

## Forecasting Analysis of PT Bank Nationalnibu Tbk Stock Prices Using the ARIMA(0,1,2) Model on Daily Data for the 2023–2026 Period

Mawar Endah Banondari Iryawan<sup>1</sup>, Safa Aulia Putri Rahmadhani<sup>2</sup>, Athara Inzira Maulia Siregar<sup>3</sup>, Citra Ardianti<sup>4</sup>

<sup>1,2,3,4</sup> Cenderawasih University, Indonesia

Email: [mawariryan@gmail.com](mailto:mawariryan@gmail.com)

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ARIMA, forecasting, stock price, NOBU, MAPE

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### Abstract

Stock price forecasting is important because investors need empirical information to reduce uncertainty in short-term investment decisions. This study aims to analyze the daily stock price movement of PT Bank Nationalnibu Tbk and to determine the feasibility of the ARIMA model for forecasting the stock price. The study used a quantitative time series approach based on daily closing prices from May 2, 2023, to April 30, 2026, with 712 observations. The analysis was conducted using RStudio through descriptive statistics, stationarity testing, first differencing, ACF and PACF identification, ARIMA model comparison, diagnostic testing, and forecast accuracy evaluation. The results show that the data were non-stationary at the original level because the Augmented Dickey-Fuller p-value was 0.1847. After first differencing, the p-value decreased to 0.0100, indicating stationarity. The ARIMA(0,1,2) model was selected because it had the lowest AIC value. The Ljung-Box test produced a p-value of 0.1675, indicating no residual autocorrelation. The model yielded an MAE of 29.2604, an RMSE of 38.9040, and a MAPE of 5.2949%. These results indicate that the ARIMA(0,1,2) model is sufficiently accurate for short-term forecasting of NOBU stock prices, although residual normality remains a limitation of the model.

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## INTRODUCTION

The capital market is a vital component of the financial system as it brings together those in need of funds with those who have excess funds through investment instruments. In the Indonesian context, stocks are a widely followed investment instrument due to their relatively high potential for returns, though this potential is always accompanied by the risk of price fluctuations. Sudipa et al., (2023) explain that the movement of Indonesian banking stocks can be analyzed using a time series approach because stock prices form historical patterns that can be studied quantitatively. (Usanti & Adji, 2020) also emphasize that stock price prediction remains a critical issue for investors because buy-sell decisions are often influenced by expectations regarding future price values.

Stock prices do not move in a fixed manner but are influenced by the interaction between internal company factors, industry conditions, market sentiment, economic policies, and investor responses to new information (Aryanti et al., 2022). Prastio et al. (2024) add that stock prices can be interpreted not only through fundamental factors but also through technical and macroeconomic aspects. Therefore, stock price forecasting research must remain mindful of the fundamental context so that prediction results are not interpreted as mere statistical figures.

PT Bank Nationalnibu Tbk is a banking sector issuer with the stock code NOBU, characterized by volatile stock prices. The price movements of NOBU stock during the study period showed clear increases, decreases, and changes in volatility, thus requiring an analytical

approach capable of systematically identifying historical patterns. Banking stocks hold a significant position in financial performance analysis because the banking sector is highly sensitive to changes in liquidity, credit risk, and market confidence (Raissa, 2025). NOBU is a suitable subject for this study as it represents a bank issuer that can be analyzed through a combination of fundamental analysis, descriptive statistics, and time series forecasting.

Time series forecasting is used to estimate future values based on past data. ARIMA is one of the benchmark methods in forecasting because this model is capable of mapping historical data patterns in a structured manner (Nuralifia & Rodiah, 2025). (Pangaribuan et al., 2023) also applied ARIMA to forecast business data and demonstrated that time series models can aid data-driven decision-making processes. In the context of stock prices, this approach is crucial because investors require a quantitative understanding of potential short-term price directions.

