Prediction of the West Texas Intermediate Crude Oil Price Using ARIMA Model and ARIMA-GARCH Model

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Keywords: Prediction, WTI Crude, ARIMA Model, GARCH Model.

Abstract: Crude oil stands as a pivotal energy source and raw material indispensable for modern life and various production activities. The fluctuations in its price are intricately linked to the seamless functioning of the macroeconomy, the healthy development of the capital market, and the choices of individual investors. However, under the influence of various external factors, international crude oil price changes are characterized by complexity and are very difficult to predict. This study delves into the monthly fluctuations of West Texas Intermediate (WTI) crude oil prices, employing the ARIMA and GARCH models to shed light on its future trajectory. Methodically, it subjects the data to normality tests, stationarity tests, and white noise tests, while leveraging the AIC information criterion and minimum MSE criterion to fine-tune the model. Through rigorous analysis, the study establishes both ARIMA (1,1,0) and ARIMA(1,1,0)-GARCH (1,1) models and both models forecast a modest uptick in oil prices over the next three months, spanning May, June, and July of 2024. This article adds GARCH model and comparing with the traditional ARIMA model, ARIMA-GARCH model takes conditional heteroskedasticity into account and can be more accurate and comprehensive in prediction, which can provide certain reference and suggestion for various investors.

1 INTRODUCTION

In recent years, driven by economic globalization, crude oil has asserted increasing dominance within the commodity market. Given its unique characteristics, the fluctuations and trajectories of international oil prices have garnered significant attention. These fluctuations reverberate across various sectors, impacting government policies, economic activities, portfolio management, risk mitigation, and more. Bastianin et al. asserted that economic policies and financial regulatory measures aimed at alleviating the adverse consequences of unforeseen oil price fluctuations should prioritize addressing the underlying causes of such shocks (Bastianin et al. 2016). Additionally, the impact of WTI crude oil price on Shanghai crude oil futures prices is asymmetric in both intensity and direction in the short and long term, with a positive effect in the short term and a negative effect in the long term (Ding, 2024).

Especially since the advent of the 21st century, with the advancement of global trade liberalization and the deepening of world economic globalization, the crude oil market has witnessed heightened frequency of fluctuations, resulting in significant volatility in crude oil prices. This market exhibits perpetual volatility, marked by conspicuous non-linearity and pronounced price swings. As a commodity, crude oil's financial characteristics have gained prominence, attributed to its pricing mechanism and the proliferation of derivatives in financial markets. The dual nature of crude oil renders its price susceptible not only to market fundamentals such as supply and demand dynamics and inventory changes but also to various other influencing factors, including fluctuations in the U.S. dollar, geopolitical tensions, economic policies, speculative forces, and more. However, there are many factors that affect crude oil, and the inherent relationship between the various influencing factors is complex. How to determine the main influencing factors and long-term influencing factors is a difficult problem.

Sari et al. found that long-term trends in oil prices are significantly impacted by global risk perceptions (Sari et al., 2011). Additionally, Le et al. posited that increases in Covid-19 cases, uncertainties surrounding U.S. economic policies, and anticipated stock market volatility collectively contributed to the decline in WTI crude oil prices in April 2020. Despite

Li, M.
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DOI: 10.5220/0012999200004601

In *Proceedings of the 1st International Conference on Innovations in Applied Mathematics, Physics and Astronomy (IAMPA 2024)*, pages 110-118
ISBN: 978-989-758-722-1

these challenges, losses in global stock markets appeared to have been notably mitigated (Le et al., 2021). Wang et al. argued that in extreme scenarios, there exists a robust causal relationship between investor sentiment and the crude oil futures market (Wang et al., 2021).

