The Impact of Soaring Crude Oil Prices on the Air Transportation Industry Index

Kaibo Wang *

College of Business and Economics Australian National University Canberra ACT 2601 Australia

* Corresponding Author Email: u7667936@anu.edu.au

Abstract. On February 24, 2022, Russian President Vladimir Putin cited "demilitarisation and de-Nazification" as a justification for military intervention, leading to the deployment of Russian forces to invade Ukraine. In addition, it is important to note that Russia and Ukraine, as prominent global oil-exporting regions, annually contribute approximately 200 million tonnes of crude oil to the global market. The conflict between these two countries has significantly influence the global crude oil prices, thereby exerting a significant influence on businesses that rely heavily on energy resources. As one of the industries with the highest energy demands, the aviation industry is also substantially affected. Examining the relationship between energy costs and the airline industry, this paper will examine fundamental concepts such as the impact of fuel prices on the aviation industry, role of fuel cost in operational costs, and the effects of fuel cost volatility on airline stock. In order to determine the effects of fuel cost fluctuations the global air transport industry, the theoretical framework for this essay including comprised of pertinent theories, Demand and Supply theory, the Perfect Competition Model, and the Market Efficiency Hypothesis. This paper argues that the rise in crude oil prices caused by the conflict between Ukraine and Russia has a considerable negative impact on the stock price of the air transportation industry.

Keywords: Ukraine—Russia War, Air transport industry, crude oil, Stock return volatility, ARIMA model.

1. Introduction

The crude oil is one of the most crucial basic materials in contemporary production.[1]. Moreover, the aviation business, as a crucial sector in the global economy, is vulnerable to a wide range of external variables. The dynamic nature of oil prices has garnered significant attention and scrutiny from both academic researchers and policymakers. The significance of this link should not be underestimated, given that fuel expenses represent a substantial portion of an airline's operational expenditures. Consequently, the aviation sector, which is known for its significant fixed costs, has seen increasing financial pressure as a consequence of the upward trend in oil prices [2].

The notion of efficient market hypothesis asserts that the pricing of stocks is impacted by the assimilation of both publicly available and privately accessible information. The study done by Huang et al. revealed that changes in crude oil prices had an adverse impact on stock prices [3]. Furthermore, based on the data from Energy Foundation China (2022), the stock market is impacted by fluctuations in petroleum oil prices through three primary mechanisms: alterations in production costs, a reduction in market demand, and an escalation in the risk of inflation [4].

2. Methodology

2.1. ARIMA Model Setting

The ARIMA model consists of a variety of components, including the auto regressive (AR) model, the moving average (MA) model, and many other model [5]. The formulation ARIMA (p, d, q) represents the model. Commonly, "p" is used to designate the order of auto-regression, while "d" represents the degree of trend difference [6]. Similarly, "q" is commonly employed to represent the order of moving average [7]. Utilising techniques such as time series stationarity, parameter estimation, model verification, and prediction, the ARIMA model was created [8].

ARIMA (p, d, q) Where:

$$Return_t = \alpha + \theta_1 Return_{t-1} + \theta_2 Return_{t-2} + \ldots + \theta_p Return_{t-p} + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \ldots \varphi_p \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

This model will facilitate comprehension of the patterns and enable the prediction of the ramifications resulting from fluctuations in oil prices on the aviation sector.

2.2. Weak Stationarity Test

The null hypothesis of the Augmented Dickey-Fuller (ADF) test is that the examined series lacks a unit root, indicating non-stationarity. In contrast, the alternative theory proposes the absence of a unit root, thereby proposing series stationarity. After applying the Augmented Dickey-Fuller (ADF) test to the dataset, the following results are obtained:

Table 1. Result of weak stationarity test

	t	p
Daily		
Raw	3.651	0.0258
1st order difference	-30.120	0.0000
2nd order difference	52.847	0.0000
Weekly		
Raw	-3.415	0.0495
1st order difference	-14.888	0.0000
2nd order difference	-22.852	0.0000
Monthly		
Raw	-3.311	0.0644
1st order difference	-7.276	0.0000
2nd order difference	-11.706	0.0000

