CHAPTER 4

THE PROSPECT AND VOLATILITY OF STOCK PRICES IN AVIATION BUSINESS

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ABSTRACT

The aviation business has had a difficult time due to the COVID-19 pandemic in the past year. As a result, people worldwide are limited to travel which causes a decrease in turnover from a business in the transportation sector, particularly aviation. This condition, indeed, also affects the company's stock price. This study examines the volatility of stock prices as an initial indication of what has happened and looks at future projections. The method used in this study is the autoregressive integrated moving average (ARIMA) in achieving research objectives. The findings found that the autoregressive combined moving average on AR1 and MA1 can show conditions based on past data and predict the projection of its volatility. The aviation business is still considered to survive with daily stock prices that are relatively positive and stable for the next upcoming period.

Keywords: ARIMA model; volatility; COVID-19 pandemic; stock prices; aviation business; financial forecasting

JEL classifications: G0; G1; G12

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1. INTRODUCTION

The aviation business is one of the business sectors that has been affected by fluctuating global conditions in recent years. The belief in the protracted pandemic problem has reduced consumer confidence in using public transportation, especially aeroplanes. As a result, data on the number of passengers showed a decrease of 5.37%, with an actual figure of 2.53 million passengers during early Indonesia 2020 compared to 2019 (Garuda Indonesia, 2020). In addition, the aviation industry is grappling with an unprecedented swell, cancellation attempts, and a significant reduction in demand as instructors require regulators to implement social distancing and travel restrictions (Nicola et al., 2020). Consequently, in this uncertain circumstance, aviation businesses need to calculate their business operation, such as attempting to predict the performance of stock prices in the market as the representative of company performance for the public. Thereby investigated at a higher level. However, there is limited literature on forecasting stock prices and volatility in the aviation sector, so we take this part to enrich the literature in financial economics.

Forecasting has been widely used in the business environment to prepare for threats and opportunities in the future. For example, Wong, Song, Witt, and Wu (2007) conducted forecasted the conditions of the tourism business with various models with the result that the combination of various autoregressive forecasting models could reduce the defect rate of each model design. Chancharat and Butda (2021) predicted the causal relationship between bitcoin, gold prices, and oil prices, which pointed out that a one-way retransmission from oil to bitcoin was observed, indicating that oil returns help to predict bitcoin returns. Ambya, Gunarto, Hendrawaty, Kesumah, and Wisnu (2020) found the excellent fit model of AR(1)-GARCH (1,1) to predict the future prices of crude oil and concluded that the use of renewable energy should be more recommended as the result from the model showed the crude oil prices would go up in the future. The study was supported by Hendrawaty, Azhar, Kesumah, Sembiring, and Metalia (2021) that measured the high volatility of crude oil prices during the pandemic in 2020 by implementing the model of GARCH. Similarly, the forecasting model was also used to predict Future Natural Gas (FNG) prices (Ambya et al., 2020). They estimated the GARCH model of AR(1)-GARCH(1,1) and found that FNG is predicted to have high volatility in the future. In the banking sector, Ahadiat and Kesumah (2021) used the model of GARCH as the measurement of future volatility in Indonesian banks to measure the probability of maximum loss from each bank. Furthermore, Guégan and Rakotomarolahy (2010) examined the *k*-nearest neighbours method to forecast the euro area's monthly economic indicator and quarterly GDP, which is better than a competitive linear VAR modelling.

Furthermore, instead of the GARCH model, we apply the ARIMA model as a Forecasting Tool. ARIMA model has come a long way and has received much proof. However, as the previous study on forecasting daily stock prices and the volatility in the airline business is limited, we decided to take a role so that future forecasting models get much empirical evidence. The reason is that level of concentration to make the right decisions in the aviation business is crucial as high operational costs, and uncertain nature conditions, so all possibilities in this business must be prepared earlier.

