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Crude Oil Price Forecasting: A Time Series Analysis Using Arima

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Abstract

Aim *– the key motive of the study is to identify the prevailing trend and to forecast the select crude oil prices considering the global price market.*

Design/Methodology/Approach—*The present study is based on time series data collected as a secondary source of information from the Federal Reserve Bank. The data was collected monthly from January 2005 to December 2022. To further utilize it, the accumulated data has been tested for stationarity.*

Findings- *the current study has analysed the trend and forecast of the selected crude oil price from the global basket. This confirms the stationarity among the selected time series data. Further analysis based on the ARIMA model has revealed the trend and forecast of the Brent and WTI Crude Oil Price. This concludes that there is an increasing trend, and a 10-year forecast has been made using the ARIMA Model.*

Research Limitation: *The current study has only focused on the trend and forecast of the selected crude oil prices.*

Originality: *The study is highly original and contributes to understanding the trend and forecast of the select Brent and WTI Crude Oil Price. The variables used in the analysis can be further used to elaborate on the study and used as a reference in different study areas.*

Keywords: *WTI Crude Oil Price, Brent Price, Trend, Forecast, ARIMA.*

Introduction

With Brent crude down 25% from its January peak, oil prices are still under pressure due to persistent macroeconomic and trade policy uncertainty. Investors, however, appear to be growing more hopeful that the worst is behind them and that the situation surrounding U.S. tariffs is now de-escalating. Additionally, there is the perception that the "Trump put," which holds that the President will move to reverse a decline in markets, is once again in effect.

J.P. Morgan Research reduced its Brent price forecast in April to $66/bbl for 2025 and $58/bbl for 2026. The forecast remains unchanged despite recent changes in trade policy. According to Natasha Kaneva, head of Global Commodities Strategy at J.P. Morgan, "there is a prevailing view that the administration's shift in focus from tariffs to taxes and deregulation, along with the tailwinds from trade deal announcements, will drive oil prices back into the mid-$70s following the recent downturn." But even though the likelihood of a bear market has decreased due to the recent de-escalation in trade negotiations, the "Trump put" does not apply to the energy sector because the administration still prioritizes lower oil prices to control inflation.[1]

The dynamics of supply and demand suggest that oil prices will decline over the next several months. Markets might be underestimating eventual tax levels on U.S. imports, and demand is still weak. According to J.P. Morgan Research, oil demand will increase by 800 kbd (thousand barrels per day) in 2025, which is 300 kbd less than what it had previously predicted. Furthermore, to guarantee that members meet their quotas, OPEC increased oil production by 411,000 barrels per day in June. "Up until now, the market has mostly ignored the apparent change in OPEC's reaction function, which we interpret as a more pessimistic argument than the possible drop in demand."[2]

The price of crude oil has fluctuated periodically due to weather, natural disasters, political upheaval around the world, and seasonal variations in industrial demand and supply. For decision-makers and business participants in the energy sector, a precise crude oil price forecast is crucial. Despite this, the energy sector is uncertain due to the instability of crude oil prices, which was especially difficult during the recent worldwide COVID-19 outbreak and the Russia-Ukraine hostilities.

Numerous techniques for forecasting crude oil prices have been proposed, and a great deal of study has been done to examine the volatility of crude oil prices (Abdollahi, 2020; Alqahtani et al., 2021; Drachal, 2021; R. Li et al., 2021a; Monge & Gil-Alana, 2021). Alqahtani et al. (2021), for instance, employed a technique called generalized autoregressive conditional heteroscedasticity (GARCH) to ascertain whether or not COVID-19 contributes to the financial effects brought on by jump processes in crude oil prices. However, the non-linearity and volatility of crude oil prices are hard for GARCH, a typical econometrics method, to adequately reflect.

Review of Literature

(Liang Shena, 2024) To address the volatility of crude oil prices, this study proposes a hybrid deep learning modeling framework called EEMD-CNN-BiLSTM-QR, which combines several well-known data analytics, including ensemble empirical mode decomposition (EEMD), convolutional neural networks (CNN), and bidirectional long short-term memory (BiLSTM)

[1] https://www.jpmorgan.com/insights/global-research/commodities/oil-price-forecast

[2] https://www.jpmorgan.com/insights/global-research/commodities/oil-price-forecast

integrated with quantile regression (QR). The EEMD-CNN-BiLSTM-QR hybrid modeling framework was validated using two sets of real-world crude oil pricing data from the Brent Crude Oil and West Texas Intermediate (WTI) markets. Given that the probability density forecast can capture the uncertainty, a thorough analysis was conducted, and the prediction accuracy was computed.

(Ming Li, 2023) This study uses weekly price data of West Texas intermediate crude oil (WTI) crude oil futures from 2011 to 2021 to build a computational intelligence-based portfolio model for crude oil price forecasting. First, the ensemble empirical modal decomposition method (EEMD) is used to break down the WTI crude oil price series. Then, the cluster analysis approach is used to reconstruct the set of component series. Second, neural network models like the GM (1, 1) gray prediction algorithm, time-delay neural network (TDNN), extreme learning machine (ELM), and multilayer perceptron (MLP) are used to model and predict the reconstructed series. The output of the model that has the best prediction effect for each component is then integrated.Lastly, the EGARCH model is employed to produce the final anticipated values and further maximize the combined model's predictive ability. The findings demonstrate that, when it comes to predicting the price of crude oil futures, the computational intelligence-based combined model outperforms individual models like GM (1, 1), ARIMA, MLP, and the combined EEMD-ELM model.