According to Table 1, it is evident that all daily, weekly, and monthly raw observations exhibit nonstationary. This conclusion is drawn based on the observation that the p-values associated with these data sets are bigger than the predetermined significance level of 5%. Consequently, the null hypothesis was not rejected. Upon performing differencing on the raw observations, it is observed that they exhibit stationarity, as evidenced by the p-value being lower than the predetermined significance level. The weekly and monthly observations are subjected to a second differencing in order to enhance their performance.

2.3. Data Source

The stock statistics pertaining to the Air transport industry, spanning from January 4, 2016, to July 21, 2023, were gathered from the Choice Financial Terminal. The ARIMA model is commonly employed in the analysis of large datasets. Based on previous research, it is recommended to partition the model into three different sizes, namely daily, weekly, and monthly. The ARIMA model was constructed using data spanning from January 4, 2016, through February 24, 2022. The models' forecasting performance was evaluated using data spanning from 24 February 2022 to 21 July 2023.

2.4. Stationarity Test

Before implementing the ARIMA model, it is necessary to conduct an Augmented Dickey-Fuller (ADF) test to ensure that the dataset is stationary [9].

2.3.1. Stationarity Features of Air Transport Industry Stock Prices

In the preliminary examination, time series plots were utilised to analyse the provided series, as depicted in Figure 1.

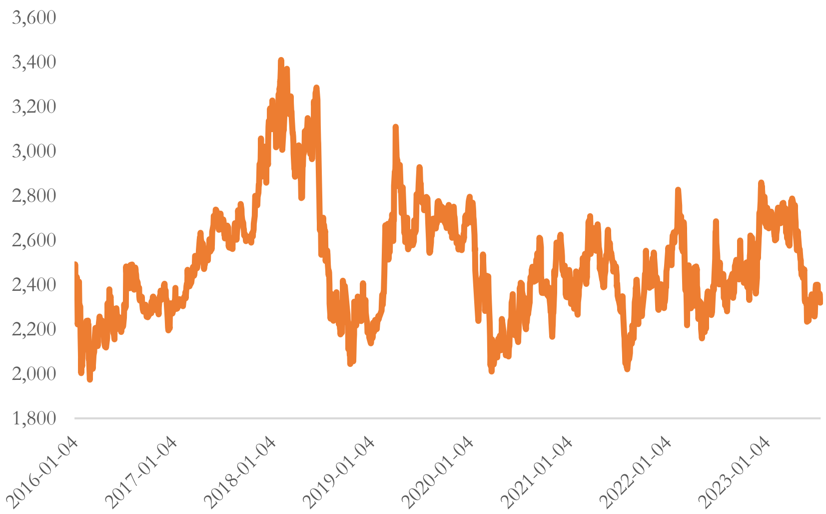

Figure 1. Daily air transport Industry Stock Price
Data Source: Choice Financial Terminal
Photo credit: Original

Upon visual inspection of the time plot, it becomes apparent that both the mean and variance exhibit non-constant patterns, so suggesting that the data lacks stationarity.

Furthermore, the investigation of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots has been used to ensure the experiment used the suitable values for the parameters p, d, and q.

2.3.2. Autocorrelation Function (ACF) Of Air Transport Industry Stock Price

The utilisation of the inspection approach to discover stationarity is complemented by the autocorrelation function (ACF) analysis of stock prices. This analysis, as depicted in figure 2, yields valuable insights indicating that the series under consideration is not stationary.

