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The MAPE Analysis of Arima (p,d,q) on LQ45 Stock Price to Determine Training Data Period

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Abstract
In time series data forecasting, the main problem is finding the correct time series data for forecasting. The next problem is the stability of the ARIMA model over a certain period. These problems have never been studied, so this research tries to solve them. The result contribution of this study can be applied to forecasting LQ45 stocks in Indonesia. This research used five kinds of training data, including daily data up to 5 years. With these five types of data series, the Arima (p,d,q) was made for LQ45 stocks. The prediction was conducted for two months after obtaining the model 5 data series of LQ45 stocks. Two months of data were used for January and February 2021 prediction test data. The results of this prediction were compared with the test data to produce the MAPE value. Based on the observations and calculation results, the most suitable stock to use the Arima (p,d,q) was ASII. In 5 years, the stocks produced the lowest MAPE value of 0.05%. Relatively stable LQ45 stocks with no change in the Arima (p,d,q) using four consecutive data series were ACES, CTRA, INTP, MIKA, and TLKM. Based on the MAPE value analysis performed in this study, we concluded that the best period to use the Arima (p,d,q) for LQ45 stocks is two years, with a median error rate of only 6.0091%.

Keywords— ARIMA(p,d,q), MAPE Analysis, Prediction Residual Test, Parameter Estimation

1 Introduction

Ownership of a specific company's worth can be demonstrated by ownership of stocks or shares. The term "saham" has Arabic origins. The word originates from the phrase “musahamah” in fiqh literature, with a plural version of “ashum” or “suhmah”, denoting a portion of ownership. [1]. Shareholders can be seen as owners of the company. Ownership and rights in a company increase as the number of shares owned by a person increases. Stocks are a significant investment that might be crucial due to their benefits. [2]. Stocks are crucial for the advancement of developing countries. [3]. In Indonesia, IHSG is the Indonesia Composite Index (ICI).

ICI was initially introduced on April 1, 1983, to display share prices on the stock exchange. ICI encompasses the price fluctuations of every share listed on the IDX. The calculation of the ICI started on August 10, 1982. The base index value on that date was 100, with 13 listed stocks. The current number of stocks is 700 and is expected to increase.

Along with the information technology development and the support of the Indonesian government in developing the capital market in Indonesia, more and more Indonesians of all ages can trade shares on the stock exchange. The government support aims to educate the public regarding stocks as an investment instrument.

This study focused on 45 stocks with high market liquidity and large capitalization on the stock exchange, supported by good company fundamentals. This list of stocks is known as LQ45 stocks listed from November 2020 to January 2021 under the NOTICE of LQ45 Minor Evaluation Index No.Peng-00315/BEI.POP/10-2020. The list of stocks is presented in Table 1.

There are two prominent types of analysis in stock movements: technical and fundamental. Technical analysis is founded on three premises: market behavior reflects all information, prices follow trends, and historical patterns tend to recur. Technical analysis studies market behavior, while fundamental analysis examines economic factors like supply and demand influencing price movements. Essential analysis evaluates all pertinent aspects influencing market prices to ascertain the inherent worth. One technical analysis used for the time series data prediction method is theRIMA model [4].

The Arima (p,d,q) is mostly used to make predictions, and several studies have been conducted related to such topic, namely:

- Muthahharah (2019) conducted an ISSI prediction study using the Autoregressive Integrated Moving Average (ARIMA) method involving 231 data divided into in and out sample data. This study resulted in the ARIMA model (1,0,0), and the AR coefficient was 0,8104. The minimum ISSI prediction result was 174.36, with a maximum of 175.31 [5].
- Aksan and Nurfadilah (2020) created a model to predict daily mobile data usage. This study uses data from March 10, 2020, to May 29, 2020. The best mobile data model obtained in this research is ARIMA(0,1,2), so the model will be used for forecasting analysis. The optimal model meets experimental requirements, specifically diagnostic studies and parameter significance testing [6].
- Buchori and Sukmono (2018) applied the ARIMA model to predict material production at PT. XYZ. PT. XYZ is a company engaged in the food sector that produces chicken meatballs and chicken dumplings. The period of training data was 36 data, and the number of test data for the prediction was 37 data to 48 data. The ARIMA (1,0,0) model was obtained [7].
- Ningsih and Jana (2018) applied ARIMA to predict Human Immunodeficiency HIV sufferers. The ARIMA model (1,1,1) was obtained with the constant AR=-0.6051 and MA=0.3299. Prediction results showed that the mean estimation value in the next four years was 221 people living with HIV. This study used annual training data from 2008 - 2017 (10 data) to predict the condition in the next four years [8].
- Gold price forecasting is necessary for investors to know the trend of gold prices in the future. For these reasons, Djami and Latupeirissa (2020) created an ARIMA model for forecasting. The model obtained is ARIMA (1,1,1) with parameter coefficients $\varphi 1 = 0.7880$, $\theta 1 = 0.9855$ and $\beta 0 = 0.5445$ [9].
- Rahmawati et al. (2020) applied the ARIMA Box-Jenkins method to predict electricity consumption. Based on research results, it was obtained that the best model from ARIMA was used for forecasting electricity consumption; ARIMA (0,1,0) has a MAPE value of 0.33% [10].
- Salwa et al. (2018) utilized bitcoin price data from January 10, 2018, to March 10, 2018, comprising 60 periods, for training purposes. The model was used to forecast the bitcoin price for the following 30 periods between March 11, 2018, and April 09, 2018. The ARIMA model derived was ARIMA (0,2,1), i.e., $Z_t = \mu - 0{,}9647Z_{t-1} + a_t$, and the model was suitable for the prediction process [11].
- Ainiyah and Bansori (2021) predict how much COVID-19 cases will increase in Sidoarjo Regency, East Java Province, using the ARIMA method. The results of this research are of two types. The model for predicting data on total cases of positive COVID-19 patients is ARIMA (2,2,1) with an MSE value of 1540.51. Meanwhile, the data prediction for total cases of recovered COVID-19 patients is ARIMA (3,1,2) with an MSE value of 526.81 [12].
- Wulandari et al. (2021) forecasted the closing price of PT Bank Central Asia Tbk shares using the Box Jenkins ARIMA method. The result of this model, which is suitable for the closing share price of PT Bank Central Asia Tbk, namely the ARIMA model (0,2,1) [13].
- Lestari and Yotenka (2022) predict the price of red chilies for the next 12 periods. The data comes from consumer prices for red chilies in Indonesia from January 2017 to December 2021. Based on the research, the best model for forecasting red chili prices is ARIMA (2,0,0). Forecasting results for January to December 2022 show that consumer prices for red chilies have increased but tend to remain stable within the same price range [14].
- Santosa et al. (2024) conducted a comparison study of Arima(p,d, q) and Holt-Winter method for LQ45 Stock Price forecasting using data from 2016 – 2021 and it concluded that Holt-Winter has bigger error based on MAPE value than ARIMA (p,d,q) at forecasting LQ45 stock prices [15]

Researchers usually directly took a lot of specific training data in a prediction model of a case using the ARIMA method. Of course, the amount of training data used to model ARIMA will affect the accuracy of the prediction results. The problem is the amount of training data used to model ARIMA, so the forecast error of the results using the model can be as low as possible.

The research above focused on obtaining the Arima (p,d,q) and the prediction process. This study's contributions and objectives are being compared to those of prior studies:

- This research tries to model ARIMA (p,d,q) on one-time series data and cross-section data spread over 45 stocks. Our research is different from the studies above.
- This research tries to find the best period for training data on the Arima (p,d,q) on LQ45 stocks based on the MAPE value because the period or the amount of training data is important for the model's accuracy.
- This research determines the stocks from the LQ45 index list that best fit the Arima (p,d,q) based on the MAPE value.

