.300**	1.010	Yes	0.628
		(5.781)	(0.458)	(3.583)	(3.217)	(−0.012)	(0.201)	(−1.947)				(−3.197)	(−2.211)	(1.361)		
	LHAR-RSV	3.077***	-0.003	0.140*	0.038	0.039	0.065	0.739***				-0.120**	-1.385**	0.602	Yes	0.604
		(6.398)	(−0.211)	(1.610)	(0.199)	(0.917)	(0.673)	(2.606)				(−2.005)	(−2.232)	(0.796)		
	LHAR-RSV-J	3.019***	0.114**	0.141*	0.019	0.091*	0.048	0.711***	-0.139***			-0.157***	-1.344**	0.719	Yes	0.608
		(6.413)	(2.299)	(1.715)	(0.103)	(1.659)	(0.488)	(2.603)	(−2.631)			(−2.749)	(−2.179)	(0.958)		
	LHAR-RV-SJ	3.028***	0.022	0.114*	0.287**	0.029						-0.099*	-1.338**	-0.197	Yes	0.601
		(6.258)	(0.953)	(1.630)	(2.097)	(1.147)						(−1.314)	(−2.066)	(−0.327)		
	LHAR-RV-SSJ(I)	2.996***	0.095*	0.111*	0.273**	-0.103			0.117**			-0.163**	-1.274**	-0.121	Yes	0.603
		(6.276)	(1.878)	(1.633)	(2.017)	(−1.535)			(2.034)			(−2.511)	(−1.989)	(−0.202)		
	LHAR-RV-SSJ(II)	2.964***	-0.002	0.342***	0.733***	0.057	-0.449**	-0.938***	-0.002	0.267***	1.108***	-0.161***	-1.459**	0.595	Yes	0.628
		(6.782)	(−0.030)	(3.092)	(3.751)	(1.002)	(−2.372)	(−3.119)	(−0.044)	(1.973)	(3.482)	(−2.956)	(−2.315)	(0.787)		

Table 5
The estimation results of HAR-type volatility models for forecasting 1-month volatility.

Volatility models		c	α_1	α_2	α_3	β_1	β_2	β_3	ϕ_1	ϕ_2	ϕ_3	λ_1	λ_2	λ_3	Structural breaks	$Adj.R^2$
Without leverage effect	HAR-RV	4.461***	0.007	0.045	0.291***										Yes	0.772
		(8.374)	(0.562)	(0.872)	(3.444)											
	HAR-RV-J	4.299***	0.088***	0.038	0.265***	-0.115***									Yes	0.778
		(8.523)	(3.657)	(0.777)	(3.246)	(−4.862)										
	HAR-CJ	3.747***	0.033**	0.128**	0.484***	-0.006	0.002	-0.279**							Yes	0.794
		(7.906)	(2.107)	(2.022)	(3.936)	(−0.869)	(0.054)	(−2.497)								
	HAR-RSV	3.916***	-0.006	0.020	-0.029	0.031**	0.069	0.722***							Yes	0.784
		(7.573)	(−0.868)	(0.443)	(−0.290)	(2.298)	(1.100)	(3.805)								
	HAR-RSV-J	3.862***	0.063***	0.023	-0.038 (−0.384)	0.067***	0.053	0.694***	-0.084***						Yes	0.786
		(7.556)	(2.628)	(0.511)		(3.214)	(0.838)	(3.656)	(−3.619)							
	HAR-RV-SJ	4.369***	0.024**	0.043	0.287***	0.043***									Yes	0.775
		(8.391)	(2.003)	(0.810)	(3.434)	(3.248)										
	HAR-RV-SSJ(I)	4.316***	0.097***	0.037	0.270***	-0.076**			0.130***						Yes	0.778
		(8.508)	(3.410)	(0.755)	(3.264)	(−2.377)			(5.188)							
	HAR-RV-SSJ(II)	3.866***	0.014	0.092	0.835***	0.023	-0.016	-1.134***	0.021	0.083	1.336***				Yes	0.812
		(8.790)	(0.727)	(1.064)	(4.383)	(0.988)	(−0.115)	(−3.573)	(1.100)	(0.812)	(4.190)					
With leverage effect	LHAR-RV	4.214***	0.001	0.022	0.316***							-0.064*	-0.706***	0.086	Yes	0.780
		(9.929)	(0.070)	(0.447)	(2.907)							(−1.733)	(−3.290)	(0.161)		
	LHAR-RV-J	4.169***	0.067***	0.018	0.298***	-0.091***						-0.045	-0.646***	0.176	Yes	0.783
		(9.962)	(3.094)	(0.400)	(2.803)	(−4.179)						(−1.234)	(−3.107)	(0.332)		
	LHAR-CJ	3.944***	0.014	0.100*	0.597***	-0.006	-0.004	-0.268**				-0.081**	-0.715***	0.973*	Yes	0.802
		(9.750)	(0.929)	(1.595)	(4.055)	(−1.029)	(−0.130)	(−2.478)				(−2.292)	(−3.836)	(1.836)		
	LHAR-RSV	4.281***	-0.005	0.058	-0.055	0.015	-0.048	0.981***				-0.050	-0.752***	1.268*	Yes	0.790
		(10.37)	(−0.614)	(1.085)	(−0.532)	(0.913)	(−0.656)	(3.278)				(−1.360)	(−3.589)	(1.704)		
	LHAR-RSV-J	4.244***	0.069***	0.059	-0.067	0.048**	-0.059	0.963***	-0.088***			-0.074*	-0.726***	1.342*	Yes	0.793
		(10.40)	(2.789)	(1.160)	(−0.672)	(2.245)	(−0.792)	(3.247)	(−3.679)			(−1.950)	(−3.453)	(1.818)		
	LHAR-RV-SJ	4.209***	0.012	0.021	0.313***	0.022*						-0.019	-0.686***	0.086	Yes	0.781
		(9.922)	(1.024)	(0.434)	(2.883)	(1.620)						(−0.412)	(−3.277)	(0.161)		
	LHAR-RV-SSJ(I)	4.179***	0.079***	0.019	0.300***	-0.099***			0.103***			-0.078*	-0.627***	0.157	Yes	0.783
		(9.991)	(3.141)	(0.400)	(2.795)	(−3.051)			(4.191)			(−1.893)	(−3.008)	(0.297)		
	LHAR-RV-SSJ(II)	4.144***	0.003	0.090	0.908***	0.012	-0.169	-0.953***	0.007	0.054	1.411***	-0.084**	-0.775***	1.119**	Yes	0.819
		(10.67)	(0.162)	(1.101)	(4.634)	(0.500)	(−1.340)	(−3.525)	(0.410)	(0.554)	(4.366)	(−2.447)	(−4.222)	(2.038)		

