STOCKS FORECASTING EXPLORATION ON LQ45 INDEX USING ARIMA(p,d,q) MODEL

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ABSTRACT

Up to now, there are 700 stocks listed on the Indonesia Stock Exchange (IDX). An example of an index listed on the IDX is the LQ45 stock index. LQ45 index contains 45 stocks, and these stocks are grouped because of their high liquidity, large market capitalization, and good company fundamentals. Since this index is a fundamental reference index for passive investors, it is necessary to model the prediction of LQ45 stocks to predict these stocks' movement accurately. One form of modeling used is the ARIMA (p, d, q) model. In this study, ARIMA (p, d, q) modeling was conducted to predict the price of 45 stocks in LQ45. The ARIMA (p, d, q) model is a time series model that is suitable for modeling LQ45 stocks because it is only based on the relationship with previous data (AR), and the resulting error is assumed to be related to the previous error (MA). The problem that arises is that the movement of shares can be seen from the visual image (plot), while the function of the movement is unknown. This modeling is expected to help observe the ARIMA functional form of each LQ45 stock and measure the Mean Absolute Percentage Error (MAPE) of each stock. ARIMA (p, d, q) consists of AR(p) and MA(q) models as well as combining d differencing processes. ARIMA (p, d, q) modeling briefly contains several processing stages: parameter estimation, residual test, and prediction. This study showed that the mean forecast error using MAPE for LQ45 stock was 10.088%, with a standard deviation of 8.968%. Furthermore, BBCA stocks had the lowest forecast error of 2.1797%, and MDKA stocks had 44.49%. The highest forecast error was due to MDKA stocks having visually and exponentially increased. Therefore, it can continue increasing exponentially or even decreasing sharply in the future price period.

Keywords: *ARIMA, parameter estimation, residual test, prediction, MAPE*

1. INTRODUCTION

Shares or stocks are proof of ownership of the value of a particular company. Shareholders are also owners of the company. The more shares a person owns, the greater his ownership and rights in the company. In addition, stocks are also a form of investment that can be an essential concern since they provide benefits [1]. In developing countries, stocks also play an essential role in the country's progress [2].

One of the stock market indexes in the international world and used by the Indonesia Stock Exchange (IDX) is ICI. The ICI is Indonesian Composite Index (ICI) or the IDX Composite. This index was first launched on April 1, 1983, and it serves as an indicator of stock prices on the stock exchange. ICI contains the price movements of all shares listed on the IDX. The beginning of the calculation of the ICI was on August 10, 1982. On that date, the base index value was 100, and the listed stocks at that time were 13 stocks. So far, the number of stocks is 700 and will continue to grow.

We choose stock exchanges in Indonesia and LQ45 stocks for several reasons. First, according to the OJK (Otoritas Jasa Keuangan) or The Financial Services Authority in Indonesia, there is an increasing trend in the Average Daily Stock Trading Value. The average daily stock trading value in 2015 was 5,763.78, and in 2020 it was worth 9,209.91 [3]. The increase can be seen in Figure 1 from IDX data.

The second reason: in the beginning, foreign investors dominated trading in the Indonesian capital market, but over time, domestic investors may also outnumber foreign investors. There is a trend of increasing the average value of daily stock trading from foreign and domestic investors from 2015 to 2020. The average value of stock trading for Foreign and Domestic investors can be seen in Figure 2 [3] from idxdata. The third

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reason: researchers chose LQ45 stocks because these 45 stocks have high liquidity, large market capitalization, and good company fundamentals in ICI.

Figure 1: JCI Developments and Average Daily Trading Value

Indikator (Rata - rata harian)		2015	2016	2017	2018	2019	2020	Indicator (Daily Average)	
Nilai perdagangan saham harian (Rp Miliar)		5.763,78	7.498,32	7.603.33	8.500,36	9.105,79	9.209,91		Average Daily Trading Value (Rp billions)
Investor Asing (Rp miliar)	Beli	2.443,97	2.798,75	2.701,45	3.037,24	3.052,76	2.801,39	Buy	Foreign Investors (Rp billion)
	Jual	2.536,55	2.733,02	2.868,97	2.851,97	2.851,97	2.999,23	Sell	
Investor Domestik (Rp miliar)	Beli	3.319,81	4.699,58	4.901,87	5.463,12	6.053,04	6.410,31	Buy	Domestic Investors (Rp billion)
	Jual	3.227,23	5.765,30	4.734,35	5.251,68	6.253,83	6.212,47	Sell	
Frekuensi Perdagangan Saham Harian		221.583	264.127	312.485	386.804	468.805	677.430		Average Daily Trading Frequency

Sumber: idxdata, diolah *Source: idxdata, processed*

Figure 2: Share Trading by Domestic and Foreign Investors

There are many stock price data on the Internet, and this data has not produced useful information for users. Data mining is the process of retrieving important and useful information in a dataset. Several data mining groups, namely text mining and visual data mining. Stock data is usually a numeric vector. This research can contribute to one of the data mining groups, namely time series data mining.

In general, several methods in data mining are classification, clustering, association, regression, and forecasting. ARIMA(p,d,q) method is used to forecast time series data. One of the accuracies in prediction for forecasting time series data is MAPE. This study will apply one of the forecasting methods, namely ARIMA(p,d,q), to LQ45 stocks and see the MAPE value.

Based on the information provided in the previous paragraph, it is necessary to analyze the pattern of capital market movements by looking at the ICI. The problem that arises is that the movement of shares can be seen from the visual image (plot), while the function of the movement is unknown. By looking at the visual image, it is only known whether the stock price trend will move up, down, or stay the same. Meanwhile, by obtaining the functional model of ARIMA (p, d, q), it will be possible to calculate the value of future prices based on the type of function of the past data. This modeling is expected to help observe the ARIMA functional form of each LQ45 stock and measure the Mean Absolute Percentage Error (MAPE) of each stock. At the time of writing, there were 36 stock indices on the IDX. These indices were formed according to their needs, and one of the existing indices was the LQ45 stock index. Since the list on the IDX involved a vast number of stocks, this study only focused on LQ45 stocks, which represented the LQ45 ICI recorded from November 2020 to January 2021 in accordance with the announcement of LQ45 Minor Evaluation Index No. Peng-00315/BEI.POP/10-2020 (https://www.idx.co.id, accessed on January 29, 2021). The objectives and benefits of the stock index include [2]:

- The index can show the sentiment in the market,
- The index is used as a passive investment product, namely the index of a Mutual Fund and ETF as well as other derivative products,
- The index is used as a benchmark for an active portfolio,
- As the proxies in measuring the model of return on investment (return), systematic risk, and investment performance in accordance with the risks taken.

This research focuses on the stocks listed in LQ45 since these 45 stocks have the characteristics of high liquidity and market capitalization and the support of good company fundamentals. The LQ45 stocks list is according to the LQ45 Minor Evaluation Index Announcement No. Peng-00315/BEI.POP/10-2020 is presented in Table 1. The objectives to be achieved in this paper are to create an ARIMA model for each LQ45 stock and measure the accuracy of the ARIMA model in predicting the price of each stock in LQ45.

The benefits that this study can provide are:

- Provide information for investors in the capital market in making the right decisions on investment in the capital market to get the expected benefits from increasing investment returns,
- For long-term investors, this study can be used as input in making decisions regarding the type of ARIMA model on LQ45 stocks, especially in diversifying portfolios.
- This study is expected to provide value-added for academics regarding the breadth and depth of prediction and time series analysis.

Due to the amount of data regarding securities and cyberspace, the researchers tried to get information and make a model from these data.