Therefore, how to accurately predict WTI crude oil prices has become a top priority, and many complex and innovative models have been built to predict WTI crude oil prices. Traditional econometric models play a crucial role across diverse economic domains, including the prediction of WTI crude oil prices. Herrera employed RiskMetrics and GARCH models for short-term forecasts, Exponential GARCH (EGARCH) for medium-term horizons, and Markov-switching GARCH (MS-GARCH) for long-term predictions (Wang and Liu, 2016 & Herrera, Hu and Pastor, 2018). Indeed, machine learning methods and hybrid models have gained significant traction in the realm of crude oil price prediction. A multitude of scholars have conducted extensive research in this area. Wu et al. leveraged a Convolutional Neural Network (CNN) model to extract text features from news media texts and Google Trends data, assessing their efficacy in explaining crude oil price predictions (Wu et al., 2021). Li et al. investigated the enduring impacts of global crude oil production and economic activities on crude oil prices. They devised a hybrid model incorporating Genetic Algorithm Optimized Support Vector Machine (GASVM) and Back Propagation Neural Network (BPNN) to analyze monthly oil price data for predictive purposes (Li, Zhu and Wu, 2019). Wang fused a multi-layer perceptron with a neural network to develop an Elman Recurrent Neural Network (ERNN) model for empirical crude oil price forecasting (Wang and Wang, 2016).

Overall, these studies highlight the need for accurate prediction of the global price of WTI crude. The econometric model can predict short-term crude oil prices more accurately, but the nonlinear, complex and non-stationary characteristics of crude oil prices make the model have certain flaws. The machine learning model uses linear and nonlinear models to enrich the experimental process and set up various scenarios to improve the applicability of the model. Then, more complex deep learning models and numerous neural network algorithms were added to forecasts, which can extract effective information and focus on trends and changes in time series. This paper will primarily concentrate on utilizing the ARIMA and GARCH models for crude oil price prediction. The aim is to offer a valuable reference for crude oil futures investors, aiding them in making informed decisions and conducting risk mitigation transactions. By leveraging these models, investors can potentially reduce their losses to a considerable extent.

2 METHODOLOGY

2.1 Data Source

Fred's global WTI crude oil price index is the source of the data used in this investigation. This dataset comprises monthly average prices of crude oil in U.S. dollars. It is meticulously documented, with no instances of missing values or outliers. For analysis, the paper has selected price data spanning from January 2000 to April 2024, amounting to 292 observations. The first 276 observations, covering the period from January 2000 to December 2022, constitute the training set, while the remaining 16 observations, spanning from January 2023 to April 2024, are designated as the test set. Ultimately, a rolling forecast approach is adopted to predict the WTI crude oil price for May, June, and July 2024.

The internationally recognized crude oil benchmark prices are WTI and Bren crude oil prices. This paper selects the price of WTI crude oil, which occupies the leading position in terms of global commodity futures trading volume because of its advantages of transparent quotations and high liquidity, as well as the status of U.S. super crude oil buyers and the world influence of the New York Stock Exchange. At the same time, this paper selected prices rather than yields, average prices rather than closing prices, and monthly data over the past decade rather than all data.

2.2 Variable Selection

Crude oil prices are obviously volatile and cyclical. Indeed, the prices of crude oil can experience substantial fluctuations, with the potential for significant rises or falls within relatively brief time frames, and they can experience rising and falling cycles over a span of several years or even ten years. Changes in oil prices are often affected by geopolitics, technological progress, and the macroeconomic environment, as illustrated in Figure 1:

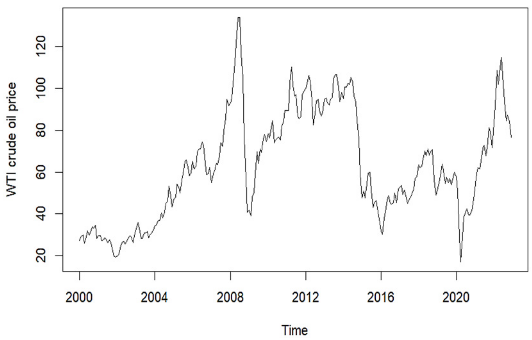

Figure 1: Global WTI crude price.

