**JOURNAL OF SCIENCE AND TECHNOLOGY**
ISSN: 2229-8460 e-ISSN: 2600-7924

**JST**

Vol. 17 No. 2 (2025) 48-63
https://publisher.uthm.edu.my/ojs/index.php/jst

# Taming The Turbulence: Modelling and Forecasting Crude Oil Price Volatility with GARCH and SARIMA Models

**Kuang Yong Ng[1]*, Zalina Zainal[1], Shamzaeffa Samsudin[2], Haitian Wei[1]**

[1] *School of Economics, Finance and Banking, Universiti Utara Malaysia, 06010 Kedah, MALAYSIA*
[2] *Economic and Financial Policy Institute (ECOFI), School of Economics, Finance and Banking (SEFB), Universiti Utara Malaysia, 06010 Sintok, Kedah, MALAYSIA*

*Corresponding Author: kuang_yong95@hotmail.com
DOI: https://doi.org/10.30880/jst.2025.17.02.005

**Article Info**

Received: 19 March 2025
Accepted: 24 October 2025
Available online: 30 December 2025

**Keywords**

Volatility, crude oil price, ARCH, GARCH

**Abstract**

The volatility is a signal of risk, either good or bad, to investors. Crude oil price is a commodity of global concern because its volatility significantly affects the economic stability of many countries. Due to the lack of comparative studies in forecasting performance, this study aims to model and forecast crude oil prices and their volatility by comparing the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The monthly crude oil price data from January 2000 to December 2019, obtained from the U.S. Energy Information Administration, are used for this analysis. The results show that the GARCH (3,1) model is the most suitable model compared to EGARCH, TGARCH, and SARIMA in capturing the volatility of crude oil prices. This indicates that the GARCH (3,1) model offers superior forecasting performance and can serve as a reliable tool for investors and policymakers to anticipate market fluctuations and manage associated risks effectively.

## 1. Introduction

Volatility plays an important role, which gives an impact on the price of financial products, including stocks, gold, exchange rates, crude oil prices, and others. Volatility provides signals about risk. A period of higher volatility means that it is riskier than others, whereas a period of lower volatility has lower risk than others [1]. When the period is riskier, the expected value for the magnitude of the disturbance terms will be greater at certain times compared to other periods. Moreover, the times of higher volatility tend to be concentrated and are followed by periods of lower volatility [2]. High volatility stock prices will have higher uncertainty because they may bring huge gains or losses to the investor [3]. Hence, volatility will affect investors' decisions because uncertainty will generate opportunity costs for investors, which impact transaction costs and the marginal cost of production.

The time series data for the crude oil price has undergone the characteristic of clustering. This is because the price of crude oil fluctuates constantly, and its price is determined by demand and supply. Normally, demand and supply are influenced by shocks from either the demand side or the supply side. For example, the decisions of the Organization of Petroleum Exporting Countries (OPEC), the Organization for Economic Co-operation and Development (OECD), economic and industrial growth and development, and geopolitical conflicts and wars will influence the price of crude oil [4]. Additionally, shocks will also contribute to crude oil price volatility [5 - 8]. From Figure 1, event A is indicated by the 2008 Global Financial Crisis (August 2008 – May 2009), event B is represented by the 2014 Oil Price Crash (June 2014 – January 2016), and event C is illustrated by the 2020 COVID-19 Pandemic Crash (January 2020 – April 2020). The crude oil price is important to developing countries whose exports are oriented towards crude oil [9]. These countries depend on the export of crude oil to generate their national income. Furthermore, fluctuations in crude oil prices will also influence inflation, as an increase in crude oil prices will have a negative impact on production costs [10].

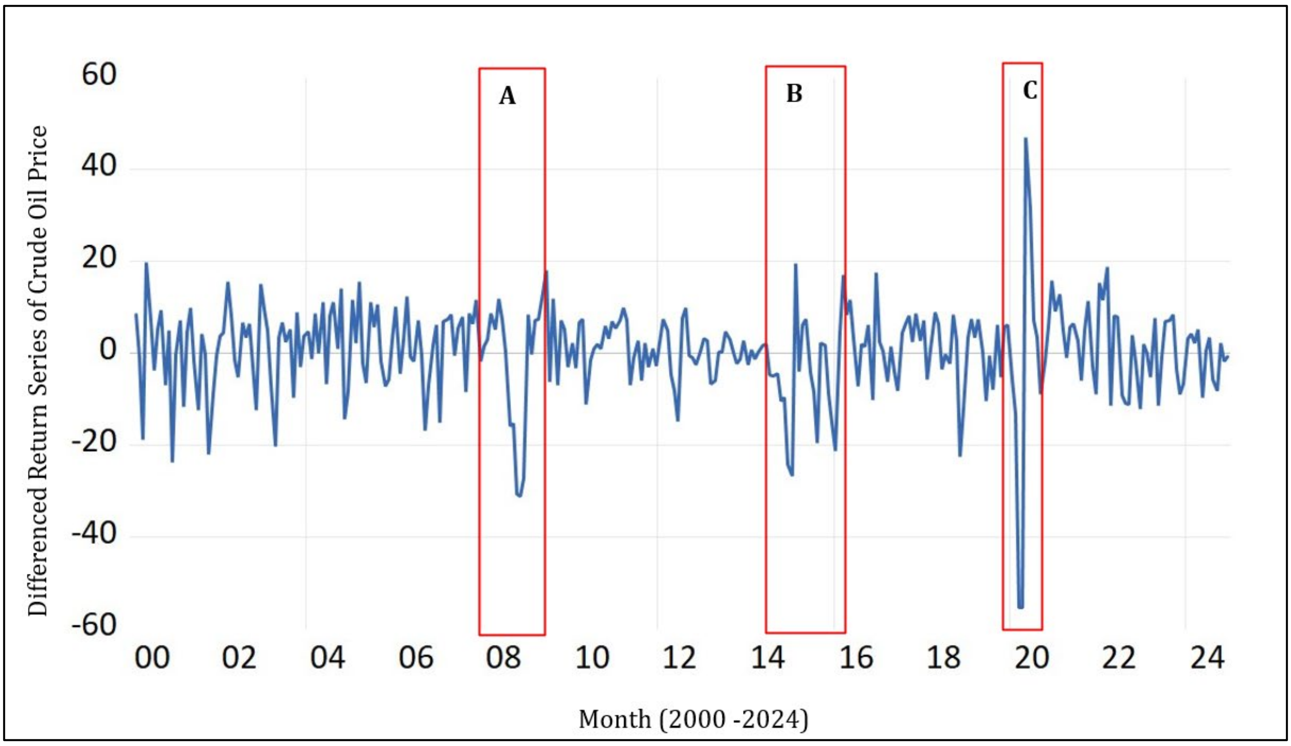



**Fig.1** *Graph of differenced series of crude oil price, January 2000 – December 2024*

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model offers valuable insights into volatility persistence and clustering, effectively capturing key dynamics within time series data [11]. It enhances forecasting performance in datasets characterized by high volatility and contributes to more precise risk evaluation [12]. Within the GARCH family, it consists of the Exponential GARCH (EGARCH) model and the Threshold GARCH (TGARCH) model. EGARCH can capture asymmetric volatility effects, where negative shocks tend to exert a greater influence on volatility compared to positive shocks of equal magnitude, while TGARCH is able to extend the conventional GARCH model by accounting for the leverage effect [13].

The crude oil price showed noticeable seasonal fluctuations, rising and falling in response to a shock. For instance, the 2008 Global Financial Crisis, the 2014 Oil Price Crash, and the 2020 COVID-19 Pandemic Crash. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model, a modified version of ARIMA, allows the model to capture recurring seasonal patterns and account for periodic variations that occur at regular intervals [14].

The comparative empirical studies on variance forecasting and the optimal estimation of time series variables exhibiting volatility using Autoregressive Integrated Moving Average (ARIMA) and GARCH models are still limited and have not been extensively investigated [15]. Hence, this study responds to the call from [15] in terms of the crude oil price. This study conducts a comparative analysis of the GARCH and SARIMA models to evaluate their performance in forecasting crude oil prices and volatility dynamics. This paper is structured as follows: Section 1 provides the introduction, while Section 2 reviews relevant literature. Section 3 outlines the methodology, Section 4 presents the results and findings, and Section 5 concludes.