This was an applicative study. The main problem to be solved in this study was determining the best period on the ARIMA model to predict LQ45 stocks. The best period can be expressed by the number of training data used for modeling. The best term is the ARIMA model with the lowest MAPE value. The limitation of this study was that the training data used were only five kinds of data series, namely one year, two years, three years, four years, and five years. The benefits of this study are twofold: first, determining the best time for the ARIMA (p, d, q) prediction model, which can be used as a reference to determine the amount of training data on LQ45 stock prediction using the ARIMA model in the future; second, one can determine the characteristics of the ARIMA model for each LQ45 stock.

This article is written in the following order: the first section is the introduction, which contains the background of the problem, the topic to be studied, and the objectives, benefits, and contributions of the study. The second section is the methodology, which contains the steps to be applied in this study. The section presents the results, discussion, and analysis of the study conducted, and the last section presents the conclusion, which contains findings and recommendations for further research.

2 Research methods

To obtain a suitable period of training data, this study performed several stages as follows:

1. Stock data used were LQ45 stock data for November 2020 to January 2021 (according to the appendix for the LQ45 No. Peng-00315/BEI.POP/10-2020).
2. Created five kinds of training data, namely “data series 1”, “data series 2”, and “data series 5”.
   - Data series 1 refers to daily time series data with a period of 1 year in 2020, namely January 2, 2020, to December 30, 2020 (242 data),
   - Data series 2 refers to daily time series data for two years from January 1, 2019 - December 30, 2020 (499 data),
   - Data series 3 refers to daily time series data for three years from January 1, 2018 – December 30, 2020 (760 data),
   - Data series 4 refers to daily time series data for four years from January 2, 2017 - December 30, 2020 (1014 data),
   - Data series 5 refers to daily time series data for five years from January 4, 2016 – December 30, 2020 (1260 data).
3. Recorded test data used to test prediction results in daily time-series data for two months, namely data for LQ45 stocks from January 4, 2021, to February 26, 2021 (39 data).
4. An ARIMA(p,d,q) was created for 45 LQ45 stocks using "series 1" data. The process of setting up the ARIMA model for the 45 stocks involved the following steps:
   1. Created data visualization for 45 LQ45 stocks by drawing a graph of the data series 1.
   2. Tested the stationarity of each training data and addressed non-stationary data using Box-Cox Transformation and Differencing.
   3. Estimated the ARIMA by analyzing the ACF and PACF plots of the training data.
   4. Conducted parameter evaluation on the model derived from the training data.
   5. Performed parameter assessment on the model created from the training data.
   6. Select the optimal model based on the lowest AICC value.
   7. Predicted 45 LQ45 stocks using the model.
   8. Measured and recorded 45 MAPE measures from data series one derived from the prediction process.
5. Repeated step 4 for data series 2 to data series 5.
6. Drew a boxplot to observe the distribution and normality of the data and whether the data had a distribution close to normal.
7. If the data had outliers, the center size was changed by median rather than mean.

Based on the research methods above, this research uses some theoretical foundations explained below. Time-series data consists of recorded values observed at regular intervals such as daily, weekly, monthly, or yearly during a specific period. Time series analysis is crucial in multiple contexts. Time series data can serve as a reference for future planning in the business environment. [16].

2.1 *Arima(p,d,q)*

Arima (p,d,q) includes three main phases: model identification, parameter estimation, and residual validation. [17]. The ARIMA model, denoted (p,d,q), is called the Box-Jenkins model and is derived from an autoregressive integrated moving average process. [18]. Arima consists of three combined processes: AR, integration with process differencing, and MA.

The time series data must exhibit a stationary variance for constructing an Arima (p,d,q). A Box-Cox transformation is required to stabilize the variance of the time series data based on the lambda value. The transformation's structure, as outlined by [19], can be seen in formula (1) as follows :

$$y_t = \begin{cases} \log(z_t) & ,if\ \lambda = 0 \\ sign(z_t)(|z_t|^{\lambda} - 1)/\lambda & otherwise \end{cases} \quad \ldots(1)$$

The Arima (p,d,q) can be identified by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the present time series data. [20].

- The <u>Autoregressive order p</u> or AR(p) can be written in the form : $y_t=\phi_1 y_{t-1}+\phi_2 y_{t-2}+\cdots+\phi_p y_{t-p}+\varepsilon_t$.
  This autoregressive (AR) model demonstrates a regression model between a value of y and a value at a specific time y_{t-k} where $k =1,2,3,..,n$. In this model, it is used ε_t as the residual at time t.
- The <u>Moving Average order q</u> or MA(q) is written in the form: $y_t=\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\cdots-\theta_q\varepsilon_{t-q}$.
  This model demonstrates a regression model between the value of yt and the residual value from the previous period, namely ε_{t-k} where $k =1,2,3,..,n$.
- The ARMA (p,q) is written with the form:
  $\phi_p(B)y_t=\theta_q(B)\varepsilon_t$
  Where:
  $\phi_p\ (B)=1-\phi_1 B-\cdots-\phi_p B^p$ is AR model coefficients
  $\theta_q\ (B)=1-\theta_1 B-\cdots-\theta_q B^q$ is MA model coefficients
  and operator B is called the Backshift operator ($By_t = y_{t-1}$, $B\varepsilon_t = \varepsilon_{t-1}$)
  This ARMA(p,q) model combines the AR(p) and MA(q) models.
- The <u>differencing process</u> can be performed by using operator (1-B).
  $z'_t = z_t - z_{t-1} = z_t - Bz_t = (1- B)$. It is usually referred to as differencing order 1.
  $z''_t = z_t - 2z_{t-1} + z_{t-2} = (1 -2B + B2)\ z_t = (1-B)^2 z_t$ is usually referred to as differencing order 2.
  In general, order d differencing can be written as $(1-B)^d z_t$.
  The differencing process can turn a non-stationary into a stationary time series.
- The <u>Autoregressive Integrated Moving Average or ARIMA (p, d, q)</u> model or Arima (p,d,q) can be written as: $$\phi_p\ (B)(1-B)^d\ y_t = \theta_q(B)\varepsilon_t \quad \ldots(2)$$

  Where :
  $\phi_p\ (B)=1-\phi_1 B-\cdots-\phi_p B^p$ is AR(p) model coefficients
  $\theta_q\ (B)=1-\theta_1 B-\cdots-\theta_q B^q$ is MA(q) model coefficients
  $(1-B)^d$ is d-order difference
  y_t is the current value time series data at time t
  ε_t is the residual at the time t

The form of the AR(p), MA(q) model, or a combination of both can be seen from the form of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series data. [17] .

Using the ARIMA model aims to find the values, thereby minimizing the desired calculation error. In mathematical statistics, many methods can be used for this estimation, such as MLE, method of moments, or least squares estimation. To carry out this computing process, we can use software packages, such as SPSS, R, Minitab, SAS and many more. [21] [22].

Forming an ARIMA model that goes through several stages requires in-depth knowledge and concepts. Our work used a software package developed by Hyndman-Khandakar. [23]. The residual test was performed on the residual data, i.e., the difference between the actual data and the prediction result data, as shown below. [17].

$$\hat{\varepsilon}_t = y_t - \left(\hat{\delta} + \sum_{i=1}^{p} \hat{\varphi}_i\, y_{t-i} + \sum_{i=1}^{q} \hat{\theta}_i\, \hat{\varepsilon}_{t-i}\right) \quad \ldots(3)$$

Residual tests often include autocorrelation tests, normality tests, residual distribution plots, and other tests required by the ARIMA model. In this study, the Shapiro-Wilktest was used to assess normality. [21].