Table 6
Preference functions.

Definition	Function	Definition	Function
Generalized criterion	$\varphi(d)=\begin{cases}0 & d\le 0\\ 1 & d>0\end{cases}$	Same level criterion	$\varphi(d)=\begin{cases}0 & \lvert d\rvert\le q\\ \frac{1}{2} & q\le\lvert d\rvert\le p\\ 1 & \lvert d\rvert>p\end{cases}$
Partial criterion	$\varphi(d)=\begin{cases}0 & -q\le d\le p\\ 1 & d<-q, d>q\end{cases}$	False criterion	$\varphi(d)=\begin{cases}0 & \lvert d\rvert\le q\\ \frac{\lvert d\rvert-q}{p-q} & q\le\lvert d\rvert\le p\\ 1 & \lvert d\rvert>p\end{cases}$
Linear optimization criterion	$\varphi(d)=\begin{cases}\frac{d}{p} & -q\le d\le p\\ 1 & d<-q, d>q\end{cases}$	Gaussian criterion	$\varphi(d)=1-e^{-\frac{d^2}{2\sigma^2}}$

The multi-criteria preference index is given as

$$\Pi(a_i,a_j)=\sum_{k=1}^{t}w_kP_k(a_i,a_j) \tag{39}$$

Step IV: Calculate the positive outranking flow and negative outranking flow of alternative a_i using the following equations:

$$\Phi^{+}(a_i)=\sum_{j=1}^{n}\Pi(a_i,a_j) \tag{40}$$

$$\Phi^{-}(a_i)=\sum_{j=1}^{n}\Pi(a_j,a_i) \tag{41}$$

Step V: Calculate the net outranking flow of alternative a_i using the following equation:

$$\Phi(a_i)=\Phi^{+}(a_i)\text{-}\Phi^{-}(a_i) \tag{42}$$

If $\Phi(a_i)>\Phi(a_j)$, alternative a_i is preferred to a_j; if $\Phi(a_i)=\Phi(a_j)$, alternative a_i and a_j have no significant differences.

Step VI: Determine the ranking of all the considered alternatives based on $\Phi(a_i)$. The higher the value of $\Phi(a_i)$, the better the alternative. Additionally, the best alternative is that which has the highest $\Phi(a_i)$ value. Therefore, PROMETHEE II provides a complete ranking.

