Energy Strategy Reviews 56 (2024) 101588

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Forecasting the volatility of crude oil futures: New evidence from jump-induced volatility

Anupam Dutta [a,*], Elie Bouri [b]

[a] School of Accounting and Finance, University of Vaasa, Finland
[b] School of Business, Lebanese American University, Lebanon

ARTICLE INFO

Handling editor: Mark Howells

Keywords:
Crude oil futures
Realized volatility
Jump-induced volatility
OVX
Leverage effects
HAR-RV models

ABSTRACT

This paper proposes an augmented heterogenous autoregressive (HAR) model with time-varying jumps to forecast the realized volatility (RV) of crude oil futures. Jump-induced volatility of crude oil futures is obtained from a GARCH-jump process, then used to augment the HAR model. The results based on both the in-sample and out-of-sample analyses suggest that jumps offer added information for forecasting the RV of crude oil futures, surpassing the incremental information contained in the crude oil implied volatility index (OVX). Various robustness tests confirm these findings. Our findings have key implications for energy market investors, risk managers, and policymakers.

1. Introduction

Forecasting the volatility of crude oil markets is a hot research topic in the energy finance and economics literature. A refined and precise estimate of oil price volatility is useful for economic development, policy formulation, financial stability, firm production operations, and energy investments [1],[1] and can play a pivotal role in portfolio management and hedging strategies [2].[2]

Previous studies apply various models to forecast the volatility of crude oil returns. They can be classified into several groups. The first relies on symmetric and asymmetric GARCH-type models for forecasting oil market risk (see Ref. [2–11] and others). The power and suitability of GARCH-based models arise from their subtlety in dealing with stylized aspects of financial return series such as volatility clustering, leverage effects, and fat-tails. A second group uses machine learning, notably neural networks (NNs), which can approximate non-linear processes without any knowledge or assumptions about the nature of the process. Some related studies include Kristjanpoller and Minutolo [12], Butler et al. [13] and Lu et al. [14], generally showing that NN processes can outperform conventional models. A third group applies the heterogeneous autoregressive (HAR) process to model and forecast the volatility of crude oil returns (see, among others, [15–19]; Luo et al., 2020). HAR-type models have gained immense popularity over the past 15 years as they embed a simple structure but account for the long memory of financial times series (e.g. crude oil) across various time periods, challenging the utility and power of traditional volatility models, including GARCH and stochastic volatility processes. Notably, they consider the application of high-frequency data, which improves its volatility forecasting power [19].

A major challenge in the forecasting of crude oil return volatility evolves around the design of proper econometric models capable of reflecting the main stylized facts of crude oil returns and the notably intensity of jump behaviour in oil return volatility. The crude oil market is complex and prone to geopolitical and economic shocks, which can

* Corresponding author.
E-mail addresses: adutta@uwasa.fi (A. Dutta), elie.elbouri@lau.edu.lb (E. Bouri).

[1] Previous studies (e.g. Ref. [52,53]; Dutta, 2018; [54]) show that oil price variations have significant impacts on agricultural and metal markets, which can influence global and regional economies.

[2] A number of studies argue that as oil prices behave differently under diverse market conditions, and it is a difficult task to obtain precise estimates of oil price volatilities [25]. For instance, Choi and Hammoudeh [55] show that oil prices tend to increase when volatility remains at lower levels. Gronwald [56], on the other hand, argues that energy prices often experience falls due to political instability, natural disasters and terrorism. Moreover, oil prices are significantly driven by the high correlations between oil and stock/metal/agriculture/exchange markets [57,58]. Hence, it is essential to precisely model the oil price risk so that energy market uncertainty can be reduced.

https://doi.org/10.1016/j.esr.2024.101588
Received 15 September 2023; Received in revised form 29 July 2024; Accepted 10 November 2024
Available online 14 November 2024

trigger abrupt changes in crude oil prices, making the volatility of crude oil returns exhibit a jumping behaviour [2,20]. While jumps carry valuable information about the level and intensity of extreme variations in asset prices, jump intensity reflects the probability of occurrence of jumps and shows notable clustering, suggesting an increased continuity [21]. In this regard, forecasting oil return volatility using jumps is pertinent and has implications for investors and policymakers.

The present study proposes an extended HAR model with time-varying jumps to forecast the realized volatility (henceforth, RV) of crude oil futures. The choice of RV is justified by several reasons. Firstly, high-frequency data, which constitute the basis for constructing RV, provide more detailed information compared to lower frequency (e.g. daily) data. Secondly, RV has been shown to measure volatility accurately and contain less noise, while avoiding complex parameter estimation ([22]; Anderson et al., 2007). This is pertinent to the case of crude oil, which represents a strategic commodity highly traded and often included in the portfolios of global investors. Thirdly, long memory is present in RV and displays a time-varying characteristic [23], which can be affected by jumps. This makes the RV of crude oil returns a suitable target for a forecasting analysis via HAR-based models.

Our current study makes several contributions to the literature. Firstly, to the best of our knowledge, this is the initial attempt to assess whether jump volatility has forecasting content for the realized volatility of crude oil futures. In particular, we examine whether and to what extent the volatility of time-dependent jumps in crude oil returns can forecast the RV of crude oil futures.[3] Such an investigation is crucial given that large jumps in financial assets often indicate an upsurge in market uncertainty [24]. Since the oil market has been highly volatile in recent years [25], time-varying jumps may have forecasting power for its volatility. Hence, using the information content of jump-induced volatility would improve the forecasting accuracy of oil return volatility. Moreover, as the jump-induced volatility might carry important information for understanding potential risk, time-varying jumps should be detected properly for the sake of various economic actors. Hence, our analysis could be useful for deriving appropriate asset pricing models, which could reduce oil price uncertainty.

Secondly, we check the forecasting ability of oil market implied volatility index (henceforth, OVX) when modelling the RV of crude oil futures. It is now well-documented in the finance literature that implied volatilities offer incremental information for equity return volatility forecasts (Kambouroudis et al., 2020). However, such literature is scarce in the context of energy markets. Some notable contributions include Haugom et al. (2014), Dutta [26], Gong and Lin [19], Dutta et al. [2], and Niu et al. [27]. While all these papers provide evidence that the information content of OVX is useful for the volatility forecasting of oil returns, our contribution is different but nicely complements those research papers in that it verifies whether the HAR process with the volatility of time-varying jumps outperforms the HAR model containing information on the OVX index.