## 2. Literature Review

Crude oil price volatility plays a critical role in shaping macroeconomic performance, particularly in developing and oil-dependent economies. Changes in oil prices affect key indicators such as inflation, output growth, exchange rates, and fiscal balances [16]. Rising oil prices lead to cost-push inflation [10]. This condition enhances production and transportation costs, thus reducing households' purchasing power and quality of life. Additionally, higher oil prices are good for oil-exporting countries but bad for oil-importing countries. For instance, they improve trade balances and fiscal revenues for oil-exporting countries but lead to a trade deficit and depreciation of the currency for oil-importing countries [17].

The daily price of crude oil between 2015 and 2016 was used by [18] to find the best model for the volatility of crude oil prices. This study stated that the best model for modelling the volatility of crude oil prices is GARCH

(1,1). To identify the volatility characteristics of Jordan's capital market, which include leptokurtosis, leverage effect, and clustering volatility, a study was carried out applying the ARCH, GARCH, and EGARCH models. The GARCH family model is applied to examine the behavior of stock return volatility for the Amman Stock Exchange (ASE) from the period of 1 January 2005 to 31 December 2014. The results from the study showed that the ARCH-GARCH model can support and capture the characteristics of the ASE, while the EGARCH cannot support the characteristics of the ASE [19]. The volatility of the stock return rate of Chengtou Holdings Limited from 4 December 2015 to 26 December 2016 was described by [20], with a total number of observations being 2911, by using the GARCH model. The study concludes that the GARCH model is effective in measuring the volatility of stock returns because it accurately describes the asymmetric phenomenon of shocks.

Two different periods of data, which covered from 2 January 2009 to 28 April 2014 and 4 January 2014 until 28 April 2014, were applied by [21] to analyze the return volatility of spot market prices of crude oil (WTI) and natural gas (Henry Hub). They applied different versions of the GARCH family models, which include GARCH, GJRGARCH, ICARCH, FIAPARCH, EGARCH, and FIGARCH, to determine the model that ensures a maximum return and minimum loss for returns on investments held by private sector budget planning decision makers, individual investors, fund managers, and state agencies forecasting about macroeconomic indicators. Moreover, the GARCH family model was adopted by [22] in their study to model price volatility and the risk-return related to crude oil export in the Nigerian crude oil market. Monthly data was used for this study from January 1987 until June 2017, and the findings show that the first order symmetric GARCH (1,1) gave a better fit. The returns on prices and sales of crude, and the risk-return related to prices and sales of crude oil off the shore of Nigeria, were modelled by [23] with the GARCH model. They compared the model between the GARCH (1,1) model and the EGARCH (1,1) model. Meanwhile, the EGARCH (1,1) provided an overall better fit and showed that the returns on prices and sales of crude are often volatile.

Additionally, the GARCH models were also utilized by [24] to analyze the oil price volatility for the Value-at-Risk. The study includes 2,192 observations which covered the period from 1 January 2009 to 31 December 2014. The results from the study show that the GARCH (1,1) model is the most adequate model, which is simple and easy to handle. Moreover, [25] forecasted the crude oil price by using daily data from 2 January 1986 to 30 September 2009, in which the methodology of Box-Jenkins and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach is applied. The results found that the ARIMA (1,2,1) and GARCH (1,1) models are the most suitable for forecasting. Besides that, [26] modelled the crude oil price volatility by using the Markov-switching multifractal (MSM) model and generalized autoregressive conditional heteroscedasticity (GARCH), which includes daily data from 3 January 1977 to 24 March 2014. The objective set by [27] was to determine the most appropriate model for forecasting the monthly crude oil prices of Pakistan in their study. They evaluated the forecasting results from the ARIMA, GARCH, and ARIMA-GARCH models by using forecasting performance. The results revealed that the ARIMA-GARCH model performs well compared to the ARIMA and GARCH models.

Recent studies have also shown that the use of GARCH models is suitable for estimating the volatility of crude oil prices. Twenty-five days of WTI crude oil price data were used by [28], spanning from 1 July 2021 to 22 December 2021, in his study. He claimed that the combination of the autoregressive integrated moving average model and generalized autoregressive conditional heteroskedasticity (ARIMA-GARCH) was appropriate for his model, particularly ARIMA (1,1,0)-GARCH (1,1). Additionally, [29] supported the combination of ARIMA and GARCH, stating that it yielded better findings and performance. They concluded that the combination of ARIMA (3,1,1) and EGARCH (1,2) was the best forecasting model for daily oil prices from 1 January 2019 to 12 December 2019. However, a comparison between ARIMA and GARCH was applied by [30] to model the volatility of crude oil prices using daily data from 10 February 2020 to 27 April 2020. They found that the ARIMA (4,1,4) model performed better than GARCH (1,1). A different perspective was offered by [31] and [32] from the aforementioned studies. They argued that GARCH models performed better in terms of the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Information Criterion (HQ). Consequently, [31] asserted that the GARCH (1,1) model was suitable for analyzing crude oil volatility during two distinct periods, from 1987 to 2022, and from 2020 to 2022. Meanwhile, [32] emphasized that GARCH (1,1) was the best model for the volatility of oil prices from 1 January 2010 to 27 April 2022. The findings were also supported by [33], which stated that GARCH (1,1) was a suitable model. However, [13] claimed that EGARCH had a better in-sample fit with Nigerian crude oil prices between 2006 and 2023. [34] utilised the GARCH–MIDAS–AES model and data from 1997 to 2022, underscoring the importance of considering threshold and leverage effects.

SARIMA is also used by scholars to forecast the crude oil price [35]. [36] asserted that SARIMA (0, 1, 2)(0, 1, 1)12 and SARIMA (1, 1, 1) (0, 1, 1)12 had better performance in terms of forecasting the crude oil price compared to ARIMA. [37] adopted the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMA-X) method to predict the crude oil prices from 2020 to 2023. The study confirmed strong evidence of the SARIMA-X model's precision and accuracy.

Although numerous studies have employed GARCH-type models to capture volatility behavior and SARIMA models for price forecasting, few have conducted a direct comparative analysis between the two approaches, particularly for long-term monthly crude oil price data. Moreover, previous research has primarily focused on daily data or country-specific cases, with limited attention given to the Europe Brent spot price. Therefore, this study seeks to fill this gap by modeling and comparing the forecasting performance of GARCH and SARIMA models in capturing crude oil price volatility dynamics. Therefore, this study applies to the comparison between the GARCH and SARIMA models to predict the crude oil price and its volatility.

## 3. Research Methodology

This part explains the source of data, the software applied for estimation, the GARCH model, the SARIMA model, and the diagnostic checking.

### 3.1 Source of Data

The crude oil price, which is monthly data from January 2000 to December 2024, is expressed in terms of the US Dollar per barrel. The data is based on the Europe Brent spot price Free on Board (FOB), with the source being the U.S. Energy Information Administration. EViews 13 is used as software to manipulate regression.

### 3.2 Testing for Arch (q) Effects

The use of the Lagrange multiplier can be tested to examine the presence of heteroscedasticity in the residuals of crude oil price [38]. Hence, the presence of the ARCH effect is checked before estimating ARCH(q) models. The test can be written in the following equation:

$$Y_t = a + B'X_t + u_t \tag{1}$$

Where:

$Y_t$ = Dependent variable.

$a$ = Constant term.

$\beta$ = Vector of coefficients.

$X_t$ = Vector of explanatory (independent) variables.

$u$ = Error term.