(Fawzy, 2022) By integrating the Auto Regressive Integrated Moving Average (ARIMA) model with Artificial Neural Networks (ANN), this paper attempts to employ a hybrid ARIMA-ANN model for time series forecasting. Two types of time series can be captured by the hybrid ARIMA-ANN model: linear time series, which can only model linear relationships, and nonlinear time series, which can only model nonlinear relationships. During the period from July 2001 to May 2021, 239 observations of the Crude Oil (petroleum) Monthly Price in Saudi Riyals per barrel were utilized as time series data. Train series are derived from the first 215 observations, whereas testing series are derived from the final 24 observations. The accuracy metrics for the hybrid combination of ARIMA and ANN were compared to the ARIMA and ANN methods. These metrics included Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The hybrid ARIMA-ANN method's MSE, MAPE, and MAE values show a notable improvement, according to the results.

(Desai, 2024) There is now a great deal of interest in examining its price fluctuations and predictions. The monthly Brent oil price dynamics from November 1994 to December 2011 were used in the analysis. The information was divided into two sections. The model was constructed throughout the first twelve years, and the accuracy of the forecasts was validated over the following twelve months, from January to December of 2012. In addition to autocorrelation testing and residual analysis to identify which ARIMA model had the best fit, they were subjected to log transformation and differencing to make them stationary. ARIMA (2,0,1) showed a good fit for predicting the price of volatility. Because of the prevalence of outliers, the study recommended using other models, such as the ARCH and GARCH models, to estimate oil prices with the highest accuracy.

(**Guangji Zheng *, 2025)** A hybrid deep learning model for predicting the price of crude oil is proposed in this work. First, raw data is broken down into multiples using the empirical wavelet transform. Three neural networks then produce initial predictions, which are then improved by an ensemble approach based on reinforcement learning. Lastly, residuals are handled by an error correction module, which improves the predicting results even more. The hybrid model was validated using three West Texas Intermediate datasets and other emergency scenarios. The results show that the suggested model outperforms three sophisticated models and sixteen benchmark approaches in terms of prediction.

Variables and Measured

This study takes into account the substantial impact of global uncertainties, such as geopolitical tensions, economic disruptions, and policy changes, which have a direct impact on swings in crude oil prices, to examine the trajectory and projection of crude oil prices in a few worldwide markets. Especially during unstable times, these swings frequently show both short-term volatility and long-term increasing trends.

The study uses a strong statistical approach to detect and examine these price swings since it understands how crucial correct modeling is in such a dynamic setting. A thorough time series dataset covering 18 years has been gathered for this purpose from reliable and reputable sources, such as the Federal Reserve Bank. This large dataset makes it possible to thoroughly examine market dynamics and create accurate forecasts using sophisticated time series methods like the ARIMA model.

Data Source and Data Collected for the Study

The study's data, which includes time series data primarily about the price of crude oil globally, was obtained from secondary sources. To achieve enough historical depth and accuracy in identifying patterns and forecasting, a total of 18 years of data, collected monthly, were taken into consideration. WTI (West Texas Intermediate) crude oil prices and Brent crude oil prices, two well-known measures of the functioning of the global oil market, are the study's primary global benchmarks for crude oil prices. The data was first analyzed using the Augmented Dickey-Fuller (ADF) test to determine stationarity, which is an essential precondition for time series modeling.

Following confirmation of the data's stationarity, forecasting was conducted using the ARIMA (AutoRegressive Integrated Moving Average) model, with model parameters chosen using statistical standards such as the Akaike Information Criterion (AIC) and Schwarz Criterion (SC). Diagnostic tests were carried out after the model was fitted in order to confirm the findings and guarantee the model's resilience. The analysis's findings led to the derivation and incorporation of pertinent recommendations and insights to support policy recommendations and decision-making about the forecasting of crude oil prices.

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Data Interpretation

IBM EViews Software was used on the collected time series data, and further the analysis was carried out using the econometric tools such as the ADF test, and ARIMA model on the variables.

Hypothesis

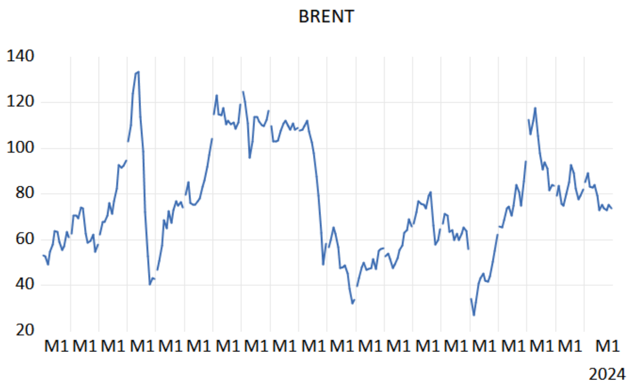
- H_0 = There is no white noise diagnostic in Brent Price.
- H_1 = There is no white noise diagnostic in the WTI crude oil price

Results and Discussion

- **Testing of Trend and Volatility of Crude Oil Prices.**
- **ARIMA Model for Brent Price and WTI Crude Oil Price**

Chart 1.1

Graph Representing Brent Price for the period 2005-2024



Source: computed using the IBM EViews

The above chart indicates the actual estimates and fluctuations of the monthly Brent price for the period 2005-2024.