From Figure 1, it can be concluded that WTI oil prices remained slightly unchanged from 2000 to 2004, then gradually increased, reaching their peak in the summer of 2008 due to geopolitical tensions, and then rapidly collapsing due to the impact of the 2008 financial crisis. , then prices rose slowly from 2009 to 2014, then dropped rapidly due to excess production, then gradually climbed higher from 2016 to 2020, and then plummeted rapidly in 2020 because of the COVID-19 pandemic's effects. It has risen rapidly in the past three years and declined rapidly in the past year. This article uses a univariate time series. The selection of variables is shown in Table 1. Month is used as the time series and price is used as the variable.

Table 1: List of Variables.

Variable	Type	Meaning
Month	Date	Month
WTI	Double	WTI crude oil price (dollar)

2.3 Model Selection

This article uses Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to process time series data of crude oil prices. ARIMA consists of autoregression (AR), difference (I) and moving average (MA). The AR part contains the impact of observations from past periods on current values. Part I transforms non-stationary time series into stationary by removing trends and seasonal characteristics through differencing. The MA part takes into account the impact of past forecast errors on the current value. The GARCH model is also called the generalized ARCH model. It not only takes into account the volatility aggregation phenomenon caused by the heteroscedasticity of the sequence like ARCH, but also takes into account several lag terms of the variance to capture more heteroskedasticity information.

3 RESULTS AND DISCUSSION

3.1 Data Processing

The data used to build the model need to be stationary. First, it is necessary to determine whether the original sequence data is stationary. By observing the time series diagram in Figure 1, the ACF diagram (Figure 2), and performing the ADF unit root test, we can see that the model is not stationary. For this purpose, it is necessary to stabilize by difference processing or logarithmic transformation processing. First, first-order difference processing is used. By analysing the timing diagram (Figure 3), ACF diagram, and PACF diagram (Figure 4) after first-order difference, we can conclude that the series has already been stationary and there is no need to perform second-order difference or logarithmic transformation. Besides, according to Table 2, the ADF test shows that when the lag order is chosen to be 1, the sequence is stationary in all three cases: including time trends and intercept terms, only intercept terms, and no definite trend (in the first case the model has already been stationary and for accuracy, the other two cases are also tested). Besides, the lag order 1 is determined step by step starting from 10 and the reason why the AIC criterion is not adopted is to make the test more accurate, because the AIC criterion cannot guarantee that serial correlation will be eliminated.

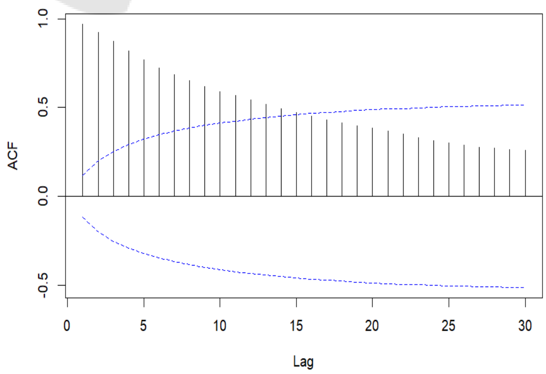

Figure 2: The ACF plot of original sequence.