The main limitations of ARIMA for time series forecasting are that this model must meet the assumption of stationarity, the assumption of linearity between past and future data, the assumption of no outliers in the data, only considers patterns in the data itself (univariate time series), and is completely based on historical patterns. This makes it less adaptive to structural changes.

2.2 *Forecasting using Arima(p,d,q)*

Once the model is obtained, the prediction process is performed using the expected price $y_{T+\tau}$ given that the previously observed values are known, namely the y_T , y_{T-1} , y_{T-2} …

$$\hat{y}_{T+\tau}(T) = E[y_{T+\tau} : y_T\ , y_{T-1}\ , y_{T-2}\ , \ldots] = \mu + \sum_{i=\tau}^{\infty} \Psi_i\, \varepsilon_{T+\tau-i} \quad \ldots(4)$$

Ψ is the presentation value linear combination of the ARIMA processes expressed from residuals. The residual has characteristics. $E[e_T(\tau)] = 0$ and $Var[e_T(\tau)] = \sigma^2 \sum_{i=0}^{\tau-1} \Psi_i{}^2 = \sigma^2(\tau)$ [19] [17]

2.3 *Accuracy of The Prediction*

Then, the y_t value was inversely transformed into the time series data value z_t using the inverse of the Box-Cox transformation with formula (5). [20]:

$$z_t = \begin{cases} \exp(y_t) & ,if\ \ \lambda = 0 \\ sign(\lambda y_t + 1)(\lambda y_t + 1)^{1/\lambda} & otherwise \end{cases} \quad \ldots(5)$$

The MAPE metric is used to measure the accuracy of the prediction computation. Typically, the MAPE value represents accuracy as a ratio determined by the formula (6):

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

A_i presents actual data; F_i is forecast data (the z_t value). In this research, we used n=39 to represents the amount of data for two months, ie. January to February 2021.

MAPE, which is the mean absolute error in percentage form, does not rely on the assumption of normality of the residual distribution because it is a direct measure of error. If the residuals are not normal, this may reflect that the model is not capturing all patterns in the data or that there are outliers. Non-normality can indicate the presence of poorly modeled variables, which can indirectly affect the MAPE value.

3 Results and Discussion

Based on the results of the computational process that had been carried out, several significant results obtained are listed in this section.

3.1. The Results

The initial stage of the modeling process was graphing data obtained from LQ45 stocks. Plotting is essential since it allows for the visualization of time series data. Plot figures are omitted in this study due to the abundance of plots. The Box-Cox transformation stabilized the variance of data series 1 to 5 five by observing the lambda values. Table 1 displays the lambda parameter utilized for the Box-Cox transformation of each data series.

Table 1: Lambda Values for Box-Cox Transformation for Data Series 1 to Data Series 5

No.	**Stock Code**	**Lambda Value**				
		Data series 1 (1 years)	**Data series 2 (2 years)**	**Data series 3 (3 years)**	**Data series 4 (4 years)**	**Data series 5 (5 years)**
1.	ACES	1.734899	1.999924	1.417274	1.417274	0.2244183
2.	ADRO	1.473296	1.47098	0.2047917	0.2047917	0.2213269
3.	AKRA	1.689419	0.7735247	0.746378	0.7244973	0.4990646

No.	Stock Code	Lambda Value				
		Data series 1 (1 years)	Data series 2 (2 years)	Data series 3 (3 years)	Data series 4 (4 years)	Data series 5 (5 years)
4.	ANTM	-0.0915821	-0.0156457	-0.020380	-0.0250335	0.01549028
5.	ASII	1.231751	1.343679	1.28114	1.266095	1.188772
6.	BBCA	1.999924	1.999924	1.999924	-0.4112318	-0.9999242
7.	BBNI	0.9837726	1.177757	1.046218	0.9862762	0.8026679
8.	BBRI	1.999924	1.999924	1.999924	1.999924	1.212655
9.	BBTN	0.4803823	1.011404	0.2542151	0.3464323	0.2849765
10.	BMRI	1.434956	1.999924	1.996036	1.820745	1.363665
11.	BSDE	0.6068954	0.8434385	0.7670525	0.9973249	0.8142677
12.	BTPS	1.686447	1.388776	0.9091251	-	-
13.	CPIN	1.503963	0.6677912	0.2686826	-0.1416572	-0.1823412
14.	CTRA	0.5402337	0.8063214	0.7779303	0.9459185	0.6739796
15.	ERAA	0.7529662	0.68734	0.6304297	-0.1265285	-0.0411178
16.	EXCL	1.999936	1.999313	1.878727	1.678283	1.311806
17.	GGRM	1.999924	1.322048	1.234923	1.144031	1.110885
18.	HMSP	1.559254	0.8111185	0.3157006	0.3753084	0.3554956
19.	ICBP	1.999924	1.999924	1.319005	0.4133001	-0.0933094
20.	INCO	0.9448763	0.9158451	0.7637985	0.6560414	0.3723542
21.	INDF	1.999924	1.999924	1.999924	1.999924	1.999924
22.	INKP	0.6412572	0.7066059	0.2362684	0.1384945	-0.0388385
23.	INTP	1.687386	1.580551	1.487348	1.222578	1.156789
24.	ITMG	0.4774951	0.5670116	0.232234	0.2267092	0.1440054
25.	JPFA	1.180322	0.4583209	0.3133212	0.2491255	0.2523515
26.	JSMR	1.778879	1.567096	1.556145	1.583491	1.446991
27.	KLBF	1.999924	1.999924	1.999924	1.999924	1.999924
28.	MDKA	0.4513201	-0.244766	-0.218556	0.02053707	0.1719472
29.	MIKA	1.516649	0.8626355	0.6696606	0.6159271	0.5189577
30.	MNCN	0.2201743	0.338632	0.2477167	0.4661841	0.3530696
31.	PGAS	0.3273144	0.4243306	0.2605426	0.4514334	0.6251741
32.	PTBA	1.001572	0.996791	0.3953202	0.3074166	0.1048992
33.	PTPP	0.2625776	0.356265	0.2183046	0.3134834	0.3633908
34.	PWON	1.270892	1.194841	1.28714	1.305186	1.204697
35.	SCMA	0.178248	0.3654298	0.5285369	0.5992663	0.4383269
36.	SMGR	1.572314	1.417339	1.114624	0.9565526	0.9055523
37.	SMRA	1.149737	0.7460242	0.7072157	0.7242994	0.639743
38.	SRIL	-0.1002818	1.216288	1.146044	-0.0045077	-0.0066084
39.	TBIG	1.999924	1.194979	1.012035	0.3153404	0.4182037
40.	TKIM	0.3339721	0.7088255	0.3486681	0.01778805	-0.0986725
41.	TLKM	1.999924	1.999924	1.999924	1.999924	1.995436
42.	TOWR	1.213575	0.462436	1.999924	1.999924	1.999924
43.	UNTR	0.6421744	0.8983296	0.5089566	0.5015269	0.354795
44.	UNVR	1.999924	1.999924	1.999924	1.999924	1.999924
45.	WIKA	0.1331875	0.601098	0.6199914	0.7954526	0.5514709

This lambda value will stabilize the variance before performing Arima (p,d,q). The transformation process was as follows: Data Series 1 was transformed by the formula (1) → the process of obtaining the Arima (p,d,q) → the forecasting process → Box-Cox inverse transformation was applied for the data series of forecasting results with the formula (2) → MAPE calculation. For BTPS stocks, data series 4 and data series 5 were not available, so only 44 stocks were used for further analysis.