Table 1.1

Test for stationarity using Correlogram for Brent Price for the period 2005-2024

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*** |	.|*** |	1	0.376	0.376	34.140	0.000
.|* |	.|. |	2	0.105	-0.041	36.843	0.000
.|. |	*|. |	3	-0.032	-0.067	37.091	0.000
.|. |	.|. |	4	-0.063	-0.028	38.054	0.000
.|. |	.|. |	5	-0.065	-0.029	39.089	0.000
*|. |	*|. |	6	-0.122	-0.103	42.784	0.000
.|. |	.|. |	7	-0.048	0.037	43.346	0.000

.|. |	.|. |	8	-0.050	-0.047	43.966	0.000
*|. |	*|. |	9	-0.078	-0.071	45.500	0.000
.|. |	.|. |	10	-0.028	0.022	45.704	0.000
.|. |	.|. |	11	0.019	0.024	45.792	0.000
.|. |	.|. |	12	0.001	-0.046	45.792	0.000
.|. |	.|. |	13	-0.041	-0.044	46.225	0.000
*|. |	*|. |	14	-0.105	-0.093	49.052	0.000
.|. |	.|* |	15	0.044	0.125	49.557	0.000
.|. |	.|. |	16	0.034	-0.027	49.854	0.000
.|. |	.|. |	17	-0.018	-0.058	49.943	0.000
.|. |	.|. |	18	-0.042	-0.030	50.396	0.000
.|. |	.|. |	19	-0.024	0.006	50.547	0.000
.|. |	.|. |	20	0.008	-0.001	50.564	0.000
.|. |	.|* |	21	0.060	0.081	51.519	0.000
.|. |	.|. |	22	0.056	-0.013	52.344	0.000
.|. |	*|. |	23	-0.022	-0.086	52.467	0.000
*|. |	*|. |	24	-0.101	-0.069	55.224	0.000
.|. |	.|* |	25	-0.002	0.107	55.225	0.000
*|. |	*|. |	26	-0.096	-0.170	57.723	0.000
*|. |	.|. |	27	-0.084	-0.020	59.641	0.000
.|. |	.|. |	28	-0.054	-0.010	60.432	0.000
.|. |	.|. |	29	-0.049	-0.023	61.084	0.000
.|. |	.|. |	30	-0.027	-0.038	61.281	0.001
.|. |	.|. |	31	-0.045	-0.033	61.836	0.001
.|. |	.|. |	32	0.001	-0.029	61.837	0.001
.|* |	.|* |	33	0.098	0.111	64.522	0.001
.|. |	.|. |	34	0.032	-0.062	64.812	0.001
.|. |	.|. |	35	0.018	0.011	64.901	0.002
.|. |	.|. |	36	0.011	-0.024	64.938	0.002

Source: computed using the IBM EViews

Table 1.1 explains the stationarity of the Brent price using a correlogram indicating autocorrelation and partial correlation. In which the condition is satisfied based on the Q statistics and P value. The model is further taken for the analysis.

Table 1.2
ARMA model for forecasting of Brent Price

Dependent Variable: D(BRENT)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.075744	0.567797	0.133400	0.8940
AR(1)	0.371520	0.045964	8.082760	0.0000

MA(6)	-0.113862	0.072109	-1.579018	0.1157
SIGMASQ	32.55321	2.616905	12.43958	0.0000
R-squared	0.152344	Mean dependent var		0.084851
Adjusted R-squared	0.141522	S.D. dependent var		6.210084
S.E. of regression	5.753895	Akaike info criterion		6.355172
Sum squared resid	7780.218	Schwarz criterion		6.413356
Log-likelihood	-755.4431	Hannan-Quinn criteria.		6.378619
F-statistic	14.07832	Durbin-Watson stat		1.956487
Prob(F-statistic)	0.000000			
Inverted AR Roots	.37			
Inverted MA Roots	.70	.35-.60i	.35+.60i	-.35+.60i
	-.35-.60i	-.70		

Source: computed using the IBM EViews

Tables 1.2 reveal the ARMA model for Brent price. The model is satisfied under the AR (1) and MA (6) based on the Autocorrelation and Partial correlation. The model is further analyzed with the R-squared, Akaike criterion, and Schwarz criterion; the smaller value is considered good for the model. Further, the model is also satisfied with the P value considering the ARMA model.

Diagnostic and Forecasting for Brent Price

H_0 = There is no white noise diagnostic in the Brent price

Table 1.3

The Q-statistics ARMA

Q-statistic probabilities adjusted for 2 ARMA terms						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.021	0.021	0.1073	
.|. |	.|. |	2	-0.017	-0.018	0.1788	
*|. |	*|. |	3	-0.077	-0.077	1.6418	0.200
.|. |	.|. |	4	-0.044	-0.042	2.1228	0.346
.|. |	.|. |	5	0.000	-0.000	2.1229	0.547
.|. |	.|. |	6	-0.001	-0.008	2.1231	0.713
.|. |	.|. |	7	0.013	0.007	2.1681	0.825
.|. |	.|. |	8	-0.030	-0.033	2.3913	0.880
*|. |	*|. |	9	-0.069	-0.069	3.5937	0.825
.|. |	.|. |	10	-0.012	-0.010	3.6300	0.889
.|. |	.|. |	11	0.035	0.030	3.9447	0.915
.|. |	.|. |	12	0.004	-0.011	3.9487	0.950
.|. |	.|. |	13	-0.009	-0.016	3.9697	0.971
*|. |	*|. |	14	-0.147	-0.146	9.5321	0.657
.|* |	.|* |	15	0.088	0.097	11.515	0.568
.|. |	.|. |	16	0.040	0.032	11.924	0.612