It is worth noting that several studies have employed the HAR model to forecast the realized volatility of crude oil prices [17,27–34]. While some of these studies consider the jump component in the HAR process, the results are conflicting. Niu et al. [27], for example, show that the HAR models accounting for the jump component outperform the baseline HAR process. Cheng et al. [31] also document that jump volatility plays an important role in predicting crude oil volatility. Prokopczuk et al. [28], however, find that although the jump component improves the predictive ability of the HAR-type models applied to stock market returns, considering the jump variation is not advantageous for the crude oil market. Besides, Wen et al. (2016) conclude that the jump component is useful for forecasting the weekly volatility only. Zhang and Zhang [30] also show that the benefit of using the jump element depends on the forecasting horizons. Notably, all these studies follow the works of Andersen et al. [35], Corsi et al. [36] and Busch et al. [37] which consider separating the realized volatility into the continuous sample path and jump variations. Hence, the prior literature mainly employs the non-parametric statistical methods to estimate the jump volatility for crude oil prices. Our study extends the existing literature by verifying the role of conditional jump volatility estimated from a parametric GARCH model (i.e., the GARCH-jump process).[4] A recent study by Dutta and Das [38] also demonstrates that the conditional jump volatility, estimated using the GARCH-jump process, has more predictive contents than the continuous sample path and jump components. While the analysis of Dutta and Das [38] is focused on the stock market volatility, we adopt this methodology for predicting crude oil volatility.

Our main findings indicate the importance of jump-induced volatility given its significant contribution to improving the forecasting accuracy of crude oil realized volatility. In fact, the HAR approach considering information on jump-induced volatility outperforms all other models used in this study, which is supported by both the in-sample and out-of-sample analyses. Given that precise estimation of time-varying volatility is useful for developing appropriate asset pricing models and hedging strategies, our findings have important implications for energy market participants. For example, investors should adjust their portfolio strategies in time to avoid the adverse impact of jump-induced uncertainty.

The rest of the paper continues as follows: Section 2 provides the dataset. Section 3 describes the methodology. Section 4 presents the results and conducts a robustness analysis. Section 5 concludes.

2. Data

Our sample includes daily observations from May 2007 to June 2022, yielding a total of 3410 data points. The beginning of our sample period is determined by the availability of the OVX index. The daily data cover WTI crude oil futures prices and the OVX index, retrieved from the Bloomberg terminal. Realized volatility (RV) data, constructed based on 5-min intra-day squared returns, are collected from Professor Dacheng Xiu's risk lab (https://dachxiu.chicagobooth.edu/#risklab).

Fig. 1 plots the realized volatility of crude oil futures prices. This graph reveals that, while the futures index is, in general, volatile, the risk increases substantially amid global financial and health crises. Fig. 2, which depicts the jump-induced volatility for crude oil returns, demonstrates that such risk elevates mainly during crisis periods.

3. Methodology

Our empirical analysis follows a two-step procedure. The first estimates the conditional jump-induced volatility (JV) using the GARCH-jump process of Chan and Maheu [24]. The second step augments the HAR model with the JV and conducts a forecasting analysis.

[3] Jumps are often observed in crude oil returns. Previous studies document the presence of time-varying jumps in oil returns (see Ref. [25,52,53,56,59,60] etc.). In this paper, unlike earlier works, we study the occurrence of such jumps in the WTI futures market and their role in forecasting RV.

[4] Wu et al. [34] extend the HAR model by incorporating the intensity of jumps occurring in the Chinese crude oil futures returns. They employ the Hawkes process (1971) to estimate the jump intensity, whereas we consider the application of the GARCH-jump process to measure the intensity of such jumps. Although the method used in our study differs from what is adopted by Wu et al. [34], our results are in line with them, suggesting that jumps play a pivotal role in forecasting the RV of crude oil futures. Wu et al. [34], however, do not examine whether the HAR process with the volatility of time-varying jumps outperforms the HAR model containing the information on crude oil volatility (i.e., OVX) index. Such investigation is important, given that previous research works [2,27] show that OVX has significant predictive contents for crude oil realized volatility. Hence, our analysis could be useful for market participants in understanding if the conditional jump-induced volatility contains more information compared to OVX.

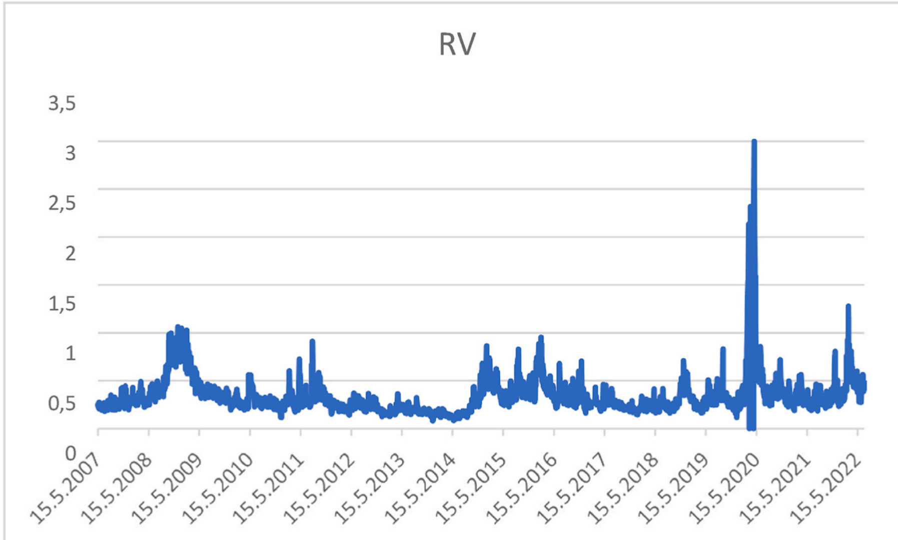

Fig. 1. The realized volatility (RV) of crude oil futures prices.

