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Predicting Indonesia's Micro Small Medium Entreprises Stock Price

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A B S T R A C T

The impact of stock prices on new enterprises, notably Micro, Small, and Medium Enterprises (MSMEs), in Indonesia is significant. Given the significance of stock prices for MSMEs, engaging in stock price forecasting is crucial. Several stock price forecasting models exist, but only a limited number are suitable for predicting stock prices using limited samples, such as the stock prices of MSMEs in Indonesia. The limited sample size is because MSMEs are newly established enterprises accessing stock prices. This study aims to predict MSME stock prices in Indonesia, namely SOUL and TGUK. The forecasting model utilized is ARIMA. The results suggest that the ARIMA (0,1,1) model provides the most precise forecast for the stock price of SOUL MSMEs, while the ARIMA (1,1,2) model yields the most outstanding performance for TGUK. Investors can use the forecast results to identify profitable investment opportunities or protect their portfolios from potential losses. Moreover, companies can employ stock price predictions to evaluate their performance, develop financial plans, and allocate resources.

1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are productive businesses owned by individuals or business entities that have met micro-enterprises' criteria (Pan, Xu, & Zhu, 2021). MSMEs play an essential role in the global economy. They contribute to job creation, innovation, and economic growth. (Rana & Choudhary, 2019). MSMEs also provide opportunities for entrepreneurship and support local communities (Pedraza, 2021). Rapid technological advances and increasingly complex global market competition have led MSMEs to expand into the stock market (Angeles, Perez-Encinas, & Villanueva, 2022). The entry of MSMEs into the stock market provides access to a broader range of funding sources and investment opportunities, allowing them to expand their operations and reach new markets. In addition, MSMEs entering the stock market can help increase their visibility and credibility, attracting more investors and potential business partners (ASEAN Coordinating Comittee on MSMEs, 2023). This development also reflects a shift in the perception of MSMEs, now seen as a viable investment option with the potential to grow the Indonesian economy (Patwardhan, 2018).

Currently, two MSMEs from Indonesia have successfully penetrated the stock market. The companies are Platinum Wahab Nusantara (TGUK) and Mitra Tirta Buwana (SOUL). Based on data from the Indonesia Stock Exchange (IDX), Platinum Wahab Nusantara entered the stock exchange on 11 July 2023, while Mitra Tirta Buwana joined on 9 January 2023. Both MSMEs are engaged in the food and beverage sector. Historical data on the daily Closed Stock Price of the two companies can be seen in Figures 1 and 2 below.

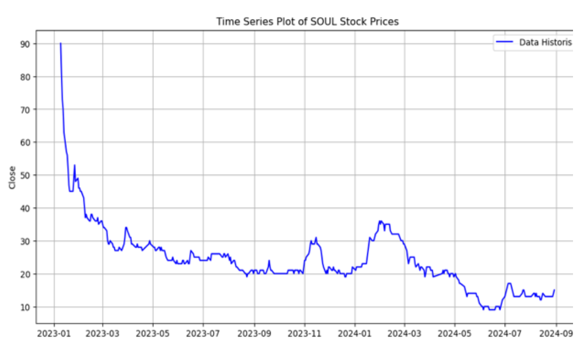


Figure 1. Time Serie Plot of Closed SOUL

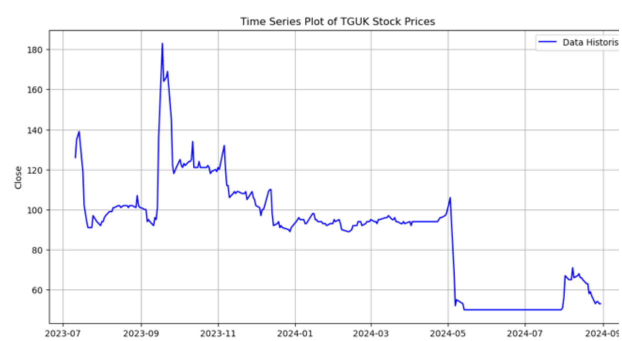


Figure 2. Time Serie Plot of Closed TGUK

Source: investing.com (accessed on 5 September 2024)