7.2.2.2. Results. MAE, MAPE, RMSE and HRMSE are defined as criteria 1, 2, 3 and 4, respectively, and the new HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models are viewed as sixteen alternatives that are denoted $a_1, a_2, \cdots, a_{16}$, respectively. All criteria have the same weight, i.e., $w_1=0.25$, $w_2=0.25$, $w_3=0.25$ and $w_4=0.25$. We use the PROMETHEE II method to compare the predictive ability of the sixteen models for forecasting the 1-day volatility of crude oil futures as follows.

Step I: Normalize the decision matrix using Eq. (36).

Step II: $P_k(a_i,a_j)=\varphi_k(\cdot)$. We choose the preference function, $\varphi_k(x)=\begin{cases}0 & x\le 0\\ 1 & x>0\end{cases}$. Based on the results of the Diebold and Mariano test, if the statistics of a_i and b_j are significantly negative in Tables A.4, A.5, A.6, A.7, A.8, A.9, A.10, A.11, A.12, A.13, A.14 or A.15, alternative a_i is preferred to alternative a_j under criterion C_k ($k=1,2,3,4$) and $\varphi_k(x)=1$. If the statistics of a_i and b_j are significantly positive or non-significant, then $\varphi_k(x)=0$.
The results are repored in Tables 7–10.

Step III: Define the multi-criteria preference outranking index, $\Pi(a_i,a_j)=\sum_{k=1}^{4}w_kP_k(a_i,a_j)$, and denote the sequential process as follows:

$a_1:\ \Pi(a_1,a_2)=0.00, \Pi(a_1,a_3)=0.25, \Pi(a_1,a_4)=0.00, \Pi(a_1,a_5)=0.00,$
$\Pi(a_1,a_6)=0.00, \Pi(a_1,a_7)=0.75, \Pi(a_1,a_8)=0.25, \Pi(a_1,a_9)=0.50,$
$\Pi(a_1,a_{10})=0.75, \Pi(a_1,a_{11})=1.00, \Pi(a_1,a_{12})=0.75, \Pi(a_1,a_{13})=0.75,$
$\Pi(a_1,a_{14})=0.75, \Pi(a_1,a_{15})=1.00, \Pi(a_1,a_{16})=0.75;$

Table 7
Results of $P_1(a_i,a_j)$.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}
a_1	–	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1
a_2	0	–	0	0	0	0	1	0	1	1	1	1	1	1	1	1
a_3	0	0	–	0	0	0	0	0	1	1	1	1	1	1	1	1
a_4	1	1	1	–	1	1	1	1	1	1	1	1	1	1	1	1
a_5	0	0	0	0	–	1	1	1	1	1	1	1	1	1	1	1
a_6	0	0	0	0	0	–	1	0	1	1	1	1	1	1	1	1
a_7	0	0	0	0	0	0	–	0	1	1	1	1	1	1	1	1
a_8	0	0	0	0	0	0	0	–	1	1	1	1	1	1	1	1
a_9	0	0	0	0	0	0	0	0	–	1	1	0	1	1	1	1
a_{10}	0	0	0	0	0	0	0	0	0	–	1	0	1	0	0	1
a_{11}	0	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0
a_{12}	0	0	0	0	0	0	0	0	0	0	1	–	1	0	0	1
a_{13}	0	0	0	0	0	0	0	0	0	0	1	0	–	0	0	0
a_{14}	0	0	0	0	0	0	0	0	0	1	1	0	1	–	1	1
a_{15}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	–	1
a_{16}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	–

Notes: The first column is a_i, and the first row is a_j.

Table 8
Results of $P_2(a_i,a_j)$.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}
a_1	–	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
a_2	1	–	0	0	0	1	1	0	1	1	1	1	1	1	1	1
a_3	1	1	–	1	1	1	1	1	1	1	1	1	1	1	1	1
a_4	1	1	0	–	1	1	1	1	1	1	1	1	1	1	1	1
a_5	1	1	0	0	–	1	1	1	1	1	1	1	1	1	1	1
a_6	0	0	0	0	0	–	1	0	1	1	1	1	1	1	1	1
a_7	0	1	0	0	0	0	–	0	1	1	1	1	1	1	1	1
a_8	1	0	0	0	0	1	1	–	1	1	1	1	1	1	1	1
a_9	1	0	0	0	0	0	0	0	–	1	1	0	1	0	0	0
a_{10}	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0	0
a_{11}	0	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0
a_{12}	0	0	0	0	0	0	0	0	0	1	1	–	1	0	0	1
a_{13}	0	0	0	0	0	0	0	0	0	0	1	0	–	0	0	0
a_{14}	0	0	0	0	0	0	0	0	0	1	1	0	1	–	0	0
a_{15}	0	0	0	0	0	0	0	0	0	1	1	0	1	0	–	0
a_{16}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	–