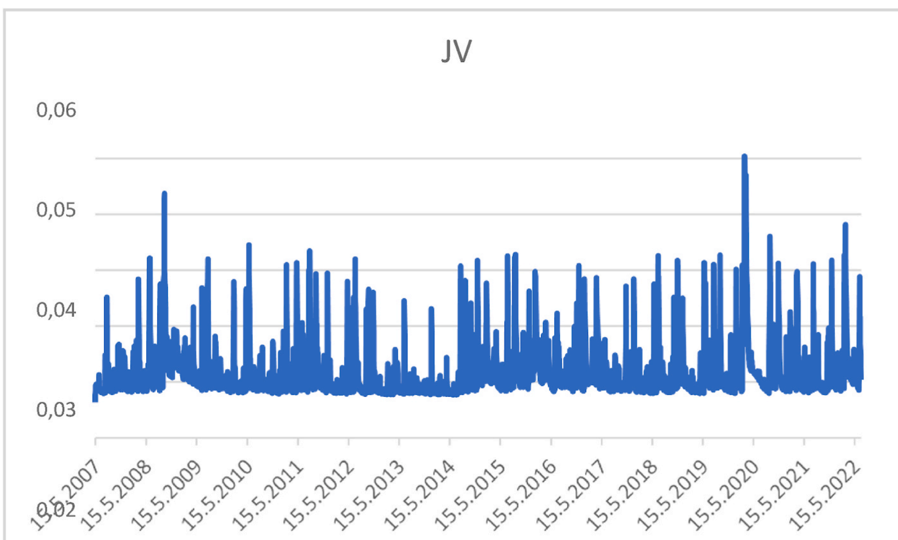

Fig. 2. The conditional jump-induced volatility (JV) of crude oil futures prices.

3.1. GARCH-jump approach

Following Chan and Maheu [24], the GARCH-jump model is specified as follows[5]:

$$r_t = \pi + \mu r_{t-1} + \epsilon_t \tag{1}$$

where r_t indicates the logarithmic difference for the crude oil futures at time t, and ϵ_t refers to the innovation term specified as:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \tag{2}$$

where ϵ_{1t} follows the GARCH (1,1) specification:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \tag{3}$$

In addition, ϵ_{2t} denotes a jump innovation, which is independent of ϵ_{1t}. It is defined as:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} J_{tl} - \theta \lambda_t \tag{4}$$

where J_{tl} is the jump size with a mean value θ and a variance ϑ^2, $\sum_{l=1}^{n_t} J_{tl}$ refers to the jump factor, and n_t represents the jump frequency at time t, following a Poisson distribution given by:

$$P(n_t = j | I_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^j}{j!}, j = 0, 1, 2, \ldots \tag{5}$$

with an autoregressive conditional jump intensity (ARJI) given as:

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1} \tag{6}$$

In equation (6), λ_t indicates the time-varying conditional jump intensity parameter, λ_0 is the constant jump intensity, and ξ_{t-1} represents the jump intensity difference, which measures the innovation of λ_{t-1}. Chan

[5] The choice of the AR(1) specification is based on the Akaike information criterion.

and Maheu [24] assume that $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$, and $\gamma > 0$.

The log-likelihood is defined as:

$$L(\Theta) = \sum_{t=1}^{T} \log f(r_t | I_{t-1}; \Theta)$$

where $\Theta = (\pi, \mu, \omega, \alpha, \beta, \theta, \vartheta, \lambda_0, \rho, \gamma)$ and I_{t-1} is the information set.

The jump-induced variance (henceforth, JV) is given as:

$$JV_t = \left(\theta^2 + \vartheta^2\right)\lambda_t \tag{7}$$

3.2. HAR models

The HAR model approximates the long memory process using a short-memory specification with a cascade structure of lags. In line with Corsi [39] and Busch et al. [37], the baseline HAR-RV process is defined as:

$$\mathbf{HAR-RV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \varepsilon_t \tag{8}$$

with h being equal to 1, 5 and 22 for the RV specifications at daily, weekly and monthly frequencies, respectively and:

$$RV_{t_1,t_2} = \frac{1}{t_2 - t_1} \sum_{t=t_1+1}^{t_2} RV_t \tag{9}$$

in our paper, a number of extensions to the baseline HAR-RV model are considered. We first define the LHAR process, proposed by Corsi and Renò [40], where leverage effects are used to extend the HAR model:

$$\mathbf{LHAR-RV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \varepsilon_t \tag{10}$$

where, $r_t^- = \min(r_t, 0)$, $r_{t-5,t}^- = \min((r_{t-4} + r_{t-3} + \ldots + r_t)/5, 0)$, and $r_{t-22,t}^- = \min((r_{t-21} + r_{t-20} + \ldots + r_t)/22, 0)$.

As mentioned, the HAR model is extended using the information content of the OVX index. This process, called LHAR-RV-IV, is given as:

$$\mathbf{LHAR-RV-IV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \delta OVX_t + \varepsilon_t \tag{11}$$

Next, we introduce the jump-induced volatility (JV) term, specified in equation (7), to the LHAR-RV process as follows[6]:

$$\mathbf{LHAR-RV-JV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \phi JV_t + \varepsilon_t \tag{12}$$

Notably, our objective is to forecast one-month ahead volatility only given that options expire at a monthly frequency. Hence, h equals 22 in our analysis. Busch et al. [37] also advocate this for forecasting the RV of bond, currency and equity markets using the US VIX index.

3.3. Volatility forecasts

3.3.1. HRMSE statistic

The forecasting performance of the various models used in this study is evaluated using the heteroskedasticity adjusted root mean square error (HRMSE) of Bollerslev and Ghysels [41], defined as:

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t - \widehat{RV_t}}{RV_t}\right)^2} \tag{13}$$

with T indicating the number of observations to be forecast, while RV_t and $\widehat{RV_t}$ specify the actual and estimated volatility on day t, respectively.

3.3.2. Mincer–Zarnowitz regression

The out-of-sample forecasting is assessed by applying the Mincer–Zarnowitz (MZ) (1969) regression approach, which allows us to examine whether the proposed models provide incremental information relative to the baseline HAR-RV model while forecasting crude oil volatility. The MZ regression is defined as follows:

$$RV_t = \varphi_0 + \varphi_1 \widehat{RV_t} + \epsilon_t \tag{14}$$

We then compare the HAR models on the basis of R^2 (coefficient of determination) statistics.

4. Empirical findings

4.1. In-sample estimates

Before considering the results of the HAR models, we briefly discuss the estimates of the GARCH-jump model, presented in Table 1. Jumps do occur in crude oil futures returns, as the parameters of the ARJI process are mostly significant. The high value of the intensity parameter ($\boldsymbol{\rho} = \mathbf{0.73}$) indicates the persistence of time-dependent jump intensity [24]. Fig. 2 depicts the jump-induced volatility, confirming the presence of high jumps during the COVID-19 crisis period. Hence, time-varying jumps may include informational content useful for forecasting the RV of oil futures returns.

