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Dynamic Analysis of the Relationship Between Market Sentiment and Stock Volatility at the Bei Using the Auto Regressive Integrated Moving Average (ARIMA) Model

Hariyanti[1], Rokhadi[2], Vena Vilenia[3].
[1]Sekolah Tinggi Ilmu Ekonomi Muhammadiyah Tuban, Tuban, Indonesia, hariyantidarmawan@gmail.com
[2]Sekolah Tinggi Ilmu Ekonomi Muhammadiyah Tuban, Tuban, Indonesia, rokhadi101074@gmail.com
[3]Sekolah Tinggi Ilmu Ekonomi Muhammadiyah Tuban, Tuban, Indonesia, venatbn61@gmail.com

Corresponding Author: hariyantidarmawan@gmail.com[1]

Abstract: This study aims to analyse the dynamic relationship between market sentiment and stock volatility on the Indonesia Stock Exchange (IDX) using the Autoregressive Integrated Moving Average (ARIMA) model. The research method used is a quantitative method with a causality approach using secondary data in the form of time series data of quarterly financial reports of PT Adhi Karya for the period 2008-2023, which is analysed through the ARIMA model for forecasting and selecting the best model based on statistical criteria. The ARIMA (1, 1, 1) model effectively represents the historical data pattern of quarterly assets of PT United Tractor with a stable trend and a slight gradual increase for the period December 2024 to December 2026. However, this model has limitations in capturing more complex variations or dynamics in the data. Accurate ARIMA models help maintain financial market stability, support efficient investment decision-making, and provide insights for macroeconomic policy planning that drives economic growth. In addition, reliable predictions increase investor confidence, both domestic and foreign, thereby strengthening financial sector risk management and encouraging investment for sustainable economic development.

Keyword: ARIMA Model, Market Sentiment, Stock Volatility

INTRODUCTION

Capital market activity in Indonesia is growing (Anhar et al., 2024). IDX data (2022) reported that the JCI performance reached a level of 6,850.52 on 28 December 2022 and increased by 4.09 per cent compared to the previous period. Indonesia's capital market activity showed positive growth, as reflected by several key performance indicators. The Jakarta Composite Index (JCI) reached the level of 6,850.52 on 28 December 2022, an increase of 4.09% compared to the position on 30 December 2021. The JCI also recorded a record high on 13 September 2022 by reaching the level of 7,318,016. On the other hand, market capitalisation on 28 December 2022 reached IDR9,509 trillion, an increase of 15.2% compared to the position at the end of 2021 which was IDR8,256 trillion. This market capitalisation had recorded a record high of IDR9,600 trillion on 27 December 2022. This achievement is the highest since the privatisation process of the Stock Exchange in 1992 and demonstrates the competitiveness of the market.

Market sentiment reveals that investor sentiment can be interpreted as a form of optimism (trust) or pessimism held by an investor during future stock market activity (Ryu et al., 2017). An investor determines his investment decisions, both his sentiment and state of mind can influence these decisions and his transaction activities in investing in stocks (Chen & Haga, 2021). Investor sentiment itself can be interpreted as the level of optimism or pessimism held by investors towards future stock market activity. Investor sentiment has an influence on investment decisions and transaction activities (Dai & Yang, 2018). Stock volatility shows a negative influence on investment decisions (Ryu et al., 2017). However, another previous study showed that asset growth has no significant effect on stock price volatility. The study added several control variables to explore the relationship between stock price volatility and dividend yield. One of the methods used in this analysis is the Autoregressive Integrated Moving Average (ARIMA) model.

ARIMA methods have the advantage of identifying and modelling trends well, but have limitations, especially in the selection of appropriate parameters and interpretation of the results (Suhermi et al., 2018). ARIMA offers advantages over simpler methods such as benchmark analysis by considering underlying trends and patterns in time series data (Nanlohy, 2021). However, the effectiveness of its ARIMA depends on the characteristics of the data. For complex patterns or situations involving many variables, machine learning may outperform ARIMA (Kontopoulou et al., 2023). The choice between these two approaches depends on the data specifications, objectives, and analyses, as well as the need for interpretation versus complexity. As investors make their investment decisions, both their sentiment and state of mind can influence those decisions as well as their transaction activity in investing in stocks (Lim & Kim, 2019). Investor sentiment itself can be defined as the level of optimism or pessimism held by investors towards future stock market activity (Qi et al., 2018). Investor sentiment has an influence on investment decisions and transaction activity.

Based on the above, it can be seen that the growth of the capital market in Indonesia is supported by the positive performance of various indicators, such as the increase in JCI, the increase in market capitalisation, and investor participation. However, stock volatility and investor sentiment remain significant factors in influencing investment decisions. On the other hand, the use of analytical methods such as ARIMA provides deeper insights into historical data patterns, although it has limitations in more complex situations. It is important to understand the relationship between investor sentiment, stock volatility and other factors such as dividend yield to provide a comprehensive view of capital market dynamics. This research is expected to contribute in several aspects. First, it deepens the understanding of the relationship between investor sentiment, stock volatility, and investment decisions in the Indonesian capital market. Second, it provides empirical analysis that can be used to strengthen investment strategies based on market dynamics. Third, this study can also provide practical recommendations for investors, regulators, and market participants to manage risks and maximise opportunities in the face of market volatility challenges. The results of this study are expected to be not only theoretically relevant, but also practically useful for the development of a more stable and competitive Indonesian capital market. The introduction section must contain justifications regarding the urgency and reasons why the research was carried out. The novelty of research supported by relevant theory and previous research must be written clearly. This section is also obliged to explain the relationship between variables, relevant research results, and supporting data (if any). This section is closed with the aim of research or a statement of the research problem.