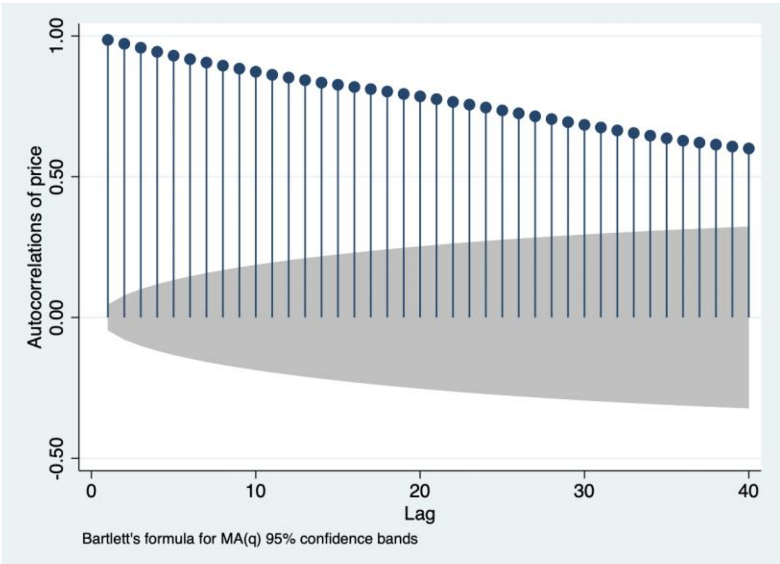

Figure 2. Daily ACF Graph
Photo credit: Original

The autocorrelation function (ACF) exhibits a consistent decrease as the number of delays rises. The occurrence of this behaviour is expected in cases when a time series is prone to exhibiting random walk characteristics. In order to get stationarity in the series, it is necessary to compute the logarithm of the series and afterwards construct a plot of the resulting ACF.

2.3.3. 1st Log Difference of Daily Stock Price

The performance shown a gradual improvement, although it remained insufficiently smooth. As depicted in Figure 3, the presence of prominent bumps and undulations was readily apparent. Consequently, we proceeded to undertake an additional logarithmic analysis.

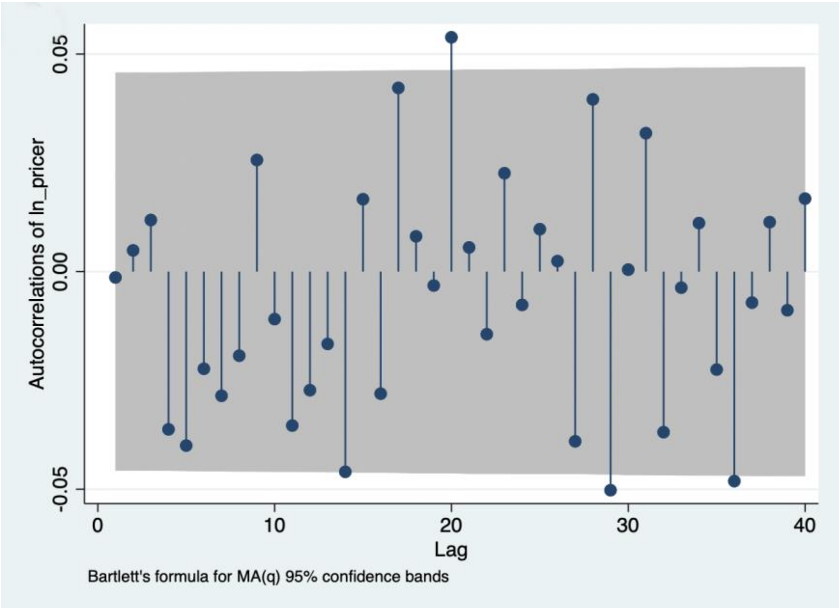

Figure 3. 1st ACF Graph
Photo credit: Original

2.3.4. 2nd Log Difference of Daily Stock Price

Calculating the initial differences of the data's natural logarithm was used to achieve stationarity by transforming the series. The transformation was carried out by introducing a new variabley_t,, which is defined as the natural logarithm of cost of the crude oil at time p_{t+1} minus the natural logarithm of price of the crude oil at time p_t. Figure 4 depicts a graph illustrating the acquired returns.