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.|. |	.|. |	17	-0.018	-0.046	12.011	0.678
.|. |	.|. |	18	-0.051	-0.058	12.697	0.695
.|. |	.|. |	19	-0.010	0.004	12.723	0.755
.|. |	.|. |	20	-0.033	-0.032	13.002	0.791
.|. |	.|. |	21	0.058	0.057	13.903	0.789
.|. |	.|. |	22	0.061	0.040	14.885	0.783
.|. |	.|. |	23	-0.014	-0.041	14.935	0.826
*|. |	*|. |	24	-0.132	-0.122	19.618	0.607
.|* |	.|* |	25	0.079	0.121	21.291	0.563
*|. |	*|. |	26	-0.097	-0.123	23.833	0.471
.|. |	.|. |	27	-0.029	-0.057	24.061	0.516
.|. |	.|. |	28	-0.007	-0.031	24.074	0.572
.|. |	.|. |	29	-0.032	-0.012	24.355	0.611
.|. |	.|. |	30	-0.013	-0.023	24.399	0.660
.|. |	.|. |	31	-0.033	-0.042	24.701	0.694
.|. |	*|. |	32	-0.029	-0.073	24.934	0.728
.|* |	.|* |	33	0.106	0.110	28.066	0.618
.|. |	.|. |	34	-0.011	-0.033	28.097	0.665
.|. |	.|. |	35	-0.002	0.008	28.098	0.710
.|. |	.|. |	36	-0.019	-0.032	28.202	0.747

Source: computed using the IBM EViews

Table 1.3 explains the Q-statistics ARMA with Autocorrelation and Partial correlation; it satisfies the criteria, and there are no outliers. the Q statistics and p-value fall within the line. It can be concluded that there are residuals that are not white noise, Hence, the null hypothesis is rejected. And a further model is taken for the analysis.

Chart 1.2

ARMA structure representing AR and MA plots for Brent Price

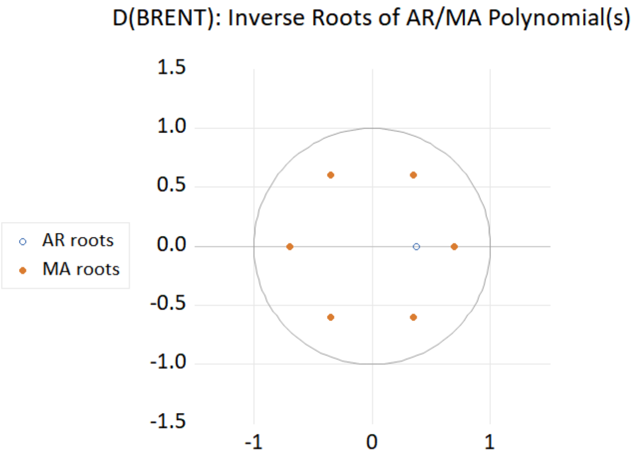

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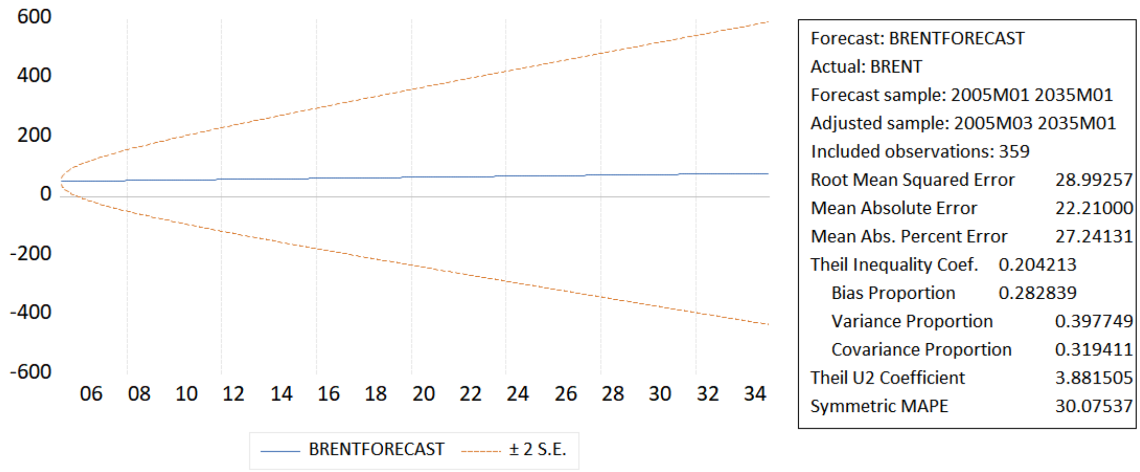
Chart 1.2 depicts the AR and MA plots in the ARMA structure. The AR and MA roots fall inside the circle. Which again fulfils the criteria of ARMA and satisfies the conditions for the forecast.