Based on Figures 1 and 2, it can be seen that both MSME stocks have experienced a decline in price over time. The persistent downturn in the stock market has an adverse impact on stock liquidity, market concentration, and investor behaviour (Hameed et al., 2010; Z. Zhang, Zhang, Zhang, & A, 2023). These declines also result in an increase in stock market concentration, reflecting an increased level of corporate inequality (Hameed et al., 2010). In addition, persistent price declines are associated with herd behaviour among investors. Stock market declines can lead to increased uncertainty regarding future employment and output fluctuations, which impacts consumer spending and business investment (Wu, Huang, & Ni, 2017). Overall, a continuous decline in the stock market has far-reaching impacts on various aspects of the economy and financial markets.

One strategy to overcome the decline in stock prices is to predict stock prices. Although stock prices are complicated to predict, there are many theories about what affects their movements. Several studies have demonstrated the effectiveness of the ARIMA (AutoRegressive Integrated Moving Average) model in predicting stock prices, underscoring its relevance in financial forecasting. While machine learning algorithms such as LSTM have shown superior performance in some scenarios, ARIMA remains a popular choice due to its convenience and consistent results in stable market conditions (Kuang, 2023; Liu, 2022; Pandey et al., 2023; Xiao et al., 2022). Research by Aditi Singh & Lavnika Markande (2023) and B. Zhang (2023) highlights that although ARIMA may not capture complex patterns as effectively as some newer algorithms, it is highly effective for linear data trends, which are common in financial time series. The studies emphasize ARIMA's utility in scenarios where model simplicity and interpretability are preferred over more complex machine learning models.

PT Platinum Wahab Nusantara Tbk (TGUK) and PT Mitra Tirta Buwana Tbk (SOUL) are companies that have just entered the stock exchange. The historical data from both companies is small (less than 500 samples) for making predictions. The use of small samples in data prediction can have significant negative impacts, such as data unrepresentativeness, overfitting, parameter misestimation, and low prediction confidence level (Barch, 2023; Kokol, Kokol, & Zagoranski, 2022; Zhou, Shao, Liu, & Yang, 2022). The appropriate model for predicting small data samples is the ARIMA model. This is because ARIMA models can capture patterns of trends and fluctuations in data, even with a limited number of observations or small sample size (Hassouna & Al-Sahili, 2020; Kaur, Parmar, & Singh, 2023; Latif et al., 2023; Watson & Nicholls, 1992). This is the same as the characteristics of the historical data of the two MSME companies, which can be seen in Figure 1 and 2. Therefore, the purpose of this paper is to predict the stock price of MSME with small sample size such as PT Platinum Wahab Nusantara Tbk (TGUK) and PT Mitra Tirta Buwana Tbk (SOUL), using the ARIMA model.

The research questions (RQ) in this study are: (1) To develop a stock prediction model for two Indonesian micro, small, and medium enterprises (MSMEs) using the ARIMA model; (2) To assess the efficacy of the developed model in predicting the future stock values of MSME enterprises; and (3) To predict the next 30-day stock price.

RESEARCH METHODS

Research design. This study employs a quantitative methodology to forecast stock prices of micro, small, and medium enterprises (MSMEs) in Indonesia. The selected approach utilizes statistical analysis, specifically ARIMA, evaluated using Phyton. This approach is appropriate for predicting stock price MSMEs because it is capable of capturing patterns of trends and variations in the data, even when there are just a few observations or a small sample size.

Data Collection. The major data utilized in this study was obtained from investing.com. The data consists of daily historical records of the "closed" stock price of two MSME businesses, specifically Platinum Wahab Nusantara (TGUK) and Mitra Tirta Buwana (SOUL). According to records from the Indonesia Stock Exchange (IDX), Platinum Wahab Nusantara was listed on 11 July 2023, whilst Mitra Tirta Buwana was listed on 9 January 2023. The TGUK dataset, consisting of 274 data points, was collected from 11 July 2023 to 30 August 2024. On the other hand, the SOUL dataset was collected from 9 January 2023 to 30 August 2024 and has 389 data points.