METHOD

This study uses a type of causality research that tests the relationship between more than one variable (Imfrianti Augtiah et al., 2024; Kumala et al., 2023). The data used in this study are time series data, namely the financial statements/asset data of PT Adhi Karya from 2008 to 2023. The data is also a type of secondary data, because researchers do not get it directly from the field but from the company's database online (Rohman & Saefudin, 2024). The variable used in this study is a quantitative approach. Quantitative research is a research method that uses data in the form of numbers and is measured and then processed and analysed to obtain scientific information behind the numbers. The variables used in this study are quarterly financial/asset data of PT Adhi Karya 2008-2023. The analysis method used to determine the monthly sales forecasting model in the coming period. The steps of the ARIMA modelling analysis carried out are as follows:

1. Identification by looking at data stationarity in graphical form using time series plots. If the data is not stationary to the variant, it is necessary to do a Box-Cox transformation and if it is not stationary to the mean, it is necessary to do differencing.
2. Make an ACF (Autocorrelation Function) plot and a PACF (Partial Autocorrelation Function) plot. Stationarity can be seen from the initial data, the data is said to be stationary to the mean if the ACF plot drops quickly to zero significantly and vice versa.
3. Make ACF and PACF plots based on data that has been stationary both variant and mean.
4. Parameter estimation of the transient ARIMA model. The ARIMA model can be estimated by looking at the ACF and PACF plots that come out of the confidence interval. The lag is used to determine the order of the provisional ARIMA model. The lag in the ACF plot is used to determine the MA model (q-order), while the PACF plot is used to determine the AR model (p-order).
5. Parameter significance test, to see whether the parameters of the estimated model (point. 4) are significant or not. If the results are significant, we can continue.
6. Residual Diagnostic Test: The assumptions that must be met in an ARIMA model that has been significant are normally distributed residuals and white noise. The results obtained must be significant and fulfil the residual diagnostic test assumptions.
7. Best Model Selection: The best model is selected based on the results of the minimum AIC, SBC, MAPE and RMSE criteria. Because the smaller the error obtained the better the result. So, later from several suitable models only one is chosen the best.
8. Forecasting data for the next 9 months: Perform forecasting based on the best model that has been obtained.

RESULTS AND DISCUSSION

Stationarity Testing

Before modelling, it is necessary to fulfil the assumptions of stationarity in variance and average. In ARIMA Box-Jenkins modelling, sample data is divided into two groups, namely in sample and out sample data (Karia et al., 2016). Of the total data of 64 data, 55 data as in sample and 9 data as out sample. Stationarity in time series is when there is no significant change in the data (Bogusz, 2015). In a data, it is possible that the data is not stationary in variance or average. The following is a time series plot for quarterly financial/asset data of PT Adhi Karya. From the plot, it can be seen that the pattern on the time series plot has been stationary in variance and mean or not. Furthermore, testing is carried out to see stationarity in variance with Box-Cox transformation.

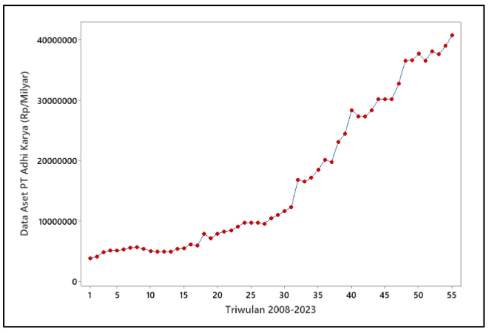


Figure 1. Time Series Plot of Adhi Karya Asset Data

Based on Figure 1 Time Series Plot for quarterly financial/asset data of PT Adhi Karya shows that the plot indicates that it is not yet stationary in variance or average where the observation points experience a sharp increase and decrease. In order to clarify the estimation of stationary to variance, it can be seen in the Box-Cox plot.

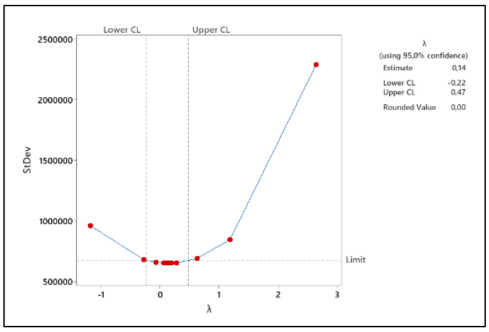


Figure 2. Cox Box Plot of Untransformed Data

Figure 2 shows that the quarterly financial/asset data of PT Adhi Karya has not been stationary in variance with a rounded value of 0.00 which is between the lower limit of -0.22 and the upper limit of 0.47. So, it is necessary to transform the data. Here are the results of the Box Cox transformation.

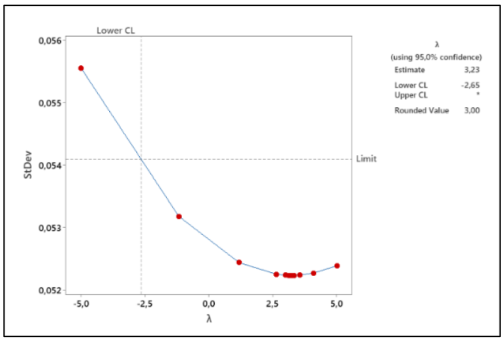


Figure 3. Cox Box Plot Data After Transformed

Figure 3 shows that after transformation, the quarterly financial/asset data variables of PT Adhi Karya are stationary in variance with a rounded value of 3.00 which is between the lower limit of -2.65 and the upper limit of infinity. So, it can be said that the data is stationary in variance. After checking the stationarity of the data in the variant, the next step is to check the stationarity in the average. To determine stationarity on average, statistical testing can be done with the Augmented Dicky Fuller Test on the data.