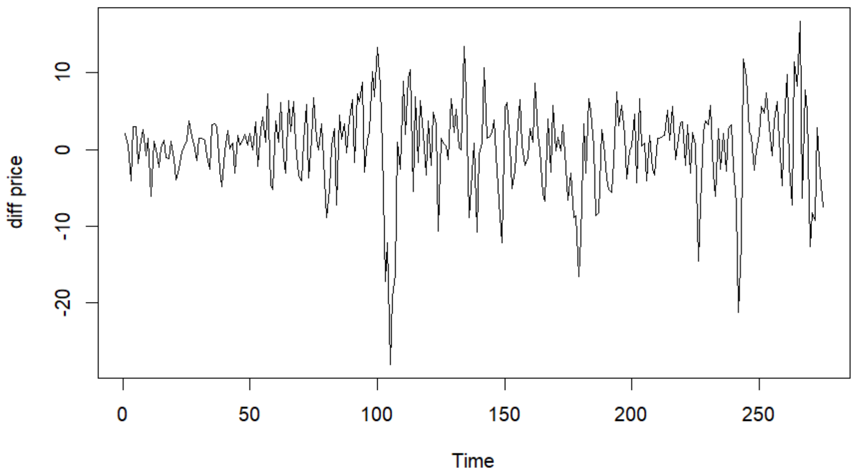

Figure 3: First-order differential timing diagram.

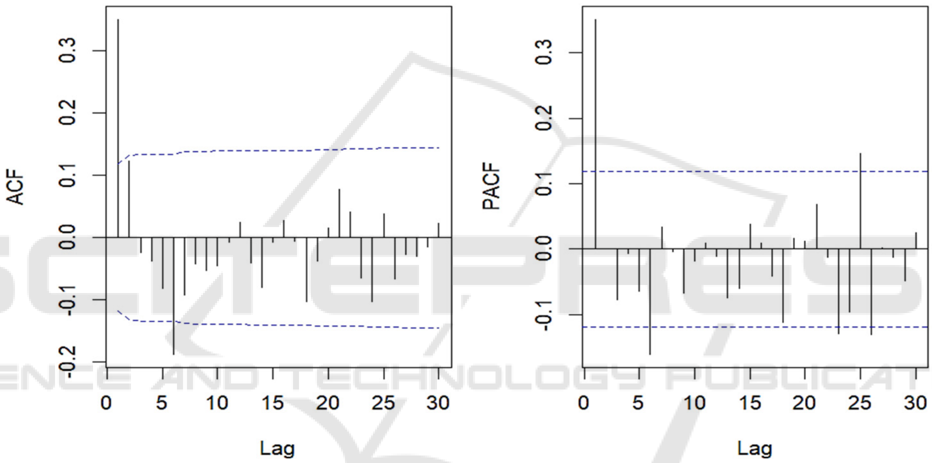

Figure 4: First-order differential ACF plot and PACF plot.

Table 2: The ADF test.

Type	Dickey-Fuller	Lag order	p-value
Intercept + time trend	-9.285	1	0.0708
Intercept only	-9.298	1	0.6143
No intercept and trend	-9.309	1	0.3368

3.2 Model Evaluation

The selection of p and q parameters can be determined through the Autocorrelative Function (ACF) plot and Partial Autocorrelative Function (PACF) plot (Figure 4). The ACF plot is employed to ascertain the coefficient (q) of the MA model, while the PACF plot is utilized to determine the coefficient (p) of the AR model. By observing the above figure, it can be seen that both figures exceed the critical value when lag equals 1 and 6. The models can be initially identified as ARIMA (0,1,1), ARIMA (0,1,6), ARIMA (1,1,0), ARIMA (6,1,0). The Akaike Information Criterion (AIC) is an assessment criterion that utilizes the notion of information entropy. It acts as a benchmark for evaluating a statistical model's complexity and the effectiveness of model fitting. The degree of model fitting is better the smaller the AIC. Firstly, fit the above four models respectively, select the two models with smaller AIC, ARIMA (1,1,0) and ARIMA (6,1,0) for further analysis, and then conduct overfitting analysis. For the two preliminary models, appropriately increase the order of MA, q, from 0 to 1, and fit the two new models. It is found that the AIC becomes larger, and the model is considered to be insufficiently fitted, so discard them. The AIC of each model are as shown in Table 3.

Table 3: Model determination.