2. RESEARCH METHOD AND DESIGN

We strive to produce accurate studies using the right design and research methods. This study uses a quantitative approach to achieving the desired results. Research results are required to show excellence that is representative, reliable, and applicable (Hair, Black, Babin, & Anderson, 2006). We observed the relevant financial data as a proxy for the condition of the company. Our data observation results converge on the daily stock prices of the airline, which is Garuda Indonesia Airlines (GIAA), as a state-owned company in the aviation sub-sector in Indonesia. In many news reports, the aviation and tourism sectors are the most affected by the pandemic that has occurred in recent times.

The ARIMA model was chosen in this study for structured reasons; namely, this approach allows the classical problems of forecasting time-series data to be resolved. ARIMA chooses the most appropriate level of distinction so that the critical issue of stationarity is resolved properly (Hassani, Heravi, & Zhigljavsky, 2009). Volatility in time-series data of financial data can be in the form of stationary or non-stationary data characteristics that can be analyzed using autoregression forecasting models, one of which is the development of ARIMA (Tsay, 2005). To initiate the ARIMA approach, we carry out a requirement: static data by examining the value of the Augmented Dickey-Fuller (ADF) unit root test. We build the hypothesis that H_0 is equal to 0 or non-stationary with the following economic math equation (Azhar, Kesumah, Ambya, Wisnu, & Russel, 2020).

$$f = \frac{\hat{\vartheta} - 1}{\mathrm{Se}(\vartheta)} \tag{1}$$

With the initial criteria we specify, we will reject the hypothesis at a value less than −2.57, and the *p*-value must be less than 0.05; with that, we will get a 95% confidence interval (Brockwell & Davis, 2002). Furthermore, Montgomery (2012) viewed the static data as well with the autocorrelation function (ACF test) and the partial autocorrelation function (PACF test), which displays in a graph a clear image of stationarity. Furthermore, if it supports the examination of white noise problems in the data, it will be carried out to increase our confidence. Finally, we quote the equation built by Brockwell and Davis (2002) in simplifying the assumptions of ARIMA as follows:

$$X_p(\mathrm{L})(1-L)^d \, \mathrm{GARUDA}_t = \alpha + X_q(L)\varepsilon_t \tag{2}$$

where,
$X_p(L) = \left(1 - X_1 L, \ \ldots, \ X_p B^p\right)$; $\theta_q(L) = \left(1 - X_1 L, \ \ldots, \ X_q L^q\right)$; $(1-L)^d$ is differencing of order d; α in constant: ε_t is residuals, and L is the notational device for lags.

However, equation (2) can be simplified by:

$$\mathrm{GARUDA}_t = \alpha + X_1\mathrm{GARUDA}_{t-1} + \ldots + X_p\mathrm{GARUDA}_{t-p} + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q} + \varepsilon_t \tag{3}$$

Our statistical design is finished with the mathematical economic considerations we built. Furthermore, we will apply this design when considering the future of the aviation business with financial data as a variable.

3. RESULT AND IMPLICATIONS

3.1 ARIMA Procedure

We use very detailed daily price data to investigate the condition of aviation. GIAA is the ticker code of Garuda Indonesia, an airline that the Indonesian government partially controls. We investigate the volatility in the last year on the grounds of a pandemic phenomenon, making the airline business no longer attractive or even down.

Fig. 1 shows the trend of increasing GIAA stock prices throughout one year.

A more detailed examination stage will be carried out in ARIMA, the initial behaviour procedure for GIIA stock data to get a mean of the working series value of 286.0795 with a standard deviation of 77.08007 data that is part of the observation is 239 daily stock data. We feel that these numbers are too big, so