Time series data analysis assumes that the data series are stationary. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used to assess the stationarity of the data. The null hypothesis for this test assumes that the examined data are stationary, while the alternative hypothesis posits that the examined time series data are not stationary. Table 2 presents the KPSS unit root test values for data series 1 – 5 LQ45 Stocks [20].

Table 2: KPSS Unit Root Test Values for Data Series 1 to Data Series 5 of LQ45 Stocks

No.	Stock Code	KPPS Value Unit Root Test				
		Data series 1 (1 year)	Data series 2 (2 years)	Data series 3 (3 years)	Data series 4 (4 yeras)	Data series 5 (5 years)
1.	ACES	1.9447	2.9441	3.4921	8.6244	13.3037
2.	ADRO	0.8624	1.6775	7.6001	8.484	2.6859
3.	AKRA	0.7198	6.498	7.4596	10.6678	13.4799
4.	ANTM	2.8049	1.1076	0.574	0.6781	2.1425
5.	ASII	0.7834	6.272	7.1983	9.0704	7.5811
6.	BBCA	0.6831	1.3117	7.3762	10.9126	-0.9999242
7.	BBNI	1.0887	6.5535	6.3496	3.4746	2.9708
8.	BBRI	1.0193	2.4952	1.4106	4.3806	9.6082
9.	BBTN	0.8384	2.4453	8.8512	7.1671	3.9353
10.	BMRI	1.0384	4.604	4.2842	1.7968	3.9557
11.	BSDE	1.0495	5.9516	6.9658	9.988	12.5532
12.	BTPS	0.787	2.8244	6.6324	--	--
13.	CPIN	0.812	0.6411	4.0218	9.155	11.1253
14.	CTRA	0.9007	4.0851	3.9168	6.6051	10.3002
15.	ERAA	1.5892	1.3946	1.255	5.8146	9.9555
16.	EXCL	0.8461	1.9253	0.8652	2.0831	3.6223
17.	GGRM	2.055	7.3835	8.0587	6.1542	5.6296
18.	HMSP	2.054	7.8005	10.2455	10.493	11.4343
19.	ICBP	1.5489	1.477	4.2207	7.1843	9.2765
20.	INCO	3.2922	1.3073	0.6518	3.0182	6.7505
21.	INDF	0.6883	0.726	0.6692	3.8051	3.0131
22.	INKP	3.0607	1.6733	5.1086	3.9418	10.5167
23.	INTP	1.5312	6.4409	3.9351	2.8839	2.4119
24.	ITMG	0.8591	6.7514	10.047	7.9269	3.6125
25.	JPFA	0.8318	5.2144	5.076	2.2343	2.4314
26.	JSMR	0.6343	5.1941	2.2072	2.3899	2.2954
27.	KLBF	1.4918	0.6312	0.3821	1.4822	0.9902
28.	MDKA	4.1972	7.3596	10.6262	12.0742	14.2491
29.	MIKA	1.2923	3.3129	5.6706	2.7771	2.5975
30.	MNCN	2.423	1.5312	1.0699	5.1028	9.6346
31.	PGAS	0.7123	6.0026	6.1059	5.9097	8.7899
32.	PTBA	0.5544	5.8511	7.5811	2.8742	4.5994
33.	PTPP	0.7702	6.113	7.4075	10.1414	13.6402
34.	PWON	0.8685	6.673	4.1838	4.2564	2.8096
35.	SCMA	1.7281	2.9413	8.0869	10.5975	13.6917
36.	SMGR	0.741	3.9697	1.3005	1.7793	2.0716
37.	SMRA	0.9199	5.0668	2.1996	4.5397	9.8269
38.	SRIL	1.1588	6.700	8.3793	6.5719	4.0378
39.	TBIG	3.4582	5.5321	3.1057	1.7899	2.0832
40.	TKIM	0.7748	4.7132	2.4299	6.4371	12.2822
41.	TLKM	2.4376	5.6457	3.7217	5.8036	3.8472
42.	TOWR	3.1013	5.4104	6.9017	4.0114	2.8693
43.	UNTR	2.7059	3.6186	8.8641	6.8651	3.3636
44.	UNVR	0.5179	6.0166	6.6886	5.8228	3.3607
45.	WIKA	0.8342	4.8136	1.7525	3.3037	7.5616

If α=5% was applied, then H0 was rejected if the critical value of the KPSS calculation was higher than 0.463. As for α=10%, then H0 was rejected if the critical value of the KPSS calculation was higher than 0.347. Both critical values can be seen in the computational results. The KPSS calculation values in Table 2 tended to be higher than the critical value for both. This meant that H0 tended to be rejected. Since the data series were not stationary, conducting a differencing process after the Box-Cox transformation was necessary. The Arima (p,d,q) and the AR and MA function coefficients for each LQ45 stock can be observed in Appendix 1.

The Shapiro-Wilk test was used to assess the normality of the residuals. The null hypothesis (H0) is that the residual data follow a normal distribution, whereas the alternative hypothesis suggests that the residual data do not conform to a normal distribution. According to Table 3, the small p-value indicates that the residual data of the Arima (p,d,q) for the LQ45 stocks time series did not follow a normal distribution.

Table 3: Shapiro values and p-values for the Residual Test Data series 1 to Data series 5 of LQ45 Stocks