ARIMA Model	AIC
(0,1,1)	1721.40
(0,1,6)	1717.89
(1,1,0)	1716.31
(6,1,0)	1716.48
Additional model	
(6,1,1)	1718.21
(1,1,1)	1718.31

3.3 Residual Analysis

In order to test the quality of the fitted model, residual analysis is needed. If the model identification is correct, the characteristics of the residuals are similar to those of the white noise sequence, and similar to independent and identically distributed normal random variables. First, check whether the residual sequence contains a trend that is not explained by the fitted model by observing the time series plot, then check whether normality is satisfied through the QQ plot and normal distribution test, and finally check whether the normality is satisfied through the ACF plot, PACF plot and Ljung-Box Test to check for autocorrelation.

It can be seen from Figure 5 that the residual timing diagram fluctuates up and down at 0. In both the ACF plot and the PACF plot, the values exceed the critical value when the lag order is 6, and also slightly exceed it when the lag order is larger (negligible). It can be seen from the QQ plot that there are a few abnormal points that do not adhere to a normal distribution. The p-value of the Shapiro-Wilk (SW) test in Table 4 is small (0.000013) so residuals do not adhere to a normal distribution. The Ljung-Box (LB) test values in Table 5 are basically greater than 0.2 except one, so it can be considered that there is no autocorrelation.

Table 4: Shapiro-Wilk test.

Model	W	p-value
ARIMA(1,1,0)	0.9711	0.000013
ARIMA(6,1,0)	0.9748	0.000051

Figure 6 makes it clear that the residual timing diagram fluctuates up and down at 0. In both the ACF plot and the PACF plot, the values slightly exceed the critical value when the lag order is larger than 15 (negligible). It can be seen from the QQ plot that there are a few abnormal points that do not obey the normal distribution. Because of the modest p-value (0.000051) of the SW test in Table 4, the residuals do not follow a normal distribution. Table 5's LB test results are unquestionably higher than 0.2, so it can be definitely considered that there is no autocorrelation.

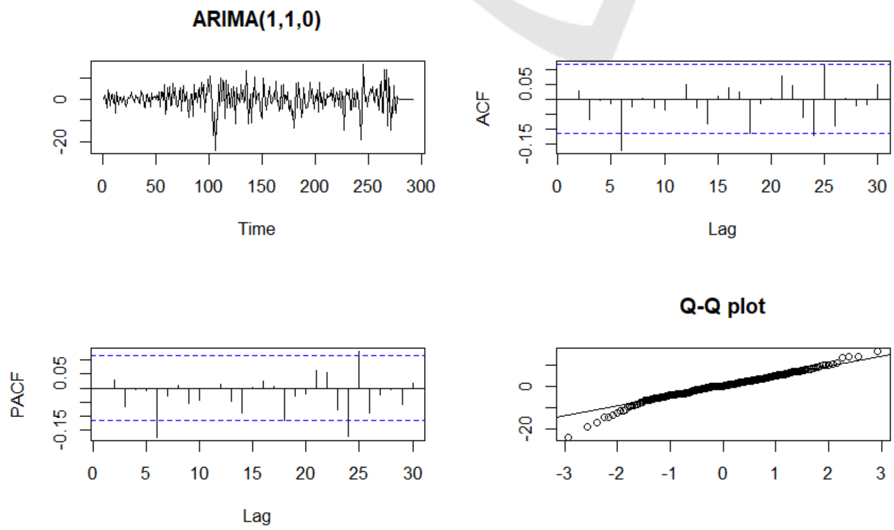

Figure 5: ARIMA (1,1,0) residuals plot, ACF plot, PACF plot, QQ plot.