Stock price forecasting is essential because price movements in the capital market cannot always be understood through visual observation alone; rather, they require a quantitative approach capable of identifying historical data patterns. The ARIMA model is a relevant method for time series analysis because it focuses on past data behavior to estimate values for future periods. Wulandari et al. (2021) explain that the ARIMA approach can be used in stock price forecasting studies because it is capable of systematically modeling historical data patterns. (Rusyida & Pratama, 2020) assert that the use of ARIMA in stock forecasting can help provide predictive insights when the market experiences unstable changes. Therefore, the use of ARIMA in this study is deemed relevant for analyzing the stock price movements of PT Bank Nationalnobu Tbk based on daily historical data.

Stock price forecasting using the ARIMA method has been widely used in capital market research, particularly for large-cap stocks, stock indices, or issuers with high liquidity. However, this trend has meant that more specific banking stocks, such as PT Bank Nationalnobu Tbk, have not yet been widely selected as the primary focus of analysis. Yet, stocks with price movements that are not always as active as those of major banks remain important to study because they can provide a more diverse picture of price behavior within the banking sector. (Milniadi & Adiwijaya, 2023) explain that the selection of a forecasting model must consider data characteristics and the level of accuracy produced. Sitompul & Sitepu (2024) also emphasize that model comparison is necessary so that the method used is not merely chosen based on popularity but is truly aligned with the patterns of the analyzed data. Therefore, this study focuses its analysis on NOBU stock, with model testing conducted in a stepwise manner.

This study not only produces forecast figures but also assesses model validity through several statistical stages. Daily NOBU stock price data over the past three years were analyzed via stationarity tests, ACF and PACF identification, AIC and BIC value comparisons, residual autocorrelation tests, residual normality tests, and accuracy evaluation using MAPE. Fauzani & Rahmi (2023) state that the application of ARIMA must be conducted sequentially ( ) so that the forecasting results can be statistically justified. Meanwhile, (Fadhilah et al., 2024) indicate that banking stock data exhibit dynamics that may require more careful analysis, particularly when residual patterns do not fully satisfy classical assumptions. Thus, this study aims to present stock price forecasting in a more critical manner, not only in terms of accuracy but also regarding the validity of the models employed.

The objectives of this study are to analyze the characteristics of the daily stock prices of PT Bank Nationalnobu Tbk, determine the best ARIMA model, evaluate the model's suitability based on stationarity tests and residual diagnostics, and assess the forecasting accuracy levels using MAE,

RMSE, and MAPE. With these objectives, this study is expected to contribute academically to the study of banking stock forecasting and provide practical insights for investors in need of short-term prediction references.

## METHODS

This study employs a quantitative approach using time series analysis methods. The quantitative approach was chosen because the research focuses on numerical stock price data and statistical model testing. The research subject is the stock of PT Bank Nationalnobu Tbk with the ticker symbol NOBU. The data used consists of daily closing prices over a three-year period, from May 2, 2023, to April 30, 2026, with a total of 712 observations. Data processing was conducted using RStudio to ensure that the entire modeling, testing, and forecasting process could be carried out systematically. The research data consists of secondary time-series data. The primary variable analyzed is the daily closing price of NOBU stock. Before analysis, the data was sorted from the oldest to the most recent dates to ensure the time-series structure aligns with the order of observations. The data was then cleaned of missing values and converted to numerical format if price values were still represented as text. Once the data is ready, the analysis proceeds with descriptive statistics to determine the mean, median, minimum, maximum, standard deviation, skewness, and kurtosis. The stages of data cleaning, exploration, modeling, and interpretation are necessary to ensure that the next step is the stationarity test using the Augmented Dickey-Fuller (ADF) test. This test is first conducted on the level data. In this study, first differencing was used because the stock price data at the level did not meet the stationarity assumption. After differencing, the data was retested with the ADF to ensure that the data was stationary and could be used in ARIMA model formation. Model identification was performed by examining the ACF and PACF graphs of the data after differencing. These plots are used to assess the potential autoregressive and moving average parameters. Subsequently, several candidate models are compared: ARIMA(0,1,0), ARIMA(0,1,1), ARIMA(0,1,2), ARIMA(1,1,1), and ARIMA(2,1,2). Model selection is based on AIC and BIC values, with priority given to the model with the smallest AIC value. The use of historical data in the ARIMA model is relevant for stock price forecasting because the model forms estimates based on price patterns in previous periods (Pramudya, 2023). The selected model is then tested through residual diagnostics. Additionally, the model's residuals are tested for normality using the Shapiro-Wilk test. Model accuracy is evaluated by calculating MAE, RMSE, and MAPE. MAE is calculated as the average of the absolute differences between actual and predicted data. RMSE is calculated as the square root of the average of the squares of the differences between the predicted and actual values. MAPE is calculated as the average of the absolute percentage error relative to the actual value. The model is considered to meet the research criteria if the MAPE value is below 8% ( ). After the best model was obtained, forecasting was performed for the next 20 periods to determine the short-term trend of NOBU stock prices.