Moving on to the results of the HAR models, Table 2 indicates several interesting findings. Firstly, including leverage effects in the HAR-RV model improves the accuracy of the baseline HAR process as the $\mathbf{R^2}$ (%) statistic increases from 69.02 to 76.61. Secondly, there is a negative association between leverage effects and RV, which is common in the finance literature [40]. Thirdly, the OVX index exerts a significant impact on RV and leads to an increase in the $\mathbf{R^2}$ statistic to some extent. This is consistent with previous studies showing that implied volatilities, in general, contain predictive information for energy markets [15,26]. Fourthly, inserting the JV factor into the LHAR-RV model increases the $\mathbf{R^2}$ statistic significantly (84.67 %), revealing the importance of using jumps information when modelling the RV of crude oil market returns. Fifthly, the jump-induced volatility offers incremental information relative to the OVX. To sum up, our empirical analysis suggests that including the leverage effect and time-varying jumps in the HAR-RV

Table 1
Outcomes of the GARCH-ARJI model.

Variable	Estimate	Standard error	*t*-statistic	*p*-value
π	0.0009**	0.0003	2.62	0.00
μ	−0.0187	0.0174	−1.07	0.28
ω	0.000005***	0.000001	4.06	0.00
α	0.0628***	0.0086	7.24	0.00
β	0.9076***	0.0104	86.94	0.00
θ	−0.0081**	0.0033	−2.42	0.02
ϑ^2	0.0392***	0.0048	8.04	0.00
λ_0	0.0250**	0.0103	2.42	0.00
ρ	0.7346***	0.1385	5.30	0.00
γ	0.5442***	0.2047	2.66	0.00
Log-likelihood	8403.51			

Note: This table presents the estimated results of the GARCH-ARJI model for the WTI index. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % levels, respectively.

[6] Dutta and Das [38] consider a similar HAR process to predict the volatility of the S&P 500 index using high-frequency data. They extend the HAR process with the information on jumps in the VIX index. The authors also employ the GARCH-jump model to estimate the jump-induced volatility.

Table 2
Estimates of HAR-RV models.

Model →	HAR-RV		LHAR-RV		LHAR-RV-IV		LHAR-RV-JV	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
c	0.0741***	0.0036	0.0952***	0.0032	0.0482***	0.0042	−0.1756***	0.0046
r_d	0.3203***	0.0228	0.1913***	0.0208	0.0166	0.0228	0.0952***	0.0139
r_w	0.4152***	0.0323	0.2263***	0.0290	0.1875***	0.0280	0.1481***	0.0193
r_m	0.0452**	0.0220	0.2077***	0.0200	0.0768***	0.0209	0.3039***	0.0134
ψ_d			−0.4289***	0.0972	−0.3450***	0.0938	−0.1356**	0.0647
ψ_w			−0.0193	0.2451	−0.1915	0.2366	−1.5590**	0.1631
ψ_m			−13.3365***	0.4849	−10.7658***	0.4934	−10.8794***	0.3243
δ					0.0044***	0.0002		
φ							7.2254***	0.4105
R^2 (%)	69.02		76.61		78.26		84.67	
Log-likelihood	3115.08		3604.62		3732.65		4328.85	

Notes: This table presents the estimates of various HAR-type specifications. Our sample runs from May 2007 to June 2022. We estimate four HAR models and the R^2 statistics are reported accordingly. r's, ψ's, φ and δ represent the coefficients of the volatility components, leverage effects, jump-induced volatility and oil implied volatility index, respectively. S.E. indicates standard error. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % levels, respectively.

model improves its accuracy.

4.2. Out-of-sample analysis

To forecast the volatility of crude oil futures, we employ the rolling window method recommended by Patton and Sheppard [42]. In doing so, we first divide the entire sample into two subsamples: the in-sample estimation period from May 2007 to June 2017 and the out-of-sample period from July 2017 to June 2022. The lengths of these two fixed windows cover 2410 and 1000 days, respectively. The estimation period is rolled forward by adding one new day and dropping the most distant day. In this manner, the sample size used to estimate the parameters of various HAR models remains fixed and the forecast values do not overlap, allowing us to obtain the daily out-of-sample volatility forecasts.

The out-of-sample forecast results based on the HMSE statistic and MZ regression model are given in Table 3, where the in-sample period is May 2007 to June 2017 and the out-of-sample period is July 2017 to June 2022. The results show that the LHAR-RV-JV process produces the lowest HRMSE statistic. The Diebold and Mariano (DM) (1995) test supports these results, rejecting the null hypothesis of equal forecast accuracy. The DM test also reveals that the LHAR-RV-JV model outperforms the LHAR-RV-IV model. Hence, the augmented HAR model with the information content of jump-induced volatility can predict the volatility of crude oil futures returns more precisely than the standard HAR-RV model. The R^2 (%) statistics produced by the MZ regression process further confirm that the HAR-type models considering jumps surpass other approaches by yielding higher R^2 values.

Our overall results thus suggest that the information on time-varying jumps in oil return volatility is essential for increasing the precision of the HAR-RV modelling. Therefore, participants in oil futures markets should analyse such jumps when forecasting the realized volatility of crude oil returns.

Note that the HAR model extended through the inclusion of jump intensity helps us to model the sudden and unexpected events occurring in global energy markets, which could play a crucial role in understanding the extreme fluctuations in oil prices and in maintaining stability in sectors that are heavily dependent on crude oil [34]. A proper knowledge of such time-varying features of oil returns would also enable the investors to have a more comprehensive understanding of energy market volatility, which is essential to precisely measure the portfolio risk. Since traditional volatility models do not capture the time-varying jumps, market participants should include the jumps-induced volatility component in their models to design more effective hedging strategies for reducing the effects of extreme fluctuations and volatility clustering in global energy prices [43]. Moreover, given that the intensity of jumps raises the likelihood of market downturns or crashes, volatility models incorporating jumps would be useful for portfolio optimization during the crisis periods. In sum, the proposed volatility model could help investors to identify the unexpected jumps, thereby avoiding the sudden loss [25].

Table 3
Out-of-sample forecast results.

Model →	HAR-RV	LHAR-RV	LHAR-RV-IV	LHAR-RV-JV
HRMSE	0.1616***	0.1486***	0.1379***	0.1157
R^2 (%)	47.07	54.59	60.60	68.82

Notes: This table shows the HRMSE statistics and the R^2 (%) statistics provided by the MZ regression model. Our in-sample estimation period is May 2007 to June 2017 and the out-of-sample period is July 2017 to June 2022. ** indicates that the Diebold-Mariano (DM) test is statistically significant at the 5 % level.