Table 9
Results of $P_3(a_i,a_j)$.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}
a_1	–	0	1	0	0	0	1	1	0	0	1	0	0	0	1	0
a_2	0	–	1	0	0	0	0	0	0	1	1	1	1	1	0	1
a_3	0	0	–	0	0	0	0	0	0	0	1	0	0	0	0	0
a_4	0	0	0	–	1	0	0	1	0	0	1	0	0	0	0	0
a_5	0	0	0	0	–	0	0	1	0	0	1	0	0	0	0	0
a_6	0	0	0	0	0	–	0	0	0	0	1	0	0	0	0	0
a_7	0	0	0	0	0	0	–	1	0	0	1	0	0	0	0	0
a_8	0	0	0	0	0	0	0	–	0	0	1	0	0	0	0	0
a_9	0	0	1	0	0	0	0	1	–	0	1	0	0	0	1	1
a_{10}	0	1	1	0	0	0	0	0	0	–	1	0	1	0	0	1
a_{11}	0	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0
a_{12}	0	0	1	0	0	0	0	0	0	0	1	–	1	0	0	0
a_{13}	0	0	0	0	0	0	0	0	0	0	1	0	–	0	0	0
a_{14}	0	0	1	0	0	0	0	0	0	0	1	0	0	–	0	1
a_{15}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	–	0
a_{16}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	–

Table 10
Results of $P_4(a_i,a_j)$.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}
a_1	–	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1
a_2	1	–	0	0	0	1	1	1	1	1	1	1	1	1	1	1
a_3	1	1	–	1	1	1	1	1	1	1	1	1	1	1	1	1
a_4	1	1	0	–	1	1	1	1	1	1	1	1	1	1	1	1
a_5	0	0	0	0	–	1	1	1	1	1	1	1	1	1	1	1
a_6	0	0	0	0	0	–	1	0	1	1	1	1	1	1	1	1
a_7	0	0	0	0	0	0	–	0	1	1	1	1	1	1	1	1
a_8	0	0	0	0	0	0	1	–	1	1	1	1	1	1	1	1
a_9	0	0	0	0	0	0	0	0	–	1	0	0	0	0	0	0
a_{10}	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0	0
a_{11}	0	0	0	0	0	0	0	0	0	0	–	0	0	0	0	0
a_{12}	0	0	0	0	0	0	0	0	1	1	1	–	1	1	1	1
a_{13}	0	0	0	0	0	0	0	0	0	0	0	0	–	0	0	0
a_{14}	0	0	0	0	0	0	0	0	0	1	0	0	0	–	0	0
a_{15}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	–	0
a_{16}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	–

$$a_2: \Pi(a_2,a_1)=0.50, \Pi(a_2,a_3)=0.25, \Pi(a_2,a_4)=0.00, \Pi(a_2,a_5)=0.00, \Pi(a_2,a_6)=0.00, \Pi(a_2,a_7)=0.75, \Pi(a_2,a_8)=0.25, \Pi(a_2,a_9)=0.75, \Pi(a_2,a_{10})=1.00, \Pi(a_2,a_{11})=1.00, \Pi(a_2,a_{12})=1.00, \Pi(a_2,a_{13})=1.00, \Pi(a_2,a_{14})=1.00, \Pi(a_2,a_{15})=0.75, \Pi(a_2,a_{16})=1.00;$$

$$a_3: \Pi(a_3,a_1)=0.50, \Pi(a_3,a_2)=0.50\ \Pi(a_3,a_4)=0.50, \Pi(a_3,a_5)=0.50, \Pi(a_3,a_6)=0.50, \Pi(a_3,a_7)=0.50, \Pi(a_3,a_8)=0.50, \Pi(a_3,a_9)=0.75, \Pi(a_3,a_{10})=0.75, \Pi(a_3,a_{11})=1.00, \Pi(a_3,a_{12})=0.75, \Pi(a_3,a_{13})=0.75, \Pi(a_3,a_{14})=0.75, \Pi(a_3,a_{15})=0.75, \Pi(a_3,a_{16})=0.75;$$

$$a_4: \Pi(a_4,a_1)=0.75, \Pi(a_4,a_2)=0.75, \Pi(a_4,a_3)=0.25, \Pi(a_4,a_5)=1.00, \Pi(a_4,a_6)=0.75, \Pi(a_4,a_7)=0.75, \Pi(a_4,a_8)=1.00, \Pi(a_4,a_9)=0.75, \Pi(a_4,a_{10})=0.75, \Pi(a_4,a_{11})=1.00, \Pi(a_4,a_{12})=0.75, \Pi(a_4,a_{13})=0.75, \Pi(a_4,a_{14})=0.75, \Pi(a_4,a_{15})=0.75, \Pi(a_4,a_{16})=0.75;$$