## RESULTS AND DISCUSSION

The daily stock price data of PT Bank Nationalnobu Tbk used in this study consists of 712 observations covering the period from May 2, 2023, to April 30, 2026. In general, the data shows fluctuating movements with a minimum price of 406 and a maximum price of 910. The mean stock price is 625.9607, while the median is 625. The closeness of the mean and median values

indicates that the data is relatively balanced, although the price chart shows several periods of sharp spikes and drops.

Table 1. Descriptive Statistics of NOBU Daily Stock Prices Over a 3-Year Period

| Mean     | Median | Minimum | Max | Standard Deviation | Skewness | Kurtosis |
|----------|--------|---------|-----|--------------------|----------|----------|
| 625.9607 | 625    | 406     | 910 | 111.0270           | 0.2026   | 2.3695   |

Table 1 shows that the standard deviation of the stock price is 111.0270. This value indicates a fairly large spread of prices from the mean. A skewness of 0.2026 indicates that the price distribution is slightly skewed to the right, but the skewness is not too extreme. A kurtosis of 2.3695 indicates that the data distribution tends to be flatter than a normal distribution. These descriptive results indicate that NOBU stock has fairly distinct price variations, making a forecasting model necessary to identify short-term trends.

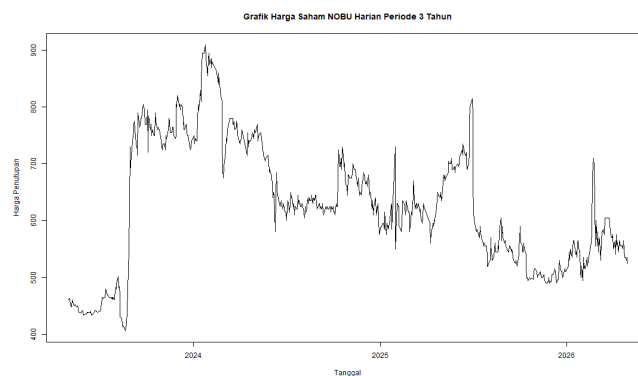


Figure 1. Daily NOBU Stock Price Chart for a 3-Year Period

Figure 1 shows that NOBU stock prices rose sharply at the beginning of the observation period, reaching a high point around early 2024, then experienced a decline and fluctuating movements in the subsequent period. From 2025 to early 2026, stock prices tended to move within a lower range compared to the previous peak, although there were still occasional increases. This pattern indicates that the data exhibits a trend and changes in variance, so its stationarity must be tested before modeling with ARIMA.

Table 2. Results of Stationarity, Autocorrelation, Normality, and MAPE Tests

| Test                           | Statistical Value | P-Value | Description              |
|--------------------------------|-------------------|---------|--------------------------|
| ADF Level                      | -2.9300           | 0.1847  | Non-stationary           |
| First-Order ADF                | -9.4098           | 0.0100  | Stationary               |
| Ljung-Box Residual             | 14.1216           | 0.1675  | No autocorrelation       |
| Shapiro-Wilk Test of Normality | 0.8316            | 0.0000  | Residuals are not normal |
| MAPE                           | 5.2949            | -       | Meets the criteria       |

The ADF test results at the level data yield a statistic of -2.9300 with a p-value of 0.1847. Since the p-value is greater than 0.05, the NOBU stock price data at the level is deemed non-stationary. After the first differencing, the ADF statistic becomes -9.4098 with a p-value of 0.0100. This value is less than 0.05, so the data after differencing is declared stationary. Thus, the integrated parameter in the ARIMA model is one, namely  $d = 1$ .