2.3.5. The Autocorrelation Function and Partial Autocorrelation Function were Computed for the Log-differenced Series

The log differentiation study conducted by Figure4 indicated that crude oil prices exhibited stationarity. Furthermore, this study examines the autocorrelation function (ACF) and partial autocorrelation function (PACF) across various lag periods to figure out the appropriate selection of variables.

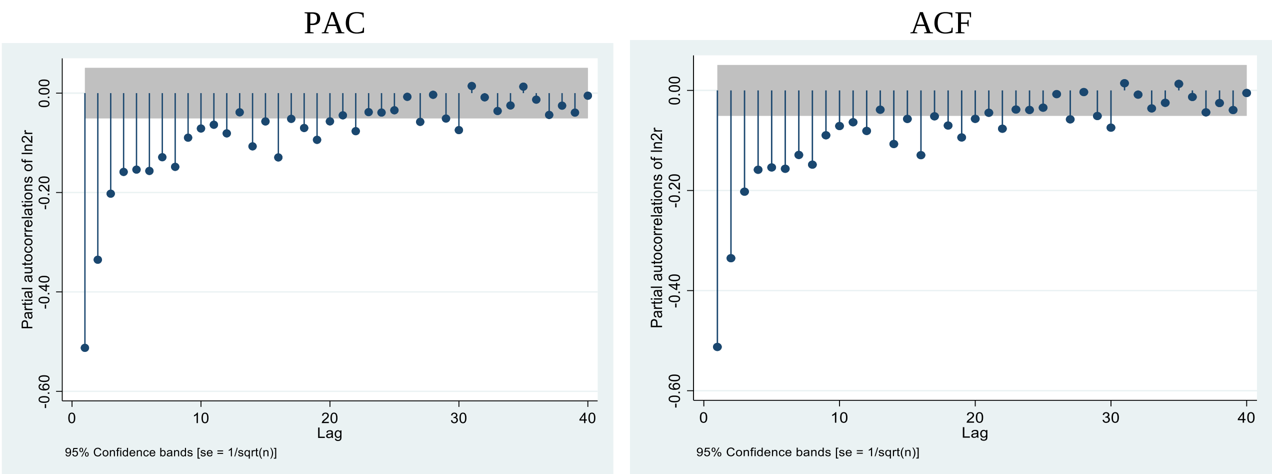

Figure 4. Daily ACF & PACF Graph
Photo credit: Original

Please note that the dependent variable on the Y-axis represents the partial autocorrelation function (PACF) and autocorrelation function (ACF) of the logarithmic return on the two semiconductor stocks. The X-axis represents the time lag order. The 95% confidence interval for AR(p) and MA(q) is determined by the region between the lines y = -2 and y = 2.

This technique is utilised by the Box-Jenkins method to determine the presence of white noise in residuals. Typically, to assess the existence of serial correlation, researchers also need to examine residuals by using plots [10]. In addition, Nyongesa and Wagala reported that the residuals adhere to a N~ (0, R, R is constant).

Based on the analysis of the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) criteria, it is determined that an ARIMA (10, 2, 1) model is suitable. This conclusion is drawn from the examination of various p and q values, as outlined in Table1, and the subsequent comparison of the corresponding PACF and ACF values. The model that demonstrates the lowest information criteria is regarded as the most optimal and suitable model for predicting daily events. In summary, the most favorable values for the parameters that indicate the day were determined to be p=10, d=2, and q=1.

2.3.6. Weekly and Monthly Data Order Identification

In a manner akin to the examination of daily data, stability tests are conducted as a first step before to the analysis of weekly and monthly data. After the test, the result shows that ARIMA (10, 2, 1) model is appropriate for weekly analysis. This conclusion is derived from an analysis of various p and q values, as shown in Figure 5.