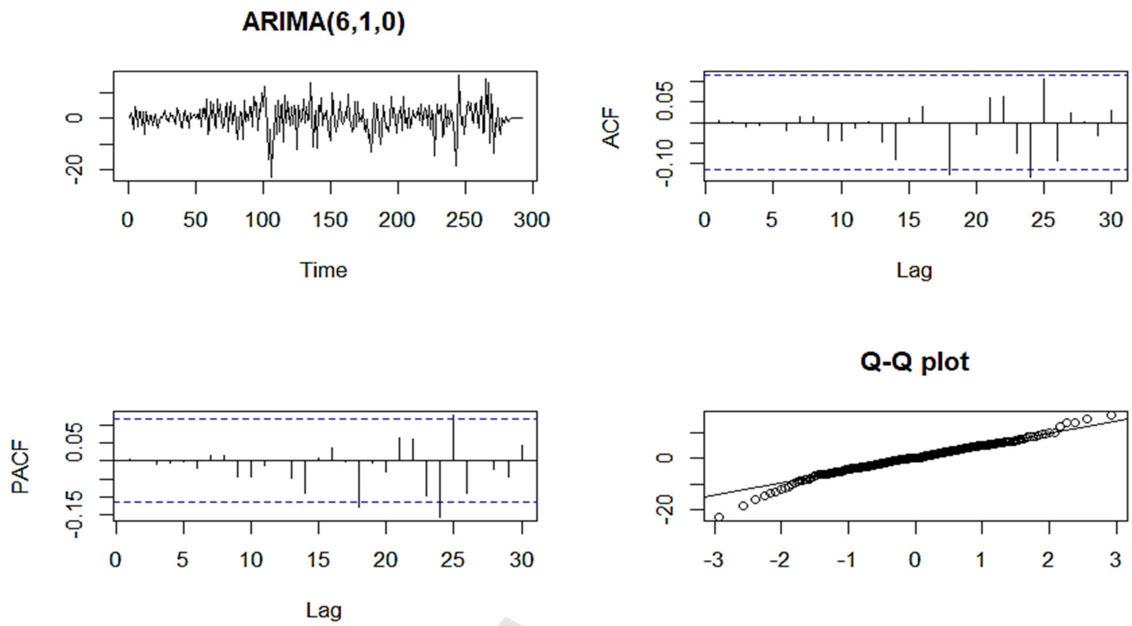

Figure 6: ARIMA (6,1,0) residuals plot, ACF plot, PACF plot, QQ plot.

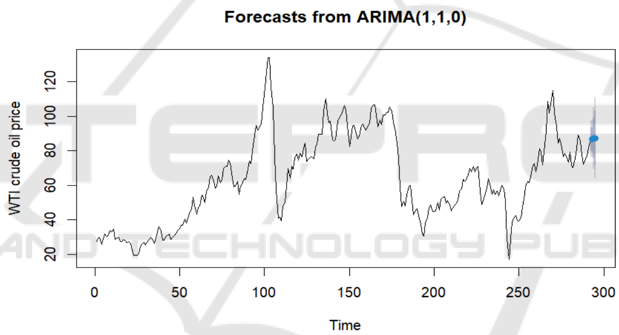

Figure 7: Forecasts from ARIMA (1,1,0).

Table 5: Ljung-Box test.

Model	Q*	df	p-value
ARIMA(1,1,0)	10.160	6	0.071
	11.737	12	0.384
	18.955	18	0.331
	27.399	24	0.239
ARIMA(6,1,0)	1.4920	12	0.960
	10.019	18	0.614
	19.929	24	0.337

3.4 Forecasting

The next process is to verify the model and make predictions. This article uses rolling forecast and sliding window width instead of multi-step forward forecast. The purpose is to incorporate the latest data points for more accurate forecasts. Because the ARIMA model is only suitable for short-term forecasts, the effect of multi-step forward forecast is often not good. good. First, establish the above two models for the training set, only perform one-step forward prediction, then incorporate a new test set data point (without deleting old data points), fit the model again, continue prediction, and repeat the above process 16 times. Then use mean square error (MSE) and mean absolute error (MAE) to verify the model fitting effect. A smaller value for both coefficients indicates better performance of the model on the test set. The MSE and MAE of ARIMA (1,1,0) and ARIMA (6,1,0) are shown in Table 6:

Table 6: Model validation.