Table 1. Augmented Dicky Fuller Test Results

Test Statistic	P-value	Result Decision	Description
-0.218019	0.936	Fail to reject H_0	Data is not stationary at the mean

Based on Table 1 on statistical testing with Augmented Dicky Fuller, the p-value is 0.936, which means that it fails to reject H0 so that the quarterly financial / asset data of PT Adhi Karya is not yet stationary on average. So that further differencing is needed so that the data is stationary in variance and average. However, previously the ACF and PACF plots were checked to determine the temporary ARIMA model.

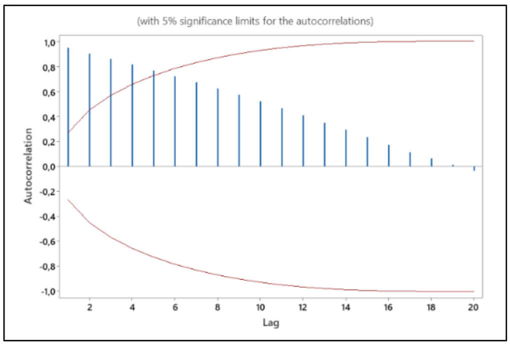


Figure 4. ACF Plot of Quarterly Asset Data of PT Adhi Karya

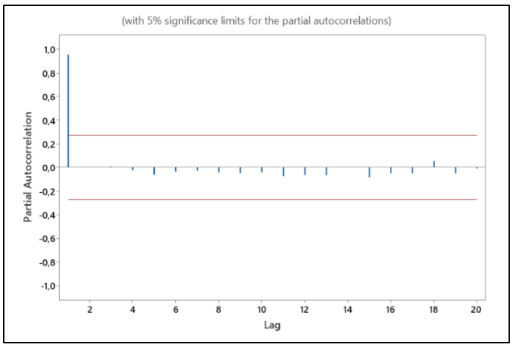


Figure 5. PACF Plot of Quarterly Asset Data of PT Adhi Karya

Based on Figures 4 and 5 it can be seen that the ACF and PACF plots for PT Adhi Karya's quarterly financial / asset data experience cut off or lag out. In the ACF plot the pattern drops exponentially even though there are lags that come out of the confidence interval, namely lags 1, 2, 3, 4 and 5. Similarly, Figure 5 in PACF shows that there is a lag that comes out, namely at lag 1.

Parameter Estimation of ARIMA Model

Before estimating the initial ARIMA model, observations are made on the ACF and PACF plots that have been stationary both variants and averages listed in Figures 4.4 and 4.5. In the initial estimation of the ARIMA model, the temporary models for PT Adhi Karya's quarterly asset data are ARIMA (1 1 0), ARIMA (0 1 5) or ARIMA (1 1 5). The next step will be the parameter significance test.

Parameter Significance Test

After determining the ARIMA model, namely the ARIMA (1 1 0), ARIMA (0 1 5) or ARIMA (1 1 5) model, the next step is to estimate the parameters whether the model is significant or not. Parameters that are not significant or p-value < α to get parameters that are significant to the model. This test is carried out with the following hypothesis.

Table 2. Parameter Significance Test of Quarterly Asset Data of PT Adhi Karya

Model	Type	Coef	SE Coef	T	P-value	Description
ARIMA (1 1 0)	AR 1	-0.219	0.135	-1.62	0.112	Not Significant
ARIMA (0 1 5)	MA 5	0.327	0.139	2.35	0.023	Significant
ARIMA (1 1 5)	ARIMA 5	0.430	0.148	2.90	0.006	Significant

Table 2 shows that all parameters in the initial ARIMA model are significant except ARIMA (1 1 0). It can be seen from the table that the ARIMA (1 1 0) model has a P-value greater than α, namely 0.05. Thus, the model is excluded and no further analysis is continued.

Residual Diagnostic Test

Next is to perform diagnostic testing which includes testing the residuals for normal distribution and white noise.

Normal Distribution Test

In time series analysis, residuals are assumed to be normally distributed. The following are the output results from minitab.

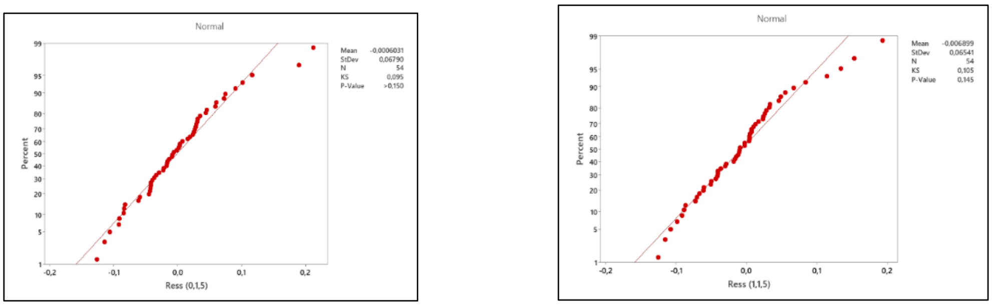


Figure 6. Normal Distribution Test, a) ARIMA (0 1 5) and b) ARIMA (1 1 5)

Based on Figure 6 shows that the shape of the residual plot 4.6 a), and b) form a diagonal straight line. So, it can be said that the residuals are normally distributed. However, visual observation will provide subjective conclusions and differ from one researcher to another. So, more details will be presented p-value in Table 3 Normal distribution hypothesis testing as follows.