Next, the residuals $\hat{u}_t$ are obtained and then the auxiliary regression of the squared residuals ($u_t^2$) is run upon the lagged squared terms ($\hat{u}_{t-1}^2$,..., $\hat{u}_{t-q}^2$) and a constant as follows:

$$\hat{u}_t^2 = \gamma_0 + \gamma_1\hat{u}_{t-1}^2 + \ldots + \gamma_q\hat{u}_{t-q}^2 + w_t \tag{2}$$

Next, compute the coefficient of determination ($R^2$) times the number of observations (T) and give the test statistic for the joint significance of the q-lagged squared residuals with q degrees of freedom. Meanwhile, the Lagrange multiplier ($TR^2$) is tested against the $\chi^2(q)$ distribution. The null hypothesis of heteroskedasticity will be rejected if there is evidence of ARCH(q) effects of $TR^2$ larger than the $\chi^2(q)$ table result.

### 3.3 Asymmetric GARCH Model

In this study, the GARCH model is the base model. Asymmetric models such as EGARCH and TGARCH are also applied to strengthen the results and findings. The GARCH model will transform the model for p = 0, as the model reduces to ARCH (q). The value of the variance scaling parameter, $h_t$, now depends both on past values of the shocks and the past value of itself. The past values of the shocks are captured by the lagged squared residual terms, while the past values of itself are captured by lagged ht terms. Hence, the GARCH (1,1) model can be written in the equation below:

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \gamma_1 u_{t-1}^2 \tag{3}$$

Where:

$h_t$ = Conditional variance at time $t$.

$\gamma_0$ = Constant term.

$\delta_1$ = GARCH term.

$\gamma_1$ = ARCH term.

$u_{t-1}^2$ = Lagged squared residual.

The GARCH (1,1) can be a parsimonious alternative to an infinite ARCH (q) process, which can be written as follows:

$$h_t = \frac{\gamma 0}{1-\delta} + \gamma_1 \sum_{j=1}^{\infty} \delta^{j-1} u_{t-j}^2 \tag{4}$$

J. of Science and Technology Vol. 17 No. 2 (2025) p. 48-63

The EGARCH model, proposed by [39], models the logarithm of conditional variance instead of the variance itself, which allows it to capture asymmetric effects or leverage effects and ensures that the variance is always positive without imposing non-negativity constraints. EGARCH captures asymmetric volatility responses through the inclusion of a leverage term ($\gamma$).

Hence, the EGARCH(1,1) form can be written as Equation 5.

$$Ln(h_t) = \omega + \beta ln(h_{t-1}) + \alpha\left(\frac{|u_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \gamma\frac{u_{t-1}}{\sqrt{h_{t-1}}} \quad (5)$$

$h_t$ = Conditional variance at time t.
$ln(h_t)$ = Log of conditional variance.
$\omega$ = Constant term.
$\beta_i$ = Persistence parameter.
$\alpha_j$ = Magnitude effect.
$\gamma_j$ = Leverage effect.
$u_{t-j}$ = Lagged residual.

The TGARCH model was proposed by [40]. It modifies the standard GARCH model by adding a threshold term that allows volatility to respond differently to negative and positive shocks. Therefore, the TGARCH(1,1) form can be structured as Equation (6).

$$h_t = \omega + \alpha u_{t-1}^2 + \gamma d_{t-1} u_{t-1}^2 + \beta h_{t-1} \quad (6)$$

where

$$d_{t-1} = \begin{cases} 1, & if\ u_{t-1} < 0 \\ 0, & if\ u_{t-1} \geq 0 \end{cases}$$

$h_t$ = Conditional variance at time t.
$\omega$ = Constant term.
$u_{t-i}^2$ = Lagged squared residuals.
$d_{t-i}$ = Dummy variable.
$\alpha_j$ = Arch term.
$\gamma_j$ = Leverage term.
$\beta_i$ = GARCH term.

Dummy variable (d) is equal to 1 when the previous shock is negative and 0 otherwise. A positive value of $\gamma$ indicates that negative shocks increase volatility more than positive shocks of the same magnitude.

## 3.4 SARIMA Model

According to [14], SARIMA model can be written in the form of Equation (7).

$$\Delta_S^d y_t = (1 - L^S)^D y_t \quad (7)$$

Where:
$\Delta_S^d$ = Δ order difference

$L^S$ = The lag operator, which demonstrated periodic seasonal behaviour.

After that, the seasonal ARMA (p,q) model for every s is rewritten into:

$$\emptyset(L^S)y_t = \theta(L^S)u_t \quad (8)$$

Where:
$u_t$ = White noise

$\theta$ = Seasonal lag parameter, $u_{t-12}$

Following the ARMA (p,q) model, Equation (8) is considered in the form of Equation (9).

$$A(L)u_t = \Theta(L)\varepsilon_t \quad (9)$$

Where:

A(L) = Polynomial for p;

$\Theta(L)\varepsilon_t$ = Polynomial for q.

The seasonal ARMA model (p,q)(p,q)s formed as a result of the replacement of Equation (10) substitutes Equation (9).

$$A(L)\emptyset(L^S)y_t = \theta(L)\Theta(L)\varepsilon_t \quad (10)$$

Lastly, Equation (11) will be modified to suit ARIMA (p,d,q)(P,D,Q)s, in which the p,d,q in front stand for ARIMA while the P,D,Q at the back represent the additional seasonal components.

$$A(L)\emptyset(L^S)(1-L)^d(1-L^S)^D y_t = \theta(L)\Theta(L)\varepsilon_t \quad (11)$$

## 3.5 Model Selection Criterion

In this study, the most adequate model among the GARCH and SARIMA models is determined according to the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Information Criterion (HQ). AIC is a statistical measure used to evaluate and compare different models to identify the one that best fits the data without overfitting. SC is applied to evaluate model adequacy by considering both goodness of fit and model simplicity. Meanwhile, HQ is another model selection criterion that penalises additional parameters more strongly than AIC but less strongly than SC, offering a compromise between underfitting and overfitting. Therefore, the model, either the GARCH or SARIMA, achieving the lowest value in AIC, SC, and HQ is considered the better model. It provides a more parsimonious model with better predictive capability.

## 3.6 Forecasting Performance

After identifying the most suitable models among the GARCH and SARIMA, both models are undergoing the forecasting procedure. Their forecasting outcomes are compared based on the forecasting performance criteria, namely mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and Theil inequality index. The lower the value among these four criteria, the better the forecasting model. Therefore, the equations for MSE, RMSE, MAPE, and the Theil inequality index can be written from Equations (12) to (15).

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t - Yt)^2 \quad (12)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t - Yt)^2} \quad (13)$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{Y}t - Yt}{Yt}\right| \quad (14)$$

$$\text{Theil inequality index, } U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t - Yt)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t)^2 + \frac{1}{T}\sum_{t=1}^{T}(Yt)^2}} \quad (15)$$

Where:

$\hat{Y}t$ = Actual output

$Yt$ = Observed output

T = Number of time-varying observations

## 3.7 Summary of the Procedure

The summary of the procedure is as below:

1. The stability of the crude oil price was examined by using the Augmented Dickey-Fuller (ADF) test. If the crude oil price was not stationary at the level, the study proceeded with the difference to achieve stationarity.
2. Before the estimation of the GARCH model, the presence of ARCH effect was examined through the ARCH-LM test.
3. After the estimation of the GARCH model, the most appropriate model was compared with the EGARCH and TGARCH.

4. Before proceeding to the forecasting, the most appropriate model among the GARCH, EGARCH, or TGARCH was checked with the ARCH-LM test and correlogram for diagnostics.
5. The values of p and q for the lags were identified through the correlogram.
6. For the SARIMA model, the parameters were estimated to determine the values of p and q based on the lowest AIC, SC, and HQ criterion.
7. The selected model was rechecked with the significance and residual diagnostic test.
8. After the diagnostic check, the most adequate SARIMA model was used for forecasting.
9. The forecasted outcomes from the GARCH models and SARIMA were compared with their performance.