Chart -1.3

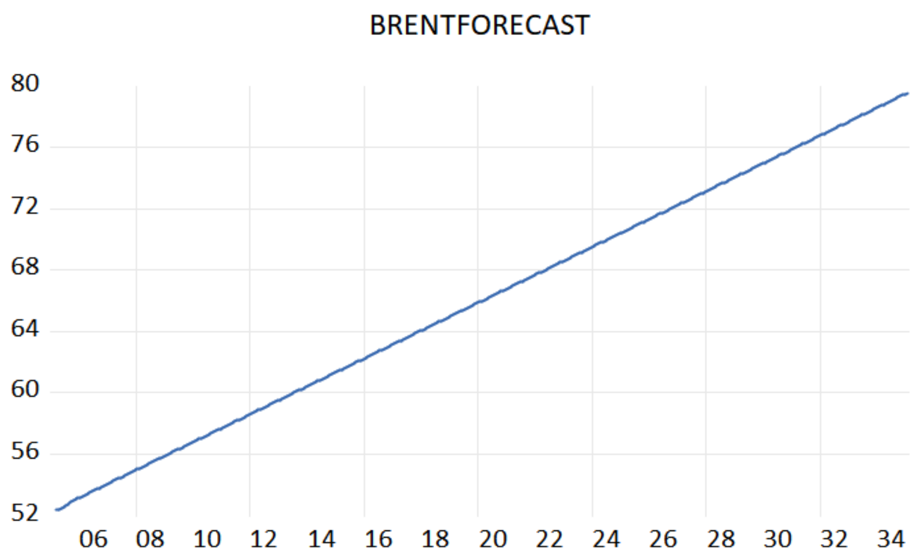
ARMA Forecast for Brent price from 2005-2035



Source: computed using the IBM EViews

Chart -3.4

ARMA Forecast Graph



Source: computed using the IBM EViews

Charts 1.3 and 1.4 show the forecast of Brent price for the period 2005-2035. The actual sample is 2005-2024; further, the estimates are forecasted for a further ten years from 2024-2034 as displayed in the image.

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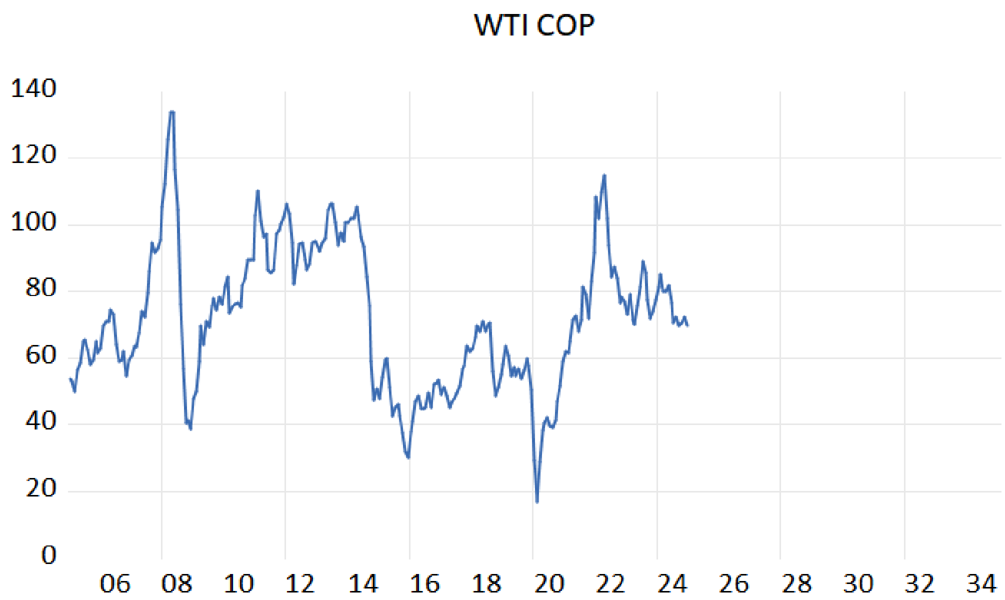
ARIMA Model for Brent Price and WTI Crude Oil Price

Chart 1.5

Graph Representing WTI Crude Oil Price for the period 2005-2024



Source: computed using the IBM EViews

Chart 1.5 indicates the actual estimates and fluctuations of monthly WTI Crude Oil prices for the period 2005-2024.

Table 1.4

Test for stationarity using Correlogram for WTI Crude Oil Price for the period 2005-2024

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*** |	.|*** |	1	0.356	0.356	30.619	0.000
.|* |	.|. |	2	0.119	-0.009	34.054	0.000
.|. |	*|. |	3	-0.032	-0.082	34.308	0.000
.|. |	.|. |	4	-0.057	-0.022	35.115	0.000
*|. |	*|. |	5	-0.099	-0.071	37.541	0.000
*|. |	*|. |	6	-0.167	-0.126	44.456	0.000
*|. |	.|. |	7	-0.085	0.021	46.235	0.000
.|. |	.|. |	8	-0.040	-0.009	46.627	0.000
.|. |	.|. |	9	-0.048	-0.061	47.212	0.000
.|. |	.|. |	10	-0.047	-0.030	47.758	0.000
.|. |	.|. |	11	-0.015	-0.002	47.818	0.000
.|. |	.|. |	12	-0.011	-0.034	47.847	0.000
.|. |	.|. |	13	-0.044	-0.054	48.346	0.000