Model	MSE	MAE
ARIMA(1,1,0)	27.615	4.676
ARIMA(6,1,0)	31.894	5.015

It can be seen that the MSE and MAE of ARIMA (1,1,0) are smaller and the model fitting effect is better, so it is used as the final model to predict WTI crude price. The last step is to predict the latest unknown data points. The crude oil price forecast for the latest three months is shown in Figure 7 and Table 7:

Table 7: Forecasts from ARIMA (1,1,0).

Time	Point forecast	L 80	H 80	L 95	H 95
2024/05	86.705	79.754	93.656	76.075	97.336
2024/06	87.173	75.525	98.821	69.360	104.987
2024/07	87.334	71.871	102.798	63.685	110.984

The blue plots show the forecasting value and the grey area shows the model's prediction limit at confidence levels of 80 and 95. From the findings above, it is evident that the predicted oil price experienced a slight increase in the next three months.

3.5 GARCH Model

It should be noted that a prerequisite of the ARIMA model is that the data is conditionally homoscedastic. However, for many financial time series data, such as the WTI crude oil price analysed in this article, their conditional variance is affected by the present and the past, and has Conditional heteroskedasticity. This kind of data has the characteristic of continuous peaks and troughs: large fluctuations are often succeeded by subsequent large fluctuations, while small fluctuations tend to be followed by additional small fluctuations. Therefore, it is necessary to use the GARCH model to model the variance of the data.

To determine whether the model exhibits heteroscedasticity, it is essential to observe the ACF and PACF plots of the square of the sequence after the difference and the square of the residual after fitting the model. If there is a significant correlation, it indicates the existence of conditional heteroskedasticity. As shown in Figure 8 and Figure 9, the squared plot of the differential sequence exceeds the critical value many times when the lag order is 1 to 5. The residual squared sequence also significantly exceeds the critical value when the lag order is 2 in the two figures. It can be considered that there is a conditional difference. variance. At the same time, McLeod-Li test, one of the white noise tests, is performed on the square sequence. According to Figure 10, the point values are all lower than the p value of 0.05, which is also considered to have conditional heteroskedasticity.

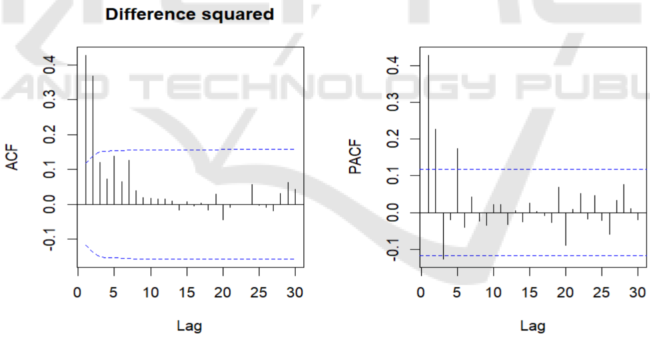

Figure 8. The ACF plot and PACF plot of difference squared.

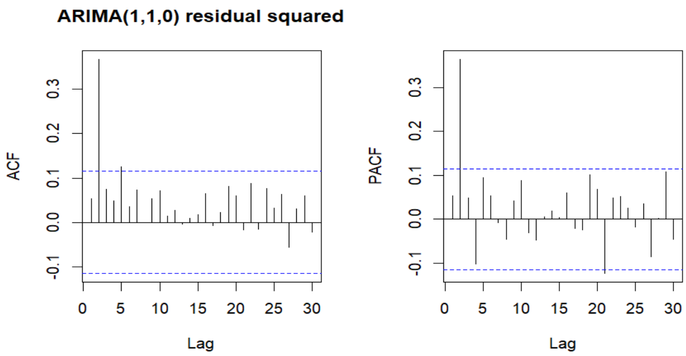

Figure 9: The ACF plot and PACF plot of ARIMA (1,1,0) residual squared.