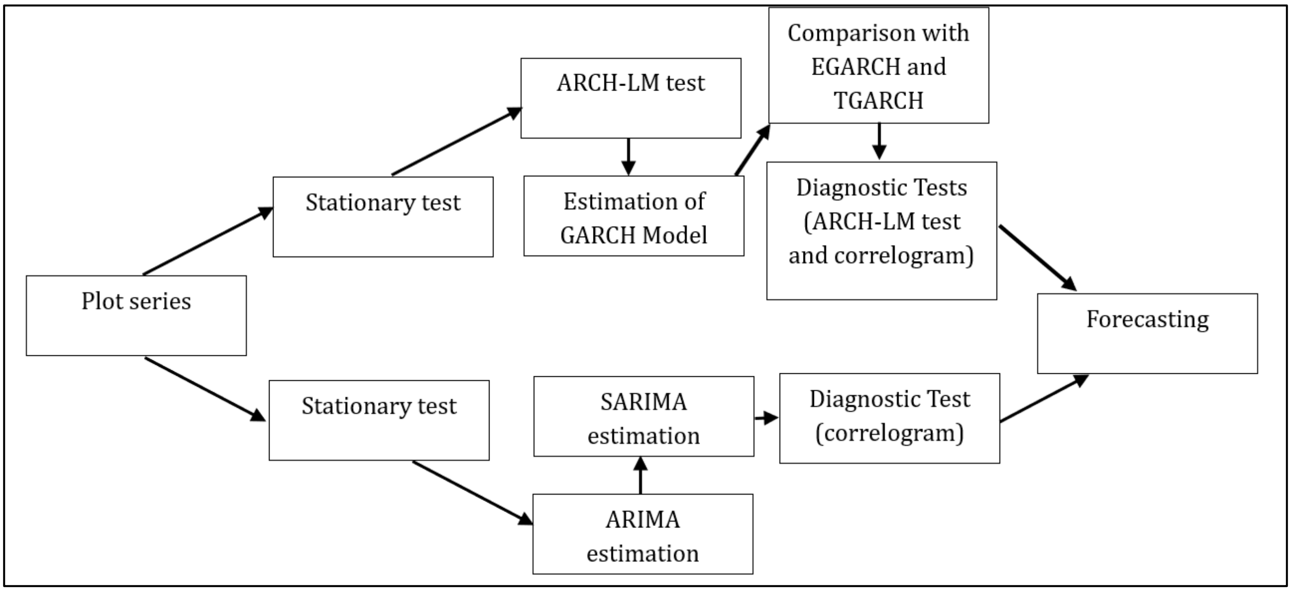



**Fig. 2** *Summary of procedure*

## 4. Results and Findings

### 4.1 Descriptive Statistics

Figure 3 reveals the descriptive statistics of crude oil, while Figure 4 demonstrates the trend of crude oil from January 2000 to December 2024. During this period, the oil price ranged between $18.38 per barrel and $132.70 per barrel. The mean oil price was $66.69 per barrel, with a median value of $64.59 per barrel. From Figure X, it shows the volatility of the data. It is supported by the minor right skewness (0.2256) and leptokurtosis (2.0890). The Jarque-Bera test also shows that the model is divergent from normalcy, with a P-value of 0.0015. These conditions emphasize the need for strong modelling approaches to accurately reflect the complex dynamics of crude oil price fluctuations.

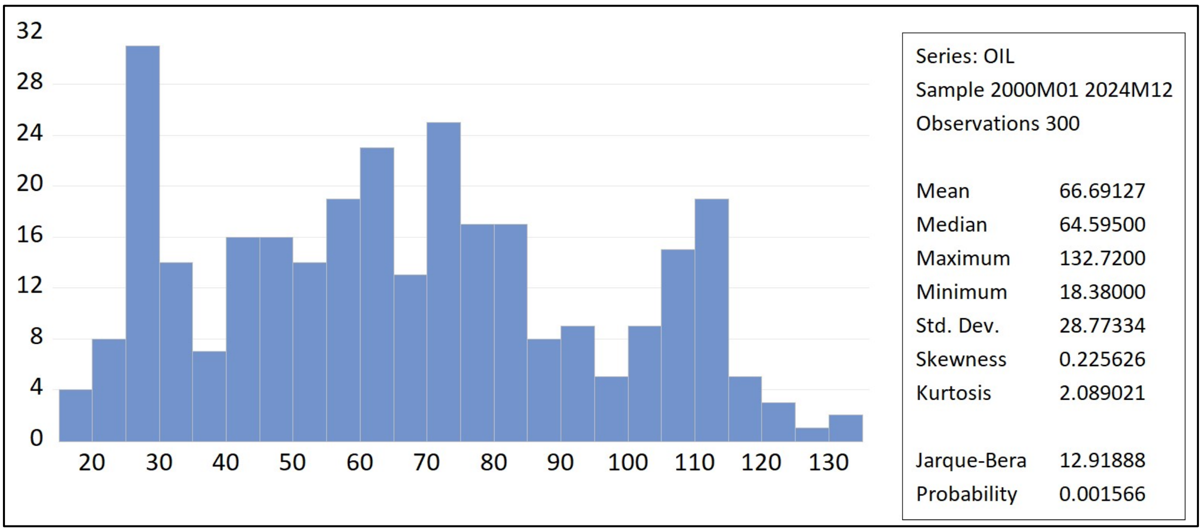



**Fig. 3** *Descriptive statistics, January 2000 – December 2024*


**Fig. 4** *Crude oil price, January 2000 – December 2024*

## 4.2 Testing for Stationary

The stationary test of this paper is using the Augmented Dickey-Fuller (ADF) test. The null hypothesis (Hn) is that the model is non-stationary, while the alternative hypothesis (Ha) is that the model is stationary. Based on Table 1, the result of the crude oil price revealed that there is no significant result for the level, either in constant form or in the constant and trend form. However, Table 2 shows that the crude oil price is stationary at first difference, either in constant form or in the constant and trend form. Hence, the null hypothesis is rejected when the first level shows there is no "unit root" problem in the model and the model is stationary. It is important to ensure that the model is free from spurious regression.

**Table 1** *The ADF test result at level*

| Criteria | Constant | Constant and Trend |
|---|---|---|
| ADF Test Statistic | -2.7123 | -2.8245 |
| Probability | 0.0731 | 0.1896 |
| 1% critical value | -3.4521 | -3.9892 |
| 5% critical value | -2.8710 | -3.4250 |
| 10% critical value | -2.5719 | -3.1356 |

**Table 2** *The ADF test result at first difference*

| Criteria | Constant | Constant and Trend |
|---|---|---|
| ADF Test Statistic | -12.5025 | -12.4899 |
| Probability | 0.0000 | 0.0000 |
| 1% critical value | -3.4521 | -3.9892 |
| 5% critical value | -2.8710 | -2.4249 |
| 10% critical value | -2.5719 | -3.1356 |

## 4.3 ARCH-LM Test

The ARCH-LM test is used to determine the existence of heteroskedasticity. The null hypothesis indicates that there is no heteroskedasticity in the model, while the alternative shows that heteroskedasticity exists in the model. The P-value will decide whether to reject the null hypothesis or not.

**Table 3** *Arch-LM test result*

| | | | |
|---|---|---|---|
| F-statistic | 24.3445 | Prob. F(1, 295) | 0.0000 |
| Obs*R-squared | 22.6411 | Prob. Chi-Square(1) | 0.0000 |

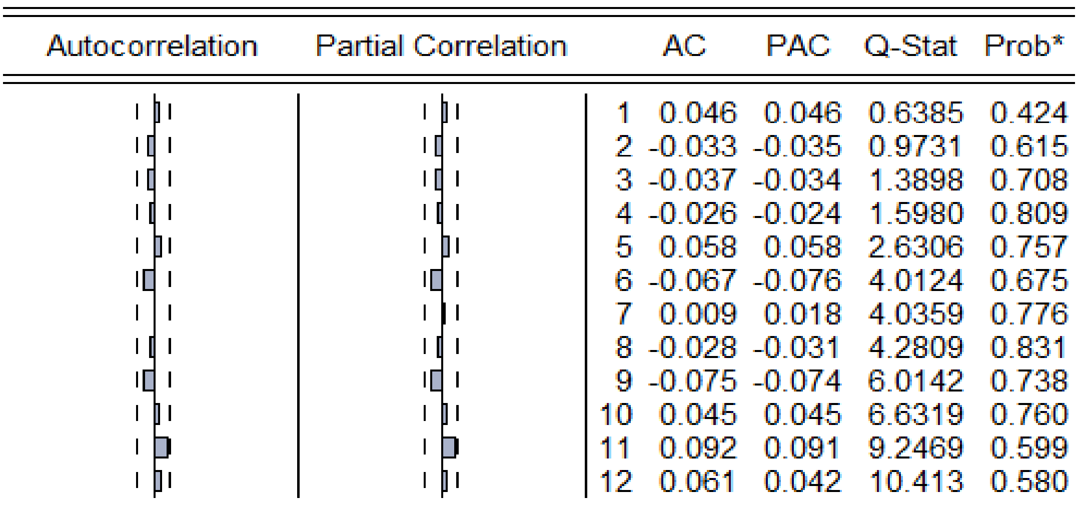
Table 3 shows that the ARCH (1) is used to estimate the model. From the results, the probability is less than 0.05 and even less than 0.01, which is significant enough to reject the null hypothesis. The results also prove that it is significant to reject the null hypothesis. Hence, the null hypothesis is rejected when the model exhibits heteroskedasticity and the ARCH effect.