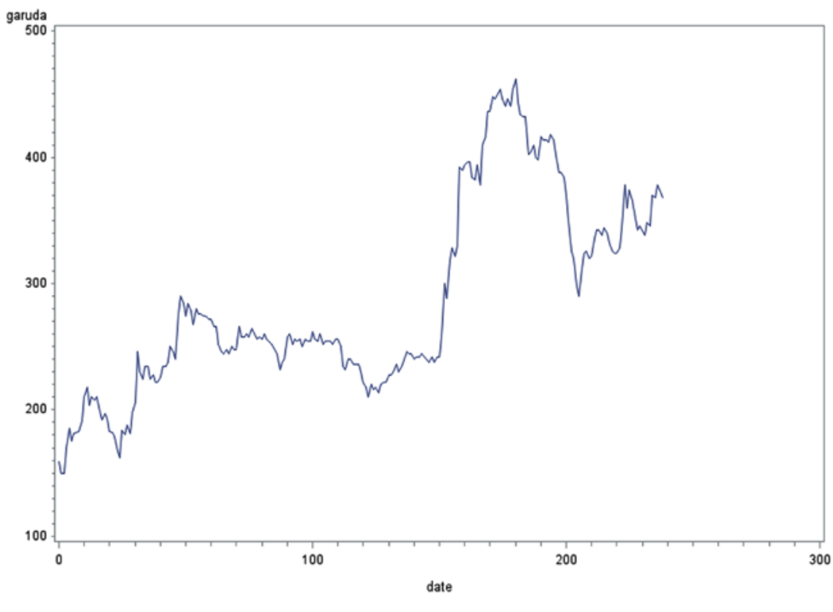

Fig. 1. The Trend of GIAA Stock Data Distribution.

our suspicions about non-stationary data are heightened. Another chart measure that can ensure Garuda stock data is not stationary is to look at the ACF chart shown in Fig. 2.

The hypothesis that the data is not stationary is confirmed because the ACF graph that is slowly decreasing is an indicator. The data need special statistical treatment by doing differencing in the hope that the data is stationary. The data after differencing has a dense, volatile behaviour with a controllable distance. The proof is in Fig. 3. We managed to provide a different treatment which gave a good signal.

Further, we will examine the ADF test more carefully, not only from the visual of the chart. To make us comfortable, we calculated the ADF test with a lag of 0–4, ensuring that everything that was significant was what we wanted. Table 1 gives our expectation to be confirmed with a positive signal p-value <0.0001.

3.2 Forecasting the Future of Airline Companies

In this section, we start by designing a model for the future of airline stock. That way, we can then predict the stock price, which is a proxy for the company's condition.

Table 2 shows us all about matters related to ARIMA. The results show a positive significance level of ARIMA, which is below <0.001. This result means giving confidence to the model, which is continued by translating it into future figures.

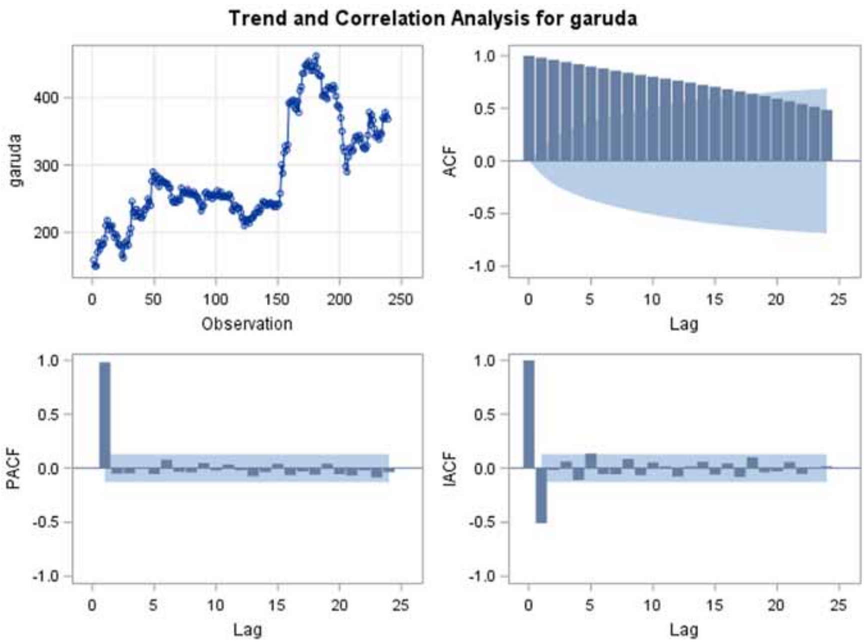

Fig. 2. ACF Graph of GIAA Stock Data.