4.3. Forecasting value-at-risk (VaR)

We conduct a VaR analysis to find the best forecast model, by testing for all the HAR-RV models with a VaR estimated for the quantile level q. To this end, the likelihood ratio (LR) test developed by Kupiec [44] is applied.

We begin with the following hit sequence:

$$Hit_t = \begin{cases} 1, if\ r_t < VaR_t \\ 0, if\ r_t \geq VaR_t \end{cases} \tag{15}$$

where r_t refers to the return on day t, and VaR_t is given by:

$$VaR_t = Z_q\sqrt{g_t} \tag{16}$$

where Z_q indicates the quantile at $100 \times q$% of the standardized probability distribution, and g_t denotes the risk predicted by the HAR-RV models under study (see Ref. [45–47]).

We then assume that N computes the frequency of VaR violations and T refers to the data points. In order to investigate $H_0 : f = q$, with f measuring the failure rate, we use the following LR test statistic proposed by Kupiec [44]:

$$LR = -2\ln\{(1-q)^N q^{T-N} / (1-N/T)^{T-N}(N/T)^N\} \sim \chi^2(1) \tag{17}$$

The p-values of this test are provided in Table 4. Our findings show failure rates for both left and right quantiles. Given that the accuracy of the HAR models increases with the increment in p-values, these numbers further reveal the significance of jumps in forecasting the RV of the crude oil futures market. Overall, our analysis suggests that both leverage effects and time-varying jumps are crucial for a more precise forecast of the VaR of crude oil returns.

Table 4
Forecasting value-at-risk.

Model ↓	LQ = 10 %	LQ = 5 %	LQ = 1 %	RQ = 10 %	RQ = 5 %	RQ = 1 %
HAR-RV	0.203	0.241	0.229	0.277	0.299	0.311
LHAR-RV	0.261	0.285	0.262	0.308	0.329	0.346
LHAR-RV-IV	0.294	0.302	0.279	0.328	0.348	0.366
LHAR-RV-JV	**0.346**	**0.353**	**0.328**	**0.370**	**0.390**	**0.401**

Notes: In this table, we present the *p*-values of the likelihood ratio test specified in equation (17). The accuracy of the HAR models increases with the increment in *p*-values. LQ = left quantile; RQ = right quantile. Numbers in bold indicate the highest *p*-values.

4.4. Additional analyses

In this section, we investigate whether the jump-induced risk improves the GARCH volatility forecasts. To this end, we employ GARCH (1,1) and EGARCH models augmented with OVX and JV. Accordingly, we estimate the following six models:

$$\text{GARCH}\ (1,1): \quad h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} \tag{18}$$

$$\text{GARCH}\ (1,1) - \text{IV}: \quad h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \delta OVX_{t-1}^2 \tag{19}$$

$$\text{GARCH}\ (1,1) - \text{JV}: \quad h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \phi JV_{t-1} \tag{20}$$

$$\text{EGARCH}\ (1,1): \log\left(h_t\right) = \omega + \alpha\frac{|\epsilon_{t-1}|}{|(h_{t-1}|} + \varrho\frac{\epsilon_{t-1}}{h_{t-1}} + \beta\log\left(h_{t-1}\right) \tag{21}$$

$$\text{EGARCH}(1,1) - \text{IV}: \log\left(h_t\right) = \omega + \alpha\frac{|\epsilon_{t-1}|}{|(h_{t-1}|} + \varrho\frac{\epsilon_{t-1}}{h_{t-1}} + \beta\log\left(h_{t-1}\right) + \delta OVX_{t-1}^2 \tag{22}$$

$$\text{EGARCH}(1,1) - \text{JV}: \log\left(h_t\right) = \omega + \alpha\frac{|\epsilon_{t-1}|}{|(h_{t-1}|} + \varrho\frac{\epsilon_{t-1}}{h_{t-1}} + \beta\log\left(h_{t-1}\right) + \phi JV_{t-1} \tag{23}$$

In equations (21)–(23), ϱ measures the asymmetry in volatility. Notably, we use daily observations to obtain the volatility forecasts.

Table 5 shows the out-of-sample forecast results for GARCH-type models, based on the HMSE statistic and MZ regression.[7] The results reveal that the EGARCH-JV model produces the lowest HRMSE statistic. The findings of the DM test also justify these results, rejecting the null hypothesis of equal forecast accuracy. The DM test also reveals that the GARCH models with jump volatility outperform those with implied volatility. Hence, consistent with the results shown in Table 3, the extended GARCH models including the information content of jump-induced volatility predict the volatility of oil futures more precisely than other extended GARCH models.

The findings presented in Table 5 further confirm that the R^2 (%) statistics produced by the MZ regression process are higher for the extended GARCH models than the conventional GARCH models. We thus conclude that the information on time-varying jumps in oil returns is essential for increasing the precision of GARCH-type models.

[7] While considering the (E)GARCH-IV models, the forecasts are obtained by inserting the OVX index into the GARCH equations. For the (E)GARCH-JV models, on the other hand, the jump-induced volatility is used as an explanatory variable for the conditional variance prediction process. For example, for the GARCH-JV model we run the following regression to generate the predations: $\widehat{h}_t = \widehat{\omega} + \widehat{\alpha}(r_t - \widehat{\pi} - \widehat{\mu}r_{t-1})^2 + \widehat{\beta}\widehat{h}_{t-1} + \widehat{\phi}\widehat{JV}_{t-1}$ Hence, we first obtain the forecasts from the GARCH model and then estimate the above equation after inserting the jump-induced volatility as a regressor.

4.5. Various robustness tests

We consider some additional methods of assessing the forecasting performance of both benchmark and extended models, which serve as a robustness check for our above results.

Firstly, we employ the out-of-sample R^2 (R^2_{OOS}) test proposed by Campbell and Thompson [48], as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}\left(RV_t - RV_t^j\right)^2}{\sum_{t=1}^{T}\left(RV_t - RV_t^0\right)^2} \tag{24}$$

where RV_t, RV_t^j, and RV_t^0 refer to the actual RV, the RV forecast by model j with j indicating one of the extended HAR models (i.e., LHAR-RV or LHAR-RV-IV or LHAR-RV-JV), and the RV forecast by the benchmark model, respectively. If R^2_{OOS} exceeds the zero value, then the extended HAR model outperforms the benchmark HAR model in terms of forecasting accuracy. Moreover, we compute the MSPE-adjusted statistic suggested by Clark and West [49] to evaluate the difference between an extended model and the benchmark model.