No.	**Stock Code**	**Value of W1 (p-value)** 1 year	**Value of W2 (p-value)** 2 years	**Value of W3 (p-value)** 3 years	**Value of W4 (p-value)** 4 years	**Value of W5 (p-value)** 5 years
1.	ACES	0.98333 (0.006157)	0.98971 (0.001437)	0.97794 (2.703e-09)	0.96546 (8.866e-15)	0.97413 (3.067e-14)
2.	ADRO	0.98586 (0.01694)	0.9835 (1.935e-05)	0.96218 (4.2e-13)	0.96017 (5.318e-16)	0.96765 (3.696e-16)
3.	AKRA	0.9746 (6.785e-05)	0.96317 (2.341e-10)	0.95487 (6.062e-15)	0.97044 (8.103e-14)	0.97577 (1.056e-13)
4.	ANTM	0.923 (6.891e-10)	0.9377 (1.35e-13)	0.92429 (2.2e-16)	0.90759 (2.2e-16)	0.90009 (2.2e-16)
5.	ASII	0.9876 (0.03474)	0.98206 (7.952e-06)	0.98941 (2.704e-05)	0.98374 (3.324e-09)	0.98464 (2.772e-10)
6.	BBCA	0.9609 (3.669e-06)	0.92093 (1.618e-15)	0.90506 (2.2e-16)	0.86023 (2.2e-16)	0.014574 (2.2e-16)
7.	BBNI	0.96647 (1.837e-05)	0.9835 (2.478e-05	0.98167 (7.366e-08)	0.97511 (1.003e-11)	0.96811 (1.549e-15)
8.	BBRI	0.96979 (5.118e-05)	0.96018 (2.294e-10)	0.96268 (5.32e-13)	0.94061 (2.2e-16)	0.93217 (2.2e-16)
9.	BBTN	0.9506 (2.492e-07)	0.97961 (1.886e-06)	0.94506 (2.2e-16)	0.9541 (2.2e-16)	0.94657 (2.2e-16)
10.	BMRI	0.97246 (0.0001215)	0.97385 (8.864e-08)	0.97369 (1.857e-10)	0.96014 (5.249e-16)	0.95681 (2.2e-16)
11.	BSDE	0.94336 4.529e-08	0.97564 2.189e-07	0.97353 1.679e-10	0.97356 1.245e-12	0.97234 8.428e-15
12.	BTPS	0.96993 (5.364e-05)	0.9573 (7.731e-11)	0.90853 (2.2e-16)	-	-
13.	CPIN	0.98607 (0.01844)	0.98494 (4.901e-05)	0.98154 (3.357e-08)	0.98046 (1.991e-10)	0.97859 (1.017e-12)
14.	CTRA	0.96626 (1.725e-05)	0.98203 (7.773e-06)	0.98477 (4.154e-07)	0.98147 (4.578e-10)	0.98341 (8.008e-11)
15.	ERAA	0.96978 (5.116e-05)	0.96202 (4.712e-10)	0.95711 (4.251e-14)	0.93901 (2.2e-16)	0.93575 (2.2e-16)
16.	EXCL	0.98181 (0.003397)	0.98534 (6.379e-05)	0.97739 (1.87e-09)	0.98185 (6.309e-10)	0.97671 (2.206e-13)
17.	GGRM	0.94858 (1.529e-07)	0.86646 (2.2e-16)	0.91079 (2.2e-16)	0.92576 (2.2e-16)	0.93503 (2.2e-16)
18.	HMSP	0.96808 (3.006e-05)	0.90743 (2.2e-16)	0.93141 (2.2e-16)	0.93165 (2.2e-16)	0.93981 (2.2e-16)
19.	ICBP	0.94271 (3.914e-08)	0.89908 (2.2e-16)	0.90357 (2.2e-16)	0.89541 (2.2e-16)	0.92214 (2.2e-16)
20.	INCO	0.9723 (0.000115)	0.9795 (1.767e-06)	0.98448 (3.279e-07)	0.97636 (8.68e-12)	0.9759 (1.162e-13)
21.	INDF	0.94986 (2.078e-07)	0.95301 (1.668e-11)	0.96107 (2.501e-13)	0.9604 (5.993e-16)	0.9705 (2.167e-16)
22.	INKP	0.96608 (1.638e-05)	0.91596 (4.953e-16)	0.9425 (2.2e-16)	0.93935 (2.2e-16)	0.91247 (2.2e-16)
23.	INTP	0.94674 (9.389e-08)	0.97624 (2.92e-07)	0.97809 (2.913e-09)	0.96535 (8.365e-15)	0.96726 (2.845e-16)
24.	ITMG	0.96813 (3.049e-05)	0.93673 (1.023e-13)	0.96388 (9.477e-13)	0.96707 (2.217e-14)	0.96692 (2.328e-16)
25.	JPFA	0.95378	0.96234	0.95625	0.9538	0.95053

No.	Stock Code	Value of W1 (p-value) 1 year	Value of W2 (p-value) 2 years	Value of W3 (p-value) 3 years	Value of W4 (p-value) 4 years	Value of W5 (p-value) 5 years
		(5.514e-07)	(5.192e-10)	(2.856e-14)	(2.2e-16)	(2.2e-16)
26.	JSMR	0.98316 (0.005754)	0.98938 (0.001118)	0.98448 (3.272e-07)	0.98536 (1.514e-08)	0.9804 (4.813e-12)
27.	KLBF	0.97953 (0.001439)	0.97403 (9.422e-08)	0.98303 (1.018e-07)	0.98179 (5.934e-10)	0.97239 (8.585e-15)
28.	MDKA	0.8779 (5.059e-13)	0.92091 (1.545e-15)	0.88474 (2.2e-16)	0.8862 (2.2e-16)	0.84853 (2.2e-16)
29.	MIKA	0.98028 (0.0019)	0.95445 (2.761e-11)	0.93326 (2.2e-16)	0.938 (2.2e-16)	0.94192 (2.2e-16)
30.	MNCN	0.93677 (1.07e-08)	0.90614 (2.2e-16)	0.90521 (2.2e-16)	0.9141 (2.2e-16)	0.91936 (2.2e-16)
31.	PGAS	0.96591 (1.556e-05)	0.9518 (1.102e-11)	0.93208 (2.2e-16)	0.92564 (2.2e-16)	0.92863 (2.2e-16)
32.	PTBA	0.95925 (2.326e-06)	0.95019 (2.196e-10)	0.94198 (2.2e-16)	0.93169 (2.2e-16)	0.94004 (2.2e-16)
33.	PTPP	0.97528 (0.0003146)	0.98527 (6.102e-05)	0.96804 (7.785e-12)	0.96594 (1.164e-14)	0.96494 (2.2e-16)
34.	PWON	0.96962 (4.856e-05)	0.98298 (1.392e-05)	0.98589 (1.067e-06)	0.98429 (3.149e-09)	0.98611 (1.333e-09)
35.	SCMA	0.9524 (3.89e-07)	0.96237 (5.401e-10)	0.96761 (6.203e-12)	0.97236 (5.63e-13)	0.97404 (2.863e-14)
36.	SMGR	0.96428 (9.614e-06)	0.97064 (1.896e-08)	0.96614 (2.909e-12)	0.95746 (2.2e-16)	0.9571 (2.2e-16)
37.	SMRA	0.97603 (0.0004078)	0.98569 (8.056e-05)	0.9846 (3.635e-07)	0.98215 (8.163e-10)	0.97671 (2.2e-13)
38.	SRIL	0.93619 (9.47e-09)	0.90275 (2.2e-16)	0.8934 (2.2e-16)	0.84642 (2.2e-16)	0.87477 (2.2e-16)
39.	TBIG	0.93267 (4.56e-09)	0.94041 (2.861e-13)	0.93701 (2.2e-16)	0.9328 (2.2e-16)	0.92844 (2.2e-16)
40.	TKIM	0.96101 (3.784e-06)	0.93955 (2.309e-13)	0.94823 (1.159e-15)	0.94681 (2.2e-16)	0.94141 (2.2e-16)
41.	TLKM	0.97833 (0.0009272)	0.98768 (0.0003214)	0.98474 (4.05e-07)	0.96974 (1.082e-13)	0.96719 (2.757e-16)
42.	TOWR	0.9675 (2.512e-05)	0.9691 (9.357e-09)	0.81953 (2.2e-16)	0.83507 (2.2e-16)	0.82878 (2.2e-16)
43.	UNTR	0.95069 (2.55e-07)	0.96393 (1.016e-09)	0.96719 (4.986e-12)	0.97335 (1.086e-12)	0.97517 (6.671e-14)
44.	UNVR	0.92971 (2.515e-09)	0.95988 (1.975e-10)	0.96437 (1.178e-12)	0.96503 (6.839e-15)	0.96516 (2.2e-16)
45.	WIKA	0.93121 (3.397e-09)	0.9571 (7.187e-11)	0.95612 (2.779e-14)	0.95599 (2.2e-16)	0.95079 (2.2e-16)

The W1 value indicates the Shapiro value using data series 1 (1-year training data), the W2 value indicates the Shapiro value using data series 2 (2 years training data), and so on until W5. The forecasting process was conducted after using the Arima (p,d,q) in Table 5. Table 5 is placed after the references section for convenience. We also compared the predicted and test data (actual data) and determined the MAPE values for data series 1 to 5. The MAPE computation results for the LQ45 stocks are shown in Table 4.