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Several studies applied the ARIMA (p, d, q) model, for example, a study conducted by Muthahharah (2019) which applied the ARIMA method to predict the Indonesian Sharia Stock Index (ISSI) by taking 231 data series. This study applied the ARIMA(1,0,0) form with the series function of Z_t = 0,8104 Z_{t-1}+ αt. The minimum ISSI forecast found was 174.36, and the maximum was 175.31 [4]. The research [5] also conducted a study and found the best ARIMA model criteria for predicting golf glove products at PT Adi Satria Abadi obtained the smallest error. The study used the Minitab tool to find the best ARIMA model and obtained the smallest MAPE value on the ARIMA model (0, 1, 1). The error value was 69291531, and the MAPE value was 17.5443% [5]. Researchers in [6] examined the inflation rate prediction in November 2010 with the Consumer Price Index (CPI) using ARIMA in a study related to public policy. Inflation indicators are critical to anticipate in making government policies and decisions. Likewise, for citizens, inflation indicators can be used to determine what information should be done regarding savings and investment. By looking at the existing criteria, it was determined that the best model was the ARIMA (1, 1, 0) model. The ARIMA(1,1,0) model turned out to be significant by having the minimum Akaike Info Criterion (AIC) and Schwarz Criterion (SC) values compared to ARIMA(0,1,1) or ARIMA (1, 1, 1). In short, the best ARIMA model used to forecast the CPI value was ARIMA (1, 1, 0) [6]. Finally, [7] applied the ARIMA method to predict the electrical loads, including daily, peak, and basic electrical loads. In this study, the accuracy of ARIMA prediction was compared with the prediction method used by PLN (in this case, the Load Coefficient method). Prediction based on ARIMA produced MAPE values of 0.8011%, 1.0362%, 0.9823%, while the load coefficient method obtained MAPE values of 0.6294%, 0.7876%, 0.7571%. The study results concluded that the Coefficient of Load method was better than the ARIMA method [7]. Some of the studies above use the ARIMA model, especially on one entity: golf glove products and the inflation rate CPI index.

In contrast, in this study, we use 45 types of time series data and can see a description of the characteristics of each stock. Research in [7] compared the predictions of the ARIMA model with the prediction method used by PLN. In contrast, our research looks at and describes the prediction accuracy of 45 stocks with the ARIMA model. Based on these references, it can be said that the ARIMA method is a prediction method that is often used, frequently researched, and reliable.

In previous studies, researchers usually used the ARIMA (p, d, q) model for predicting only one object. The differences and contributions of this study compared to previous studies are:

- This study involved a case study of 45 stocks with different characteristics so that the ARIMA (p, d, q) model can be obtained from each stock.
- The study will be able to classify 45 LQ45 stocks according to the ARIMA (p, d, q) model.
- This study also measures accuracy after the ARIMA (p, d, q) model is applied for forecasting. Based on the smallest MAPE value, what stocks are most suitable to use ARIMA (p, d, q) in the forecasting process will be known.

Some additional studies only use the ARIMA model instead of machine learning methods because the ARIMA model is a simple model for univariate time-series data. The data we have is relatively small and simple. Judging from the type of data that the ARIMA model has, it is enough to make predictions. This study does not use artificial intelligence because artificial intelligence uses more time-series data and is multivariate.

This paper has the writing structure as follows: the first part is The Introduction, which contains the background of the problem, the methods offered, the objectives, and the benefits of the study. The second part is The Materials and Method, which discusses the methods and research data. The following section is The Results and Discussion, which contains the results of a study that has been carried out and a complete analysis. Finally, the findings are summarized in The Conclusions, the concluding part of this article, along with recommendations for further study.

2. LITERATURE REVIEW

In article [8], researchers conducted a study on predicting the stock price of INFRATEL to comply with various methods. ARIMA is a linear model, while deep learning is a non-linear model. This study also compares the method with the ARIMA method. Furthermore, it turns out that the Deep Learning model is superior to the ARIMA model for dynamic multivariate data [8]. Our study only used the ARIMA model, but we compared the ARIMA-ARIMA models based on MAPE for various stocks (45 types of stocks).

In article [9], we can compare three models, namely LSTM, AAN, and ARIMA, and their prediction results. The result is that the LSTM model has the best predictive ability but is strongly influenced by data processing. The ANN model performs better than the ARIMA model. While in this study, we compare the ARIMA model in predicting stocks that are included in LQ45 stocks based on MAPE, then group them in the ARIMA(p,d,q) model in LQ45 stocks.

Article [10] conducted a study using the ARIMA model using three-sector data from the NSE (National Stock Exchange) from April 2018 to February 2021 every month and predicting prices until December 2021. The study results were a sharp decline for three sectors from March 2021 to December 2021. Meanwhile, our research uses daily stock data and calculates MAPE.

Article [11] researched the use of ARIMA with Netflix stock data for five years, from April 7, 2015, to April 7, 2020. There are three potential ARIMA models to be used, namely ARIMA(4,1,4), ARIMA(1,1, 33), and ARIMA(1,2,33). The result is that ARIMA (1,1,33) has the most accurate value in calculating MAP. This study looks for the ARIMA model suitable for Netflix stock, while our study uses many stock cases.

Article [12] conducted research based on three stages of ARIMA, model identification, parameter estimation, and diagnostic checking for various ARIMA forms. The data used is the JOHANNESBURG STOCK EXCHANGE index from August 1, 2019, to July 31, 2020. The study confirmed that the ARIMA (4, 1, 4) model is stable and most suitable for forecasting the South African stock price index for the next two years [12].

Article [13] used time-series data on the share price of PT BNI (Persero) Tbk. from January 3, 2017, to December 28, 2019, and June daily. So that the ARIMA model (3,1,3) is obtained, which is the most appropriate model to predict the stock price of PT. Bank Negara Indonesia (Persero) Tbk, this research focuses on modeling ARIMA for one case only. However, we will explore the ARIMA model for 45 cases.

This recent literature shows that many researchers still use the ARIMA model, and the result was good. The ARIMA model is suitable for prediction cases and has excellent predictions. Based on this literature, we will conduct this research that predicts the LQ45 stock trade differs from the above references.

The previous research focused on one-time series data, the modeling process, and its accuracy. In this research, the purpose is on ARIMA(p,d,q) modeling, evaluation based on MAPE, and exploration of each stock on the sector on the IDX now.

2.1 Analysis of Time Series Data

In statistics and signal processing, time-series data are data series in the form of measurement values (observations) made within a certain period, based on time with uniform (same) intervals. Time series analysis is a method that studies time series, both in terms of the underlying theory and for making forecasts (predictions). Time-series Prediction means making a model (modeling) predict the value (prediction) in the future based on past data [14]. In the business world, time-series data are used to make current and projected decisions and future planning [15].

2.2. Identification of sub subsections

ARIMA (p, d, q) modeling contains three main stages: model identification, parameter estimation, and residual test [14]. The ARIMA (p, d, q) model is often referred to as the Box-Jenkins model based on the Autoregressive Integrated Moving Average or ARIMA process. ARIMA consists of AR (p), MA(q), and differencing processes as much as d, which are used to make the time-series data stationary. A Box-Cox transformation is carried out before determining the ARIMA (p, d, q) model [16] to create stability in the variance. The form of the transformation can be seen in Formula 1.

$$yt = \begin{cases} \log(z_t) & , if\ \lambda = 0 \\ sign(z_t)(|z_t|^{\lambda} - 1)/\lambda & for\ the\ others \end{cases} \quad (1)$$

Furthermore, the inverse transformation is used for prediction, as shown in Formula 2.

$$z_t = \begin{cases} \exp(y_t) & , if\ \lambda = 0 \\ sign(\lambda y_t + 1)(\lambda y_t + 1)^{1/\lambda} & for\ the\ others \end{cases} \quad (2)$$

Identifying the ARIMA (p, d, q) model can be done by looking at the ACF and PACF functions from the existing time series data.