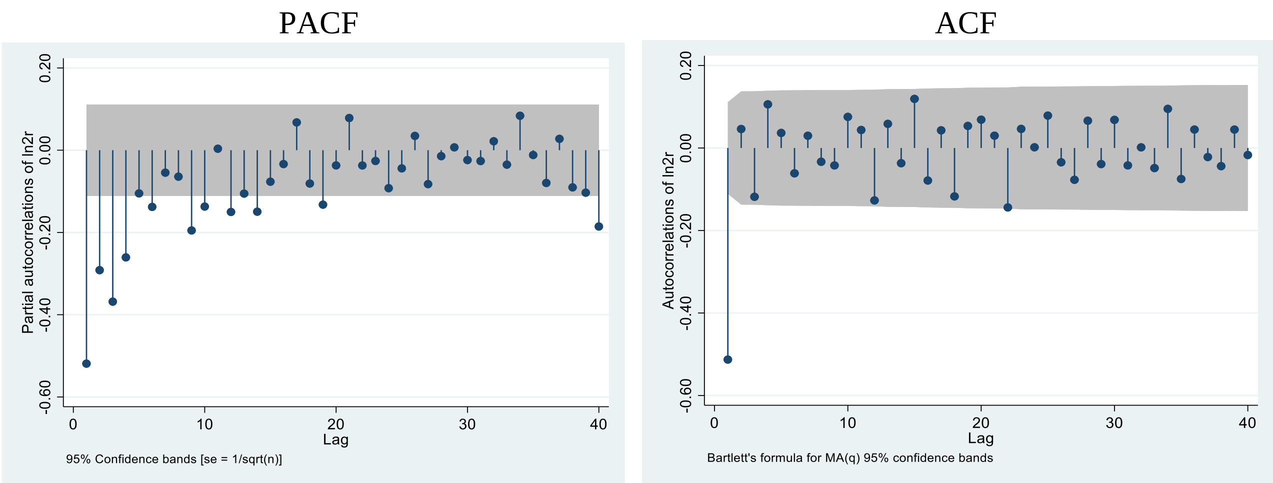

Figure 5. Weekly ACF & PACF Graph
Photo credit: Original

In addition, stability also need to test before the month analysis. The test result indicates that the ARIMA (8, 1, 8) model is suitable for weekly analysis. This conclusion is based on an examination of various p and q values, as depicted in Figure 6.

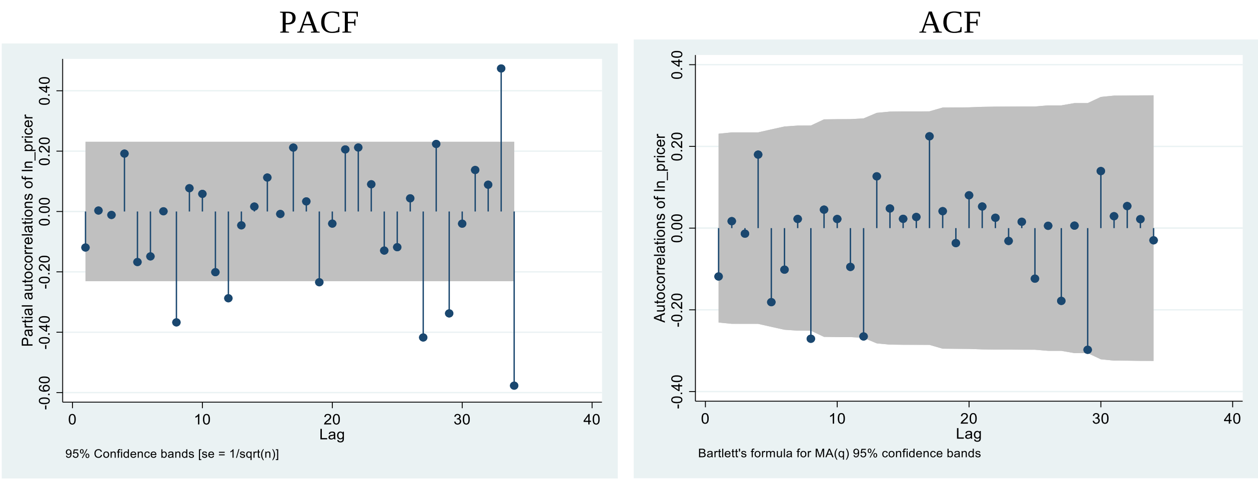

Figure 6. Monthly ACF & PACF Graph
Photo credit: Original

In summary, the most favorable values for the parameters that indicate the week and month were determined to be p=10, d=2, and q=1, and p=8, d=1, q=8.