Table 3. Normal Distribution Test on Residuals

Conjecture Model	KS	P-*value*	Normal Distribution
ARIMA (0 1 5)	0.095	0.150	Yes
ARIMA (1 1 5)	0.105	0.145	Yes

Based on table 3, the p-value of each residual ARIMA (0 1 5) and ARIMA (1 1 5) is greater than 5%, namely 0.150 and 0.145. This means that the residuals have met the normal distribution assumption.

White Noise Test

In addition to the normal distribution test, the residuals are assumed to be independent and identical, so the residuals must meet the white noise assumption. So, it is necessary to use the Ljung-Box statistics test to see that the residuals have met the white noise requirements (Lee, 2022). The hypothesis in this test is as follows.

Table 4. Ljung-Box Test Output Quarterly Asset Data of PT. Adhi Karya

Model	Lag	Chi-Square	DF	P-value	Description
ARIMA (0 1 5)	12	2.09	6	0.911	White Noise
	24	21.15	18	0.272	White Noise
	36	27.45	30	0.599	White Noise
	48	34.65	42	0.782	White Noise
ARIMA (1 1 5)	12	1.84	5	0.871	White Noise
	24	19.75	17	0.287	White Noise
	36	25.69	29	0.642	White Noise
	48	32.37	41	0.830	White Noise

It can be seen from table 4 that all ARIMA (0 1 5) and ARIMA (1 1 5) models with each lag have a p-value greater than α of 5% so that the decision fails to reject H0 and it can be said that the residual requirements are white noise. So, only these two models can be continued in the selection of the best model.

Best Model Selection

In determining the best model from several selected models using in-sample and out-sample criteria. Some in-sample criteria include AIC and SBC while out-sample includes MAPE and RMSE.

Table 5. Best Model Selection

Criteria	ARIMA (0 1 5)	ARIMA (1 1 5)
Normal Distribution	Yes	Yes
White Noise	Yes	Yes
AIC	1680.09	1681.89
SBC	1692.02	1695.81
MAPE	13.18%	14.44%
RMSE	4910131.713	5344499.837

Based on Table 5, it is concluded that all models meet the residual criteria for normal distribution and white noise. Furthermore, from the in-sample criteria using the AIC and SBC values, the minimum value is the ARIMA (0 1 5) model. While the out-sample criteria of MAPE and RMSE values, the minimum value is also found in the ARIMA (0 1 5) model. So, it can be concluded that the best model based on the fulfillment of all criteria is ARIMA (0 1 5). The ARIMA model for quarterly financial/asset data of PT Adhi Karya is modeled as follows.

$$Zt = 0{,}044 + Z_{t-1} + 0{,}243a_{t-1} - 0{,}160a_{t-2} - 0{,}114a_{t-3} - 0{,}254a_{t-4} + 0{,}327a_{t-5} + a_t$$

Forecasting

After analyzing using ARIMA with a long enough step, the best model was finally obtained. The best model of the best obtained is ARIMA (0 1 5), then the forecasting results are obtained for the quarterly financial / asset data of PT Adhi Karya. The following are the results of the forecast for the next 9 months which will be presented in Table 6 as follows.

Table 6. Forecast Value of Quarterly Asset Data of PT Adhi Karya (Rp/billion)

Month	Data Projection	Forecasting Results	Lower Limit	Upper Limit
March'24	39,900,337	41,442,179	39,113,412	43,770,947
June'24	37,682,562	42,125,470	38,832,095	45,418,844
Sept'24	37,682,562	42,808,760	38,775,216	46,842,304
Des'24	37,682,562	43,492,050	38,834,515	48,149,586
March'25	39,986,417	44,175,341	38,968,058	49,382,623
June'25	39,151,850	44,858,631	39,154,339	50,562,924
Sept'25	39,345,389	45,541,922	39,380,582	51,703,261
Des'25	39,418,721	46,225,212	39,638,463	52,811,961
March'26	40,492,030	46,908,502	39,922,200	53,894,805

The following are the plot results between the projection and forecast data from Table 4.6 presented in Figure 7.

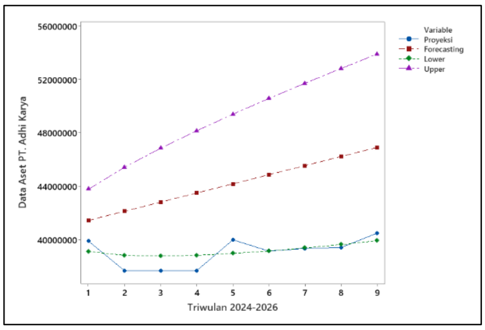


Figure 7. Plot of Projected Data and Forecasting Quarterly Assets of PT Adhi Karya

Based on figure 7 the results of the forecast value are obtained which are between the upper limit and the lower limit. PT Adhi Karya's quarterly asset forecasting tends to always be above its projection data and always tends to increase in each quarter. However, if you look at the plot of the forecast results with the projection data, it is not good because it tends to be monotonous (constant).

Stationarity Testing

Before modeling, it is necessary to fulfill the assumptions of stationarity in variance and average. In ARIMA Box-Jenkins modeling, sample data is divided into two groups, namely in sample and out sample data. Of the total data of 71 data, 62 data as in sample and 9 data as out sample. Stationarity in time series is when there is no significant change in the data (Zuo, 2019). In a data, it is possible that the data is not stationary in variance or average (Rivera, 2015). The following is a time series plot for quarterly financial/asset data of PT United Tractor. From the plot, it can be seen that the pattern on the time series plot has been stationary in variance and mean or not. Furthermore, testing is carried out to see stationarity in variance with Box-Cox transformation.