Table 4: MAPE values from Data series1 to Data series5 for LQ45 Stocks

No.	Stock Code	MAPE value (%) 1 year	MAPE value (%) 2 years	MAPE value (%) 3 years	MAPE value (%) 4 years	MAPEvalue (%) 5 years
1.	ACES	5.1539	5.5633	5.5027	5.495	6.6409
2.	ADRO	12.4558	12.456	12.4558	12.4558	13.9977
3.	AKRA	7.2728	5.4724	5.5837	5.5516	5.3693

No.	Stock Code	MAPE value (%) 1 year	MAPE value (%) 2 years	MAPE value (%) 3 years	MAPE value (%) 4 years	MAPEvalue (%) 5 years
4.	ANTM	13.0432	28.469	28.4678	28.4689	26.3682
5.	ASII	0.07315	0.052128	0.051919	0.051993	0.051952
6.	BBCA	2.3782	2.3782	2.307	2.414	2.7408
7.	BBNI	3.138	3.1412	3.1709	3.1412	3.1412
8.	BBRI	9.0096	9.0096	9.0096	8.8519	8.8377
9.	BBTN	5.5688	6.4752	6.475	6.475	6.475
10.	BMRI	4.1951	4.107	4.1312	4.1258	4.1233
11.	BSDE	9.4852	3.6691	3.6703	3.8866	3.6369
12.	BTPS	5.2558	5.2557	5.2558	-	-
13.	CPIN	5.8028	5.7271	5.7167	5.727	5.9536
14.	CTRA	7.3464	7.3464	7.3464	7.3464	7.3464
15.	ERAA	16.2644	16.2645	16.2644	16.2644	16.2645
16.	EXCL	14.068	14.0678	14.2285	14.0679	14.068
17.	GGRM	4.5877	4.5876	4.652	4.5874	4.5877
18.	HMSP	6.0093	1.3955	2.5415	3.8902	6.2899
19.	ICBP	4.338116	4.1511	4.1715	4.1715	4.5913
20.	INCO	17.1542	17.1541	17.1541	17.0161	17.0802
21.	INDF	6.9743	6.9071	6.8954	6.8713	6.8448
22.	INKP	21.0807	21.0807	21.0807	24.8507	17.9273
23.	INTP	4.9558	4.9558	4.9513	4.8332	4.9558
24.	ITMG	20.2022	8.0385	8.3197	8.1249	8.4314
25.	JPFA	3.2168	3.2899	3.2167	3.2029	3.2167
26.	JSMR	3.8731	3.8732	3.8732	3.0618	3.9209
27.	KLBF	4.5498	4.4864	4.4522	4.3713	4.5627
28.	MDKA	3.8518	3.9947	3.9173	3.5489	3.7228
29.	MIKA	6.7171	6.6295	6.6477	6.6576	6.6718
30.	MNCN	5.5807	5.5807	5.5807	5.5807	5.5807
31.	PGAS	21.8959	9.9909	9.9816	9.9815	9.9815
32.	PTBA	6.0089	6.0091	6.2299	6.2289	6.2386
33.	PTPP	34.0114	9.6346	8.5647	8.5945	8.5646
34.	PWON	5.1273	5.1273	5.1274	4.9324	4.874
35.	SCMA	40.3923	23.3173	6.9458	6.9458	6.9021
36.	SMGR	9.221	9.2212	9.2213	9.206	9.45
37.	SMRA	6.6162	5.814	5.8475	5.8151	5.8333
38.	SRIL	6.3271	6.3272	6.2823	6.3271	6.2917
39.	TBIG	18.9038	18.8355	18.9858	18.9615	18.9407
40.	TKIM	29.7337	29.5318	29.5743	25.9564	25.7169
41.	TLKM	3.6965	3.701	3.6899	3.6888	3.6872
42.	TOWR	**6.3314**	6.3314	6.1424	6.1471	6.1954
43.	UNTR	9.6221	9.2541	9.6134	9.6558	9.6521
44.	UNVR	3.7554	3.6519	3.6249	3.7593	3.8349
45.	WIKA	6.3561	6.3595	6.3669	6.3591	6.3299
	Mean	9.813375	8.41525	8.073107	8.128438	8.088463
	Stan. Dev.	8.605583	6.769021	6.366228	6.355405	5.796208
	Minimum	0.07315	0.052128	0.051919	0.051993	0.051952
	Maximum	40.3923	29.5318	29.5743	28.4689	26.3682
	Median	6.3314	6.0091	6.1424	6.1470	6.2908

Based on Table 4, it can be seen that the most reduced cruel figure mistake for the information arrangement of LQ45 stocks was 8.07311%, with a standard deviation of 6.36623%. In the meantime, the biggest cruel estimate of blunder for the information arrangement of LQ45 stocks was 9.813375%, with a standard deviation of 8.605583%. In this manner, three a long time was the leading time for determining LQ45 stocks based on the MAPE of the Arima (p,d,q).

Table 4 also indicated that the standard deviation values of the MAPE measurement for the 5 data series were tremendous, so it was necessary to make a boxplot diagram to determine the shape of the distribution. Based on Figure 1, it can be seen that the five data series had many upper outliers, so the median was more suitable to use as the center size than the mean . Based on the median calculation, it turned out that the period of two years produced the lowest median.

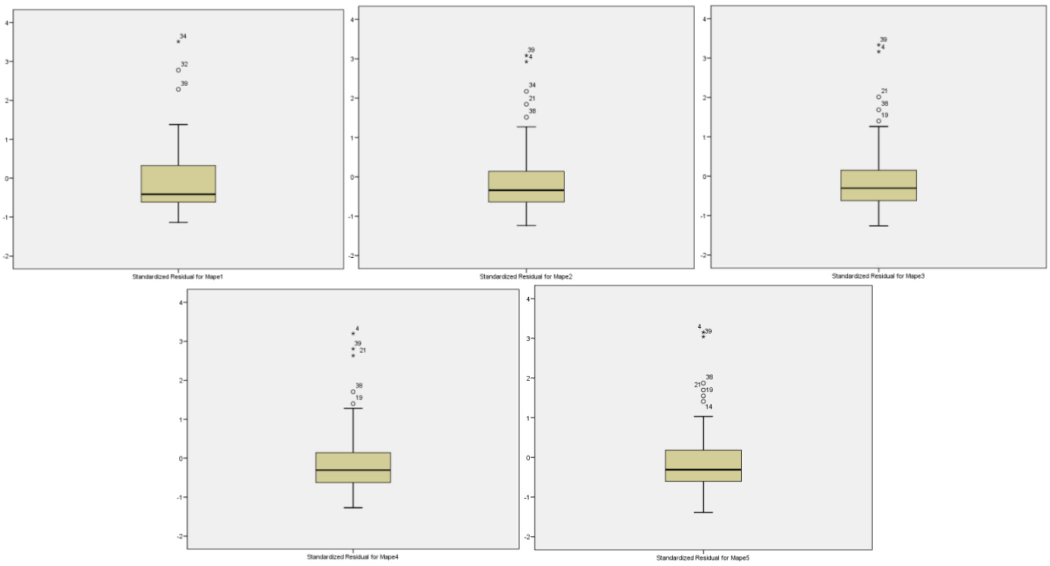

Figure 1: Boxplot Diagram for 5 Data series of LQ45 stocks

The shape of the ASII stock graph and the forecasting results can be seen in Figure 2. In Figure 2, the light blue color is the forecasting result in the form of a 95% confidence interval. Meanwhile, those in dark blue are the results of forecasting with an 80% confidence interval.