<u>The moving average (MA) model</u> shows a relationship between the value of y_t and the residual value in the previous time, namely a_{t-k}. θ_i is a coefficient with a value of -1 to 1. The MA model of order q is written MA (q) in the form of:

$y_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q}$

<u>The autoregressive (AR) model</u> shows a relationship between a value of y and a value at time $yt-k$ where k =1,2,3,..,n with ϕ is the coefficient of the AR model and εt is the residual at time t. order p AR Model or AR (p) can be written mathematically:

$yt=\phi 1yt-1+\phi 2yt-2+\cdots+\phi pyt-p+\varepsilon t$

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The differencing process can be performed by using operator (1-B) with the Backshift (B) operator of Byt = yt-1, B(Byt) = yt-2, and so on.
y't = yt – yt-1 = yt – Byt = (1- B) yt is called differencing 1
y''t = yt – 2yt-1 + yt-2 = (1 -2B + B2) yt = (1-B)2yt is called differencing 2.
In general, order d differencing can be written: (1-B)dyt. Differencing processes to make time-series data stationary can use the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [17].
The Autoregressive Moving Average model or ARMA (p,q) combines the AR and MA models. In the ARMA model (p,q), ϕp is the AR model coefficient and θq is the MA coefficient, while εt is the residual at time t. Combination of AR(p) and MA(q) can be written mathematically as follows:
$(B)yt=\theta q(B)\varepsilon t$
where:
$(B)=1-\phi 1B-\cdots-\phi pBp$
$(B)=1-\theta 1B-\cdots-\theta qBq$
Autoregressive Integrated Moving Average or ARIMA (p, d, q) model is a time series model that is not stationary concerning the mean and runs the differencing process to be stationary. $(1-B)y_t$ modeling is the order of differencing and is assigned to the ARMA model (p, q) to become an ARIMA stationary process (p, d, q). y is the current value, ϕp is the model coefficient of AR, B is the d-order difference, θq is the model coefficient of MA, while ε_t is the residual at the time *t*. Based on the description above, the ARIMA model (p, d, q) can be mathematically written according to Formula 3 [17].

$$(B)\,(1-B)^d y_t = (B)\varepsilon_t \qquad (3)$$

Identification of AR (p) and MA(q) models can be seen in Table 1 [14] based on the ACF and PACF functions.

Table 1: Identification Of Ar(P) And Ma(Q) Models And Their Combination

Model	ACF	PACF
MA (q)	Fast down after lagging to q	Down exponentially/ sinusoidally damped
AR (p)	Down exponentially/ sinusoidally damped	Fast down after lagging top
ARMA (p,q)	Down exponentially/ sinusoidally damped	Down exponentially/ sinusoidally damped

To estimate model parameters, namely ϕ and θ values, the moment method of MLE (Maximum Likelihood Estimator) or least square estimator can be used. Much automated software such as Minitab, SAS, SPSS [18], and R [19] can perform these computations. This study used the auto ARIMA package modeled by Hyndman-Khandakar [20]. Meanwhile, the residual test was carried out with residual data, namely the difference between the actual and predicted data,s shown in Formula 4 [14].

$$\hat{\varepsilon}_t = y_t - \left(\hat{\delta} + \sum_{i=1}^{p} \hat{\varphi}_i\, y_{t-i} + \sum_{i=1}^{q} \hat{\theta}_i\, \hat{\varepsilon}_{t-i}\right) \qquad (4)$$

Residual tests are usually performed through autocorrelation, normality, observation of residual distribution graphs, and other tests assumed in the ARIMA model.

2.3. Prediction using ARIMA (p, d, q)

After the model was obtained, the prediction was conducted using the expected price yT+t provided that the previous observation values were known, namely the values of yT , yT-1 , yT-2 … as shown in Formula 5.

$$\hat{y}_{T+\tau}(T) = E[y_{T+\tau}\!: y_T\ , y_{T-1}\ , y_{T-2}\ , \dots] = \mu + \sum_{i=\tau}^{\infty} \Psi_i\, \varepsilon_{T+\tau-i} \qquad (5)$$

Ψ is the presentation coefficient of the AR and MA processes expressed as a linear combination. Since $E[e_T(\tau)] = 0$ and $Var[e_T(\tau)] = \sigma^2 \sum_{i=0}^{\tau-1} \Psi_i{}^2 = \sigma^2(\tau)$, then the variance can be used to form a confidence interval of (1-α)% for the prediction point [17] [14].

2.4. The Accuracy of Prediction

For the result of the accuracy of the prediction process, the MAPE measure (MAPE = Mean Absolute Percentage Error) was used. MAPE, also known as Mean Absolute Percentage Deviation (MAPD), measures the accuracy of a prediction method in statistics. It usually expresses accuracy as a ratio determined by formula 6.

$$MAPE = \sum_{i=1}^{n} \left|\frac{A_i - F_i}{A_i}\right| \qquad (6)$$

Ai is the actual value, and Fi is the prediction value. In this study, n = 39 indicates the data for two months (January to February 2021). MAPE is sometimes expressed as a percentage, resulting from the above equation multiplied by 100%. The difference between Ai and Fi was further divided by the actual value of Ai. The absolute value in this calculation was added up for each predicted time point and divided by the number of all points, i.e., n.

3. RESEARCH METHODOLOGY

This study involved data on the IDX (Indonesian Stock Exchange) through particular security to produce an interpretation that is expected to be helpful for the development of science and the world of capital markets in the future. The steps taken in this study are as follows:

1. Researchers obtained data on LQ45 stocks from the IDX.
2. The authors made an ARIMA (p, d, q) model for each LQ45 stock (45 LQ45 stocks). The steps in establishing the ARIMA model for the 45 stocks were as follows:
    a) Made a description of LQ45 stock data by drawing a graph.
    b) Partitioned the data and selected one partition to be analyzed as training and testing data. Training data were obtained for ten years from 2010-to 2020, while testing data were obtained for two months, from January to February 2021.
    c) Usually, in supervised learning, the ratio of training data and test data is set by the ratio of 80:20 or 70:30, but in this study, we do not use that method. We use 2730 training data and 39 testing data because, based on our knowledge, there is no ARIMA research about the specific ratio of training and test data. However, considering a large amount of training data, it will increasingly reveal patterns in the time-series data. This technique can be a recommendation for the following research.
    d) Observed the stationarity of the training data and overcame the non-stationary training data using Box-Cox Transformation and Differencing.
    e) The ARIMA model is estimated to use the ACF and PACF plots on the training data.
    f) We performed a parameter estimation of the model obtained from the training data.
    g) Conducted a residual assumption test on the training data model.
    h) Choose the best model by choosing a small AICc.
3. The authors forecast LQ45 stocks using a model based on training data. We assessed the MAPE of the ARIMA prediction process based on existing testing data.

4. RESULTS AND DISCUSSION

The first step in modeling was plotting the data derived from LQ45 stocks, as shown in Appendix 1. Plots of the data are presented in the appendix to make them easier to read due to the many plot images. The next step was looking for lambda values in the Box-Cox transformation to stabilize the overall data variance. The lambda values regarding the Box-Cox transformation for each stock can be seen in Table 2.

Tabel 2: Bo-Cox Transformation Values For Lq45 Stocks

No.	Emitent Code	Lambda Value	No.	Emitent Code	Lambda Value
1.	ACES	0.1518	24.	ITMG	0.1896
2.	ADRO	0.2026	25.	JPFA	0.2273
3.	AKRA	0.2073	26.	JSMR	0.8239
4.	ANTM	0.2481	27.	KLBF	0.3247
5.	ASII	1.0251	28.	MDKA	0.1503
6.	BBA	0.1634	29.	MIKA	0.5455
7.	BBNI	0.4216	30.	MNCN	0.3001
8.	BBRI	0.0297	31.	PGAS	0.6432
9.	BBTN	0.1550	32.	PTBA	0.2518
10.	BMRI	0.3415	33.	PTPP	0.3151
11.	BSDE	0.6407	34.	PWON	0.1868
12.	BTPS	0.9091	35.	SCMA	0.2375
13.	CPIN	0.1130	36.	SMGR	0.7070
14.	CTRA	0.2090	37.	SMRA	0.2574
15.	ERAA	-0.0592	38.	SRIL	-0.3473
16.	EXCL	0.5338	39.	TBIG	0.01990
17.	GGRM	0.7298	40.	TKIM	-0.1089
18.	HMSP	0.2595	41.	TLKM	0.2278
19.	ICBP	0.1052	42.	TOWR	1.9999
20.	INCO	0.6065	43.	UNTR	0.3134
21.	INDF	0.7508	44.	UNVR	0.4598
22.	INKP	-0.0641	45.	WIKA	0.1752
23.	INTP	0.9885			

The lambda values presented in Table 2 were then used to conduct ARIMA (p, d, q) modeling on LQ45 stocks, while the inverse Box-Cox transformation was used for prediction. In the analysis of data stationarity, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was applied. In this test, the null hypothesis states that the data is stationary or the alternative hypothesis is that the null hypothesis was false (the data is non-stationary) should be found. Table 3 shows the KPSS unit root test values for LQ45 stocks before and after differencing process.