*|. |	*|. |	14	-0.090	-0.078	50.398	0.000
.|. |	.|. |	15	0.014	0.065	50.448	0.000
.|. |	.|. |	16	0.043	0.010	50.927	0.000
.|. |	.|. |	17	-0.003	-0.057	50.929	0.000
*|. |	*|. |	18	-0.072	-0.084	52.288	0.000
.|. |	.|. |	19	-0.053	-0.021	53.030	0.000
.|. |	.|. |	20	-0.012	-0.005	53.065	0.000
.|. |	.|* |	21	0.061	0.077	54.048	0.000
.|. |	.|. |	22	0.044	-0.007	54.561	0.000
.|. |	*|. |	23	-0.042	-0.112	55.029	0.000
*|. |	*|. |	24	-0.083	-0.078	56.862	0.000
.|. |	.|* |	25	0.043	0.124	57.368	0.000
.|. |	*|. |	26	-0.063	-0.135	58.439	0.000
.|. |	.|. |	27	-0.030	0.004	58.681	0.000
.|. |	.|. |	28	-0.031	-0.019	58.935	0.001
.|. |	.|. |	29	-0.015	-0.034	58.994	0.001
.|. |	.|. |	30	-0.003	-0.011	58.996	0.001
.|. |	.|. |	31	-0.042	-0.045	59.493	0.002
.|. |	.|. |	32	0.024	0.001	59.652	0.002
.|* |	.|* |	33	0.112	0.106	63.169	0.001
.|* |	.|. |	34	0.074	-0.006	64.702	0.001
.|. |	.|. |	35	0.002	-0.046	64.703	0.002
.|. |	*|. |	36	-0.060	-0.086	65.727	0.002

Source: computed using the IBM EViews

Table 1.4 explains the stationarity for the WTI Crude oil price using a correlogram indicating the autocorrelation and partial correlation. In which the condition is satisfied based on the Q statistics and P value. The model is further taken for the analysis.

Table 1.5
ARMA model for forecasting WTI Crude oil Price

Dependent Variable: D(WTI_COP)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.055874	0.518198	0.107824	0.9142
AR(1)	0.343342	0.051990	6.604039	0.0000
MA(6)	-0.147129	0.067048	-2.194380	0.0292
SIGMASQ	33.45401	2.595085	12.89129	0.0000
R-squared	0.144783	Mean dependent var		0.066311
Adjusted R-squared	0.133865	S.D. dependent var		6.267528
S.E. of regression	5.832961	Akaike info criterion		6.382594
Sum squared resid	7995.508	Schwarz criterion		6.440777

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Log-likelihood	-758.7199	Hannan-Quinn criteria.		6.406040
F-statistic	13.26131	Durbin-Watson stat		1.986707
Prob(F-statistic)	0.000000			
Inverted AR Roots	.34			
Inverted MA Roots	.73	.36+.63i	.36-.63i	-.36+.63i
	-.36-.63i	-.73		

Source: computed using the IBM EViews

Tables 1.5 reveal the ARMA model for the WTI crude oil price. The model is satisfied under the AR (1) and MA (6) based on the Autocorrelation and Partial correlation. The model is further analyzed with the R-squared, Akaike criterion, and Schwarz criterion; the smaller value is considered good for the model. Further, the model is also satisfied with the P value considering the ARMA model.

Diagnostic and Forecasting for WTI Crude Oil Price

H_0 = There is no white noise diagnostic in the WTI crude oil price

Table 1.6

The Q-statistics ARMA

<table>
<tr><td colspan="7">Q-statistic probabilities adjusted for 2 ARMA terms</td></tr>
<tr><td>Autocorrelation</td><td>Partial Correlation</td><td></td><td>AC</td><td>PAC</td><td>Q-Stat</td><td>Prob</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.006</td><td>0.006</td><td>0.0080</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.020</td><td>0.020</td><td>0.1084</td><td></td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>3</td><td>-0.083</td><td>-0.083</td><td>1.7739</td><td>0.183</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>-0.023</td><td>-0.022</td><td>1.9018</td><td>0.386</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.038</td><td>-0.034</td><td>2.2549</td><td>0.521</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.001</td><td>-0.005</td><td>2.2552</td><td>0.689</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.029</td><td>-0.032</td><td>2.4634</td><td>0.782</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.011</td><td>-0.018</td><td>2.4955</td><td>0.869</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.035</td><td>-0.036</td><td>2.7965</td><td>0.903</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.029</td><td>-0.035</td><td>3.0137</td><td>0.933</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>-0.002</td><td>-0.004</td><td>3.0145</td><td>0.964</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.004</td><td>-0.012</td><td>3.0186</td><td>0.981</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.025</td><td>-0.033</td><td>3.1744</td><td>0.988</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>14</td><td>-0.111</td><td>-0.118</td><td>6.3179</td><td>0.899</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.041</td><td>0.038</td><td>6.7543</td><td>0.914</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.055</td><td>0.052</td><td>7.5372</td><td>0.912</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>0.003</td><td>-0.024</td><td>7.5391</td><td>0.941</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>18</td><td>-0.089</td><td>-0.098</td><td>9.5873</td><td>0.887</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.024</td><td>-0.026</td><td>9.7417</td><td>0.914</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>-0.047</td><td>-0.045</td><td>10.326</td><td>0.921</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>21</td><td>0.074</td><td>0.056</td><td>11.765</td><td>0.895</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.056</td><td>0.046</td><td>12.592</td><td>0.894</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>23</td><td>-0.039</td><td>-0.069</td><td>13.000</td><td>0.909</td></tr>
</table>