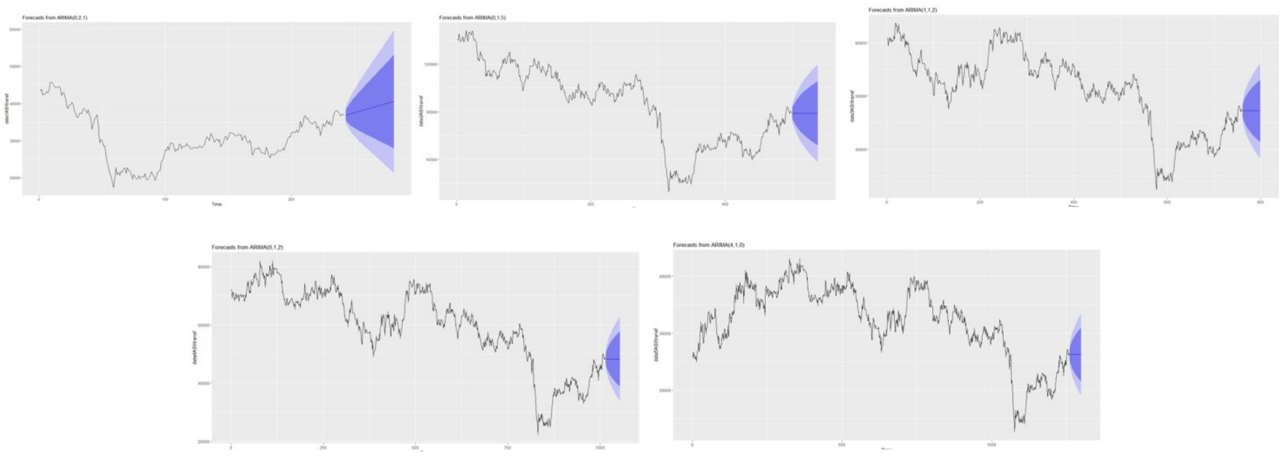

Figure 2: Shape of the ASII stock graph and the forecasting results for 5 Data Series

Figure 2 also shows that the forecasting form for data series 1 has an upward trend, while for data series 2 to 5 the form tends to remain flat and constant. Some specific stocks in the LQ45 stocks have better performance than other stocks in forecasting using ARIMA, this is because these stocks meet the assumptions in the ARIMA model, namely the stationarity assumption, the linearity assumption between past and future data, the assumption of no outliers in the data, stock data that only considers patterns in the data itself (univariate time series), and these stocks are not too affected by external factors.

ARIMA is useful for forecasting relatively simple, linear, and stationary time series. Still, its limitations in handling unique data properties such as non-stationarity, volatility, non-linearity, and the influence of external variables make it less than ideal for forecasting complex data. Since the time series data used in this study is simple and only considers historical patterns (univariate time series), the ARIMA model is sufficient for forecasting. Suppose external factors such as interest rates, inflation, policies, certain conditions or many other company economic indicators are considered. In that case, alternative machine learning models (such as GARCH, neural networks, or ensemble methods) can be used, and these are expected to be more appropriate for capturing patterns and dynamics in the data.

The results of this study, when associated with portfolio management, namely forecasting with ARIMA, can be used to estimate short-term asset returns, which are useful in asset allocation or portfolio rebalancing. ARIMA is relatively simple compared to complex machine learning models, and its simplicity can make it a quick choice for initial analysis without requiring high computing power. While this study, when associated with stock trading strategies in the capital market, is based on stationary or nearly stationary price patterns, ARIMA can provide useful estimates for buying and selling decisions in short-term trend-following strategies (two years).

4 Conclusion

From the results of this study, it can be concluded that:

- If the mean metric is used, the best training data period is three years because it has the smallest average, 8.073107%. However, the mean measure to see the comparison of 5 periods of training data is not suitable because the standard deviation of the measurements is very large, and there are outliers in each of the 5 time series data, so the median metric is used.
- The best period to use the Arima (p,d,q) based on MAPE was two years, with a median error rate of only 6.0091%.
- The largest MAPE value using the Arima (p,d,q) was 40.3923% for SCMA stocks using training data for one year.
- ASII stocks were suitable for using the Arima (p,d,q) since they could produce a minimum MAPE value of around 0.05% within five years.
- Relatively stable LQ45 stocks with no change in the Arima (p,d,q) using four consecutive data series were ACES, CTRA, INTP, MIKA, and TLKM.

5 Suggestion

Several recommendations derived from this study to be applied are:

- Conducting a study regarding the reason for a very large MAPE value of SCMA by using other types of time series models to obtain forecasting results that are close to the test data and can reduce the MAPE value.
- Further investigation should be conducted so that the residuals from the modeling output can be normally distributed according to the assumptions.

6 Acknowledgments

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Table 5: Arima (p,d,q) and its coefficients for the forecasting process after the differencing process of $y'_t = y_t - y_{t-1}$

No.	Stock Code	ARIMA Model	ARIMA Coefficient
1.	ACES (1 years)	ARIMA(2,1,0)	ar1= -0.1308 ; ar2= -0.1100
	ACES (2 years)	ARIMA(1,1,1)	ar1= 0.698 ; ma1=-0.8116
	ACES (3 years)	ARIMA(1,1,1)	ar1= 0.7378 ; ma1=-0.8416
	ACES (4 years)	ARIMA(1,1,1)	ar1= 0.7233 ; ma1=-0.8256
	ACES (5 years)	ARIMA(1,1,1) with drift	ar1=0.7365 ; ma1=-0.8370 ; drift=0.0031
2.	ADRO (1 years)	ARIMA(0,1,0)	
	ADRO (2 years)	ARIMA(0,1,3)	ma1= 0.0305 ; ma2=-0.0441 ; ma3=0.1137
	ADRO (3 years)	ARIMA(2,1,3)	ar1=0.1311 ; ar2=-0.6955 ; ma1=-0.0989 ; ma2=0.7026 ; ma3=0.1226
	ADRO (4 years)	ARIMA(3,1,2)	ar1=0.1014 ; ar2=-0.6667 ; ar3=0.1042 ; ma1=-0.0777 ; ma2=0.650
	ADRO (5 years)	ARIMA(3,1,2)	ar1=0.0813 ; ar2=-0.6186 ; ar3=0.0916 ; ma1=-0.0756 ; ma2=0.5867
3.	AKRA (1 years)	ARIMA(0,2,1)	ma1= -0.9693
	AKRA (2 years)	ARIMA(2,1,2)	ar1= -1.0583 ; ar2=-0.9112 ; ma1=1.1118 ; ma2=0.9323
	AKRA (3 years)	ARIMA(0,1,1)	ma1=0.0672
	AKRA (4 years)	ARIMA(3,1,2)	ar=11.5119 ; ar2= -1.0006 ; ar3= 0.0660 ; ma1= -1.4525 ; ma2=0.8750
	AKRA (5 years)	ARIMA(2,1,3)	ar1=1.4416 ; ar2=-0.8937 ; ma1=-1.4084 ; ma2=0.7923 ma3=0.0527
4.	ANTM (1 years)	ARIMA(0,2,1)	ma1=-0.9748
	ANTM (2 years)	ARIMA(1,1,4)	ar1= -0.9128 ; ma1=0.9722 ; ma2=0.0443 ; ma3=0.0812 ; ma4= 0.1263
	ANTM (3 years)	ARIMA(1,1,1)	ar1=0.8958 ; ma1=-0.8621
	ANTM (4 years)	ARIMA(0,1,0)	
	ANTM (5 years)	ARIMA(1,1,1)	ar1= 0.9334 ; ma1=-0.9060
5.	ASII (1 years)	ARIMA(0,2,1)	ma1= -0.9760
	ASII (2 years)	ARIMA(0,1,5)	ma1=-0.0286 ; ma2=-0.1185 ; ma3=0.0639 ; ma4=-0.0438 ; ma5=0.1209
	ASII (3 years)	ARIMA(1,1,2)	ar1= -0.6299 ; ma1=0.6318 ; ma2=-0.1008
	ASII (4 years)	ARIMA(0,1,2)	ma1=-0.0091 ; ma2=-0.1113
	ASII (5 years)	ARIMA(4,1,0)	ar1=-0.0086 ; ar2=-0.1094 ; ar3=-0.0233 ; ar4=-0.0709
6.	BBCA (1 years)	ARIMA(3,1,0)	ar1= 0.0137 ; ar2=-0.0290 ; ar3=0.1700
	BBCA (2 years)	ARIMA(3,1,0)	ar1=-0.0039 ; ar2= -0.0266 ; ar3=0.1396
	BBCA (3 years)	ARIMA(3,1,0)	ar1= -0.0245 ; ar2=-0.0301 ; ar3=0.1290
	BBCA (4 years)	ARIMA(1,1,4) with drift	ar1= 0.8045 ; ma1=-0.8393 ; ma2=-0.0368 ; ma3= 0.1320 ; ma4=-0.1103 ; drift = 0
	BBCA (5 years)	ARIMA(2,1,2)	ar1=-1.2658 ; ar2=-0.6828 ; ma1= 1.2328 ; ma2=0.6147
7.	BBNI (1 years)	ARIMA(0,2,1)	ma1=-0.9354
	BBNI (2 years)	ARIMA(3,1,2)	ar1= 1.8260 ; ar2=-1.0301 ; ar3= 0.0877 ; ma1=-1.7946 ; ma2=0.9465
	BBNI (3 years)	ARIMA(0,1,1)	ma1=0.0586
	BBNI (4 years)	ARIMA(2,1,2)	ar1= -0.1846 ; ar2= -0.8964 ; ma1= 0.2036 ; ma2=0.8610
	BBNI (5 years)	ARIMA(2,1,2)	ar1= -0.2099 ; ar2=-0.8827 ; ma1= 0.2344 ; ma2=0.8526
8.	BBRI (1 years)	ARIMA(0,1,0)	
	BBRI (2 years)	ARIMA(1,1,3)	ar1=0.8421 ; ma1= -0.8100 ; ma2=-0.1177 ; ma3=0.1301
	BBRI (3 years)	ARIMA(0,1,3)	ma1= 0.0265 ; ma2=-0.0909 ; ma3=0.0730