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Table 3: Kpss Unit Root Test Values For Lq45 Stocks Before And After The Differencing Process

	Before Differencing		After Differencing	
No.	**Emitent Code**	**Test Value**	**Emitent Code**	**Test Value**
1.	ACES	24.0985	ACES	0.0254
2.	ADRO	5.5715	ADRO	0.0602
3.	AKRA	9.4088	AKRA	0.2934
4.	ANTM	16.0578	ANTM	0.4823
5.	ASII	4.6692	ASII	0.1501
6.	BBCA	25.3303	BBCA	0.1094
7.	BBNI	16.5528	BBNI	0.0865
8.	BBRI	24.476	BBRI	0.0225
9.	BBTN	9.9164	BBTN	0.102
10.	BMRI	21.3372	BMRI	0.048
11.	BSDE	7.5956	BSDE	0.1073
12.	BTPS	6.5787	BTPS	0.0673
13.	CPIN	15.5939	CPIN	0.0413
14.	CTRA	11.251	CTRA	0.0948
15.	ERAA	3.1104	ERAA	0.096
16.	EXCL	17.2958	EXCL	0.2104
17.	GGRM	11.0187	GGRM	0.2441
18.	HMSP	12.9464	HMSP	0.6322
19.	ICBP	26.2229	ICBP	0.0551
20.	INCO	3.9065	INCO	0.1298
21.	INDF	13.973	INDF	0.076
22.	INKP	13.6331	INKP	0.1384
23.	INTP	3.2873	INTP	0.0805
24.	ITMG	18.0548	ITMG	0.0751
25.	JPFA	10.3299	JPFA	0.064
26.	JSMR	5,4067	JSMR	0.1941
27.	KLBF	17.0152	KLBF	0.1799
28.	MDKA	13.3318	MDKA	0.712
29.	MIKA	3.7494	MIKA	0.0756
30.	MNCN	5.5794	MNCN	0.2711
31.	PGAS	16.3621	PGAS	0.0983
32.	PTBA	5.3884	PTBA	0.0676
33.	PTPP	10.0981	PTPP	0.2164
34.	PWON	20.9591	PWON	0.0743
35.	SCMA	6.9307	SCMA	0.2982
36.	SMGR	3.3374	SMGR	0.0748
37.	SMRA	7.0442	SMRA	0.1554
38.	SRIL	3.2251	SRIL	0.0437
39.	TBIG	6.4736	TBIG	0.1178
40.	TKIM	13.3866	TKIM	0.0846
41.	TLKM	22.4042	TLKM	0.1117
42.	TOWR	17.6217	TOWR	0.0975
43.	UNTR	4.6186	UNTR	0.055
44.	UNVR	23.3795	UNVR	0.2039
45.	WIKA	10.3717	WIKA	0.1235

The test value on KPSS before the differencing process was applied on the time series data tended to be high, meaning it rejected Ho or the data was not stationary. Meanwhile, the KPSS test value after differencing process was applied did not tend to reject Ho, which meant that the data was stationary according to a specific Alpha choice. Thus, LQ45 stock data indeed needed differencing process. The critical values of the KPSS test on various types of Alpha often used can be seen in Table 4 [21] If Alpha = 2.5% is used, it can be seen that the HMSP and MDKA are not stationary even though they use a differencing process with d=1.

Table 4: Critical Values For Several Levels Of Significance Of The Kpss Test

Alpha	Critical Value
10 %	0.347
5 %	0.463
2.5 %	0.574
1 %	0.739

The form of the ARIMA (p, d, q) model for each stock in LQ45 can be observed in Table 5.

Table 5: ARIMA (P, D, Q) Model In Functional Form For The Prediction Process After The Differencing Process Of Y't = Yt – Yt-1

No	Emitent Code	ARIMA Model		
1.	ACES	ARIMA(1,0,1)		
$y'_t = 0{,}00058213 + 0{,}7469\, y'_{t-1} - 0.8264\, \varepsilon_{t-1} + \varepsilon_t$				
2.	ADRO	ARIMA(2,02)		
$y'_t = -0{,}3223 - 0{,}8608\, y'_{t-1} + 0{,}3167\varepsilon_{t-1} + 0{,}8275\, \varepsilon_{t-2} + \varepsilon_t$				
3.	AKRA	ARIMA(2,0,2)		
$y'_t = 1{,}2924 y'_{t-1} - 0{,}7531 y'_{t-2} - 1{,}2491\varepsilon_{t-1} + 0{,}6794\, \varepsilon_{t-2} + \varepsilon_t$				
4.	ANTM	ARIMA(0,0,0)		
$y'_t = \varepsilon_t$				
5.	ASII	ARIMA(1,0,4)		
$y'_t = -0{,}6269 + 0{,}6107\, \varepsilon_{t-1} - 0{,}0831\varepsilon_{t-2} - 0{,}1056\, \varepsilon_{t-3} - 0{,}0817\varepsilon_{t-4} + \varepsilon_t$				
6.	BBCA	ARIMA(0,0,4)		
$y'_t = 0{,}0033 - 0{,}0615\, \varepsilon_{t-1} - 0{,}0318\varepsilon_{t-2} - 0{,}0135\, \varepsilon_{t-3} - 0{,}0701\varepsilon_{t-4} + \varepsilon_t$				
7.	BBNI	ARIMA(0,0,1)		
$y'_t = 0{,}0504 y'_{t-1} + \varepsilon_t$				
8.	BBRI	ARIMA(0,0,4)		
$y'_t = 8e\text{-}4 + 0{,}0506\, \varepsilon_{t-1} - 0{,}0748\varepsilon_{t-2} - 0{,}0189\, \varepsilon_{t-3} - 0{,}0534\varepsilon_{t-4} + \varepsilon_t$				
9.	BBTN	ARIMA(0,0,0)		
$y'_t = \varepsilon_t$				
10.	BMRI	ARIMA(4,0,1)		
$y'_t = -0{,}5063 y'_{t-1} - 0{,}0605\, y'_{t-2} - 0{,}0525\, y'_{t-3} - 0{,}0654\, y'_{t-4} + 0{,}5218\varepsilon_{t-1} + \varepsilon_t$				
11.	BSDE	ARIMA(2,0,1)		
$y'_t = 0{,}8524\, y'_{t-1} - 0{,}0483 y'_{t-2} - 0{,}8410\varepsilon_{t-1} + \varepsilon_t$				
12.	BTPS	ARIMA(0,0,0)		
$y'_t = \varepsilon_t$				
13.	CPIN	ARIMA(2,0,2)		