$$a_5: \Pi(a_5,a_1)=0.25, \Pi(a_5,a_2)=0.25, \Pi(a_5,a_3)=0.00, \Pi(a_5,a_4)=0.00, \Pi(a_5,a_6)=0.75, \Pi(a_5,a_7)=0.75, \Pi(a_5,a_8)=1.00, \Pi(a_5,a_9)=0.75, \Pi(a_5,a_{10})=0.75, \Pi(a_5,a_{11})=1.00, \Pi(a_5,a_{12})=0.75, \Pi(a_5,a_{13})=0.75, \Pi(a_5,a_{14})=0.75, \Pi(a_5,a_{15})=0.75, \Pi(a_5,a_{16})=0.75;$$

$$a_6: \Pi(a_6,a_1)=0.00, \Pi(a_6,a_2)=0.00, \Pi(a_6,a_3)=0.00, \Pi(a_6,a_4)=0.00, \Pi(a_6,a_5)=0.00, \Pi(a_6,a_7)=0.75, \Pi(a_6,a_8)=0.00, \Pi(a_6,a_9)=0.75, \Pi(a_6,a_{10})=0.75, \Pi(a_6,a_{11})=1.00, \Pi(a_6,a_{12})=0.75, \Pi(a_6,a_{13})=0.75, \Pi(a_6,a_{14})=0.75, \Pi(a_6,a_{15})=0.75, \Pi(a_6,a_{16})=0.75;$$

$$a_7: \Pi(a_7,a_1)=0.00, \Pi(a_7,a_2)=0.25, \Pi(a_7,a_3)=0.25, \Pi(a_7,a_4)=0.00, \Pi(a_7,a_5)=0.00, \Pi(a_7,a_6)=0.25, \Pi(a_7,a_8)=0.25, \Pi(a_7,a_9)=0.75, \Pi(a_7,a_{10})=0.75, \Pi(a_7,a_{11})=1.00, \Pi(a_7,a_{12})=0.75, \Pi(a_7,a_{13})=0.75, \Pi(a_7,a_{14})=0.75, \Pi(a_7,a_{15})=0.75, \Pi(a_7,a_{16})=0.75;$$

$$a_8: \Pi(a_8,a_1)=0.25, \Pi(a_8,a_2)=0.00, \Pi(a_8,a_3)=0.00, \Pi(a_8,a_4)=0.00, \Pi(a_8,a_5)=0.00, \Pi(a_8,a_6)=0.25, \Pi(a_8,a_7)=0.50, \Pi(a_8,a_9)=0.75, \Pi(a_8,a_{10})=0.75, \Pi(a_8,a_{11})=1.00, \Pi(a_8,a_{12})=0.75, \Pi(a_8,a_{13})=0.75, \Pi(a_8,a_{14})=0.75, \Pi(a_8,a_{15})=0.75, \Pi(a_8,a_{16})=0.75;$$

$$a_9: \Pi(a_9,a_1)=0.25, \Pi(a_9,a_2)=0.00, \Pi(a_9,a_3)=0.25, \Pi(a_9,a_4)=0.00, \Pi(a_9,a_5)=0.00, \Pi(a_9,a_6)=0.00, \Pi(a_9,a_7)=0.00, \Pi(a_9,a_8)=0.25, \Pi(a_9,a_{10})=0.75, \Pi(a_9,a_{11})=0.75, \Pi(a_9,a_{12})=0.00, \Pi(a_9,a_{13})=0.50, \Pi(a_9,a_{14})=0.25, \Pi(a_9,a_{15})=0.50, \Pi(a_9,a_{16})=0.50;$$

$$a_{10}: \Pi(a_{10},a_1)=0.00, \Pi(a_{10},a_2)=0.25, \Pi(a_{10},a_3)=0.25, \Pi(a_{10},a_4)=0.00, \Pi(a_{10},a_5)=0.00, \Pi(a_{10},a_6)=0.00, \Pi(a_{10},a_7)=0.00, \Pi(a_{10},a_8)=0.00, \Pi(a_{10},a_9)=0.00, \Pi(a_{10},a_{11})=0.50, \Pi(a_{10},a_{12})=0.00, \Pi(a_{10},a_{13})=0.50, \Pi(a_{10},a_{14})=0.00, \Pi(a_{10},a_{15})=0.00, \Pi(a_{10},a_{16})=0.50;$$