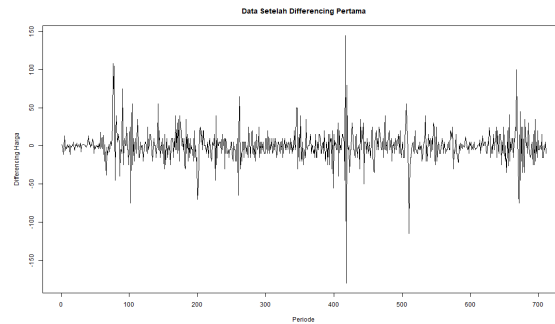


Figure 2. Data Plot After First Differencing

Figure 2 shows that the data after differencing moves more stably around the centerline. Although there are still some positive and negative spikes, the trend patterns visible in the level data have diminished. Large spikes in some periods indicate fairly extreme daily price changes, but in general, the differenced data meets the conditions for mean stationarity. These results support the use of ARIMA with a first-order differencing.

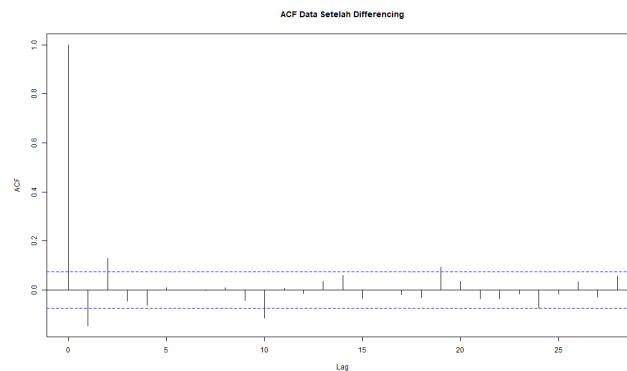


Figure 3. ACF Plot of Data After Differencing

Figure 3 shows the ACF pattern of the data after differencing. Most lags are within the significance threshold, although there are a few that exceed it. This pattern indicates that the correlation of the data after differencing is much smaller compared to the original data. Since the ACF plot does not show a strong long-term declining trend, the data can proceed to the process of selecting a moving average model candidate by considering the results of the AIC and BIC comparison.

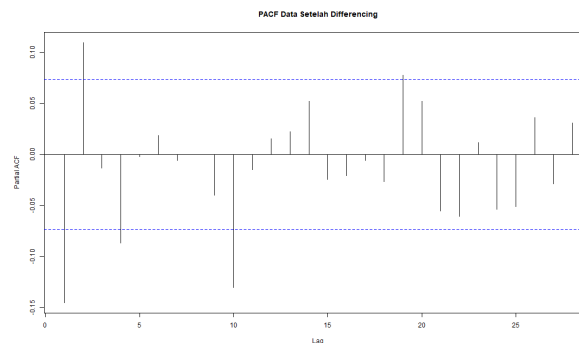


Figure 4. PACF Plot of Data After Differencing

Figure 4 shows the PACF pattern after differencing. There are several early lags that exceed the significance threshold, while most subsequent lags fall within the threshold. This condition

suggests the possible presence of an autoregressive component that needs to be tested through model candidates. However, the final selection is not based solely on the shape of the graph but also on a comparison of model information values and residual diagnostic results.