Model development. Five stages are conducted to address the study's objectives: stationarity, model selection, analysis, model evaluation, and prediction. The Figure 3 depicted in the accompanying picture illustrates these stages.

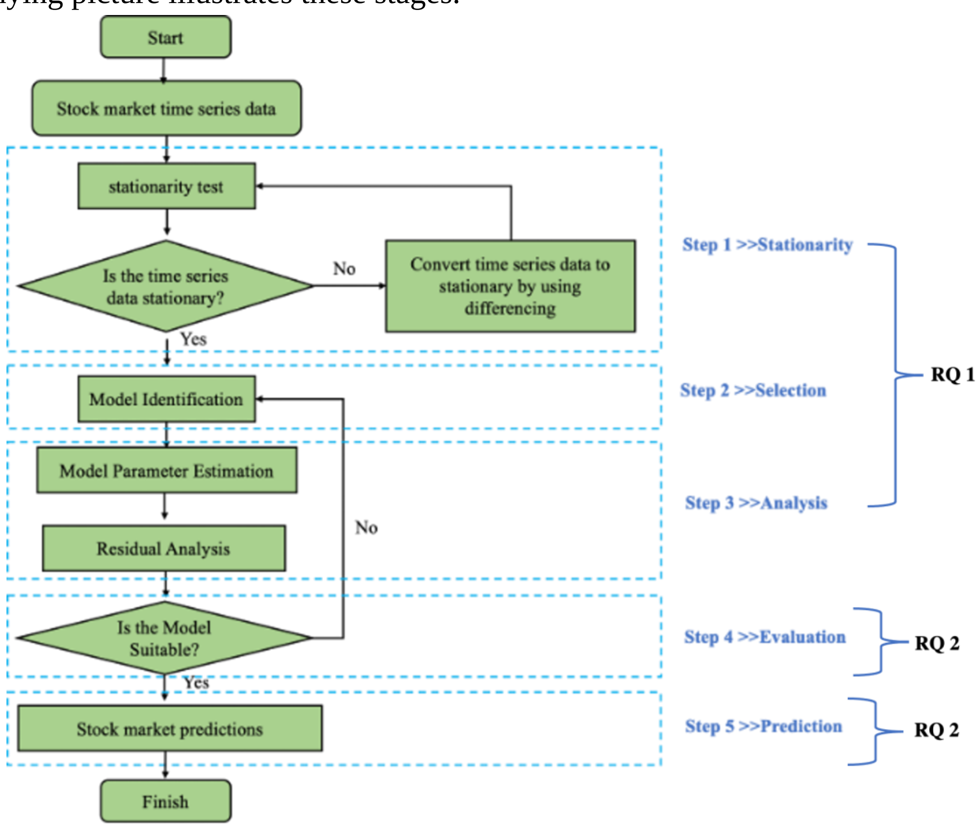


Figure 3. the stages of research

Source: Processed Data, 2024

In this study, the Box-Cox transformation is used to address non-stationarity in the data by stabilizing variance and making the data more normally distributed and ARIMA model determination based on Table 1. The Box-Cox method was devised by Box and Tiao Cox (Hwang & Basawa, 2004) and is represented by equation 1:

$$T(Y_t) = \begin{cases} \dfrac{{Y_t}^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \ln Y_t\,, & \lambda = 0 \end{cases} \qquad (1)$$

Table 1. Determination of ARIMA model
(Fattah, Ezzine, Aman, El Moussami, & Lachhab, 2018)

Process	ACF	PACF
AR (*p*)	Exhibits exponential decay or follows a sinusoidal pattern	Truncated at *p*-th lag
MA (*q*)	Truncated at *q*-th lag	Exhibits exponential decay or follows a sinusoidal pattern
ARMA(*p*,*q*)	Truncated at (*q*-*p*)-th lag	Truncated at (*q*-*p*)-th lag