$$a_{11}: \Pi(a_{11},a_1)=0.00, \Pi(a_{11},a_2)=0.00, \Pi(a_{11},a_3)=0.00, \Pi(a_{11},a_4)=0.00, \Pi(a_{11},a_5)=0.00, \Pi(a_{11},a_6)=0.00, \Pi(a_{11},a_7)=0.00, \Pi(a_{11},a_8)=0.00, \Pi(a_{11},a_9)=0.00, \Pi(a_{11},a_{10})=0.00, \Pi(a_{11},a_{12})=0.00, \Pi(a_{11},a_{13})=0.00, \Pi(a_{11},a_{14})=0.00, \Pi(a_{11},a_{15})=0.00, \Pi(a_{11},a_{16})=0.00;$$

$$a_{12}: \Pi(a_{12},a_1)=0.00, \Pi(a_{12},a_2)=0.00, \Pi(a_{12},a_3)=0.25, \Pi(a_{12},a_4)=0.00, \Pi(a_{12},a_5)=0.00, \Pi(a_{12},a_6)=0.00, \Pi(a_{12},a_7)=0.00, \Pi(a_{12},a_8)=0.00, \Pi(a_{12},a_9)=0.25, \Pi(a_{12},a_{10})=0.50, \Pi(a_{12},a_{11})=1.00, \Pi(a_{12},a_{13})=1.00, \Pi(a_{12},a_{14})=0.25, \Pi(a_{12},a_{15})=0.25, \Pi(a_{12},a_{16})=0.25;$$

$$a_{13}: \Pi(a_{13},a_1)=0.00, \Pi(a_{13},a_2)=0.00, \Pi(a_{13},a_3)=0.00, \Pi(a_{13},a_4)=0.00, \Pi(a_{13},a_5)=0.00, \Pi(a_{13},a_6)=0.00, \Pi(a_{13},a_7)=0.00, \Pi(a_{13},a_8)=0.00, \Pi(a_{13},a_9)=0.00, \Pi(a_{13},a_{10})=0.00, \Pi(a_{13},a_{11})=0.75, \Pi(a_{13},a_{12})=0.00, \Pi(a_{13},a_{14})=0.00, \Pi(a_{13},a_{15})=0.00, \Pi(a_{13},a_{16})=0.00;$$

$$a_{14}: \Pi(a_{14},a_1)=0.00, \Pi(a_{14},a_2)=0.00, \Pi(a_{14},a_3)=0.25, \Pi(a_{14},a_4)=0.00, \Pi(a_{14},a_5)=0.00, \Pi(a_{14},a_6)=0.00, \Pi(a_{14},a_7)=0.00, \Pi(a_{14},a_8)=0.00, \Pi(a_{14},a_9)=0.00, \Pi(a_{14},a_{10})=0.75, \Pi(a_{14},a_{11})=0.75, \Pi(a_{14},a_{12})=0.00, \Pi(a_{14},a_{13})=0.50, \Pi(a_{14},a_{15})=0.25, \Pi(a_{14},a_{16})=0.50;$$

$$a_{15}: \Pi(a_{15},a_1)=0.00, \Pi(a_{15},a_2)=0.00, \Pi(a_{15},a_3)=0.00, \Pi(a_{15},a_4)=0.00, \Pi(a_{15},a_5)=0.00, \Pi(a_{15},a_6)=0.00, \Pi(a_{15},a_7)=0.00, \Pi(a_{15},a_8)=0.00, \Pi(a_{15},a_9)=0.00, \Pi(a_{15},a_{10})=0.25, \Pi(a_{15},a_{11})=0.75, \Pi(a_{15},a_{12})=0.00, \Pi(a_{15},a_{13})=0.25, \Pi(a_{15},a_{14})=0.00, \Pi(a_{15},a_{16})=0.25;$$

$$a_{16}: \Pi(a_{16},a_1)=0.00, \Pi(a_{16},a_2)=0.00, \Pi(a_{16},a_3)=0.00, \Pi(a_{16},a_4)=0.00, \Pi(a_{16},a_5)=0.00, \Pi(a_{16},a_6)=0.00, \Pi(a_{16},a_7)=0.00, \Pi(a_{16},a_8)=0.00, \Pi(a_{16},a_9)=0.00, \Pi(a_{16},a_{10})=0.00, \Pi(a_{16},a_{11})=0.75, \Pi(a_{16},a_{12})=0.00, \Pi(a_{16},a_{13})=0.00, \Pi(a_{16},a_{14})=0.00, \Pi(a_{16},a_{15})=0.00.$$