**Table 3. Comparison of ARIMA Models Based on AIC and BIC**

| <b>Model</b> | <b>AIC</b> | <b>BIC</b> |
|--------------|------------|------------|
| ARIMA(0,1,0) | 5087.7917  | 5092.1338  |
| ARIMA(0,1,1) | 5078.0614  | 5086.7456  |
| ARIMA(0,1,2) | 5070.2351  | 5083.2614  |
| ARIMA(1,1,1) | 5073.7901  | 5086.8164  |
| ARIMA(2,1,2) | 5072.8517  | 5094.5623  |

Table 3: Model comparison shows that ARIMA(0,1,2) has the lowest AIC value, which is 5070.2351. The ARIMA(0,1,1) model has an AIC of 5078.0614, ARIMA(1,1,1) has an AIC of 5073.7901, ARIMA(2,1,2) has an AIC of 5072.8517, while ARIMA(0,1,0) has an AIC of 5087.7917. Based on the AIC criterion, the ARIMA(0,1,2) model was selected as the primary model because it is the most efficient in explaining the data pattern compared to the other candidates.

The Ljung-Box test on the ARIMA(0,1,2) residuals yields a statistic of 14.1216 with a p-value of 0.1675. Since the p-value is greater than 0.05, the model's residuals do not exhibit significant autocorrelation. This indicates that the correlation patterns in the data have been sufficiently captured by the model. However, the Shapiro-Wilk normality test yielded a p-value of 0.0000, indicating that the residuals are not normally distributed. This result is not excluded from the study but is noted as a limitation because stock data often contains spikes influenced by market sentiment and new information.

**Table 4. ARIMA(0,1,2) Model Error Values**

| <b>Model</b> | <b>MAE</b> | <b>RMSE</b> | <b>MAPE</b> |
|--------------|------------|-------------|-------------|
| ARIMA(0,1,2) | 29.2604    | 38.9040     | 5.2949      |

Table 4 The model accuracy evaluation shows that ARIMA(0,1,2) produces an MAE of 29.2604, an RMSE of 38.9040, and a MAPE of 5.2949%. The MAPE value is below the 8% threshold, so the model meets the accuracy criteria established in the study. In other words, the average percentage of prediction error is relatively small, and the model can be used for short-term forecasting of NOBU stock prices.

**Table 5. NOBU Stock Price Forecast Results for the Next 20 Periods**

| <b>Period</b> | <b>Forecast</b> | <b>Lo 80</b> | <b>Hi 80</b> | <b>Lo 95</b> | <b>High 95</b> |
|---------------|-----------------|--------------|--------------|--------------|----------------|
| 1             | 529.2443        | 502.4335     | 556.0550     | 488.2408     | 570.2478       |
| 2             | 530.0279        | 494.6660     | 565.3898     | 475.9465     | 584.1093       |
| 3             | 530.0279        | 485.6673     | 574.3884     | 462.1843     | 597.8715       |
| 4             | 530.0279        | 478.2085     | 581.8473     | 450.7769     | 609.2789       |
| 5             | 530.0279        | 471.6957     | 588.3601     | 440.8165     | 619.2393       |
| 6             | 530.0279        | 465.8404     | 594.2154     | 431.8615     | 628.1943       |
| 7             | 530.0279        | 460.4762     | 599.5796     | 423.6578     | 636.3980       |
| 8             | 530.0279        | 455.4972     | 604.5586     | 416.0430     | 644.0128       |
| 9             | 530.0279        | 450.8305     | 609.2253     | 408.9060     | 651.1498       |
| 10            | 530.0279        | 446.4240     | 613.6318     | 402.1667     | 657.8891       |

|    |          |          |           |           |          |
|----|----------|----------|-----------|-----------|----------|
| 11 | 530.0279 | 442.2383 | 617.8175  | 395.7653  | 664.2905 |
| 12 | 530.0279 | 438.2433 | 621.8125  | 389.6555  | 670.4003 |
| 13 | 530.0279 | 434.4151 | 625,640.6 | 383,8008  | 676.2550 |
| 14 | 530,0279 | 430,7344 | 629,3214  | 378.1716  | 681.8841 |
| 15 | 530,0279 | 427.1854 | 632,870.4 | 372.7438  | 687.3120 |
| 16 | 530.0279 | 423.7548 | 636.3010  | 367.4971  | 692.5586 |
| 17 | 530.0279 | 420.4315 | 639.6243  | 362.4146  | 697.6412 |
| 18 | 530.0279 | 417.2060 | 642.8497  | 357,497.1 | 702.5740 |
| 19 | 530.0279 | 414,0703 | 645.9855  | 352.6861  | 707.3697 |
| 20 | 530.0279 | 411.0172 | 649.0386  | 348.0167  | 712.0391 |