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$y'_t = 0,0015329 + 1,3558\, y'_{t-1} - 0,7233\, y'_{t-2} - 1,3408\, \varepsilon_{t-1} + 0,6801\varepsilon_{t-2} + \varepsilon_t$				
14.	CTRA	ARIMA(0,0,3)		
$y'_t = 0,0198\, \varepsilon_{t-1} + 0,0021\varepsilon_{t-2} - 0,0459\varepsilon_{t-3} + \varepsilon_t$				
15.	ERAA	ARIMA(1,0,1)		
$y'_t = 0,5480y_{t-1} – 0,4844\varepsilon_{t-1} + \varepsilon_t$				
16.	EXCL	ARIMA(1,0,1)		
$y'_t = 0,7033y_{t-1} - 0,7548\varepsilon_{t-1} + \varepsilon_t$				
17.	GGRM	ARIMA(2,0,2)		
$y'_t = 1,3273\, y'_{t-1} - 0,6180\, y'_{t-2} - 1,3121\varepsilon_{t-1} + 0,5618\varepsilon_{t-2} + \varepsilon_t$				
18.	HMSP	ARIMA(5,1,0)		
$y''_t = -0,7954y''_{t-1} -0,6864y''_{t-2} -0,5199\, y''_{t-3} - 0,3776y''_{t-4} - 0,1864y''_{t-5} + \varepsilon_t$				
19.	ICBP	ARIMA(3,0,1)		
$y'_t = 0,000531 + 0,6661\, y'_{t-1} - 0,0003y'_{t-2} -0,0433\, y'_{t-3} - 0,7234\, \varepsilon_{t-1} + \varepsilon_t$				
20.	INCO	ARIMA(0,0,1)		
$y'_t = 0,0646\, \varepsilon_{t-1} + \varepsilon_t$				
21.	INDF	ARIMA(3,0,1)		
$y'_t = 0,3877y'_{t-1} - 0,0517y'_{t-2} -0,0839y'_t - 0,3996\, \varepsilon_{t-1} + \varepsilon_t$				
22.	INKP	ARIMA(0,0,0)		
$y'_t = \varepsilon_t$				
23.	INTP	ARIMA(2,0,1)		
$y'_t = 0,6865\, y'_{t-1} - 0,0531y'_{t-2} - 0,7212\, \varepsilon_{t-1} + \varepsilon_t$				
24.	ITMG	ARIMA(1,0,0)		
$y'_t = 0,0853y'_{t-1} + \varepsilon_t$				
25.	JPFA	ARIMA(1,0,0)		
$y'_t = 0,0435y'_{t-1} + \varepsilon_t$				
26.	JSMR	ARIMA(0,0,3)		
$y'_t = 0,0126\varepsilon_{t-1} - 0,0634\varepsilon_{t-2} - 0,0348\varepsilon_{t-3} + \varepsilon_t$				
27.	KLBF	ARIMA(1,0,4)		
$y'_t = 0,0808605 -0,5855\, y'_{t-1} + 0,5405\varepsilon_{t-1} -0,0622\varepsilon_{t-2} - 0,0705\varepsilon_{t-3} -0,0887\varepsilon_{t-4} + \varepsilon_t$				
28.	MDKA	ARIMA(5,1,0)		
$y''_t = -0,9415\, y''_{t-1} -0,7895y''_{t-2} -0,5787\, y''_{t-3} -0,3419\, y''_{t-4} -0,1591y''_{t-5} + \varepsilon_t$				
29.	MIKA	ARIMA(1,0,1)		
$y'_t = 0,4460\, y_{t-1} - 0,5368\varepsilon_{t-1} + \varepsilon_t$				
30.	MNCN	ARIMA(5,1,0)		
$y''_t = -0,8044\, y''_{t-1} -0,6112y''_{t-2} -0,4824\, y''_{t-3} -0,3394\, y''_{t-4} -0,1824y''_{t-5} + \varepsilon_t$				
31.	PGAS	ARIMA(0,0,3)		
$y'_t = 0,0055\, \varepsilon_{t-1} - 0,0681\varepsilon_{t-2} - 0,0466\, \varepsilon_{t-3} + \varepsilon_t$				
32.	PTBA	ARIMA(3,0,2)		
$y'_t = -0,0317y'_{t-1} - 0,9046y'_{t-2} + 0,0464\, y'_t + 0,0567\, \varepsilon_{t-1} + 0,8837\varepsilon_{t-2} + \varepsilon_t$				
33.	PTPP	ARIMA(0,0,1)		
ma1=0,0864 , mean=0				
$y'_t = 0,0864\, \varepsilon_{t-1} + \varepsilon_t$				
34.	PWON	ARIMA(2,0,0)		
$y'_t = 0,0089y'_{t-1} - 0,0479y'_{t-2} + \varepsilon_t$				
35.	SCMA	ARIMA(5,1,0)		
$y''_t = -0,8569\, y''_{t-1} -0,7308y''_{t-2} - 0,5332\, y''_{t-3} - 0,3417\, y''_{t-4} - 0,2025y''_{t-5} + \varepsilon_t$				
36.	SMGR	ARIMA(2,0,1)		
$y'_t = 0,8169y'_{t-1} - 0,0305y'_{t-2} - 0,8209\, \varepsilon_{t-1} + \varepsilon_t$				
37.	SMRA	ARIMA(0,0,3)		
$y'_t = 0,0582\varepsilon_{t-1} - 0,0093\varepsilon_{t-2} - 0,0511\varepsilon_{t-3} + \varepsilon_t$				
38.	SRIL	ARIMA(2,0,0)		
$y'_t = 0,0969\, y'_{t-1} - 0,0463\, y'_{t-2} + \varepsilon_t$				
39.	TBIG	ARIMA(0,0,1)		
$y'_t = -0,0855\, \varepsilon_{t-1} + \varepsilon_t$				
40.	TKIM	ARIMA(0,0,1)		
$y'_t = 0,0631\varepsilon_{t-1} + \varepsilon_t$				
41.	TLKM	ARIMA(0,0,4)		
$y'_t = -0,0505\varepsilon_{t-1} -0,1314\varepsilon_{t-2} -0,0307\varepsilon_{t-3} -0,0726\, \varepsilon_{t-4} + \varepsilon_t$				
42.	TOWR	ARIMA(2,0,3)		
$y'_t = -0,8990y'_{t-1} - 0,4970y'_{t-2} + 0,5676\, \varepsilon_{t-1} + 0,3120\, \varepsilon_{t-2} - 0,1817\varepsilon_{t-3} + \varepsilon_t$				
43.	UNTR	ARIMA(2,0,1)		
$y'_t = 0,6008\, y'_{t-1} - 0,0490y'_{t-2} - 0,6275\varepsilon_{t-1} + \varepsilon_t$				
44.	UNVR	ARIMA(1,0,1)		
$y'_t = 0,5895\, y'_{t-1} - 0,6889\varepsilon_{t-1} + \varepsilon_t$				
45.	WIKA	ARIMA(1,0,1)		
$y'_t = -0,8395y'_{t-1} + 0,8654\varepsilon_{t-1} + \varepsilon_t$				

The summary of the distribution of the ARIMA (p, d, q) model of LQ45 Stocks from Table 5 can be seen in Table 6.

Table 6: Distribution of the ARIMA (p, d, q) model of LQ45 Stocks after 1-time differentiation process

No	ARIMA(p,d,q)	Emitents	Count
1	ARIMA(1,0,1)	ACES,ERAA,EXCL, MIKA,UNVR,WIKA	6
2	ARIMA(2,0,2)	ADRO,AKRA,CPIN, GGRM	4
3	ARIMA(0,0,0)	ANTM,BBTN,BTPS, INKP	4
4	ARIMA(1,0,4)	ASII,KLBF	2
5	ARIMA(0,0,4)	BBCA,BBRI,TLKM	3
6	ARIMA(0,0,1)	BBNI,PTPP	2
7	ARIMA(4,0,1)	BMRI	1
8	ARIMA(2,0,1)	BSDE,INTP,SMGR, UNTR	4
9	ARIMA(0,0,3)	CTRA,JSMR,PGAS, SMRA	4
10	ARIMA(5,1,0)	HMSP,MDKA,MNC N,SCMA	4
11	ARIMA(3,0,1)	ICBP,INDF	2
12	ARIMA(0,0,1)	INCO,TBIG,TKIM	3
13	ARIMA(1,0,0)	ITMG,JPFA	2
14	ARIMA(3,0,2)	PTBA	1
15	ARIMA(2,0,0)	PWON,SRIL	2
16	ARIMA(2,0,3)	TOWR	1

The Shapiro-Wilk test was applied for the residual test. This test aims to test whether the residuals are normally distributed or not. In this case, H0 refers to normally distributed data. Based on

Table 7, it turned out that the p-value was very small, so it can be said that the residual data for the time series of the LQ45 stocks were not normally distributed.