Step IV: Based on $\Phi^+(a_i)=\sum_{j=1}^{15}\Pi(a_i,a_j)$ and $\Phi^-(a_i)=\sum_{j=1}^{15}\Pi(a_j,a_i)$, the positive and negative outranking flows of alternative a_i are defined as follows:

$$\Phi^+(a_1)=7.50, \Phi^+(a_2)=9.75, \Phi^+(a_3)=9.75, \Phi^+(a_4)=11.50, \Phi^+(a_5)=9.25, \Phi^+(a_6)=7.00, \Phi^+(a_7)=6.75, \Phi^+(a_8)=7.25, \Phi^+(a_9)=4.00, \Phi^+(a_{10})=2.00, \Phi^+(a_{11})=0.00, \Phi^+(a_{12})=4.25, \Phi^+(a_{13})=0.75, \Phi^+(a_{14})=3.00, \Phi^+(a_{15})=1.50, \Phi^+(a_{16})=0.75;$$

$$\Phi^-(a_1)=2.50, \Phi^-(a_2)=2.00, \Phi^-(a_3)=1.75, \Phi^-(a_4)=0.50, \Phi^-(a_5)=1.50, \Phi^-(a_6)=2.75, \Phi^-(a_7)=4.75, \Phi^-(a_8)=3.50, \Phi^-(a_9)=6.00, \Phi^-(a_{10})=8.50, \Phi^-(a_{11})=13.25, \Phi^-(a_{12})=6.25, \Phi^-(a_{13})=9.00, \Phi^-(a_{14})=6.75, \Phi^-(a_{15})=7.25, \Phi^-(a_{16})=8.75.$$

Step V: Calculate the net outranking flow of alternative a_i based on the difference between positive and negative outranking flows of alternative a_i, i.e., $\Phi(a_i)=\Phi^+(a_i)-\Phi^-(a_i)$:

$$\Phi(a_1)=5.00, \Phi(a_2)=7.75, \Phi(a_3)=8.00, \Phi(a_4)=11.00, \Phi(a_5)=7.75, \Phi(a_6)=4.25, \Phi(a_7)=2.00, \Phi(a_8)=3.75, \Phi(a_9)=\text{-}2.00, \Phi(a_{10})=\text{-}6.50, \Phi(a_{11})=\text{-}13.25, \Phi(a_{12})=\text{-}2.00, \Phi(a_{13})=\text{-}8.25, \Phi(a_{14})=\text{-}3.75, \Phi(a_{15})=-5.75, \Phi(a_{16})=\text{-}8.00.$$

Step VI: The alternatives are ranked in terms of the values of $\Phi(a_i)$ from large to small: $a_4 \succ a_3 \succ a_2 \succ a_5 \succ a_1 \succ a_6 \succ a_8 \succ a_7 \succ a_9 \cap a_{12} \succ a_{14} \succ a_{15} \succ a_{10} \succ a_{16} \succ a_{13} \succ a_{11}$. Therefore, the forecasting performance of the sixteen HAR-type volatility models is ranked from strong to weak as follows: the HAR-RSV, HAR-CJ, HAR-RV-J, HAR-RSV-J, HAR-RV, HAR-RSV-SJ, HAR-RV-SSJ(II), HAR-RV-SSJ(I), LHAR-RV, LHAR-RSV, LHAR-RSV-SJ, LHAR-RV-SSJ(I), LHAR-RV-J, LHAR-RV-SSJ(II), LHAR-RSV-J and LHAR-CJ models.

Employing the same method, we obtain a net outranking flow of alternative a_i when all the models forecast the 1-week volatility of crude oil futures.

$\Phi(a_1) = 3.25, \Phi(a_2) = 5.75, \Phi(a_3) = 8.50, \Phi(a_4) = 8.25, \Phi(a_5) = 5.00,$
$\Phi(a_6) = 7.25, \Phi(a_7) = 4.00, \Phi(a_8) = 6.75, \Phi(a_9) = \text{-}2.00,$
$\Phi(a_{10}) = -6.00, \Phi(a_{11}) = -6.50, \Phi(a_{12}) = -7.75, \Phi(a_{13}) = -11.75,$
$\Phi(a_{14}) = -2.25, \Phi(a_{15}) = -6.50, \Phi(a_{16}) = -6.00.$

The alternatives are ranked in terms of the values of $\Phi(a_i)$ from largest to smallest: $a_3 \succ a_4 \succ a_6 \succ a_8 \succ a_2 \succ a_5 \succ a_7 \succ a_1 \succ a_9 \succ a_{14} \succ a_{10} \cap a_{16} \succ a_{11} \cap a_{15} \succ a_{12} \succ a_{13}$. Therefore, the forecasting performance of the sixteen HAR-type volatility models is ranked from strongest to weakest as follows: HAR-CJ, HAR-RSV, HAR-RSV-SJ, HAR-RV-SSJ(II), HAR-RV-J, HAR-RSV-J, HAR-RV-SSJ(I), HAR-RV, LHAR-RV, LHAR-RSV-SJ, LHAR-RV-J, LHAR-RV-SSJ(II), LHAR-CJ, LHAR-RV-SSJ(I), LHAR-RSV and LHAR-RSV-J models.