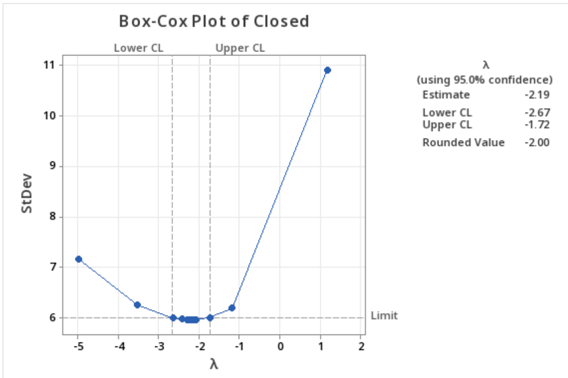
Source: Fattah et al.,2018

The model's forecasting accuracy is assessed using the evaluation methods of Akaike Information Criterion (AIC). This research endeavours to create a precise and resilient forecasting model. The model's purpose is to aid investors, analysts, and policymakers in making well-informed decisions within the dynamic and fast-expanding MSME sector of the Indonesian stock market.

2. RESULTS & DISCUSSION

In this section, we present results and discussions based on daily historical data of the closing stock prices of two micro, small, and medium enterprises (MSMEs), namely Platinum Wahab Nusantara (TGUK) and Mitra Tirta Buwana (SOUL). The ARIMA model is applied to both datasets to predict future stock prices, despite the challenges posed by the limited sample size. There are 5 steps in answering this research question, each of which will be explained in the following sub-sections.

Stationarity. The first step in forecasting using ARIMA is to check the data's stationarity. Figures 1 and 2 show that the data is not stationary in variance. The following Box-Cox Test also proves this.



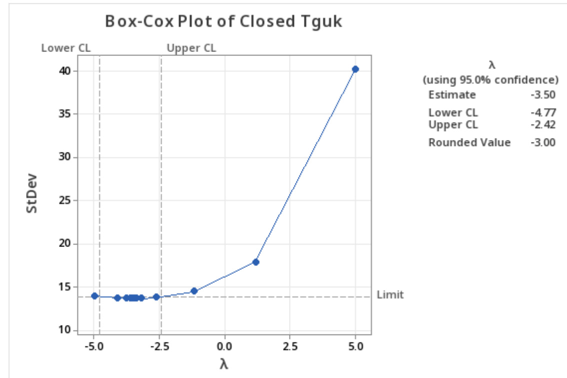
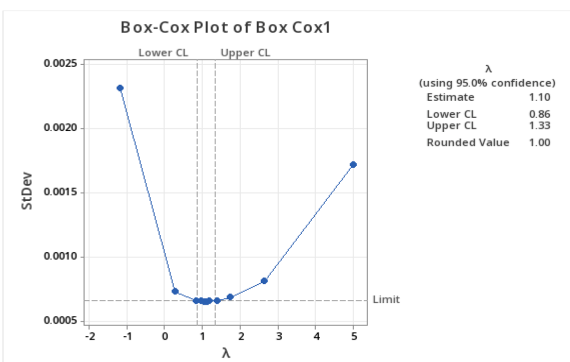


Figure 4. Box-Cox of SOUL data

Figure 5. Box-Cox of TGUK data

Source: Processed Data, 2024

Figures 4 and 5 indicate that the Rounded value is -2.00 and -3.00, respectively. Historical data on SOUL and TGUK stocks can be deemed non-stationary. Hence, it is imperative to carry out a differencing procedure. The process of differentiation is performed utilising the Box-Cox method, and the outcomes are presented in the subsequent Figure 6 and 7.



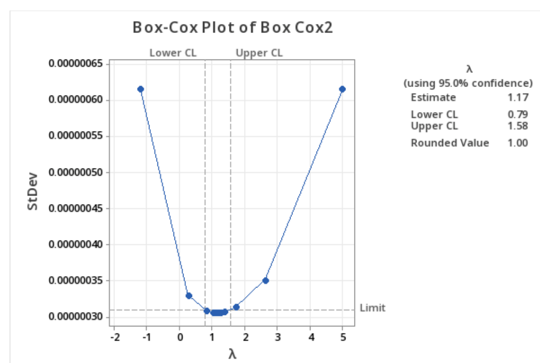


Figure 6. First differencing results using Box-Cox of SOUL data

Figure 7. First differencing results using Box-Cox of TGUK data

Source: Processed Data, 2024

The first differencing results show that both SOUL and TGUK already have a rounded value of 1.00, meaning that the data is stationary after differencing once.