Table 6 reports the R^2_{OOS} statistics. Note that we now consider a new measure of realized volatility calculated using the 15-min intra-day squared returns instead of the 5-min intra-day squared returns. The related data is also collected from Professor Dacheng Xiu's risk lab. Panel B of Table 5 shows the results based on these 15-min intra-day squared returns, which confirm that the LHAR-RV-JV process outperforms other approaches, thereby emerging as the best forecasting model. For example, the LHAR-RV-JV model produces the largest R^2_{OOS} statistic of 2.7301 %, which is statistically significant at the 1 % level.

Secondly, we employ the model confidence set (MCS) test proposed by Hansen et al. [50] to compare the HAR models under study. Applying this test is advantageous, as it does not require a specific benchmark model. Furthermore, the MCS test allows for the possibility that more than one model can be the 'best'.

Note that, while applying the MCS test we also employ the quasi-maximum likelihood loss function error (QLIKE) along with HRMSE. The use of QLIKE strengthens the out-of-sample forecast analysis, given that it is considered a robust loss function.[8] This loss function is defined as:

$$QLIKE = \frac{1}{T}\sum_{t=m+1}^{m+T}\left(\ln(\widehat{RV_t}) + \frac{RV_t}{\widehat{RV_t}}\right) \tag{25}$$

To explain the MCS test, let us consider a set, M_0, which contains a finite number of models, indexed by $i = 1, 2, \cdots, m_0$. The null hypothesis of this test, which assumes that there is no difference in accuracy associated with two models within M_0, is given as:

$$H_{0,M}: E\left(d_{uv,t}\right) = 0\ \forall u, v \in M \subset M_0$$

where d_{uv} refers to the difference between models u and v under the loss function HRMSE or QLIKE. Furthermore, we use the range statistic (T_R) and the semi-quadratic statistic (T_{SQ}) to assess the various HAR models. These two statistics are defined as follows:

$$T_R = \max_{u,v\in M}\frac{|\overline{d}_{uv}|}{\sqrt{var(d_{uv})}} \tag{26}$$

$$T_{SQ} = \max_{u,v\in M}\frac{(\overline{d}_{uv})^2}{var(\overline{d}_{uv})} \tag{27}$$

[8] Patton [61] compares a range of loss functions and finds MSE and QLIKE to be robust, but prefers QLIKE to MSE as the former is less sensitive to extreme observations.

Table 5
Out-of-sample forecast results based on GARCH models.

Models →	GARCH (1,1)	GARCH (1,1)-IV	GARCH (1,1)-JV	EGARCH	EGARCH-IV	EGARCH-JV
HRMSE	0.000546***	0.000461***	0.000383***	0.000506***	0.000427***	0.000354
R^2 (%)	38.22	44.68	49.01	40.19	46.76	49.87

Notes: This table shows the HRMSE statistics and the R^2 (%) statistics provided by the MZ regression model. Our in-sample estimation period is May 2007 to June 2017 and the out-of-sample period is July 2017 to June 2022. ** indicates that the Diebold-Mariano (DM) test is statistically significant at the 5 % level.

Table 6
Out-of-sample R^2 ($\boldsymbol{R^2_{OOS}}$) results.

Model →	HAR-RV	LHAR-RV	LHAR-RV-IV	LHAR-RV-JV
Panel A: 5-min				
R^2_{OOS} (%)	–	0.9851	2.1189	2.7143
MSPE-adjusted	–	1.3332*	1.9168**	2.5982***
Panel A: 15-min				
R^2_{OOS} (%)	–	0.9799	2.1062	2.7301
MSPE-adjusted	–	1.3461*	1.8992**	2.6222***

Notes: This table presents the out-of-sample R^2 (R^2_{OOS}) statistics proposed by Campbell and Thompson [48]. Our in-sample estimation period is May 2007 to June 2017 and the out-of-sample period is July 2017 to June 2022. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % levels, respectively.

where $\overline{d}_{uv} = \frac{1}{T}\sum_{t=m+1}^{m+T} d_{uv,t}$.

The null hypothesis is rejected when the p-values of the T_R and T_{SQ} statistics surpass critical values. Notably, as the real distributions of T_R and T_{SQ} are somewhat complex, bootstrapping is often needed to compute the corresponding statistical values and p-values. In line with previous studies [34,51], we choose the critical value of 0.5 to indicate satisfactory model performance when the p-value of the MCS test surpasses 0.5.

Table 7 presents the results of the MCS test, showing that the LHAR-RV-JV model exhibits the highest p-value of 1. Hence, the results confirm that the LHAR-RV-JV approach produces better forecasts than the other HAR models. It is also noteworthy that only the LHAR-RV-JV and LHAR-RV-IV models enter the MCS with p-values larger than 0.5. These results hold irrespective of the loss functions used. Overall, the findings suggest that both oil price uncertainty (i.e., OVX) and jump-induced volatility play pivotal roles in forecasting the realized volatility of crude oil futures.

5. Conclusion

This paper forecasts the realized volatility of WTI futures returns using a HAR-RV model augmented with the time-dependent jumps observed in the oil futures index. Specifically, we obtain an estimate of the jump-induced volatility from the GARCH- jump process and consider it in the HAR model. Both the in-sample and out-of-sample analyses show that jumps offer extra information which is not provided by the standard HAR models. A novel finding is that the jump-induced volatility offers incremental information relative to the crude oil implied volatility index (OVX). In summary, our results indicate that the HAR-RV process comprising jump volatility can forecast RV more precisely than standard HAR-type models. Several robustness checks confirm our results.

Table 7
Results of MCS tests.

Model ↓	5-min		15-min	
	T_R	T_{SQ}	T_R	T_{SQ}
Panel A: HRMSE				
HAR-RV	0.011	0.013	0.038	0.029
LHAR-RV	0.249	0.223	0.201	0.287
LHAR-RV-IV	0.827	0.764	0.809	0.873
LHAR-RV-JV	**1.000**	**1.000**	**1.000**	**1.000**
Panel B: QLIKE				
HAR-RV	0.004	0.006	0.003	0.007
LHAR-RV	0.009	0.012	0.005	0.010
LHAR-RV-IV	0.685	0.729	0.701	0.679
LHAR-RV-JV	**1.000**	**1.000**	**1.000**	**1.000**

Notes: This table presents the MCS test results for the loss functions HRMSE and QLIKE. Our in-sample estimation period is May 2007 to June 2017 and the out-of-sample period is July 2017 to June 2022. We compute the realized volatility using both 5-min and 15-min intra-day squared returns. The numbers indicated in bold show the largest p-values.