In addition, we can obtain the net outranking flow of alternative a_i when all models forecast the 1-month volatility of crude oil futures.

$\Phi(a_1) = 1.75, \Phi(a_2) = 6.25, \Phi(a_3) = 5.75, \Phi(a_4) = 7.75, \Phi(a_5) = 5.25,$
$\Phi(a_6) = 7.50, \Phi(a_7) = 6.75, \Phi(a_8) = 7.50, \Phi(a_9) = -3.50,$
$\Phi(a_{10}) = -5.25, \Phi(a_{11}) = -9.00, \Phi(a_{12}) = -8.25,$
$\Phi(a_{13}) = -10.25, \Phi(a_{14}) = -1.75, \Phi(a_{15}) = -4.00, \Phi(a_{16}) = \text{-}6.50.$

The alternatives are ranked in terms of the values of $\Phi(a_i)$ from largest to smallest: $a_4 \succ a_6 \cap a_8 \succ a_7 \succ a_2 \succ a_3 \succ a_5 \succ a_1 \succ a_{14} \succ a_9 \succ a_{15} \succ a_{10} \succ a_{16} \succ a_{12} \succ a_{11} \succ a_{13}$. Therefore, the forecasting performance of the sixteen HAR-type volatility models is ranked from strongest to weakest as follows: the HAR-RSV, HAR-RSV-SJ, HAR-RV-SSJ(II), HAR-RV-SSJ(I), HAR-RV-J, HAR-CJ, HAR-RSV-J, HAR-RV, LHAR-RSV-SJ, LHAR-RV, LHAR-RV-SSJ(I), LHAR-RV-J, LHAR-RV-SSJ(II), LHAR-RSV, LHAR-CJ and LHAR-RSV-J models.

Based on the evaluation results of the PROMETHEE II method, we find that different models exhibit different predictive powers to forecast the 1-day, 1-week and 1-month volatilities of crude oil futures. When the new HAR-type models forecast 1-day and 1-month volatilities, the new HAR-RSV models perform the best. However, when these models forecast 1-week volatility, the new HAR-CJ model performs the best.

8. Conclusion

The volatility of crude oil futures is an important input for investment, pricing and risk management; no consensus regarding the most effective models for forecasting the volatility of crude oil futures. In this paper, we introduce the HAR-RV, HAR-RV-J, HAR-CJ, HAR-RSV, HAR-RSV-J, HAR-RSV-SJ, HAR-RV-SSJ(I), HAR-RV-SSJ(II), LHAR-RV, LHAR-RV-J, LHAR-CJ, LHAR-RSV, LHAR-RSV-J, LHAR-RSV-SJ, LHAR-RV-SSJ(I) and LHAR-RV-SSJ(II) models with structural breaks. We then use 5-min high-frequency transaction data from the NYMEX-CME for the front-month WTI crude oil futures contract as a sample, and we employ OLS with Newey–West standard errors to estimate the model parameters. The estimation results indicate that the historical realized volatility, the continuous sample path variation, the negative realized semivariance, the signed jump and the signed semi-jumps contain more information for forecasting the volatility of crude oil futures than do the discontinuous jump variation and the positive realized semivariance. In addition, we find that structural breaks and the leverage effect exist in the volatility of crude oil futures. The volatility of crude oil futures is substantially affected by short- and long-term information, but it is little affected by medium-term information.

Thereafter, loss functions are employed to assess the forecasting performance of the above sixteen HAR-type models with structural breaks. We reveal that the loss functions cannot distinguish the performance of different models. Thus, we use the PROMETHEE II method to further evaluate the forecasting power of these models. The results show that different models exhibit different predictive power in forecasting the 1-day, 1-week and 1-month volatility of crude oil futures. Specifically, when the new HAR-type models forecast 1-day and 1-month volatilities, the new HAR-RSV model performs best, but when these models forecast 1-week volatility, the new HAR-CJ model performs best.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.07.014.

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