Selection model. The second step in forecasting the number of visitors is to develop the ARIMA model. The process of developing ARIMA is done by building ACF and PACF plots.

Visualization of the results of the ACF and PACF plots of stock price SOUL data is depicted in Figures 8.

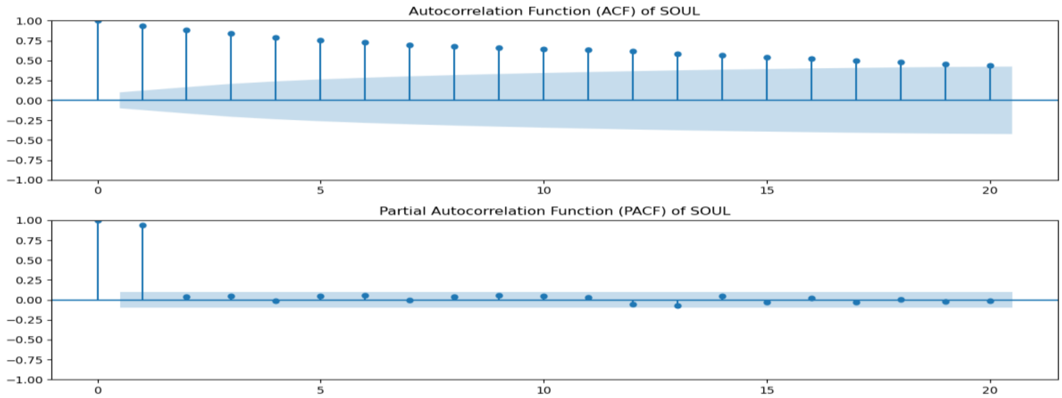


Figure 8. ACF and PACF plots of stock price SOUL

Source: Processed Data, 2024

The ACF plot decreases exponentially in SOUL stock, and the PACF plot also has a sine wave pattern. When viewed from the rules of Table 1, there are several possible models, namely ARIMA (0,1,1), and ARIMA (0,1,2). The ACF and PACF plots for the TGUK stock price data are shown in Figures 9.

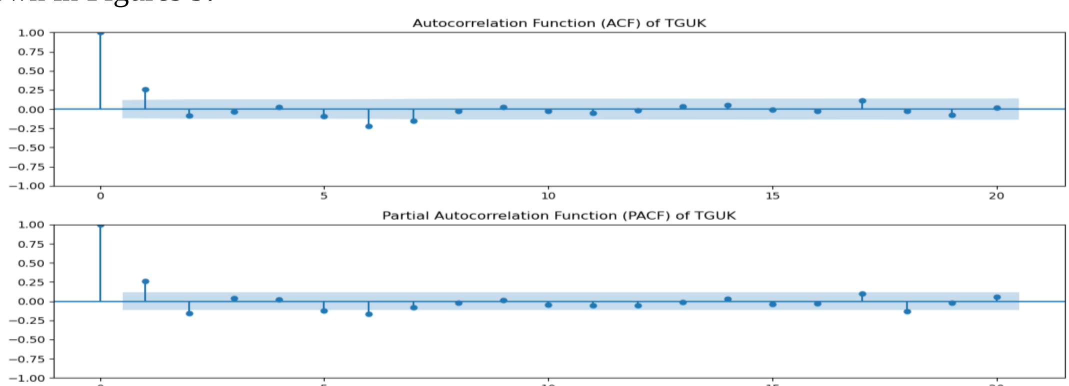


Figure 9. ACF and PACF plots of stock price TGUK

Source: Processed Data, 2024

The ACF and PACF plots exhibit a sinusoidal pattern. When considering the guidelines outlined in Table 1, multiple potential models can be used, specifically ARIMA (2,1,2), ARIMA (1,1,2), ARIMA (0,1,2), ARIMA (1,1,1), and ARIMA (0,1,1).