Table 7: Shapiro Value And P-Value For Residual Data Of Lq45 Stocks

No.	Emitent Code	W value	p-value <	No.	Emitent Code	W value	p-value <
1.	ACES	0.96257	2.2e-16	24.	ITMG	0.97367	2.2e-16
2.	ADRO	0.96635	2.2e-16	25.	JPFA	0.94249	2.2e-16
3.	AKRA	0.97331	2.2e-16	26.	JSMR	0.95591	2.2e-16
4.	ANTM	0.91272	2.2e-16	27.	KLBF	0.95238	2.2e-16
5.	ASII	0.98342	2.2e-16	28.	MDKA	0.87906	2.2e-16
6.	BBCA	0.93359	2.2e-16	29.	MIKA	0.94879	2.2e-16
7.	BBNI	0.95942	2.2e-16	30.	MNCN	0,94394	2.2e-16
8.	BBRI	0.95137	2.2e-16	31.	PGAS	0.95641	2.2e-16
9.	BBTN	0.93974	2.2e-16	32.	PTBA	0.95231	2.2e-16
10.	BMRI	0.96002	2.2e-16	33.	PTPP	0.95038	2.2e-16
11.	BSDE	0.96192	2.2e-16	34.	PWON	0.96368	2.2e-16
12.	BTPS	0.9089	2.2e-16	35.	SCMA	0.95797	2.2e-16
13.	CPIN	0.9632	2.2e-16	36.	SMGR	0.95075	2.2e-16
14.	CTRA	0.97358	2.2e-16	37.	SMRA	0.98085	2.2e-16
15.	ERAA	0.93477	2.2e-16	38.	SRIL	0.89398	2.2e-16
16.	EXCL	0.96057	2.2e-16	39.	TBIG	0.93286	2.2e-16
17.	GGRM	0.95111	2.2e-16	40.	TKIM	0.90154	2.2e-16
18.	HMSP	0.87992	2.2e-16	41.	TLKM	0.96159	2.2e-16
19.	ICBP	0.95197	2.2e-16	42.	TOWR	0.7428	2.2e-16
20.	INCO	0.97363	2.2e-16	43.	UNTR	0.97608	2.2e-16
21.	INDF	0.94911	2.2e-16	44.	UNVR	0.93677	2.2e-16
22.	INKP	0.88297	2.2e-16	45.	WIKA	0.93551	2.2e-16
23.	INTP	0.96447	2.2e-16				

The results of the MAPE calculation for LQ45 stocks are presented in Table 8.

Table 8: MAPE Value of LQ45 Stocks

No.	Emitent Code	MAPE Value (%)		No.	Emitent Code	MAPE Value (%)
1.	ACES	6.8392		24.	ITMG	8.4129
2.	ADRO	12.4559		25.	JPFA	3.2431
3.	AKRA	5.1773		26.	JSMR	3.9788
4.	ANTM	28.469		27.	KLBF	3.6568
5.	ASII	4.7428		28.	MDKA	44.4900
6.	BBCA	2.1797		29.	MIKA	6.686
7.	BBNI	3.1649		30.	MNCN	28.2688
8.	BBRI	7.7772		31.	PGAS	10.3037
9.	BBTN	6.6408		32.	PTBA	6.0091
10.	BMRI	4.9121		33.	PTPP	8.5608
11.	BSDE	3.637		34.	PWON	5.0241
12.	BTPS	5.2558		35.	SCMA	25.2924
13.	CPIN	7.5191		36.	SMGR	9.221
14.	CTRA	7.2624		37.	SMRA	5.8308
15.	ERAA	16.8566		38.	SRIL	6.2826
16.	EXCL	14.4416		39.	TBIG	19.0069
17.	GGRM	4.7982		40.	TKIM	29.3543
18.	HMSP	3.0168		41.	TLKM	3.7094
19.	ICBP	5.6074		42.	TOWR	6.1822
20.	INCO	17.2474		43.	UNTR	9.700
21.	INDF	6.7765		44.	UNVR	3.7712
22.	INKP	21.0807		45.	WIKA	6.3104
23.	INTP	4.8191				
	Average	**10.0883**				
	Stand. Dev	**8.9678**				
	Maximum	**44.49**				
	Minimum	**2.1797**				

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Based on Table 8, it can be seen that the average forecast error for LQ45 stocks was 10.088%, with a standard deviation of 8.968%. BBCA stocks had the lowest forecast error of 2.1797%, and MDKA stocks had 44.49%. The highest forecast error was due to MDKA stocks having visually and exponentially increased (as observed in the Appendices). Therefore, it can continue increasing exponentially or even decreasing sharply in the future price period.

Based on our research, we can discuss some results such: first, this study only uses univariate time series data without considering other factors. In contrast, stock price fluctuations depend not only on changes in time but also on economic factors, socio-political factors, environmental factors, and other external influences (Ma, 2020). Second, in this study, we have not considered much data used as training and testing data to produce optimal predictions. In addition, the ARIMA model has not been investigated yet, which is suitable for forecasting how much data will be in the future. In this study, it is only used to predict 39 future data. Third, the ARIMA model for the above predictions does not mean it will show high accuracy in the real stock market.

There are some contributions to our research, such as:

1. MDKA shares have a very large MAPE. There are two reasons why MDKA's shares started the IPO on June 19, 2015, so it has not been ten years. Meanwhile, the prediction data using the ARIMA(5,2,0) model has a downward trend. This result contrasts the actual price, which shows an upward trend. So that this situation makes the MAPE of great value; as shown in Figure 3, MDKA shares have an exponential (non-linear) increase pattern even though the ARIMA model can only model static and linear time series data [8].

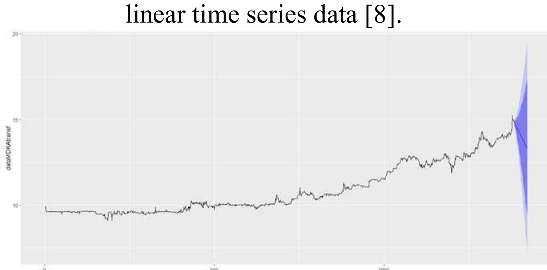

Figure 3: Point prediction and interval prediction for MDKA stocks

2. LQ45 stocks in Indonesia can also be classified into several sectors. WHEN GROUPED BY SECTOR, the MAPE calculation results from the ARIMA(p,d,q) model will produce a description as shown in Table 9. It can be seen that the finance sector and the non-cycle industrial sector have a low average MAPE, namely 4.9884 and 4.9618. In practice, the two types of sectors are less volatile and stable. The raw goods sector (primary material) and non-primary consumers (Consumer Cyclical) have a high MAPE, namely 22.0974 and 16.7079, and in fact, the stock price movement is very volatile. So the nature of stock price movements in these four sectors can be described by MAPE. In Indonesia, conservative investors can choose stocks from the IDXFINANCE or IDXINONCYC sector, while aggressive investors can invest in IDXBASIC or IDXCYCLIC sector.

Table 9: Description of MAPE Calculation by Sector in LQ45 stock

Sector	Mean	Stand. Dev	Min	Max	N
IDXBASIC	22.0974	13.4387	4.8191	44.4900	7
IDXCYCLIC	16.7079	10.1667	6.2826	28.2688	5
IDXENERGY	8.4718	3.0063	5.1773	12.4559	5
IDXFINANCE	4.9884	2.0880	2.1797	7.7772	6
IDXHEALTH	5.1714	2.1420	3.6568	6.6860	2
IDXINDUST	7.2214	3.5053	4.7428	9.7000	2
IDXINFRA	8.8843	5.7478	3.7094	19.0069	7
IDXINONCYC	4.9618	1.7527	3.0168	7.5191	7
IDXPROPERT	5.4386	1.5163	3.6370	7.2624	4
					45

The strength of this study is the application of the ARIMA(p,d,q) model for data mining and evaluation based on the MAPE so that real information is obtained that in Indonesia, conservative investors can choose stocks from the IDXFINANCE or IDXINONCYC sectors, while aggressive investors can invest in the IDXBASIC sector. or IDXCYCLIC. While the weakness in this

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study is the residual error of the model is not normally distributed. This weakness needs to be corrected, perhaps with other newer methods such as Deep Learning.