## 4.4 ARCH-GARCH Model

The different ARCH (q) and GARCH (q) models are estimated. Table 4 reveals the results on the coefficients of the estimation, while Figure 5 demonstrates the correlogram of the GARCH model.

**Table 4** *GARCH model estimation*

| | Adjusted R-squared | AIC | SC | HQ |
|---|---|---|---|---|
| GARCH 1,1 | 0.0659 | 6.1794 | 6.2414 | 6.2042 |
| GARCH 2,1 | 0.0783 | 6.1693 | 6.2437 | 6.1991 |
| GARCH 2,2 | 0.0786 | 6.1757 | 6.2626 | 6.2105 |
| **GARCH 3,1** | **0.0804** | **6.1192** | **6.2060** | **6.1539** |
| GARCH 3,2 | 0.0810 | 6.1257 | 6.2249 | 6.1654 |
| GARCH 3,3 | 0.0790 | 6.1266 | 6.2382 | 6.1713 |
| GARCH 4,1 | 0.0794 | 6.1264 | 6.2256 | 6.1661 |
| GARCH 4,2 | 0.0806 | 6.1853 | 6.2970 | 6.2300 |
| GARCH 4,3 | 0.0818 | 6.1545 | 6.2786 | 6.2042 |
| GARCH 4,4 | 0.0821 | 6.1366 | 6.2731 | 6.1912 |



| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | 0.046 | 0.046 | 0.6385 | 0.424 |
| | | 2 | -0.033 | -0.035 | 0.9731 | 0.615 |
| | | 3 | -0.037 | -0.034 | 1.3898 | 0.708 |
| | | 4 | -0.026 | -0.024 | 1.5980 | 0.809 |
| | | 5 | 0.058 | 0.058 | 2.6306 | 0.757 |
| | | 6 | -0.067 | -0.076 | 4.0124 | 0.675 |
| | | 7 | 0.009 | 0.018 | 4.0359 | 0.776 |
| | | 8 | -0.028 | -0.031 | 4.2809 | 0.831 |
| | | 9 | -0.075 | -0.074 | 6.0142 | 0.738 |
| | | 10 | 0.045 | 0.045 | 6.6319 | 0.760 |
| | | 11 | 0.092 | 0.091 | 9.2469 | 0.599 |
| | | 12 | 0.061 | 0.042 | 10.413 | 0.580 |

**Fig. 5** *Correlogram of GARCH (3,1) model*

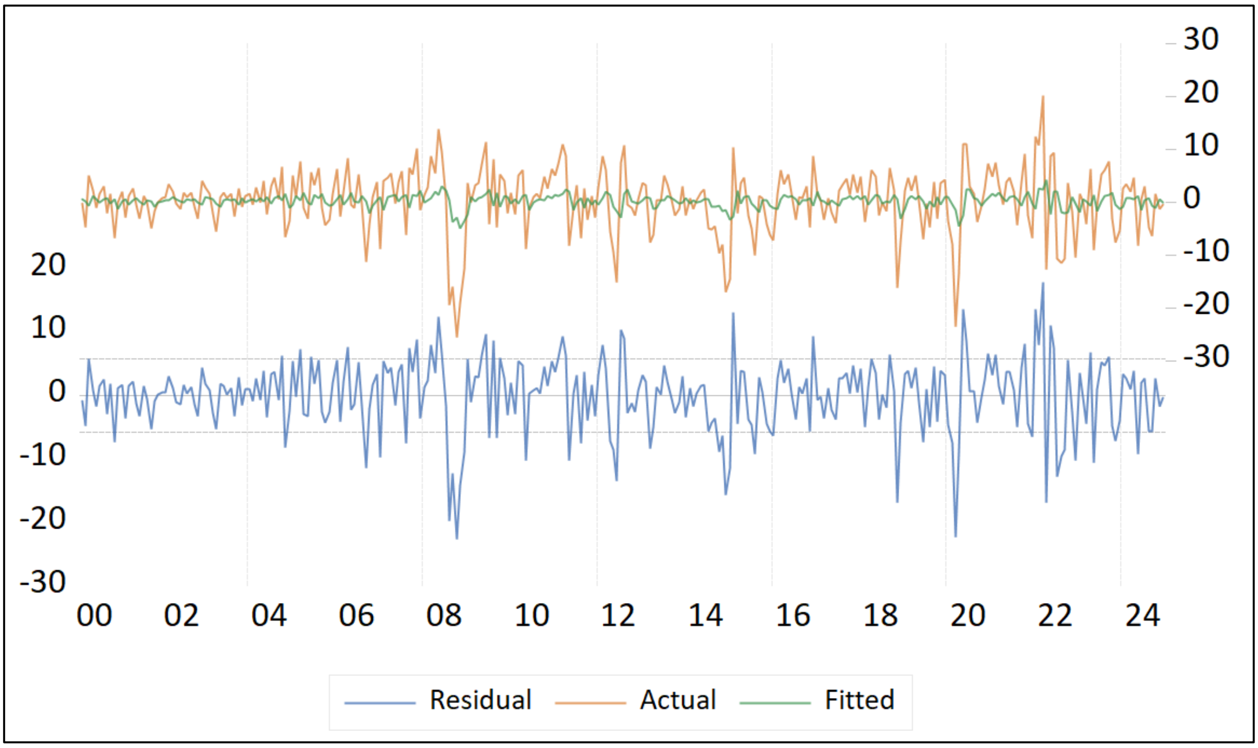



**Fig. 6** *Residuals-actual-fitted plot of GARCH (3,1)*

From Table 3, ten GARCH models have been tested. Among the GARCH models, the GARCH (3,1) model is the most adequate model because it has the lowest in terms of the AIC (6.1192), BC (6.2060), and HQ (6.1539) criteria. After checking the most adequate model, the autocorrelation (ACF) and partial autocorrelation (PACF) analysis show that the GARCH (3,1) model can be inferred to exhibit no serial correlation in the residuals. This is also supported by Figure 6. Additionally, the result from Table 5 also denotes that the model is free from the ARCH effect. This is because the probability Chi-Square is 0.6448, which is greater than 0.05.

**Table 5** *Arch-LM test result*

| | | | |
|---|---|---|---|
| F-statistic | 0.2112 | Prob. F(1, 295) | 0.6462 |
| Obs*R-squared | 0.2124 | Prob. Chi-Square(1) | 0.6448 |

**Table 6** *Type of GARCH variant models estimation*

| Type of model | Adjusted R-squared | AIC | SC | HQ |
|---|---|---|---|---|
| **GARCH** | **0.0804** | **6.1192** | **6.2060** | **6.1539** |
| EGARCH | 0.0804 | 6.1296 | 6.2289 | 6.1693 |
| TGARCH | 0.0803 | 6.1641 | 6.2633 | 6.2038 |

Table 6 shows the estimation of the type of GARCH variant models. From the results, the GARCH model is compared with its family, namely the EGARCH and TGARCH. From the comparison of the criteria, the GARCH model is still the best fit to capture oil price volatility. For instance, the GARCH model has the lowest values of AIC (6.1192), BC (6.2060), and HQ (6.1539).