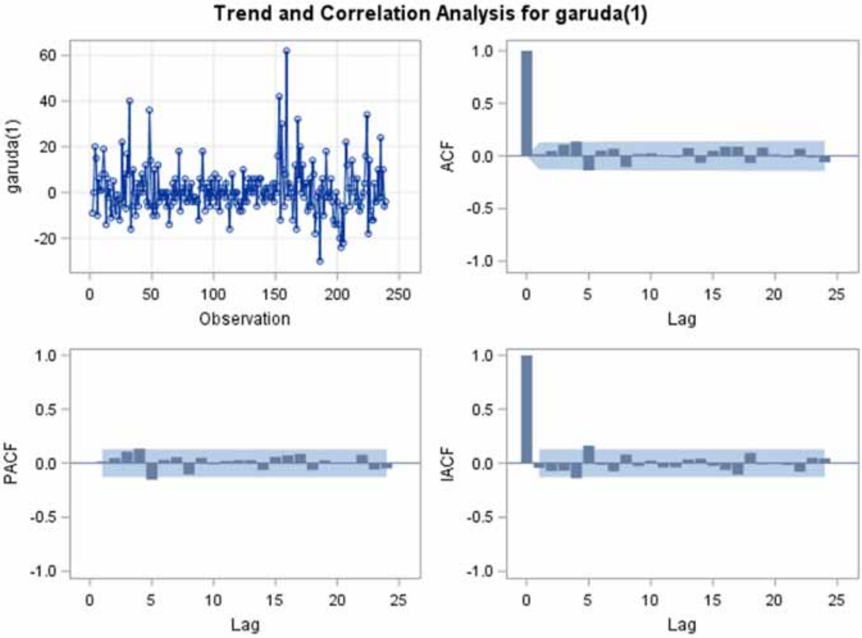

Fig. 3. Plot Graph of GIAA Stock Data After Differencing.

Table 1. ADF Unit Root Tests.

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	*F*	Pr > *F*
Zero Mean	0	−231.660	0.0001	−15.04	<0.0001		
	1	−207.124	0.0001	−10.13	<0.0001		
	2	−149.491	0.0001	−7.52	<0.0001		
	3	−97.6572	<0.0001	−5.91	<0.0001		
Single Mean	0	−233.277	0.0001	−15.11	<0.0001	114.17	0.0010
	1	−211.409	0.0001	−10.21	<0.0001	52.14	0.0010
	2	−154.023	0.0001	−7.58	<0.0001	28.70	0.0010
	3	−100.842	0.0001	−5.95	<0.0001	17.72	0.0010
Trend	0	−233.516	0.0001	−15.10	<0.0001	114.00	0.0010
	1	−212.039	0.0001	−10.21	<0.0001	52.14	0.0010
	2	−154.569	0.0001	−7.57	<0.0001	28.63	0.0010
	3	−101.020	0.0001	−5.93	<0.0001	17.63	0.0010

Table 2. Conditional Least Squares Estimation.

Parameter	Estimate	Standard Error	*t*-Value	Approx. Pr > |*t*|	Lag
MU	0.89561	0.92343	0.97	0.3331	0
MA1,1	0.81228	0.25977	3.13	0.0020	1
AR1,1	0.85746	0.22968	3.73	0.0002	1

Table 3 is our second boundary, so that we believe in its level of significance. The variance estimate is 118.6831, with a reasonably low error rate of 10.89418. From all data with the name number of residuals 238, we show convincing AIC and SBC values. The following is the design of the forecasting model:

$$\text{GARUDA}_t = 0.127659 + 0.81228_{t-1} + 0.85746_{t-1} + \varepsilon_t$$

With this model, our final step is to show the forecasting results shown in Fig. 4.

Fig. 4 shows the upward trend in Garuda's stock price for the next 30 days. Short ranges of forecasting are an attempt to reduce the error rate. However, as

Table 3. ARIMA Statistical Result.