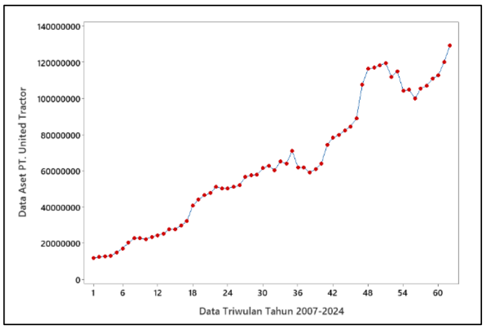


Figure 8. Time Series Plot of Asset Data of PT United Tractor

Based on Figure 8 Time Series Plot for quarterly financial/asset data of PT United Tractor, it shows that the plot indicates that it is not yet stationary in variance or average where the observation points experience a sharp increase and decrease. In order to clarify the estimation of stationary to variance, it can be seen in the Box-Cox plot.

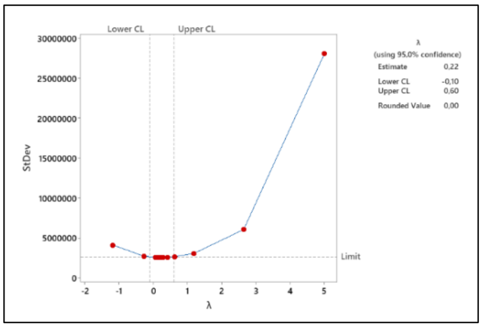


Figure 9. Cox Box Plot of Untransformed Data

Figure 9 shows that the quarterly financial/asset data of PT Adhi Karya is not yet stationary in variance with a rounded value of 0.00 which is between the lower limit of -0.10 and the upper limit of 0.60. So, it is necessary to transform the data. The following are the results of the Box Cox transformation.

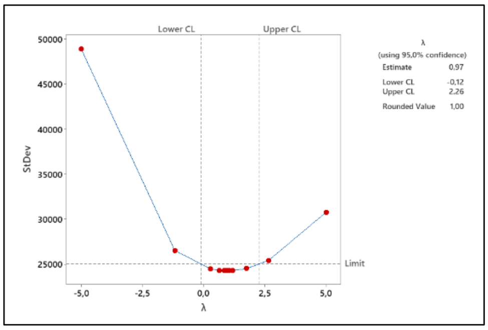


Figure 10. Cox Box Plot of Data After Transformed 2x

Figure 10 shows that after transformation, the quarterly financial/asset data variables of PT United Tractor are stationary in variance with a rounded value of 1.00 which is between the lower limit of -0.12 and the upper limit of 2.26. So, it can be said that the data is stationary in variance. After checking the stationarity of the data on the variant, the next step is to check the stationarity in the average. To determine stationarity on average, statistical testing can be done with the Augmented Dicky Fuller Test on the data.

Table 7. Augmented Dicky Fuller Test Results

Test Statistic	P-*value*	Result Decision	Description
-188079	0.341	Fail to reject H_0	Data is not stationary at the mean

Based on Table 7 on statistical testing with Augmented Dicky Fuller, the p-value is 0.341, which means that it fails to reject H0 so that the quarterly financial / asset data of PT. United Tractor is not yet stationary on average. So that further differencing is needed so that the data is stationary in variance and average. However, previously the ACF and PACF plots were checked to determine the temporary ARIMA model.

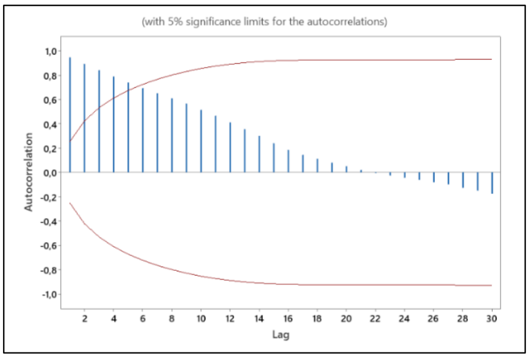


Figure 11. ACF Plot of Quarterly Asset Data of PT United Tractor

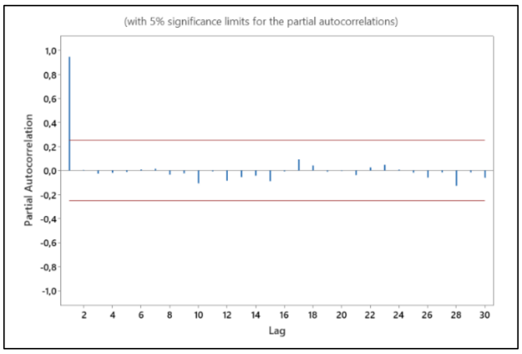


Figure 12. PACF Plot of Quarterly Asset Data of PT United Tractor

Based on Figures 11 and 12, it can be seen that the ACF and PACF plots for quarterly financial / asset data of PT United Tractor experience cut off or lag out. In the ACF plot the pattern drops exponentially even though there are lags that come out of the confidence interval, namely lags 1, 2, 3, 4 and 5. Similarly, Figure 12 in PACF shows that there is a lag that comes out, namely at lag 1.

Parameter Estimation of ARIMA Model

Before estimating the initial ARIMA model, observations are made on the ACF and PACF plots that have been stationary both variants and averages listed in Figures 4 and 5 In the initial estimation of the ARIMA model, the temporary models for the quarterly asset data of PT United Tractor are ARIMA (1 1 0), ARIMA (1 1 1), ARIMA (0 1 2), ARIMA (0 1 5) or ARIMA (1 1 5). The next step will be to test the significance of the parameters.