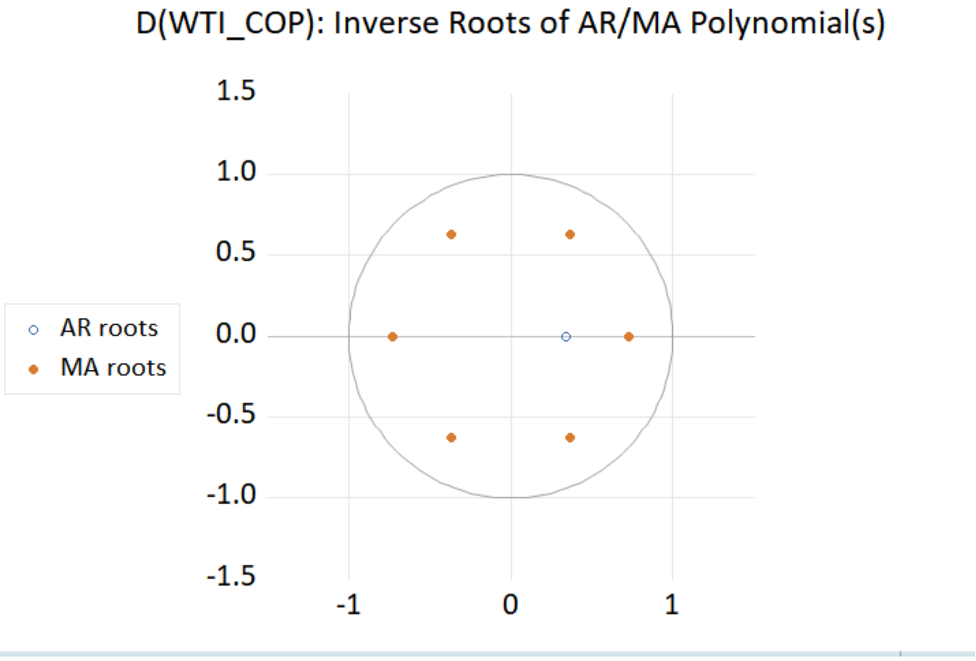
*|. |	*|. |	24	-0.122	-0.133	16.956	0.766
.|* |	.|* |	25	0.103	0.120	19.837	0.652
*|. |	*|. |	26	-0.094	-0.095	22.210	0.567
.|. |	.|. |	27	0.022	-0.020	22.346	0.616
.|. |	.|. |	28	-0.005	-0.014	22.353	0.669
.|. |	.|. |	29	-0.013	-0.026	22.397	0.717
.|. |	.|. |	30	-0.009	0.000	22.418	0.762
.|. |	*|. |	31	-0.049	-0.070	23.073	0.773
.|. |	.|. |	32	-0.007	-0.039	23.089	0.812
.|* |	.|* |	33	0.099	0.090	25.845	0.729
.|. |	.|. |	34	0.049	0.041	26.525	0.740
.|. |	.|. |	35	-0.006	-0.002	26.535	0.780
*|. |	*|. |	36	-0.068	-0.081	27.841	0.763

Source: computed using the IBM EViews

Table 1.6 explains the Q-statistics ARMA with Autocorrelation and Partial correlation; it satisfies the criteria, and there are no outliers. the Q statistics and p-value fall within the line. It can be concluded that there are residuals that are not white noise, Hence, the null hypothesis is rejected. And a further model is taken for the analysis.

Chart 1.6

ARMA structure representing AR and MA plots for WTI Crude Oil Price

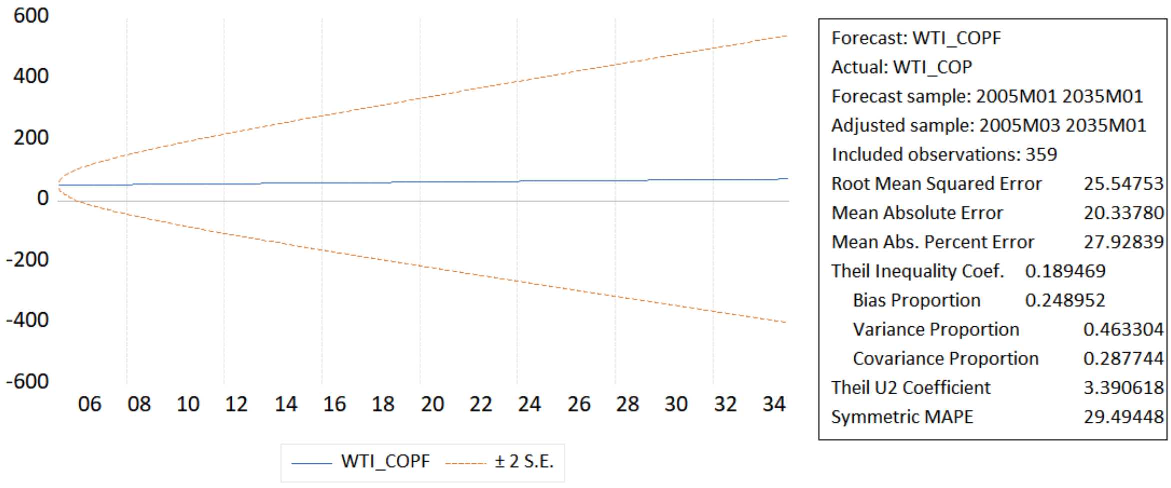


Source: computed using the IBM EViews

Chart 1.6 depicts the AR and MA plots in the ARMA structure. The AR and MA roots fall inside the circle. Which again fulfils the criteria of ARMA and satisfies the conditions for the forecast.