Analysis. Based on the outcomes of model identification, the subsequent task involves computing the estimates of model parameters and conducting tests on them. The estimation test is conducted by considering the hypothesis stated below. Level of significance: 5%, the parameter test output is shown in Table 2 and 3.

H_0 : ARIMA model with non-significant parameters

H_1 : ARIMA model with significant parameters

Table 2. Parameter test output of ARIMA model for SOUL data

	Type	Coef	SE Coef	T-Value	P-Value	Test Result
ARIMA (1,1,1)	AR 1	0.9944	0,0149	66.52	0,000	Significant
	MA 1	0.7685	0.0338	22.76	0.000	Significant
	Constant	-0.0009	0.0146	-0.06	0.953	Not Significant
ARIMA (0,1,1)	MA 1	-0.2917	0.0486	-6.01	0.000	Significant
	Constant	-0.1976	0.0842	-2.35	0.019	Significant
ARIMA (1,1,0)	AR 1	0.3614	0.0472	7.65	0,000	Significant
	Constant	-0.1305	0.0640	-2.04	0,042	Significant

Source: Processed Data, 2024

A significant model is defined as a model with a P-value lower than the predetermined significance criterion of 5%. Based on the study results presented in Table 2, it can be inferred that the major models for SOUL prediction are ARIMA (0,1,1), and ARIMA (1,1,0) models.

Table 3. Parameter test output of ARIMA model for TGUK data

	Type	Coef	SE Coef	T-Value	P-Value	Hasil Uji
ARIMA (2,1,2)	AR 1	0.8335	0.0624	13.36	0.000	Significant
	AR 2	-0.0644	0.0671	0.96	0.338	Not Significant
	MA 1	0.57492	0.00307	187.39	0.000	Significant
	MA 2	0.4299	0.0287	15.00	0.000	Significant
	Constant	-0.02184	0.00255	-8.57	0.000	Significant
ARIMA (1,1,2)	AR 1	0.9110	0.0303	30.04	0.000	Significant
	MA 1	0.641663	0.000174	3683.91	0.000	Significant
	MA 2	0.38021	0.00320	118.69	0.000	Significant
	Constant	-0.008915	0.000968	-9.21	0.000	Significant
ARIMA (0,1,2)	MA 1	-0.3033	0.0607	-4.99	0.000	Significant
	MA 2	0.0548	0.0607	0.90	0.368	Not Significant
	Constant	-0.258	0.418	-0.62	0.537	Not Significant
ARIMA (1,1,1)	AR 1	-0.117	0.184	-0.64	0.525	Not Significant
	MA 1	-0.429	0.167	-2.56	0.011	Significant
	Constant	-0.287	0.487	-0.60	0.549	Not Significant
ARIMA (0,1,1)	MA 1	-0.3278	0.0574	-5.71	0.000	Significant
	Constant	-0.256	0.444	-0.58	0.565	Not Significant

Source: Processed Data, 2024

Table 3 indicates that the primary model for predicting TGUK is the ARIMA (1,1,2) model.

Evaluation. The analysis focuses on determining the optimal model based on the model with the lowest the Akaike Information Criterion (AIC) value. The AIC values of the prominent models employed for predicting the stock price of SOUL are presented in Table 4.

Table 4. The value of the AIC model for stock price forecasting SOUL

Model	AIC
ARIMA (1,1,1)	1263.33
ARIMA (0,1,1)	1262.61
ARIMA (1,1,0)	1340.07

Source: Processed Data, 2024

Table 4 shows that the ARIMA (0,1,1) model shows the lowest AIC value among all models. Thus, it can be concluded that the ARIMA (0,1,1) model is the most optimal model for predicting SOUL stock prices in the future. This is reinforced by the results of the Ljung-Box test analysis presented in Table 5. The ARIMA model is effective and feasible to use for forecasting if it passes the Ljung-Box model adequacy test.