## 4.5 SARIMA Model

Figure 7 demonstrates the correlogram for the first difference series of crude oil prices. This situation arose because the autocorrelation at lags 1, 6, 15, and 23 was greater than the bounds of the correlogram. Therefore, it is suitable to apply the SARIMA model.

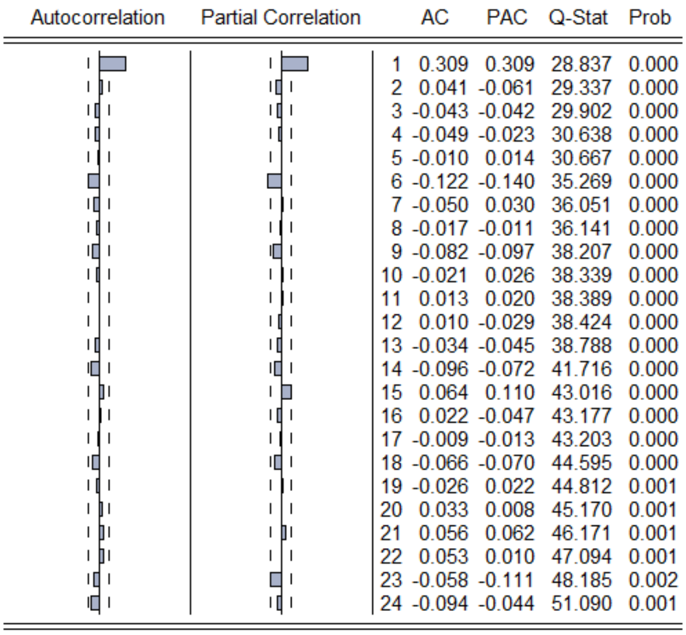



**Fig. 7** *Correlogram of crude oil price in first difference*

Before the estimation of the SARIMA, the base model is the ARIMA. To identify the best model, several ARIMA models are constructed and tested with the criterion. The first lag and sixth lag were selected as they are greater than the bounds of the correlogram (Figure 7). Table 7 shows the estimation results of the ARIMA model. Among the four models tested, ARIMA (6,1,1) is the most suitable model as it has the lowest AIC (6.3520), SC (6.4015), and HQ (6.3718).

**Table 7** *Estimation of the ARIMA model*

| ARIMA model | (1,1,1) | (1,1,6) | **(6,1,1)** | (6,1,6) |
|---|---|---|---|---|
| AIC | 6.3659 | 6.3524 | **6.3520** | 6.4340 |
| SC | 6.4154 | 6.4019 | **6.4015** | 6.4835 |
| HQ | 6.3857 | 6.3722 | **6.3718** | 6.4538 |

**Table 8** *Estimation of the SARIMA model*

| SARIMA model | **(6,1,1) $(1,1,1)_{12}$** | (6,1,1) $(1,1,0)_{12}$ | (6,1,1) $(0,1,1)_{12}$ | (6,1,1) $(2,1,0)_{12}$ | (6,1,1) $(2,1,1)_{12}$ | (6,1,1) $(1,1,2)_{12}$ | (6,1,1) $(2,1,2)_{12}$ |
|---|---|---|---|---|---|---|---|
| AIC | **6.3390** | 6.3586 | 6.3569 | 6.3428 | 6.3470 | 6.3406 | 6.3405 |
| SC | **6.4133** | 6.4205 | 6.4188 | 6.4047 | 6.4213 | 6.4149 | 6.4148 |
| HQ | **6.3688** | 6.3834 | 6.3817 | 6.3676 | 6.3767 | 6.3704 | 6.3703 |

Table 8 shows the results of the SARIMA model. From the models tested, the most adequate model is SARIMA (6,1,1) $(1,1,1)_{12}$. The model is selected based on the lowest criterion among AIC (6.3390), SC (6.4133), and HQ (6.3688). After the estimation, this SARIMA model is undergoing the diagnostic test with a correlogram. From the correlogram, the results show that the p-value for both the autocorrelation and partial autocorrelation coefficients exceeded 0.05, suggesting that all lag terms were insignificant. Consequently, the residuals exhibited no autocorrelation, confirming the model's suitability for forecasting.

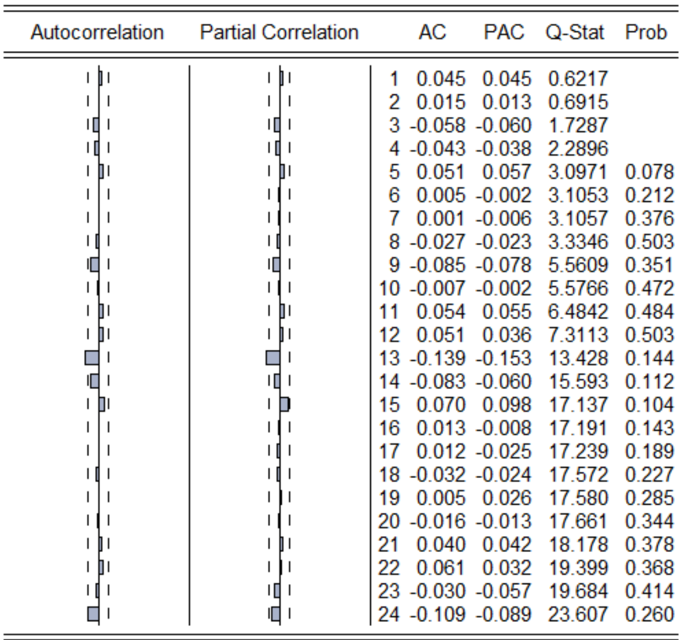



**Fig. 8** *Correlogram of SARIMA (6,1,1) (1,1,1)$_{12}$*

## 4.6 Comparative The Performance of the Forecasting Between GACRH and SARIMA Models

From the findings, the most adequate GARCH model is GARCH (3,1), while the most suitable SARIMA model is SARIMA (6,1,1) (1,1,1)$_{12}$. Both models are undergoing forecasting. Table 9 displays the performances of these two models based on root mean squared error, mean absolute error, Theil inequality coefficient, and symmetric MAPE. By comparing the forecasting performance criteria, GARCH (3,1) in static form has better performance. It has the lowest root mean squared error (5.8123), mean absolute error (4.4173), Theil inequality coefficient (0.7964), and symmetric MAPE (161.8140). The GARCH (3,1) is a good fit for forecasting purposes in terms of the volatility of crude oil prices.

**Table 9** *Comparative performance between GARCH (3,1) and SARIMA (6,1,1)(1,1,1)$_{12}$*

| Method | Type of forecasting | Forecasting performance | | | |
|---|---|---|---|---|---|
| | | Root Mean Squared Error | Mean Absolute Error | Theil Inequality Coefficient | Symmetric MAPE |
| GARCH (3,1) | Dynamic | 6.0717 | 4.4767 | 0.9705 | 180.9136 |
| | **Static** | **5.8123** | **4.4173** | **0.7964** | **161.8140** |
| SARIMA (6,1,1) (1,1,1)$_{12}$ | Dynamic | 6.1599 | 4.5666 | 0.9622 | 180.5037 |
| | Static | 5.8818 | 4.4737 | 0.8738 | 162.1290 |

By adopting the GARCH (3,1), the forecasted crude oil price was compared with the actual crude oil price. However, this study only focused on three periods: the 2008 global financial crisis (August 2008 – May 2009), the 2014 oil price crash (June 2014 – January 2016), and the 2020 COVID-19 pandemic crash (January 2020 – April 2020). From Figures 9, 10, and 11, the forecasted oil price was able to capture the volatility of each period by providing the same trends as the actual oil price. However, the forecasted oil prices are higher than the actual oil prices. It fulfils the characteristics of the GARCH model, which captures the volatility but not the actual value.