Chart -1.7

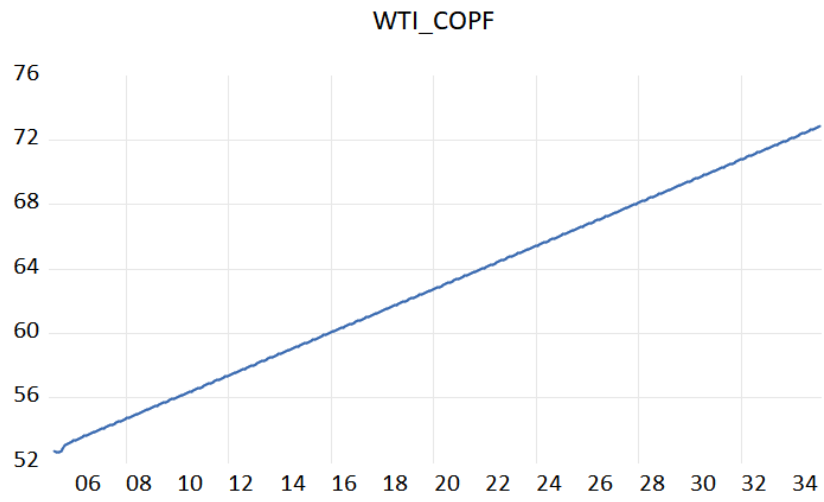
ARMA Forecast for Brent price from 2005-2035



Source: computed using the IBM EViews

Chart -3.8

ARMA Forecast Graph



Source: computed using the IBM EViews

Charts 1.7 and 1.8 show the forecast of the WTI Crude Oil price for the period 2005-2035. The actual sample is 2005-2024; further, the estimates are forecasted for the next ten years from 2024-2034 is are displayed in the image.

Findings of the study

- **Findings based on the ARIMA Model for Brent Price and WTI Crude Oil Price**

Test for stationarity using the Correlogram for Brent Price - The stationarity of the Brent price is indicated by a correlogram indicating autocorrelation and partial correlation. The condition is satisfied based on the Q statistics and P value. The model is further taken for the analysis. The stationarity for the WTI Crude oil price using a correlogram indicating the autocorrelation and partial correlation. The condition is satisfied based on the Q statistics and P value. The model is further taken for the analysis.

- **ARIMA model for forecasting of Brent Price and WTI Crude Oil Price**

The model is satisfied under the AR (1) and MA (6) based on the Autocorrelation and Partial correlation. The model is further analyzed with the R-squared, Akaike criterion, and Schwarz criterion; the smaller value is considered good for the model. Further, the model is also satisfied with the P value considering the ARMA model. The model is satisfied under the AR (1) and MA (6) based on the Autocorrelation and Partial correlation. The model is further analyzed with the R-squared, Akaike criterion, and Schwarz criterion; the smaller value is considered good for the model. Further, the model is also satisfied with the P value considering the ARMA model.

- **Diagnostic and Forecasting for Brent Price and WTI Crude Oil Price**

The Q-statistics ARMA The above explains the Q-statistics ARMA with Autocorrelation and Partial correlation; it satisfies the criteria, and there are no outliers. the Q statistics and p-value fall within the line. It can be concluded that there are residuals that are not white noise, Hence, the null hypothesis is rejected. And a further model is taken for the analysis. The above explains the Q-statistics ARMA with Autocorrelation and Partial correlation; it satisfies the criteria, and there are no outliers. the Q statistics and p-value fall within the line. It can be concluded that there are residuals that are not white noise, Hence, the null hypothesis is rejected. And a further model is taken for the analysis.

Conclusion

The purpose of the study was to use the ARIMA model technique to model and forecast the prices of Brent and WTI crude oil. Both the Brent and WTI price series satisfied the requirements for additional time series modeling, according to preliminary stationarity tests that were carried out using correlograms and validated by Q-statistics and p-values. Based on autocorrelation and partial autocorrelation analysis, the ARIMA model—more especially, the parameters AR(1) and MA(6)—was determined to be suitable.

Favorable R-squared, Akaike Information Criterion (AIC), and Schwarz Criterion (SC) values, all of which indicated a solid model fit, further confirmed the model's adequacy. The null hypothesis was rejected and more model improvement was prompted after diagnostic tests employing Q-statistics revealed the lack of significant outliers and validated the statistical soundness of the model, even though the residuals were not entirely white noise.

All things considered, the ARIMA model successfully represented the fundamental patterns and dynamics in changes in the price of crude oil, offering a trustworthy instrument for short-term forecasting of both Brent and WTI crude oil prices. These results highlight how useful ARIMA models are for financial time series forecasting, particularly when it comes to volatile commodities like crude oil.

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