5. CONCLUSIONS

Based on the study findings, it can be concluded that:

1. The ARIMA (p, d, q) model on LQ45 stock prices was distributed into 16 models.
2. The ARIMA (p, d, q) model in this study used the differencing process of d=1 or d=2. This was applied to model the time series data to become stationary time series data.
3. Only four stocks applied the d=2 process based on observations, namely HMSP, MDKA, MNCN, and SCMA stocks.
4. The mean forecast error for LQ45 stocks was 10.088%, with a standard deviation of 8.968%. Meanwhile, BBCA stocks had the lowest prediction error of 2.1797%, and MDKA stocks had 44.49%. The highest forecast error was due to MDKA stocks having visually and exponentially increased (can be observed in the Appendices). Therefore, it can continue increasing exponentially or even decreasing sharply in the future price period.

Some recommendations to be applied based on this study are:

1. Based on the results of this study, further study should observe the effect of Box-Cox transformation on the accuracy of prediction on LQ45 stocks.
2. Further study can also investigate how many best time-series data can be used for the ARIMA (p, d, q) model prediction process on LQ45 stocks.

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Appendix A: The Plots Of LQ45 Stocks

The plots of LQ45 stocks can be seen in Figures 1 to 45 below.

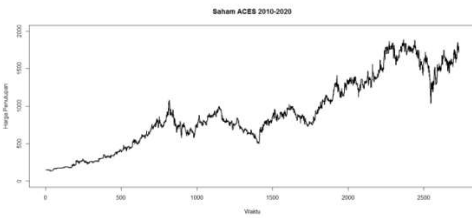

Figure 1: Plot of ACES Stock

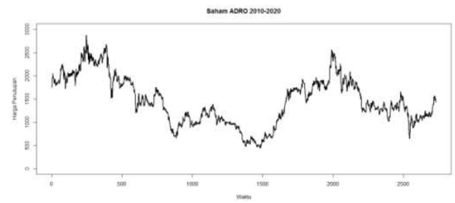

Figure 2: Plot of ADRO Stock

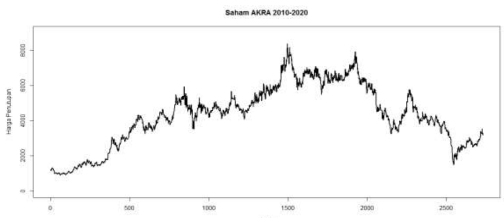

Figure 3: Plot of AKRA Stock

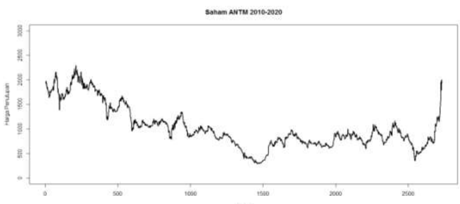

Figure 4: Plot of ANTM Stock

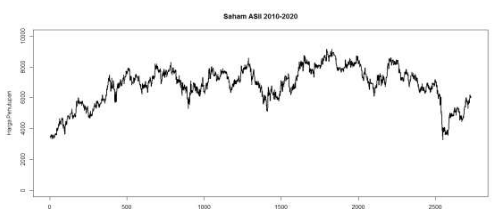

Figure 5 : Plot of ASII Stock

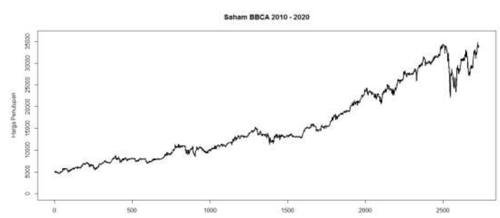

Figure 6: Plot of BBCA Stock

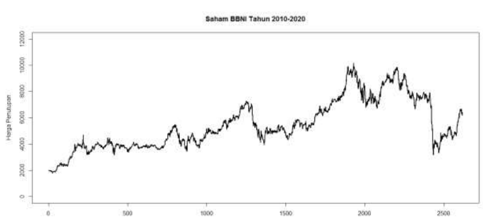

Figure 7: Plot of BBNI Emitent

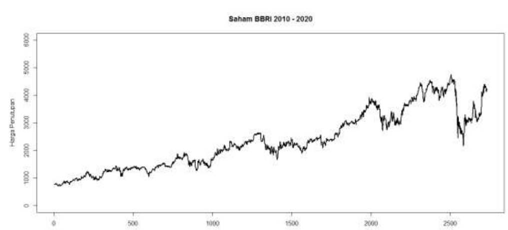

Figure 8: Plot of BBRI Stock

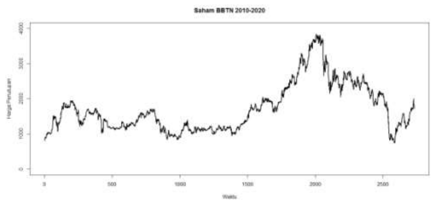

Figure 9: Plot of BBTN Stock

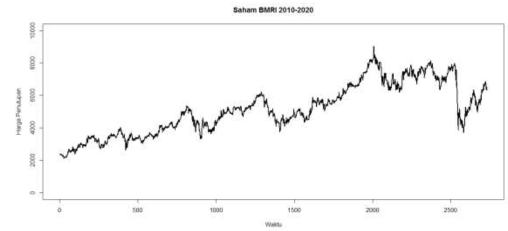

Figure 10 : Plot of BMRI Stock

Figure 11: Plot of BSDE Stock