Parameter Significance Test

After determining the ARIMA model, namely the ARIMA (1 1 0), ARIMA (1 1 1), ARIMA (0 1 2), ARIMA (0 1 5) or ARIMA (1 1 5) model, the next step is to estimate the parameters whether the model is significant or not. Parameters that are not significant or p-value < α to get parameters that are significant to the model. This test is carried out with the following hypothesis. Hipotesis:

Table 8. Parameter Significance Test of Quarterly Asset Data of PT. United Tractor

Model	Type	Coef	SE Coef	T	P-value	Description
ARIMA (1 1 0)	AR 1	0.288	0.128	2.25	0.028	Significant
ARIMA (1 1 1)	ARIMA	0.590	0.193	3.05	0.003	Significant
ARIMA (0 1 2)	MA 2	-0.374	0.122	-3.05	0.003	Significant
ARIMA	MA 5	0.153	0.135	1.13	0.262	Not Significant

(0 1 5)						
ARIMA (1 1 5)	ARIMA	0.039	0.175	0.22	0.824	Not Significant

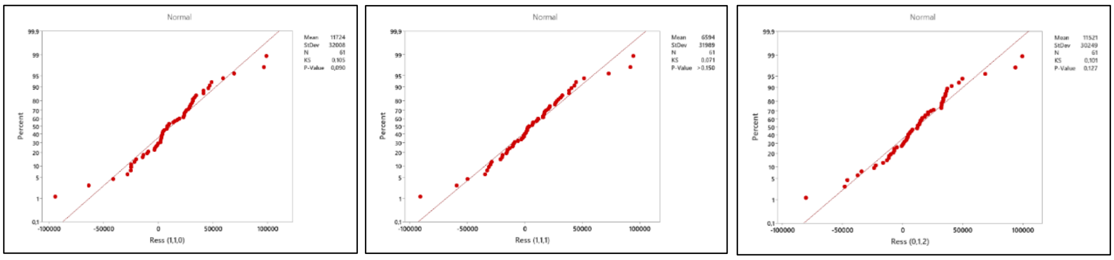
Based on table 8 shows that the initial ARIMA model parameters are significant in ARIMA (1 1 0), ARIMA (1 1 1) and ARIMA (0 1 2). For the rest the results are not significant, it can be seen from the table that the ARIMA (0 1 5) and ARIMA (1 1 5) models have a P-value greater than α, which is 0.05. Thus, the model is excluded and does not continue further analysis.

Residual Diagnostic Test

Next is to perform diagnostic testing which includes testing for normally distributed residuals and white noise.

Normal Distribution Test

In time series analysis, residuals are assumed to be normally distributed. The following are the output results from minitab.



(a) (b) (c)

Figure 13. Normal Distribution, a) ARIMA (1 1 0), b) ARIMA (1 1 1) and c) ARIMA (0 1 2)

Based on Figure 13 it shows that the shape of the residual plot 4.13 (a), (b) and (c) forms a diagonal straight line. So, it can be said that the residuals are normally distributed. However, visual observation will provide subjective conclusions and differ from one researcher to another. So, more details will be presented in table 9 Normal distribution hypothesis testing as follows.

Table 9. Normal Distribution Test on Residuals

Model Conjecture	KS	P-*value*	Normal Distribution
ARIMA (1 1 0)	0.105	0.090	Yes
ARIMA (1 1 1)	0.071	>0.150	Yes
ARIMA (0 1 2)	0.101	0.127	Yes

Based on Table 9 the p-value of each residual ARIMA (1 1 0), ARIMA (1 1 1) and ARIMA (0 1 2) is greater than 5%, namely 0.090; >0.150 and 0.127. This means that the residuals have fulfilled the normal distribution assumption.

White Noise Test

In addition to the normal distribution test, the residuals are assumed to be independent and identical, so the residuals must meet the white noise assumption. So, it is necessary to use the Ljung-Box statistics test to see that the residuals have met the white noise requirements. The hypothesis in this test is as follows.

Table 10. Ljung-Box Test Output Quarterly Asset Data of PT United Tractor

Model	Lag	Chi-Square	DF	P-value	Description
ARIMA (1 1 0)	12	29.21	11	0.002	No White Noise*
	24	34.18	23	0.063	White Noise
	36	40.44	35	0.242	White Noise

	48	50.73	47	0.329	White Noise
ARIMA (1 1 1)	12	17.01	10	0.074	White Noise
	24	21.83	22	0.470	White Noise
	36	29.54	34	0.686	White Noise
	48	42.07	46	0.638	White Noise
ARIMA (0 1 2)	12	8.85	10	0.547	White Noise
	24	17.72	22	0.723	White Noise
	36	24.57	34	0.883	White Noise
	48	36.79	46	0.832	White Noise

It can be seen from table 10 that the ARIMA (1 1 1) and ARIMA (0 1 2) models have a p-value greater than α of 5% so that the decision fails to reject H0 and it can be said that the residual requirements are white noise. So, only these two models can be continued in the selection of the best model.

Selection of the Best Model

In determining the best model from several selected models using in-sample and out-sample criteria. Some in-sample criteria include AIC and SBC while out-sample includes MAPE and RMSE.