Table 5. Modified Box-Pierce (Ljung-Box) Chi-Square Statistic ARIMA (0,1,1)

Lag	12	24	36	48
Chi-Square	41.71	54.07	61.48	73.75
DF	10	22	34	46
P-Value	0.056	0.060	0.093	0.138

Source: Processed Data, 2024

The Ljung-Box results in Table 5 indicate that the P-Value is more than 5%. This suggests that the ARIMA (0,1,1) model is a suitable choice for forecasting the stock price of SOUL. The forecasting model is represented by equation (2) below.

$$Y_t = -0.1976 + Y_{t-1} + \varepsilon_t - 0.2917\varepsilon_{t-1} \qquad (2)$$

While the AIC value of the TGUK stock price prediction model is displayed in Table 6 below.

Table 6. The value of the AIC model for stock price forecasting TGUK

Model	AIC
ARIMA (2,1,2)	1730.5456
ARIMA (1,1,2)	1727.6228
ARIMA (0,1,2)	1728.1092
ARIMA (1,1,1)	1733.7486
ARIMA (0,1,1)	1751.215

Source: Processed Data, 2024

According to Table 6. the ARIMA (1,1,2) model has the lowest AIC value among all the models. Thus, it can be inferred that the ARIMA (1,1,2) model is the most optimal choice for predicting TGUK stock prices. This is further supported by the Ljung-Box model test findings displayed in Table 7. The Ljung-Box results in Table 7. suggest that the P-value exceeds 5%. Therefore, it can be inferred that the ARIMA (1,1,2) model is an appropriate selection for predicting the stock price of TGUK. Equation (3) below represents the forecasting model.

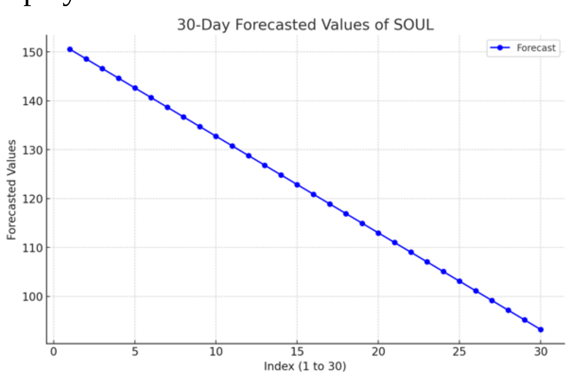
Table 7. The value of the AIC model for stock price forecasting TGUK

Lag	**12**	**24**	**36**	**48**
Chi-Square	10.20	21.76	29.14	39.27
DF	8	20	32	44
P-Value	0.251	0.354	0.612	0.674

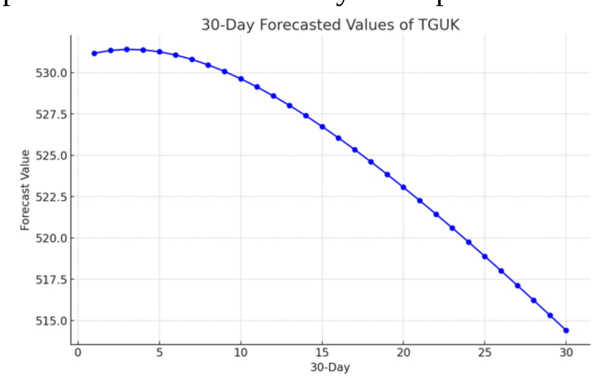
Source: Processed Data, 2024

$$Y_t = Y_{t-1} + 0.9110(Y_{t-1} - Y_{t-2}) - 0.008915 + \varepsilon_t + 0.641663\varepsilon_{t-1} + 0.38021\,\varepsilon_{t-2} \quad (3)$$

Prediction. The final stage of this process is forecasting the prices of SOUL and TGUK stocks. The ARIMA (0,1,1) model is employed for predicting the SOUL stock price, whereas the ARIMA (1,1,2) model is utilized for forecasting the TGUK stock price. Figures 10 and 11 display the outcomes of the SOUL and TGUK predictions the next 30-day stock price.