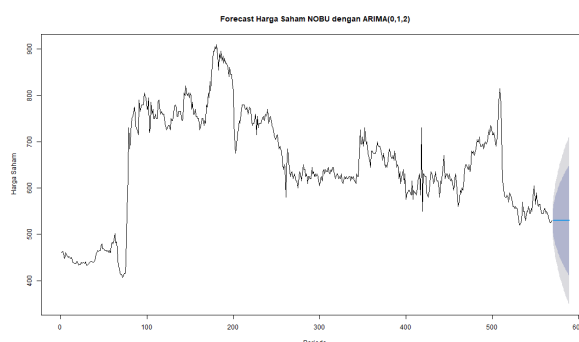


Figure 5. NOBU Stock Price Forecast Chart using ARIMA(0,1,2)

The forecast results for the next 20 periods show that the forecast values move relatively stably around the price of 530. The first period yields a forecast of 529.2443, while the second through the 20th periods move closer to 530.0279. The prediction interval widens over longer periods. This indicates that uncertainty increases as the forecasting horizon extends. Therefore, the ARIMA(0,1,2) forecast results are more appropriate for short-term projections rather than as the sole basis for long-term investment decisions.

## DISCUSSION

The results of the study indicate that NOBU's stock prices were not stationary at the original level but became stationary after the first differencing. This finding aligns with the general characteristics of stock price data, which often follow trends and only stabilize after a differencing transformation. Susanti & Adji (2020) also noted that capital market data must undergo a time series modeling process to allow for a more precise analysis of movement patterns. (Nuralifia & Rodiah, 2025) emphasize that forecasting with ARIMA requires consideration of the data's characteristics before the model is compared to other methods. Thus, the use of first- -differencing in this study can be understood as a necessary statistical step, not merely a technical procedure.

The selection of ARIMA(0,1,2) as the best model is supported by the lowest AIC value compared to other candidate models. This result aligns with Wulandari et al., (2021b), who demonstrated that ARIMA can be used to capture fluctuations in banking stock prices through the model selection process. Sudipa et al. (2023) also concluded that ARIMA can be used for trend forecasting of bank stocks in Indonesia, particularly when models are evaluated based on error rates. Differences in the research subjects indicate that ARIMA can be applied to various banking stocks, but the best model is not always the same because each stock has distinct historical patterns.

A MAPE value of 5.2949% indicates that the ARIMA(0,1,2) model has good accuracy for NOBU data. These results can be compared with the study by Sitompul & Sitepu (2024), which found that ARIMA can produce low MAPE in stock forecasting when the data patterns align with the model's structure. Milniadi & Adiwijaya (2023) also demonstrated that ARIMA can still compete with LSTM models in certain stock categories when evaluated using error metrics. Thus, the findings of this study reinforce the view that classical statistical models remain relevant for stock forecasting, particularly for academic purposes and short-term analysis.

The Ljung-Box test indicates that the residuals do not contain autocorrelation, suggesting the model adequately captures the temporal relationships in the data. Pangaribuan et al. (2023) emphasize that a well-specified ARIMA model must undergo residual testing to ensure that residual patterns are no longer systematic. Fauzani & Rahmi (2023) also highlight diagnostic tests as a crucial component of ARIMA application, as error values alone are insufficient to validate the model's suitability. Based on these results, the ARIMA(0,1,2) model can be said to satisfy the assumption of residual autocorrelation.

However, the model's residuals do not meet the normality assumption based on the Shapiro-Wilk test. This finding should be interpreted critically, as stock prices are often influenced by sudden events that cause the residual distribution to be non-normal. Fadhillah et al. (2024) demonstrate that in banking stock data, hybrid models such as ARIMA-GARCH can be considered when residual volatility becomes a significant issue. Raissa (2025) also compared ARIMA, ARIMA-GARCH, and LSTM in the context of banking stocks, so the results of this study open opportunities for the development of advanced models. Thus, the unmet assumption of residual normality does not mean the research results must be discarded, but rather serves as a note on limitations and a basis for suggestions for future research.