Table 11. Best Model Selection

Criteria	ARIMA (1 1 1)	ARIMA (0 1 2)
Normal Distribution	**Yes**	Yes
White Noise	Yes	Yes
AIC	2045.20	2041.65
SBC	2051.53	2047.98
MAPE	8.19%	10.40%
RMSE	12522450.55	16718090.94

Based on table 11, it is concluded that all models meet the residual criteria for normal distribution and white noise. Furthermore, from the in-sample criteria using the AIC and SBC values, the minimum value is the ARIMA (0 1 2) model. While the out-sample criteria of MAPE and RMSE values, the minimum value is also found in the ARIMA (1 1 1) model. In this case, a model with a smaller out-sample value should be chosen, because the model can be better generalized. Thus, it can be concluded that the best model based on the fulfillment of all criteria is ARIMA (1 1 1). The ARIMA model for quarterly financial/asset data of PT United Tractor is modeled as follows.

$$Zt = (1\text{-}0{,}865)Z_{t-1} + 0{,}865Z_{t-1} - 0{,}590a_{t-1} + a_t$$

Forecasting

After analyzing using ARIMA with a long enough step, the best model was finally obtained. The best model of the best obtained is ARIMA (1 1 1), then the forecasting results are obtained for the quarterly financial / asset data of PT United Tractor. The following are the results of the forecast for the next 9 months which will be presented in table 12 as follows.

Table 12. Forecast Value of Quarterly Asset Data of PT. United Tractor (Rp / billion)

Month	Data Projection	Forecasting Results	Lower Limit	Upper Limit
Des’24	140,170,657	133,081,320	124,341,109	141,821,531
Mar’25	140,478,220	136,064,217	121,910,512	150,217,920
Juni’25	150,701,142	13,8378,999	119,168,386	157,589,612
Sep’25	134,487,106	140,175,313	116,148,828	164,201,797
Des’25	153,141,630	141,569,285	112,950,883	170,187,687
Mar’26	154,028,248	142,651,033	109,658,818	175,643,248
Jun’26	161,426,775	143,490,490	106,335,169	180,645,810

Sep’26	168,064,765	144,141,923	103,024,045	185,259,800
Des’26	165,873,508	144,647,447	99,755,492	189,539,402

The following are the plot results between the projection and forecast data from Table 13 presented in Figure 14.

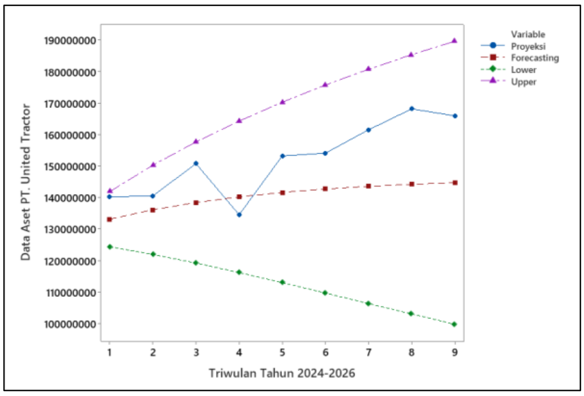


Figure 14. Plot of Projected Data and Forecasting Quarterly Assets of PT. United Tractor

Based on Table 14, the results of the appropriate forecast value are obtained which is between the upper limit and the lower limit. Quarterly asset forecasting of PT United Tractor tends to be stable and tends to increase in each quarter. However, if you look at the plot of the forecast results with the projection data, it is not good because it tends to be monotonous (constant).

After selecting the ARIMA (1, 1, 1) model as the best model, quarterly asset value forecasting of PT United Tractor was conducted for the period December 2024 to December 2026. The forecasting results show that the quarterly asset value tends to stabilize with a gradual increase. For example, assets projected at Rp 133.08 billion in December 2024 are predicted to increase to Rp 144.65 billion in December 2026. Each projection comes with a prediction interval in the form of a lower and upper bound, which gives a range of possible asset values with a certain level of confidence (Allende et al., 2015). Interestingly, these prediction intervals get wider with time, reflecting the increasing uncertainty in long-term forecasting.

The comparison graph between the projected data and the forecasting results (Figure 4.14) reveals some important findings. The forecasting curve follows the trend pattern of the historical data, indicating that the ARIMA (1, 1, 1) model is able to represent the data movement pattern quite well. The forecasting also shows the stability of United Tractor's asset performance, with no major fluctuations in the forecast results. However, the monotonous trend is one of the limitations of this model, which may be due to the nature of the data or the limitations of the ARIMA model in capturing more complex dynamics (Asadi et al., 2012).

These forecasting results provide strategic insights for the management of PT United Tractor in planning financial management for the medium to long term.Information on the lower and upper limits of projected assets is also useful in anticipating risks or uncertainties, especially in the worst-case scenario.However, this model still has limitations in capturing more complex or volatile patterns.Therefore, a combination with other methods such as machine learning could be considered to improve accuracy. This finding also supports the literature that ARIMA models are effective for stable data, but a more flexible approach may be needed to handle data with high volatility (Nanlohy, 2021; Wijesinghe & Rathnayaka, 2020; Yaziz et al., 2013).

CONCLUSION

United Tractor's quarterly assets for the period December 2024 to December 2026. The forecasting results show a stable trend with a slight gradual increase in quarterly asset values. The model is able to represent the historical data pattern well, as evidenced by the forecast results that are consistently between the lower and upper bounds of the prediction interval. The forecasting results graph also shows that ARIMA (1, 1, 1) is an effective model for data with stable patterns. However, the monotonous forecasting reflects the limitations of this model in capturing more complex variations or dynamics in asset data.

To improve forecasting accuracy in the future, it is recommended to consider using more complex models, such as a combination of ARIMA with machine learning or deep learning methods, which are better able to capture dynamic data patterns. In addition, regular monitoring and updating of the model is necessary as asset data patterns may change due to external factors such as market conditions or economic policies. Adding other variables, such as market sentiment or macroeconomic indicators, can also help improve the forecasting quality. Furthermore, the prediction intervals generated by the model can be utilized by management as a guide to anticipate risks and devise better mitigation strategies. However, this ARIMA model has some limitations. The forecasting results tend to be monotonous because the model only relies on historical data patterns and is less able to capture dynamic changes outside the observed data. Long-term uncertainty is also a challenge, as reflected by the prediction intervals that widen over time. In addition, the limitations of ARIMA in managing non-stationary data require additional transformation steps that may affect the interpretation of the results. External factors such as policy changes or industry dynamics are also ignored in this model, which may affect forecasting accuracy. By understanding these limitations, management is expected to be wiser in their decisions.