From this study, between the GARCH and SARIMA models, the most appropriate model to model the price or volatility of crude oil from January 2000 to December 2024 is GARCH (3,1). This result is the same as [30], which mentioned that the GARCH model has better performance compared to ARIMA. However, this study provides a different view from [13] and [33], by confirming that the GARCH (3,1) is the best model to gauge the volatility of crude oil within the period from January 2000 to December 2024.

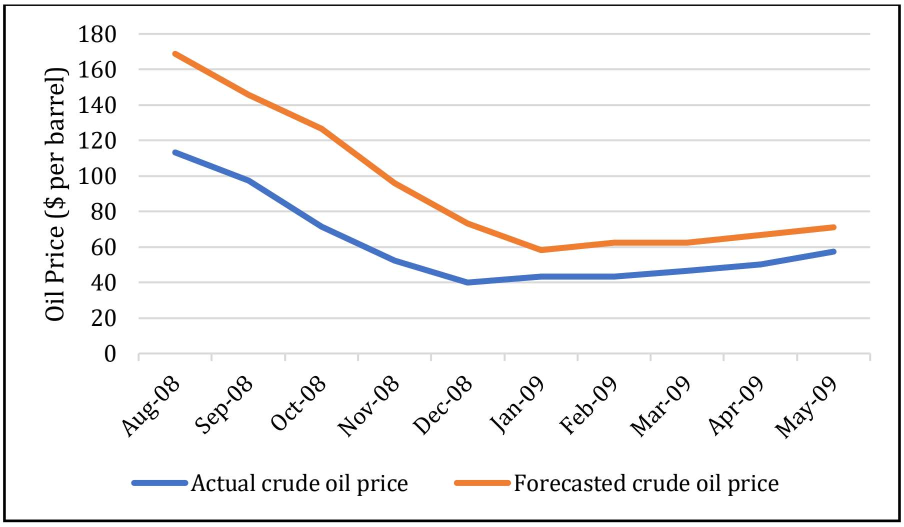



**Fig. 9** *Actual and forecasted crude oil price, August 2008 – May 2009*

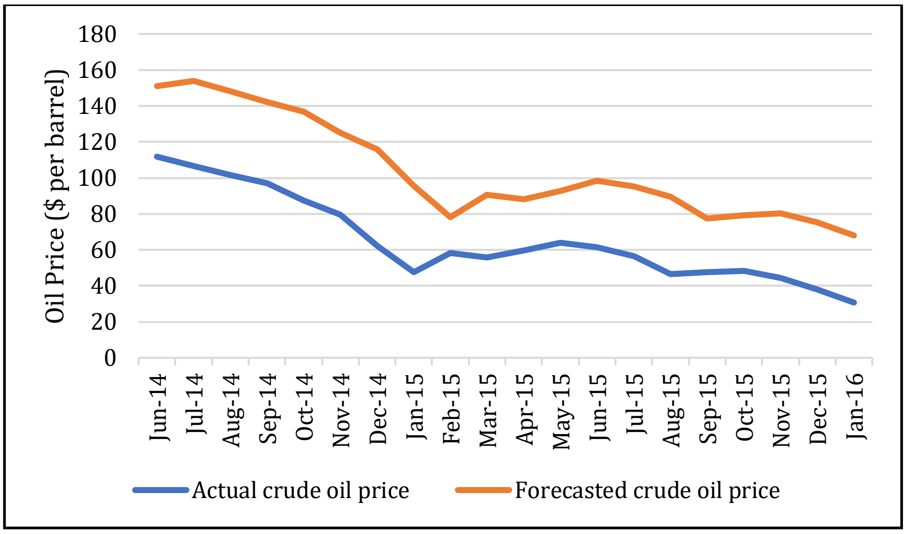



**Fig. 10** *Actual and forecasted crude oil price, Jun 2014 – January 2016*

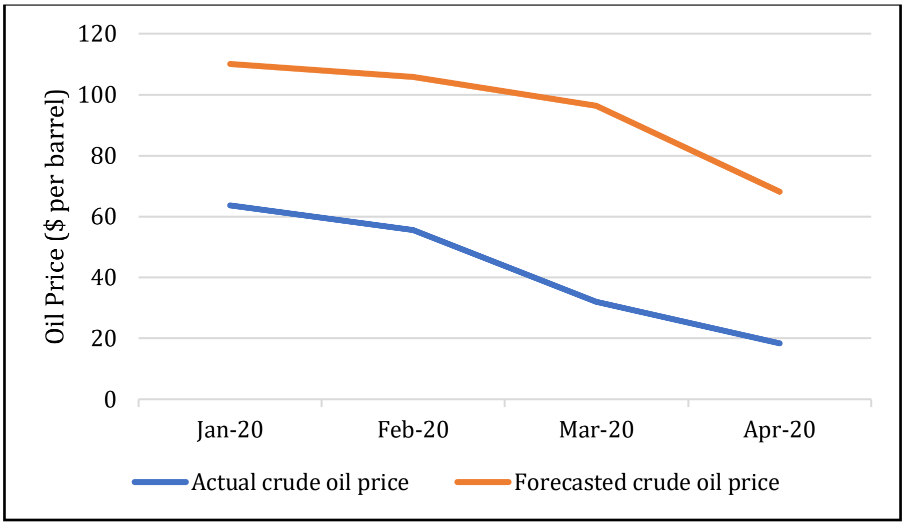



**Fig. 11** *Actual and forecasted crude oil price, January 2020 – April 2020*

## 5. Conclusion

Crude oil is a vital global commodity in which many countries invest heavily. Consequently, fluctuations in its price have significant economic implications, influencing national growth either positively or negatively. Therefore, understanding and estimating its volatility is crucial for investors and policymakers in managing risk and making informed decisions. The main objective of this study is to model and forecast the volatility of crude oil prices. A comparative analysis of the GARCH and SARIMA models evaluates their performance in forecasting crude oil prices and volatility dynamics. Monthly crude oil prices from January 2000 to December 2024 are adopted in this study. The results show that the GARCH (3,1) has better performance than the SARIMA (6,1,1) (1,1,1)12 in predicting crude oil prices. This condition proves that SARIMA works well for short-term trend forecasting but underperforms during volatile periods [41]. By using the GARCH (3,1) model, we compare the forecasted values and the actual values of crude oil prices in three crises: the 2008 global financial crisis, the 2014 oil price crash, and the 2020 COVID-19 pandemic crash. We find that the volatility is captured by the forecasted values but not the actual values. The findings from the GARCH (3,1) model that can reasonably well account for crude oil price volatility carry important policy and investment ramifications. For investors, understanding patterns of volatility enables superior hedging to offset risks due to sudden price changes. Volatility projections precisely enable companies that manage portfolios to diversify energy holdings and time investments to yield optimal returns. From a policy perspective, reliable estimates of volatility are important in guaranteeing energy security and fiscal stability in oil-exporting nations. Governments may utilise such forecasts to construct contingency plans. For instance, strategic petroleum reserve or subsidies, which to to cushion against price fluctuations. Moreover, since oil price volatility directly reflects inflation and production costs, central banks can utilise such forecasts in formulating monetary policy to stabilize prices and keep inflationary pressures in check. Overall, the GARCH (3,1) model provides meaningful insights to guide strategic investment decisions as well as macroeconomic policymaking in very volatile energy markets. Overall, the findings demonstrate that the GARCH (3,1) model provides a more reliable framework for modeling crude oil price volatility. Future research may explore hybrid approaches that integrate the strengths of both GARCH and SARIMA models to enhance forecasting accuracy, which leveraging GARCH's ability to capture volatility clustering and SARIMA's capacity to model trend and seasonality.

## Acknowledgement

The authors would like to acknowledge the Universiti Utara Malaysia which have contributed greatly to the preparation of the research until the publication of this work.

## Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

## Author Contribution

*The authors confirm their contribution to the paper as follows:* ***study conception and design****: Kuang Yong Ng, Zalina Zainal, Shamzaeffa Samsudin;* ***data collection****: Shamzaeffa Samsudin, Haitian Wei;* ***analysis and interpretation of results****: Kuang Yong Ng, Zalina Zainal, Shamzaeffa Samsudin, Haitian Wei;* ***draft manuscript preparation****: Kuang Yong Ng; All authors reviewed the results and approved the final version of the manuscript.*

## References

[1] Asteriou, D., & Hall, S. G. (2021). *Applied econometrics*. Bloomsbury Publishing.

[2] Wang, Y., Xiang, Y., Lei, X., & Zhou, Y. (2022). Volatility analysis based on GARCH-type models: Evidence from the Chinese stock market. *Economic research-Ekonomska istraživanja, 35*(1), 2530-2554.

[3] Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.

[4] Gyagri, M., Marto, S. A., & Amarfio, E. M. (2017). Determinants of global pricing of crude oil – A theoretical review. *International Journal of Petroleum and Petrochemical Engineering, 3*(3), 7–15.

[5] Ural, M. (2016). The impact of the global financial crisis on crude oil price volatility. *Yönetim ve Ekonomi Araştırmaları Dergisi*, *14*(2), 64-76.

[6] Fantazzini, D. (2016). The oil price crash in 2014/15: Was there a (negative) financial bubble? *Energy Policy*, *96*, 383-396.

[7] Stocker, M., Baffes, J., Some, Y. M., Vorisek, D., & Wheeler, C. M. (2018). The 2014-16 oil price collapse in retrospect: sources and implications. *World Bank Policy Research Working Paper*, (8419).

[8] Bourghelle, D., Jawadi, F., & Rozin, P. (2021). Oil price volatility in the context of Covid-19. *International Economics*, *167*, 39-49.

[9] Czech, K., & Niftiyev, I. (2021). The impact of oil price shocks on oil-dependent countries' currencies: The case of Azerbaijan and Kazakhstan. *Journal of Risk and Financial Management, 14*(9), 431.

[10] Taghizadeh-Hesary, F., & Yoshino, N. (2015). Macroeconomic effects of oil price fluctuations on emerging and developed economies in a model incorporating monetary variables. *Economics and Policy of Energy and Environment: 2, 2015*, 51-75.

[11] Khan, M., Kayani, U. N., Khan, M., Mughal, K. S., & Haseeb, M. (2023). COVID-19 pandemic & financial market volatility; Evidence from GARCH models. *Journal of Risk and Financial Management, 16*(1), 50. https://doi.org/10.3390/jrfm16010050

[12] Verma, S. (2021). Forecasting volatility of crude oil futures using a GARCH–RNN hybrid approach. *Intelligent Systems in Accounting, Finance and Management, 28*(2), 130–142. https://doi.org/10.1002/isaf.1489

[13] Adams, S. O., & Olives, P. I. (2025). Modelling and Forecasting of Crude Oil Price Return Volatility from 2006-2023: An Application of the Garch Models. *Journal of Science and Technology*, *17*(1), 94-107.

[14] Ng, K. Y., Zainal, Z., & Samsudin, S. (2023). COMPARATIVE PERFORMANCE OF ARIMA, SARIMA AND GARCH MODELS IN MODELLING AND FORECASTING UNEMPLOYMENT AMONG ASEAN-5 COUNTRIES. *International Journal of Business & Society*, *24*(3).

[15] Azimi, M. N., & Shahidzada, S. F. (2019). A correcting note on forecasting conditional variance using ARIMA vs. GARCH model. *International Journal of Economics and Finance, 11*(5), 145. https://doi.org/10.5539/ijef.v11n5p145

[16] Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy, 91*(2), 228-248.

[17] Jiménez-Rodríguez*, R., & Sánchez, M. (2005). Oil price shocks and real GDP growth: empirical evidence for some OECD countries. *Applied economics*, *37*(2), 201-228.

[18] Yildirim, H. (2017). ARCH-GARCH model on volatility of crude oil. *International Journal of Disciplines Economic & Administrative Sciences Studies, 3*(1), 17–22.

[19] Al-Najjar, D. (2016). Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market. *Asian Journal of Finance & Accounting, 8*(1), 152–167.

[20] Hu, L. (2017). Research on stock return and volatility-based on ARCH-GARCH model. *Advances in Intelligent Systems Research, 156*, 181–184.

[21] Saltik, O., Degirmen, S., & Ural, M. (2015). Volatility modelling in crude oil and natural gas prices. *Istanbul Conference of Economics and Finance*, Istanbul, Turkey.

[22] Deebom, D. Z., & Essi, I. D. (2017). Modeling price volatility of Nigerian crude oil markets using GARCH model: 1987-2017. *International Journal of Applied Science and Mathematical Theory, 3*(4), 23–49.

[23] Moujieke, G. B. L., & Essi, I. D. (2019). Modeling returns on prices and sales of crude oil using GARCH model between 1997-2017. *International Journal of Applied Science and Mathematical Theory, 5*(1), 28–45.

[24] Halim, Z., & Fatima, Z. B. (2015). Use of the GARCH models to energy markets: Oil price volatility. *Global Journal of Pure and Applied Mathematics, 11*(6), 4385–4394.

[25] Lee, C. N. (2009). *Application of ARIMA and GARCH models in forecasting crude oil prices* (Master's thesis). Universiti Teknologi Malaysia.

[26] Lux, T., Segnon, M., & Gupta, R. (2015). *Modeling and forecasting crude oil price volatility: Evidence from historical and recent data* (No. 31). FinMaP-Working Paper.

[27] Aamir, M., & Ani, S. (2015). Modelling and forecasting monthly crude oil prices of Pakistan: A comparative study of ARIMA, GARCH and ARIMA-GARCH models. *AIP Conference Proceedings, 1750*, 060015.

[28] Xiang, Y. (2022). Using ARIMA-GARCH Model to Analyze Fluctuation Law of International Oil Price. *Mathematical Problems in Engineering*, *2022*(1), 3936414.

[29] Merabet, F., Zeghdoudi, H., Yahia, R. H., & Saba, I. (2021). Modelling of oil price volatility using ARIMA-GARCH models. *Adv. Mathematics*, *10*, 2361-2380.

[30] Haque, M. I., & Shaik, A. R. (2021). Predicting crude oil prices during a pandemic: A comparison of arima and garch models. *Montenegrin Journal of Economics*, *17*(1), 197-207.

[31] Mușetescu, R. C., Grigore, G. E., & Nicolae, S. (2022). The use of GARCH autoregressive models in estimating and forecasting the crude oil volatility. *European Journal of Interdisciplinary Studies*, *14*(1), 13-38.

[32] Gbolagade, S. D., Oyeyemi, G. M., Abidoye, A. O., Adejumo, T. J., & Okegbade, A. I. (2022). Performance of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models in Modeling Volatility of Brent Crude Oil Price. *Ilorin Journal of Science*, *9*(1), 20-32.

[33] Rao, A., Sharma, G. D., Tiwari, A. K., Hossain, M. R., & Dev, D. (2025). Crude oil Price forecasting: Leveraging machine learning for global economic stability. *Technological Forecasting and Social Change*, *216*, 124133.

[34] Zheng, S., Xu, M., & Zhu, M. (2025). Generalized Modeling of Oil Futures Volatility Through Uncertainty Indicator Selection: A GARCH–MIDAS–AES Framework. *Journal of Futures Markets*.

[35] Cheng, M. L., Chu, C. W., & Hsu, H. L. (2023). A study of univariate forecasting methods for crude oil price. *Maritime Business Review*, *8*(1), 32-47.

[36] Agyare, S., Odoi, B., & Wiah, E. N. (2024). Predicting petrol and diesel prices in Ghana, a comparison of ARIMA and SARIMA models. *Asian Journal of Economics, Business and Accounting*, *24*(5), 594-608.

[37] Agrawal, A., Kadam, S., Kapoor, P. A., & Rashid, M. (2025). Predicting crude oil prices using SARIMA-X method: An empirical study. *International Journal of Financial Engineering*, *12*(01), 2450007.

[38] Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica, 50*, 987–1008.

[39] Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, 347-370.

[40] Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779-1801.

[41] Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, *2014*(1), 614342.