From a fundamental perspective, company performance must serve as the context for interpreting forecast results. Aryanti et al., (2022b) demonstrate that banking ratios such as ROA, ROE, LDR, CAR, and NPL can be correlated with bank stock prices, so price forecasting should not stand alone. In 2025, Nobu Bank reported a 46.30% increase in net profit to Rp481.3 billion, with a CAR of 22.29%, ROA of 1.67%, ROE of 13.07%, and LDR of 83.68%. These conditions indicate relatively positive fundamental support, but stock prices may still fluctuate as the market responds not only to financial performance but also to investor expectations and sentiment.

Forecast results that tend to be stable around the price of 530 indicate that over the next 20 periods, the model does not detect strong signals of an upward or downward trend. This aligns with the nature of ARIMA, Rusyida & Pratama (2020) which emphasizes historical patterns and tends to be conservative when recent data is flat. noted that ARIMA results for stock data can follow historical patterns but remain sensitive to market changes occurring outside past data. Therefore, these forecast results should be used as an additional reference, not as the sole basis for investment decisions.

Compared to previous studies, the contribution of this article lies in its focus on NOBU stock and the transparent presentation of diagnostic results. Purnama & Juliana (2020) utilized ARIMA in predicting the IHSG, whereas this study focuses on a single issuer. Wulandari et al., (2024) applied ARIMA to BCA stock, whereas this study examines a different bank issuer with distinct price fluctuation characteristics. This research adds to the empirical evidence that ARIMA can be applied to banking sector stocks; however, model evaluation must still consider stationarity, autocorrelation, residual normality, and MAPE.

The results indicate that ARIMA(0,1,2) can help investors identify short-term trends in NOBU stock. However, investors should still combine forecasting results with fundamental analysis, market conditions, interest rates, banking sector sentiment, and risk management. Dewi & Pusparini (2024) emphasize that fundamental ratios provide information that investors can use to assess stock prices, while Prastio et al. (2024b) indicate that technical and macroeconomic factors also need to be considered. Therefore, the ARIMA results in this study are more appropriately positioned as an analytical tool rather than direct instructions to buy or sell stocks.

## CONCLUSION

Based on the research results, the daily stock price of PT Bank Nationalnobu Tbk from May 2, 2023, to April 30, 2026, exhibits a fluctuating pattern with an average value of 625.9607 and a standard deviation of 111.0270. The price data was initially non-stationary with an ADF p-value of 0.1847, but became stationary after the first differencing with a p-value of 0.0100. The best model based on the AIC comparison is ARIMA(0,1,2), and the Ljung-Box test yielded a p-value of 0.1675, indicating that the residuals do not contain autocorrelation. Accuracy evaluation yields an MAE of 29.2604, an RMSE of 38.9040, and a MAPE of 5.2949%, so the model meets the criterion of an error rate below 8%. The 20-period forecast indicates that the stock price tends to remain stable around 530, but the prediction interval is widening, so the model is more suitable for short-term forecasting. The main limitation of this study is that the model's residuals do not follow a normal distribution based on the Shapiro-Wilk test, so the forecasting results should still be interpreted with caution. Given these limitations, future research could expand the analytical approach by considering the characteristics of stock data, which tend to be dynamic and sensitive to market changes. The use of methods that are more adaptive to volatility patterns could be an option for obtaining more comprehensive forecasting results. Research development could also be conducted by incorporating supporting information from the company's fundamental side as well as macroeconomic conditions so that the interpretation of stock price movements does not rely solely on historical price data. For investors, the results of this study can serve as one of the considerations in analyzing short-term stock price trends, while still taking into account the company's financial information and overall market conditions. For academics, this study can serve as a foundation for developing research on banking stock forecasting with a wider range of subjects, time periods, and analytical approaches.

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