REFERENCE

Allende, H., Ulloa, G., & Allende-Cid, H. (2015). Prediction intervals in linear and nonlinear time series with sieve bootstrap methodology. In *Advanced Studies in Theoretical and Applied Econometrics*. https://doi.org/10.1007/978-3-319-03122-4_16

Anhar, M., Maronrong, R., Burda, A., & Sumail, L. O. (2024). Dynamics of Indonesian stock market interconnection: Insights from selected ASEAN countries and global players during and after the COVID-19 pandemic. *Investment Management and Financial Innovations*, *21*(2), 180–190. https://doi.org/10.21511/imfi.21(2).2024.14

Asadi, S., Tavakoli, A., & Hejazi, S. R. (2012). A new hybrid for improvement of auto-regressive integrated moving average models applying particle swarm optimization. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2011.11.002

Bogusz, J. (2015). Geodetic aspects of GPS permanent station non-linearity studies. *Acta Geodynamica et Geomaterialia*. https://doi.org/10.13168/AGG.2015.0033

Bursa Efek Indonesia. (2022). *Statistik pasar modal: Indeks Harga Saham Gabungan (IHSG) dan kapitalisasi pasar*. Diakses dari https://www.idx.co.id.

Chen, S. T., & Haga, K. Y. A. (2021). Using E-GARCH to Analyze the Impact of Investor Sentiment on Stock Returns Near Stock Market Crashes. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2021.664849

Dai, Z. M., & Yang, D. C. (2018). Positive Feedback Trading and Investor Sentiment. *Emerging Markets Finance and Trade*. https://doi.org/10.1080/1540496X.2018.1469003

Imfrianti Augtiah, Saefudin Saefudin, & Sujatmiko Sujatmiko. (2024). Financial literacy improvement strategy to encourage fintech adoption and MSMEs performance in Karanganyar Regency. *World Journal of Advanced Research and Reviews*, *22*(3), 1109–1116. https://doi.org/10.30574/wjarr.2024.22.3.1807

Karia, A. A., Hakim, T. A., & Bujang, I. (2016). World edible oil prices prediction: Evidence from mix effect of ever difference on Box-Jenkins approach. *Journal of Business and*

Retail Management Research.

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. In *Future Internet*. https://doi.org/10.3390/fi15080255

Kumala, I. W., Saefudin, S., & Adibatunabillah, S. R. (2023). Pemodelan Loyalitas Pengguna Aplikasi Ovo Di Kota Malang: Peran Kualitas Layanan Dan Citra Merek Dengan Kepuasan Sebagai Pemediasi. *Jurnal MD: Jurnal Manajemen Dakwah UIN Sunan Kalijaga Yogyakarta*, *09*(1), 132–154.

Lee, T. (2022). Wild bootstrap Ljung–Box test for residuals of ARMA models robust to variance change. *Journal of the Korean Statistical Society*. https://doi.org/10.1007/s42952-022-00172-6

Lim, Y., & Kim, K. T. (2019). Afraid of the stock market. *Review of Quantitative Finance and Accounting*. https://doi.org/10.1007/s11156-018-0766-x

Qi, Y., Li, H., Liu, N., Hao, X., & Guan, Q. (2018). Transmission characteristics of investor sentiment for energy stocks from the perspective of a complex network. *Journal of Statistical Mechanics: Theory and Experiment*. https://doi.org/10.1088/1742-5468/aac916

Rivera, J. P. R. (2015). The role of stationarity in business and economic research. *Journal of Economics and Economic Education Research*.

Rohman, M. A. F., & Saefudin. (2024). Determinant Factors in Stock Returns of Food and Beverage Industry Companies in Indonesia. *Journal of Management Studies and Development*, *3*(01), 42–55. https://doi.org/10.56741/jmsd.v3i01.448

Ryu, D., Kim, H., & Yang, H. (2017). Investor sentiment, trading behavior and stock returns. *Applied Economics Letters*. https://doi.org/10.1080/13504851.2016.1231890

Suhermi, N., Suhartono, Prastyo, D. D., & Ali, B. (2018). Roll motion prediction using a hybrid deep learning and ARIMA model. *Procedia Computer Science*. https://doi.org/10.1016/j.procs.2018.10.526

W. A. Nanlohy, Y. (2021). Autoregressive Integrated Moving Average (ARIMA). *Tensor*.

Wijesinghe, G. W. R. I., & Rathnayaka, R. M. K. T. (2020). Stock market price forecasting using ARIMA vs ANN; A Case study from CSE. *ICAC 2020 - 2nd International Conference on Advancements in Computing, Proceedings*. https://doi.org/10.1109/ICAC51239.2020.9357288

Yaziz, S. R., Azizan, N. A., Zakaria, R., & Ahmad, M. H. (2013). The performance of hybrid ARIMA-GARCH modeling in forecasting gold price. *Proceedings - 20th International Congress on Modelling and Simulation, MODSIM 2013*. https://doi.org/10.36334/modsim.2013.f2.yaziz

Zuo, X. (2019). Several Important Unit Root Tests. *2019 2nd IEEE International Conference on Information Communication and Signal Processing, ICICSP 2019*. https://doi.org/10.1109/ICICSP48821.2019.8958557