Our analysis could be of interest to energy market investors and risk managers given that the jump-induced volatility, estimated by applying the jump process, is useful for measuring the risk of investment portfolios. In addition, as jumps increase the probability of market crashes, they might play a pivotal role in risk assessment, portfolio optimization and hedging strategies. Moreover, as crude oil is considered a major production input, policymakers and risk managers might use our results to acquire sound knowledge of the dynamics of energy market risk and develop appropriate hedging strategies to reduce oil price uncertainty. Specifically, the time-varying nature of jumps noted in crude oil futures returns may help them make more informed decisions regarding dynamic hedging strategies during turmoil periods. Researchers could also build on our findings when developing refined volatility forecasting models.

Our study is not free of limitations. Firstly, we consider time-varying jumps only in crude oil returns, while such jumps in the implied volatility index (i.e., OVX) could be a good predictor of oil market risk.[9] Secondly, we do not assess the performance of the proposed models under various market conditions. Since the risk prediction process could be highly influenced by the high and low volatility regimes, it is relevant to test the performance of forecasting models considering various volatility conditions. To do so, the high and low volatility levels could be estimated using the median realized volatility value of crude oil futures. Thirdly, since the use of jump-induced volatility in forecasting the risk for energy futures markets is a novel area of financial economics, it could be difficult to fully understand the role of such jumps in forecasting the risk of energy market investments. Therefore, more sophisticated econometric tools could be needed to shed more light on how information on jump-induced volatility can be used to obtain improved volatility forecasts during crisis periods. These exercises are left for future research.

CRediT authorship contribution statement

Anupam Dutta: Conceptualization, Validation, Analysis; Final Revision, Writing – original draft. **Elie Bouri:** Writing; Analysis; Final Revision, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

[9] A recent study by Dutta et al. [62] shows that the time-varying jumps occurring in OVX have better predictive content for crude oil volatility than OVX itself.