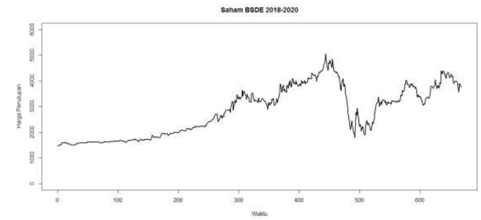

Figure 12: Plot of BTPS Stock

Figure 13: Plot of CPIN Stock

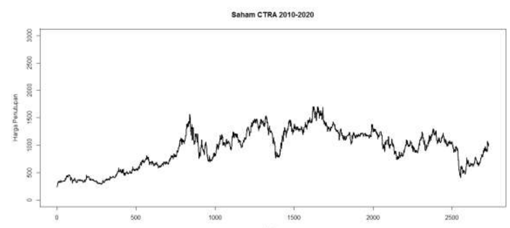

Figure 14: Plot of CTRA Stock

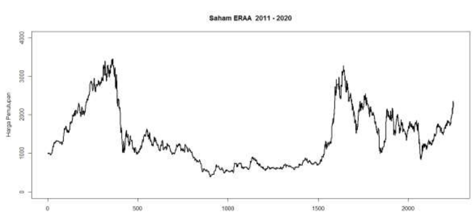

Figure 15: Plot of ERAA Stock

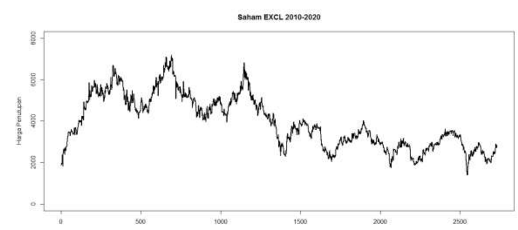

Figure 16 : Plot of EXCL Stock

Figure 17: Plot of GGRM Stock

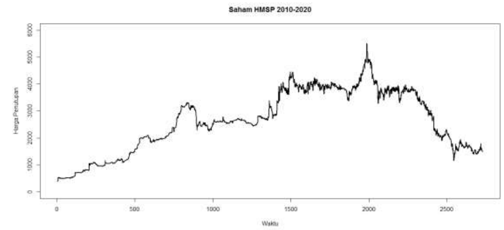

Figure 18 : Plot of HMSP Stock

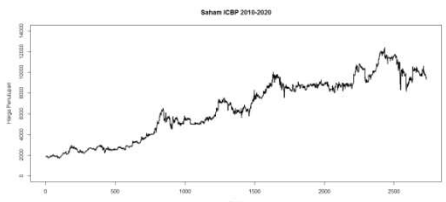

Figure 19: Plot of ICBP Stock

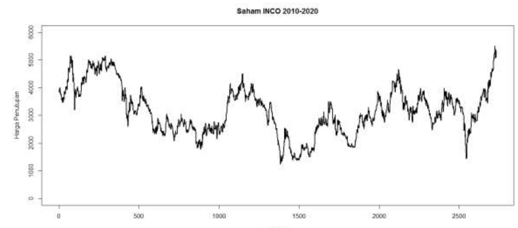

Figure 20: Plot Saham INCO Stock

Figure 21: Plot of INDF Stock

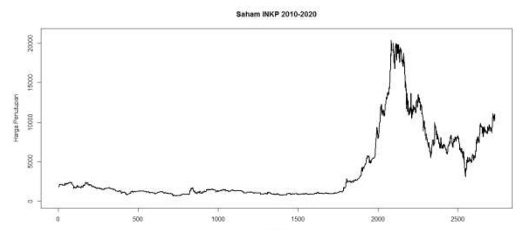

Figure 22: Plot of INKP Stock

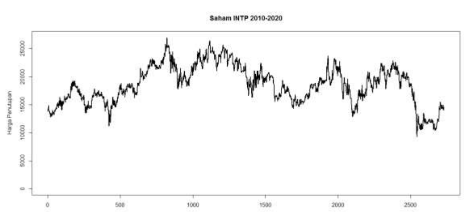

Figure 23: Plot of INTP Stock

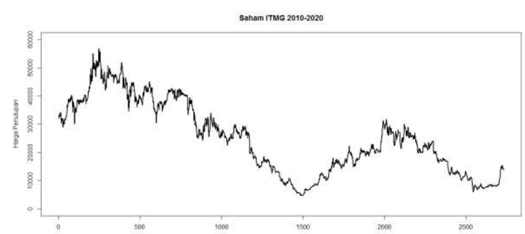

Figure 24: Plot of ITMG Stock

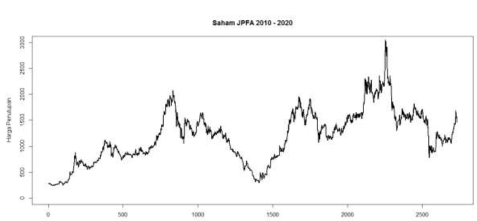

Figure 25: Plot of JPFA Stock

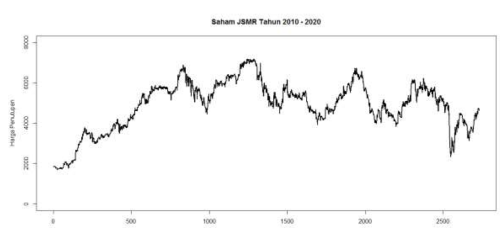

Figure 26: Plot ofJSMR Stock

Figure 27: Plot of KLBF Stock

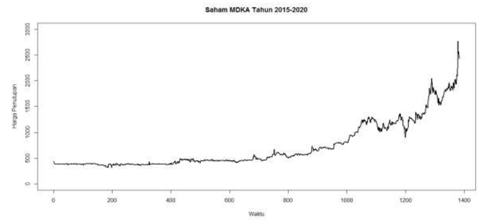

Figure 28: Plot of MDKA Stock

Figure 29: Plot of MIKA Stock

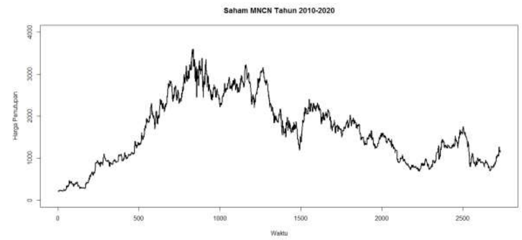

Figure 30: Plot Saham MNCN Stock

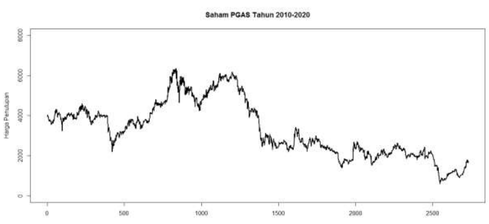

Figure 31: Plot of PGAS Stock

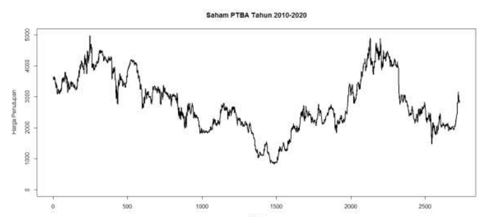

Figure 32: Plot of PTBA Stock

Figure 33: Plot of PTPP Stock

Figure 34: Plot of PWON Stock

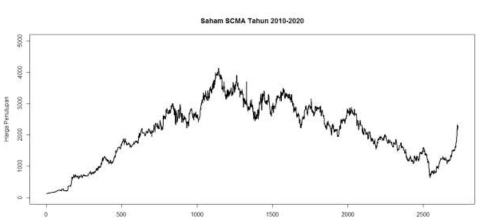

Figure 35: Plot of SCMA Stock

Figure 36: Plot of SMGR Stock

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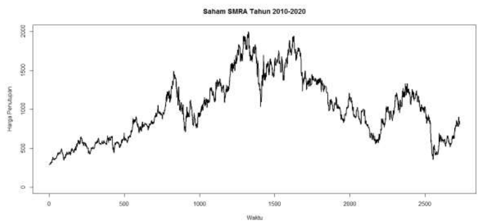

Figure 37: Plot of SMRA Stock

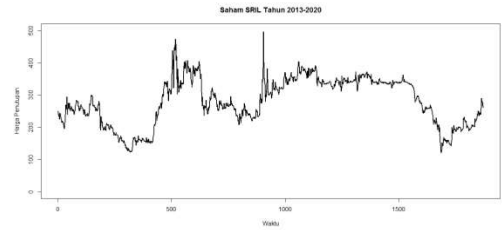

Figure 38: Plot of SRIL Stock

Figure 39: Plot of TBIG Stock

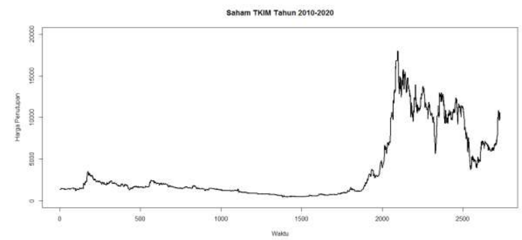

Figure 40: Plot of TKIM Stock

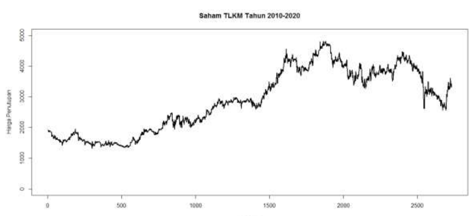

Figure 41: Plot of TLKM Stock

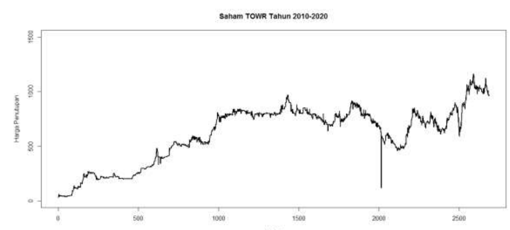

Figure 42: Plot of TOWR Stock

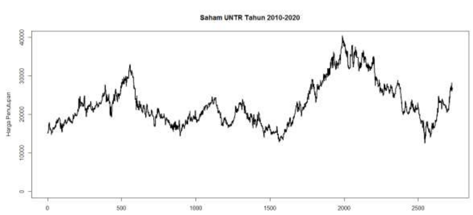

Figure 43: Plot of UNTR Stock

Figure 44: Plot of UNVR Stock

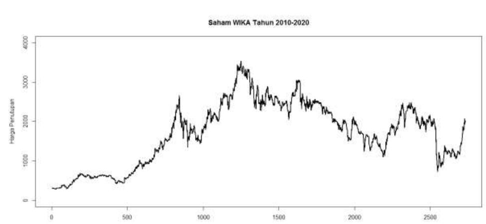

Figure 45: Plot of WIKA Stock