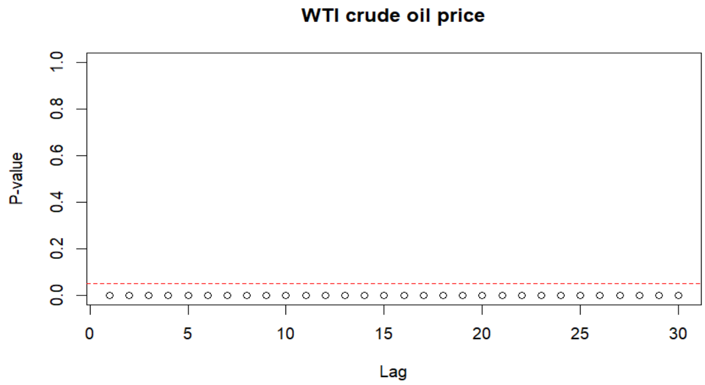

Figure 10: The ACF plot and PACF plot of ARIMA (1,1,0) residual squared.

Considering conditional heteroskedasticity, an ARIMA-GARCH model is established to fit the data, and the ARIMA (1,1,0) determined previously and the GARCH (1, 1) most commonly used for financial time series data are combined to fit the WTI crude oil price data. Then, carry out residual analysis and conduct Ljung-Box test on residual and residual square respectively to test the fitting effect of ARIMA model and GARCH model. As can be seen from Table 8, the p values are large, both are greater than 0.1, and it can be considered that the fit is good.

Table 8: Ljung-Box test for ARIMA-GARCH model.

Object	Q*	df	p-value
residual	2.305	1	0.129
	2.307	2	0.128
	2.846	5	0.471
Residual squared	0.074	1	0.785
	2.475	5	0.511
	4.093	9	0.573

Results of the predictions are displayed in Table 9. It is evident that throughout the next three months, oil prices will continue to rise marginally.

Table 9: Forecasts from ARIMA (1,1,0)-GARCH (1,1).

Time	Point forecast	Sigma
2024/05	86.140	4.989
2024/06	86.299	5.067
2024/07	86.331	5.144

3.6 Critical Thinking

Although this article is very detailed and comprehensive in modeling, and combines ARIMA and GARCH, two very commonly used time series models, to fit the data, it can be said that the predictions under this large framework will be very accurate. But in fact, no one can know which model the data obeys, especially for financial time series data, which is characterized by very high volatility and uncertainty, and is extremely susceptible to external interference. This article does not consider derivative models of GARCH, such as Threshold GARCH (TGARCH) or Asymmetric Power GARCH (APARCH), etc. It does not take into account the asymmetric effect and Taylor effect. At the same time, in terms of machine learning, algorithms such as CNN and SVM are not integrated into oil price predictions, and in terms of external factors, there is no way to take into account the interference of oil price factors, such as oil supply and demand and geopolitical risks.

4 CONCLUSION

This article forecasts monthly WTI crude oil prices using the ARIMA and ARIMA-GARCH models, and conducts tests such as stationarity test, normality test, white noise test, and model fitting goodness. The model is finally determined to be ARIMA (1,1,0) and ARIMA(1,1,0)-GARCH(1,1) respectively predict that oil prices will rise slightly and even slightly in the next three months, that is, in May, June, and July 2024.

However, a variety of factors will affect the price of crude oil amid the current global economic downturn. Oil prices will become more difficult to anticipate due to the production strategies of countries that produce crude oil, geopolitical events, the development of new energy technologies, and the activities of futures markets and commodity exchange-traded funds, such as exchange traded fund (ETF) in the financial market. It should be noted that the research in this article does not take into account realistic and complex scenarios. For macro managers who hope that the crude oil futures market will operate effectively and achieve stable futures prices, and speculators who hope to have the opportunity to achieve excess profits, the model selected in this article is relatively simple. It does not constitute investment advice and can only be used as a reference to a certain extent.

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