the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] E. Bouri, D. Lien, D. Roubaud, S.J.H. Shahzad, Directional predictability of implied volatility: from crude oil to developed and emerging stock markets, Finance Res. Lett. 27 (2018) 65–79.
[2] A. Dutta, E. Bouri, D. Roubaud, Modelling the volatility of crude oil returns: jumps and volatility forecasts, Int. J. Financ. Econ. 26 (2021) 889–897.
[3] P. Sadorsky, Modeling and forecasting petroleum futures volatility, Energy Econ. 28 (2006) 467–488.
[4] P.K. Narayan, S. Narayan, Modelling oil price volatility, Energy Pol. 35 (2007) 6549–6553.
[5] C.W. Cheong, Modeling and forecasting crude oil markets using ARCH-type models, Energy Pol. 37 (2009) 2346–2355.
[6] S.H. Kang, S.M. Kang, S.M. Yoon, Forecasting volatility of crude oil markets, Energy Econ. 31 (2009) 119–125.
[7] M.E.H. Arouri, A. Lahiani, A. Lévy, D.K. Nguyen, Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long memory models, Energy Econ. 34 (2012) 283–293.
[8] A. Hou, S. Suardi, A nonparametric GARCH model of crude oil price return volatility, Energy Econ. 34 (2012) 618–626.
[9] T. Klein, T. Walther, Oil price volatility forecast with mixture memory GARCH, Energy Econ. 58 (2016) 46–58.
[10] T. Lux, M. Segnon, R. Gupta, Forecasting crude oil price volatility and value-at-risk: evidence from historical and recent data, Energy Econ. 56 (2016) 117–133.
[11] M. Manera, M. Nicolini, I. Vignati, Modelling futures price volatility in energy markets: is there a role for financial speculation? Energy Econ. 53 (2016) 220–229.
[12] W. Kristjanpoller, M. Minutolo, Forecasting volatility of oil price using an Artificial Neural Network-GARCH model, Expert Syst. Appl. 65 (15) (2016) 233–241.
[13] Sunil Butler, Piotr Kokoszka, Hong Miao, Han Lin Shang, Neural network prediction of crude oil futures using B-splines, Energy Econ. 94 (C) (2021).
[14] X. Lu, Feng Ma, Jin Xu, Zehui Zhang, Oil futures volatility predictability: new evidence based on machine learning models11All the authors contribute to the paper equally, Int. Rev. Financ. Anal. 83 (2022), 2022, 102299, Luo, Jiawen & Ji, Qiang & Klein, Tony & Todorova, Neda & Zhang, Dayong, (2020). On realized volatility of crude oil futures markets: Forecasting with exogenous predictors under structural breaks. Energy Economics, 89(C).
[15] E. Haugom, H. Langeland, P. Molnár, S. Westgaard, Forecasting volatility of the US oil market, J. Bank. Finance 47 (14) (2014) 1–14.
[16] B. Sévi, Forecasting the volatility of crude oil futures using intraday data, Eur. J. Oper. Res. 235 (2014) 643–659.
[17] F. Wen, X. Gong, S. Cai, Forecasting the volatility of crude oil futures using HAR-type models with structural breaks, Energy Econ. 59 (2016) 400–413.
[18] F. Ma, M.I.M. Wahab, D. Huang, W. Xu, Forecasting the realized volatility of the oil futures market: a regime switching approach, Energy Econ. 67 (2017) 136–145.
[19] Xu Gong, Boqiang Lin, The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market, Energy Econ. 74 (C) (2018) 370–386.
[20] F. Ma, Y. Liao, Y. Zhang, Y. Cao, Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks, J. Empir. Finance 52 (2019) 40–55.
[21] Y. Aït-Sahalia, J. Cacho-Diaz, R.J. Laeven, Modeling financial contagion using mutually exciting jump processes, J. Financ. Econ. 117 (3) (2015) 585–606.
[22] T.G. Andersen, T. Bollerslev, Answering the skeptics: yes, standard volatility models do provide accurate forecasts, Int. Econ. Rev. (1998) 885–905.
[23] O. Lieberman, P.C. Phillips, Refined inference on long memory in realized volatility, Econom. Rev. 27 (1–3) (2008) 254–267.
[24] W.H. Chan, J.M. Maheu, Conditional jump dynamics in stock market returns, J. Bus. Econ. Stat. 20 (2002) 377–389.
[25] A. Dutta, U. Soytas, D. Das, A. Bhattacharyya, In search of time-varying jumps during the turmoil periods: evidence from crude oil futures markets, Energy Econ 114 (2022) 106275.
[26] A. Dutta, Modeling and forecasting oil price risk: the role of implied volatility index, J. Econ. Stud. 44 (6) (2017) 1003–1016.
[27] Z. Niu, F. Ma, H. Zhang, The role of uncertainty measures in volatility forecasting of the crude oil futures market before and during the COVID-19 pandemic, Energy Econ. 112 (2022) 106120.
[28] M. Prokopczuk, L. Symeonidis, C. Wese Simen, Do jumps matter for volatility forecasting? Evidence from energy markets, J. Futures Mark. 36 (2016) 758–792.
[29] H. Zhang, X. Zhao, W. Gao, Z. Niu, The role of higher moments in predicting China's oil futures volatility: evidence from machine learning models, Journal of Commodity Markets 32 (2023) 100352.
[30] Y.J. Zhang, H. Zhang, Volatility forecasting of crude oil futures market: which structural change-based HAR models have better performance? Int. Rev. Financ. Anal. 85 (2023) 102454.
[31] W. Cheng, K. Ming, M. Ullah, Oil price volatility prediction using out-of-sample analysis–Prediction efficiency of individual models, combination methods, and machine learning based shrinkage methods, Energy 300 (2024) 131496.
[32] L. Feng, H. Rao, B. Lucey, Y. Zhu, Volatility forecasting on China's oil futures: new evidence from interpretable ensemble boosting trees, Int. Rev. Econ. Finance 92 (2024) 1595–1615.
[33] N. Haukvik, H. Cheraghali, P. Molnár, The role of investors' fear in crude oil volatility forecasting, Res. Int. Bus. Finance 70 (2024) 102353.
[34] H. Wu, P. Li, J. Cao, Z. Xu, Forecasting the Chinese crude oil futures volatility using jump intensity and Markov-regime switching model, Energy Econ. 134 (2024) 107588.
[35] T.G. Andersen, T. Bollerslev, F.X. Diebold, Roughing it up: including jump components in the measurement, modeling, and forecasting of return volatility, Rev. Econ. Stat. 89 (2007) 701–720.
[36] F. Corsi, D. Pirino, R. Renò, Threshold bipower variation and the impact of jumps on volatility forecasting, J. Econom. 159 (2) (2010) 276–288.
[37] T. Busch, B.J. Christensen, M.O. Nielsen, The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets, J. Econom. 160 (1) (2011) 48–57.
[38] A. Dutta, D. Das, Forecasting realized volatility: new evidence from time-varying jumps in VIX, J. Futures Mark. 42 (2022) 2165–2189.
[39] F. Corsi, A simple approximate long memory model of realized volatility, J. Financ. Econom. 7 (2009) 174–196.
[40] F. Corsi, Roberto Renò, Discrete-time volatility forecasting with persistent leverage effect and the link with continuous-time volatility modeling, J. Bus. Econ. Stat. 30 (3) (2012) 368–380.
[41] T. Bollerslev, E. Ghysels, Periodic autoregressive conditional heteroscedasticity, J. Bus. Econ. Stat. 14 (2) (1996) 139–151.
[42] A.J. Patton, K. Sheppard, Good volatility, bad volatility: signed jumps and the persistence of volatility, Rev. Econ. Stat. 97 (3) (2015) 683–697.
[43] L. Zhang, Y. Chen, E. Bouri, Time-varying jump intensity and volatility forecasting of crude oil returns, Energy Econ. 129 (2024) 107236.
[44] P. Kupiec, Techniques for verifying the accuracy of risk measurement models, J. Deriv. 2 (1995) 173–184.
[45] P. Giot, Implied volatility indexes and daily value-at-risk models, J. Deriv. 12 (2005) 54–64.
[46] P. Giot, S. Laurent, Value-at-risk for long and short trading positions, J. Appl. Econom. 18 (2003) 641–664.
[47] P. Giot, S. Laurent, Modelling daily value-at-risk using realized volatility and ARCH type models, J. Empir. Finance 11 (2004) 379–398.
[48] J.Y. Campbell, S.B. Thompson, Predicting excess stock returns out of sample: can anything beat the historical average? Rev. Financ. Stud. 21 (4) (2008) 1509–1531.
[49] T.E. Clark, K.D. West, Approximately normal tests for equal predictive accuracy in nested models, J. Econom. 138 (1) (2007) 291–311.
[50] P.R. Hansen, A. Lunde, J.M. Nason, The model confidence set, Econometrica 79 (2) (2011) 453–497.
[51] Y. Wei, J. Liu, X. Lai, Y. Hu, Which determinant is the most informative in forecasting crude oil market volatility: fundamental, speculation, or uncertainty? Energy Econ. 68 (2017) 141–150.
[52] C. Zhang, X. Qu, The effect of global oil price shocks on China's agricultural commodities, Energy Econ. 51 (2015) 354–364.
[53] C. Zhang, X. Tu, The effect of global oil price shocks on China's metal markets, Energy Pol. 90 (2016) 131–139.
[54] D. Das, V. Bhatia, S. Kumar, S. Basu, Do precious metals hedge crude oil volatility jumps? Int. Rev. Financ. Anal. 83 (2022) 102257.
[55] K. Choi, S. Hammoudeh, Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment, Energy Pol. 38 (2010) 4388–4399.
[56] M. Gronwald, A characterization of oil price behavior — evidence from jump models, Energy Econ. 34 (2012) 1310–1317.
[57] M.L. Liu, Q. Ji, Y. Fan, How does oil market uncertainty interact with other markets? An empirical analysis of implied volatility index, Energy 55 (2013) 860–868.
[58] A.K. Tiwari, G.C. Aye, R. Gupta, K. Gkillas, Gold-oil dependence dynamics and the role of geopolitical risks: evidence from a Markov-switching time-varying copula model, Energy Econ. 88 (2020) 104748.
[59] C. Zhang, X. Chen, The impact of global oil price shocks on China's stock returns: evidence from the ARJI(−ht)- EGARCH model, Energy Pol. 36 (2011) 6627–6633.
[60] C. Zhang, F. Liu, D. Yu, Dynamic jumps in global oil price and its impacts on China's bulk commodities, Energy Econ. 70 (2018) 297–306.
[61] A.J. Patton, Volatility forecast comparison using imperfect volatility proxies, J. Econom. 160 (1) (2011) 246–256.
[62] A. Dutta, K. Kanjilal, S. Ghosh, D. Park, G.S. Uddin, Impact of crude oil volatility jumps on sustainable investments: evidence from India, J. Futures Mark. 43 (2023) 1450–1468.