3. Empirical Results and Analysis

Once the models have been selected, they are executed using the daily, weekly, and monthly data, respectively. The residuals of each model are projected in order to assess the validity of the regressions. The Portmanteau test is employed in this particular instance, and the subsequent table presents the outcomes.

Table 2. Residual test

Model	Portmanteau (Q) statistic	Prob > chi2
Daily-ARIMA(10,2,1)	44.6455	0.2828
Weekly-ARIMA(10,2,1)	35.9120	0.6548
Monthly-ARIMA(8,1,8)	37.0227	0.6050

The Portmanteau test is grounded on the null hypothesis that the residuals have no autocorrelation, thereby suggesting that the error term adheres to a white noise process. The selected threshold of significance for this investigation is 0.05. The probability depicted in Table 2 exceed the threshold of 0.05. Consequently, it may be inferred that none of the models exhibited sufficient evidence to refute the null hypothesis, thereby signifying their validity.

After the testing phase is concluded, the results are analysed using virtualization techniques to graphically represent the difference between the observed data (referred to as the actual value) and the predicted values of the treatment group (referred to as the fitted value).

3.1. Daily Result

The model predicted a distinct negative correlation between oil prices and airline revenues. In the context of the weekly aspect, it was shown that a 15.7% increase in oil prices exhibited a negative correlation with a 9.14% fall in monthly airline revenues.

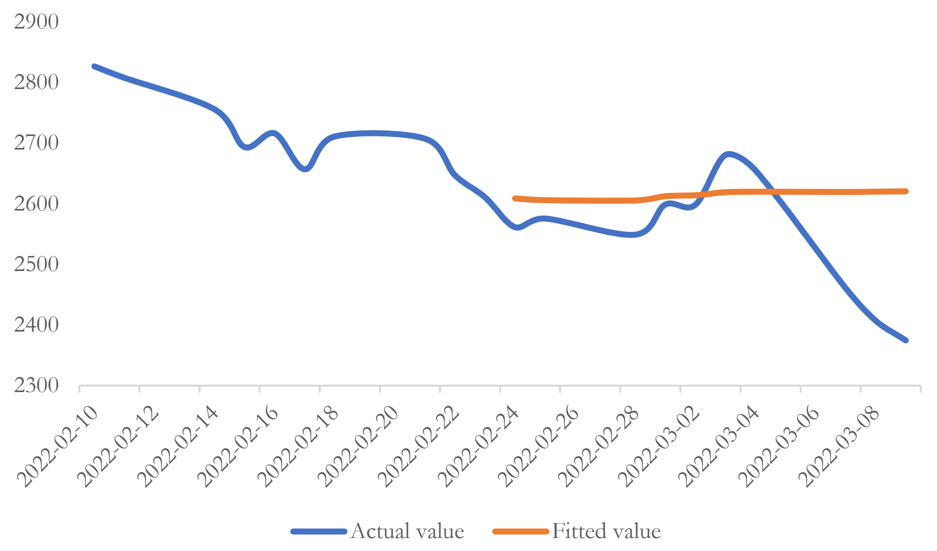

Figure 7. Actual value and fitted value, daily
Photo credit: Original

3.2. Weekly and Monthly Price Forecast

Based on the empirical evidence obtained from the experiments, it can be deduced that in the event of the non-occurrence of the Russian-Ukrainian conflict and the subsequent substantial disruption in the global crude oil supply, the stock price of the aerospace sector would have demonstrated a relatively steady trajectory, characterized by negligible fluctuations. The stock price of the aviation industry has exhibited substantial volatility following the initiation of the Russia-Ukraine conflict. Notably, starting from March 2022, there has been a discernible decrease in stock prices. This discovery provides evidence to support our hypothesis that variations in oil prices have a negative impact on the stock performance of the aviation industry [11].