Constant estimate	0.127659
Variance estimate	118.6831
SE estimate	10.89418
AIC	1,815.192
SBC	1,825.609
Number of residuals	238

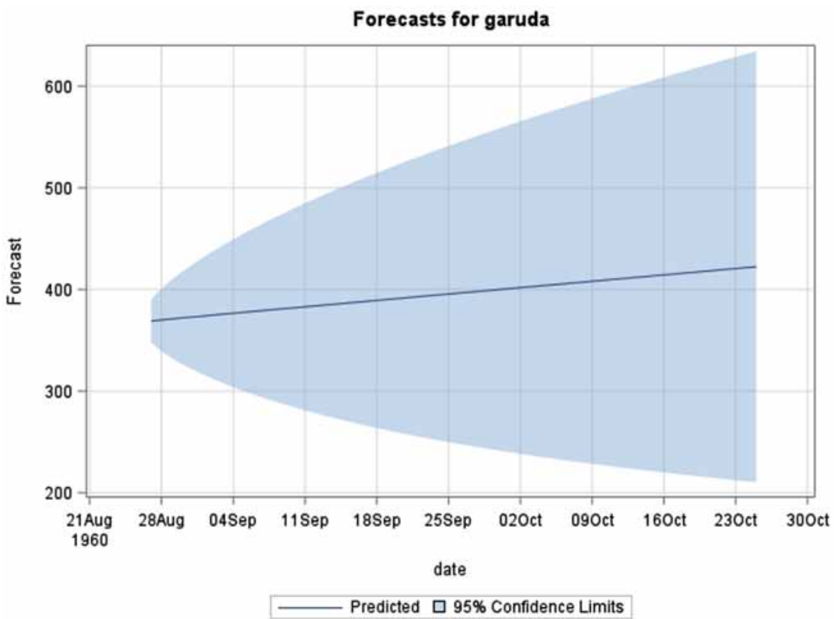

Fig. 4. Forecast for Garuda.

we can see, the assumptions formed from the model result in an error rate that gets wider over time with the length of the research period. The implications of the process and statistical analysis that has been carried out are the essential components of this research. Next, we will discuss how the strategic actions of airlines, as a solution to the conditions experienced, are considered.

3.3 Aviation Business Strategic Preparation

The model of ARIMA (1,1) confirmed a previous study conducted by Wahyudi, Nabella, and Sari (2021), which found ARIMA model predicts that the next six-month Indonesian inflation still is vulnerable due to COVID-19. Thereby, action response to harmful conditions caused by a pandemic is a strategic matter that must be done as such an uncertain condition is considered a risk that needs to solve immediately so that business can be sustained (Yan & Nettayanun, 2019). The increased short-term forecast results but still sloping in detail signal that the airline company is trying hard to maintain its profit levels. A marketing strategy in social media (Yusida, Qurrata, Purnamasari, & Huang, 2021) that increases the confidence to fly is a good thing. The distribution of advertisements regarding the airline's information maintains the cleanliness of facilities, and air must continue to be carried out. Psychologically builds the level of consumer confidence in reusing the airline. Some digital media can be used as a suitable medium for conveying these things (Batra & Keller, 2016). Marketing communications that are carried out continuously can change consumer information patterns so that they feel safe. Consumers who were financially affected due to the pandemic carried out more communication than those who were not affected. However, the intention to enjoy their outside world was higher than that of consumers who were not affected due to flight, whereas to target consumers who were financially affected, marketers could provide promotions and discounts (Pan, Shu, Kitterlin-Lynch, & Beckman, 2021).

The design of alternative strategies when a crisis occurs must be provided, then strategy optimization, and analysis of consumer needs, also at the same time, which is no less crucial is the implementation of a business strategy (Varelas & Apostolopoulos, 2020). Urgent responses can strategize product lines stretching to meet urgent needs and proactively adjust products in response to emerging needs, further migrate to digital distribution, and invest in new customer-focused advertising and promotions (Kang, Diao, & Zanini, 2021).

4. CONCLUSION

The research that has been completed describes the performance of the econometric model in forecasting the future. Our research finds an econometric model that can be used in designing aviation business forecasts. ARIMA (1,1) came out as the best. This model shows excellence with very relevant evidence in forecasting the future of the airline business with stocks as the critical variable. In more detail, we will find that the share price of the airline business can show performance but is not significant. As a high-tech business, this business must adapt to manage cash flow operations so that business continuity is maintained.

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