Figures 10. Plot of the next 30-day stock price prediction of SOUL



Figures 11. Plot of the next 30-day stock price prediction of TGUK

Source: Processed Data, 2024

Stock price prediction is crucial for investors, traders, UMKM, and even governments. It aids in formulating intelligent investing choices, devising efficient trading tactics, and enhancing risk management. The ARIMA model is a suitable forecasting method for stock prices with limited samples, such as SOUL and TGUK stocks. Despite sample size limitations, the first question focuses on developing a stock prediction model using ARIMA. This study uses ARIMA (0,1,1) for SOUL stock and ARIMA (1,1,2) for TGUK stock. Despite the limited sample size, the applied ARIMA model could effectively capture the patterns of both stocks. The development process confirms that ARIMA models can function well even when the available data is not abundant, as shown in several previous studies using ARIMA on datasets of limited size (D. et al., 2024; Garner, Pan, & Shi, 2024; Li, 2023; Liang, Wu, & Zhao, 2024).

The second question is related to the model's effectiveness in predicting future stock prices. The effectiveness of the ARIMA model in this study is measured using the Akaike Information Criterion (AIC) value, where a lower AIC value indicates that the model used has a better level of accuracy. The ARIMA models applied to SOUL (0,1,1) and TGUK (1,1,2) stocks show low AIC values, indicating adequate predictive ability. This is based on the findings of Tan & Biswas (2012) which states that the smaller the AIC value, the more effective a model is in predicting results. Based on the AIC value, the ARIMA model can provide a reasonably accurate picture of the stock price trend for the two MSMEs, although there is a downward trend in the prices of the two stocks. This decline signals companies to take precautionary measures, such as improving financial strategies or re-evaluating business measures.

In the third question, stock price predictions for the next 30 days provided important insights for both companies. The prediction results for SOUL stock show a steady downward trend, while TGUK shows a sharp decline after an initial stability phase. The company can use the predicted decline in SOUL's share price to analyse the causes, improve internal aspects, or re-evaluate investment strategies. The more significant decline in TGUK's share price after initial stability can also signal companies to adjust their strategies proactively. In the context of MSMEs, share prices play an important role in financial strategies and long-term expansion plans, which is in line with research by Iskandar et al., (2019), which states that share price movements are closely related to the welfare of the company and society as a whole.

Overall, the results of this study show that the ARIMA model is an effective method to predict stock prices in the short term despite the limited data available. These predictions have significant practical implications for MSME companies in formulating better business strategies in the future. With the foresight of stock price movement trends, companies can make more informed decisions regarding investment, risk management, and expansion strategies. According to Fattah, Ezzine, Aman, El Moussami, & Lachhab (2018) accurate predictions from time series models such as ARIMA help in short-term decision-making and provide a competitive advantage in overall business planning. For MSMEs, which often operate with limited resources, the ability to predict stock price fluctuations with simple models such as ARIMA becomes crucial to remain competitive in an often-volatile market. Therefore, this research reinforces the validity of using ARIMA in the context of MSME stocks and offers an essential foundation for implementing more intelligent and informed financial strategies in the micro, small, and medium enterprise sectors.

3. CONCLUSIONS

The conclusion of this study shows that the ARIMA model is an effective method for predicting stock prices in the short term, despite sample size limitations, as found for SOUL and TGUK stocks, two MSME companies in Indonesia. The ARIMA (0,1,1) model for SOUL stock and ARIMA (1,1,2) for TGUK stock successfully captured the pattern of stock price movements, and the low Akaike Information Criterion (AIC) value indicates an adequate level of prediction accuracy. Although the predictions indicate a downward trend in share prices, this information has significant practical implications for MSME companies in formulating better business strategies, including financial planning, risk management, and expansion.

In addition, the share price predictions for the next 30 days provide essential insights for both companies to take proactive preventive measures, such as improving internal aspects and reassessing investment strategies. In the context of MSMEs that often operate with limited resources, the ability to predict stock price fluctuations using simple models such as ARIMA is crucial in maintaining competitiveness in a volatile market. As such, this study reinforces the validity of ARIMA models in predicting MSME share prices and provides a solid foundation for implementing more informed and intelligent financial strategies in the micro, small and medium enterprise sectors.

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