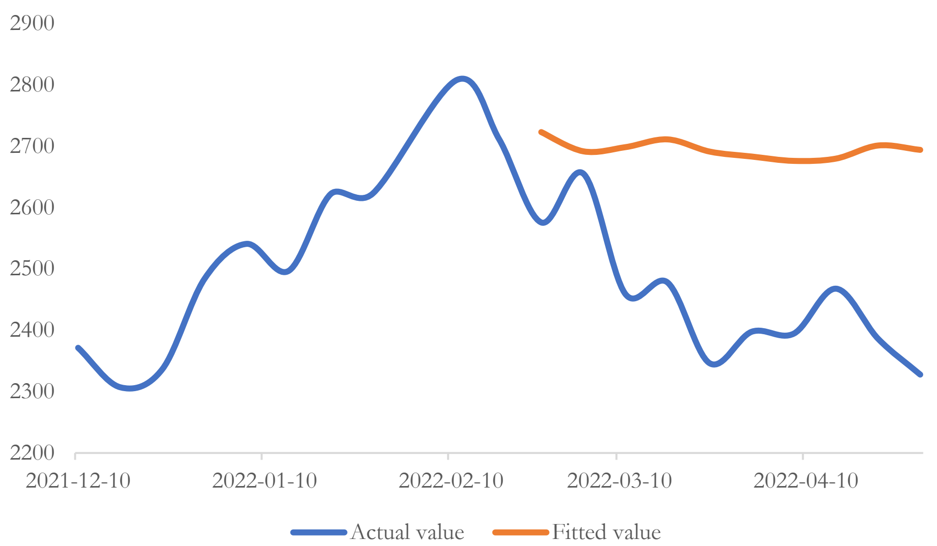

Figure 8. Actual value and fitted value, weekly
Photo credit: Original

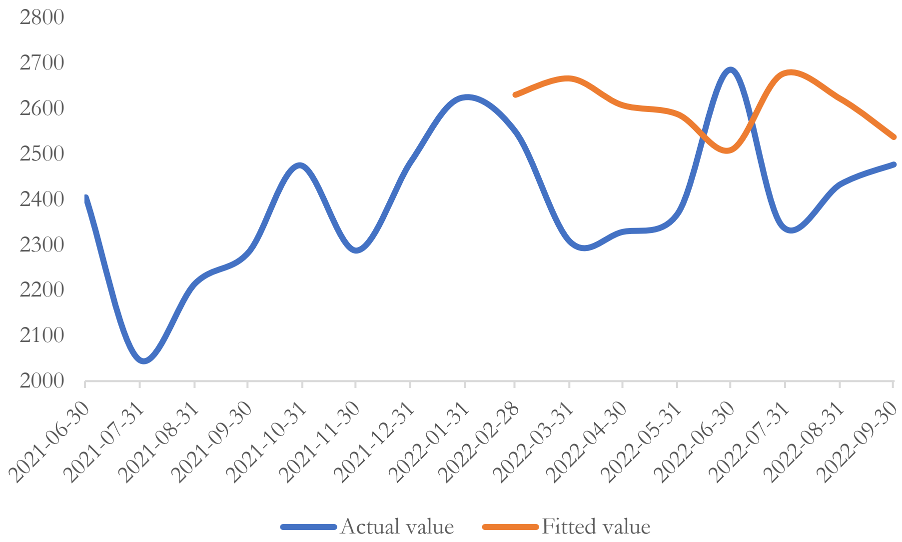

Figure 9. Actual value and fitted value, monthly
Photo credit: Original

In order to forecast the future trajectory of production, the baseline dataset is modified to incorporate the duration of the projected time period. Based on the projected production forecasting trend for the year 2022, the graph depicted below depicts the prospective weekly and monthly outcomes for the future and their corresponding performance. The scenarios presented in this analysis consist of an optimistic scenario and a pessimistic scenario. These scenarios are defined as departures of ± 2 standard errors from the observed production trends, as illustrated in Figure 8 & 9.

4. Conclusion

The findings from the ARIMA analysis suggest that the ARIMA (10,2,1) model outperforms other potential combinations of autoregressive and moving average components, and it is suitable for both daily and weekly analysis, while ARIMA (8,1,8) performance better than ARIMA (10,2,1) in monthly analysis. This suggests that there is a considerable relationship between the most recent four days' pricing data and news, and the ability to anticipate future crude oil price, especially the weekly size, there is almost negative 10% change when the crude oil price is change.

The results underscored the vulnerability of the air transportation industry to fluctuations in oil prices. The correlation shown between fluctuations in oil prices and airline revenues underscores the substantial impact of fuel cost volatility on the aviation sector. The observed association between this relationship suggests a significant influence of fuel charges on the operational expenses of airlines. The increase in oil prices has a direct influence on fuel expenditures, leading to either reduced profitability or the necessity to elevate flying expenses. The rise in hiking activities could potentially result in a decline in the demand for air travel, thereby affecting income.

Future research could be further upon in three key areas, including:

(1) identify more suitable prediction methods for constructing a hybrid ensemble model to forecast crude oil prices.

(2) propose additional metrics to evaluate training accuracy, beyond the traditional use of root mean square error (RMSE); and

(3) evaluate the scalability of the autoregressive integrated moving average (ARIMA) model to different time series datasets, including weekly and monthly price series, with varying data volumes.

References

[1] Solaymani S, Kari F. Environmental and economic effects of high petroleum prices on transport sector [J]. Energy, 2013, 60: 435 - 441.

[2] Morrison J, Bonnefoy P, Hansman R J, et al. Investigation of the impacts of effective fuel cost increase on the us air transportation network and fleet[C]//10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference. 2010: 9202.

[3] Huang R D, Masulis R W, Stoll H R. Energy shocks and financial markets [J]. Journal of Futures markets, 1996, 16 (1): 1 - 27.

[4] Yun X, Yoon S M. Impact of oil price change on airline's stock price and volatility: Evidence from China and South Korea [J]. Energy Economics, 2019, 78: 668 - 679.

[5] [5] Wu J, Chen Y, Zhou T, et al. An adaptive hybrid learning paradigm integrating CEEMD, ARIMA and SBL for crude oil price forecasting [J]. Energies, 2019, 12 (7): 1239.

[6] Jianwei E, Bao Y, Ye J. Crude oil price analysis and forecasting based on variational mode decomposition and independent component analysis[J]. Physica A: Statistical Mechanics and its Applications, 2017, 484: 412 - 427.

[7] Etuk E H. Seasonal ARIMA model to Nigerian consumer price index data [J]. American Journal of Scientific and Industrial Research, 2012, 3 (5): 283 - 287.

[8] Ariyanti V P, Yusnitasari T. Comparison of ARIMA and SARIMA for Forecasting Crude Oil Prices[J]. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 2023, 7 (2): 405 - 413.

[9] Waheed Bhutto A, Ahmed Bazmi A, Qureshi K, et al. Forecasting the consumption of gasoline in transport sector in pakistan based on ARIMA model[J]. Environmental Progress & Sustainable Energy, 2017, 36 (5): 1490 - 1497.

[10] Gasper L, Mbwambo H. Forecasting crude oil prices by using ARIMA model: evidence from Tanzania [J]. 2023.

[11] Zhou J, Sun M, Han D, et al. Analysis of oil price fluctuation under the influence of crude oil stocks and US dollar index—Based on time series network model [J]. Physica A: Statistical Mechanics and its Applications, 2021, 582: 126218.