No.	Stock Code	ARIMA Model	ARIMA Coefficient
	BBRI (4 years)	ARIMA(0,1,3)	ma1= 0.0224 ; ma2=-0.0876 ; ma3=0.0634
	BBRI (5 years)	ARIMA(0,1,3)	ma1= 0.0402 ; ma2= -0.1008 ; ma3=0.0600
9.	BBTN (1 years)	ARIMA(0,2,1)	ma1=-0.9536
	BBTN (2 years)	ARIMA(1,1,3)	ar1= 0.7216 ; ma1= -0.6853 ; ma2= -0.0391 ; ma3=0.1066
	BBTN (3 years)	ARIMA(4,1,0)	ar1=-0.0002 ; ar2= -0.0165 ; ar3= 0.1370 ; ar4=0.0705
	BBTN (4 years)	ARIMA(1,1,4)	ar1= -0.8548 ; ma1= 0.8618 ; ma2= -0.0039 ; ma3=0.1176 ; ma4=0.1462
	BBTN (5 years)	ARIMA(1,1,4)	ar1=-0.8696 ; ma=10.8855 ; ma2=-0.0045 ; ma=30.0821 ; ma4=0.1159
10.	BMRI (1 years)	ARIMA(1,1,1)	ar1=-0.6482 ; ma1=0.7750
	BMRI (2 years)	ARIMA(2,1,1)	ar1= -0.5712 ; ar2= -0.0762 ; ma1=0.6194
	BMRI (3 years)	ARIMA(2,1,1)	ar1= -0.6561 ; ar2=-0.0710 ; ma1= 0.6751
	BMRI (4 years)	ARIMA(1,1,2)	ar1= -0.5748 ; ma1= 0.5855 ; ma2=-0.0753
	BMRI (5 years)	ARIMA(1,1,2)	ar1= -0.5475 ; ma1= 0.5699 ; ma2=-0.0782
11.	BSDE (1 years)	ARIMA(1,2,2)	ar1= -0.8179 ; ma1= -0.0419 ; ma2=-0.9255
	BSDE (2 years)	ARIMA(0,1,2)	ma1= 0.0548 ; ma2=-0.1403
	BSDE (3 years)	ARIMA(1,1,1)	ar1= -0.8632 ; ma1=0.9212
	BSDE (4 years)	ARIMA(0,1,2)	ma1= 0.0130 ; ma2=-0.0932
	BSDE (5 years)	ARIMA(0,1,4)	ma1= 0.0051 ; ma2=-0.0388 ; ma3= -0.012 ; ma4=-0.0704
12.	BTPS (1 years)	ARIMA(0,1,0)	
	BTPS (2 years)	ARIMA(0,1,0)	
	BTPS (3 years)	ARIMA(0,1,0)	
	BTPS (4 years)	-	
	BTPS (5 years)	-	
13.	CPIN (1 years)	ARIMA(0,1,0)	
	CPIN (2 years)	ARIMA(0,1,0)	
	CPIN (3 years)	ARIMA(0,1,0)	
	CPIN (4 years)	ARIMA(0,1,2)	ma1= 0.0148 ; ma2=-0.0894
	CPIN (5 years)	ARIMA(0,1,2)	ma1= 0.0197 ; ma2=-0.0824
14.	CTRA (1 years)	ARIMA(0,1,1)	ma1=0.1301
	CTRA (2 years)	ARIMA(0,1,1)	ma1=0.0766
	CTRA (3 years)	ARIMA(0,1,1)	ma1=0.0647
	CTRA (4 years)	ARIMA(0,1,1)	ma1=0.0495
	CTRA (5 years)	ARIMA(0,1,0)	
15.	ERAA (1 years)	ARIMA(0,1,0)	
	ERAA (2 years)	ARIMA(0,1,0)	
	ERAA (3 years)	ARIMA(0,1,0)	
	ERAA (4 years)	ARIMA(2,1,2)	ar1=1.5726 ; ar2= -0.6968 ; ma1=-1.5932 ; ma2=0.7416
	ERAA (5 years)	ARIMA(2,1,2)	ar1= -1.0902 ; ar2= -0.9581 ; ma1=1.0826 ; ma2=0.9738
16.	EXCL (1 years)	ARIMA(0,1,3)	ma1= -0.0134 ; ma2=-0.1214 ; ma3=0.1829
	EXCL (2 years)	ARIMA(2,1,1)	ar1= -0.8104 ; ar2= -0.1051 ; ma1=0.7966
	EXCL (3 years)	ARIMA(0,1,2)	ma1= 0.0321 ; ma2=-0.1121
	EXCL (4 years)	ARIMA(0,1,2)	ma1= -0.0085 ; ma2=-0.0731
	EXCL (5 years)	ARIMA(0,1,0)	
17.	GGRM (1years)	ARIMA(0,1,0)	
	GGRM (2years)	ARIMA(0,1,0)	
	GGRM (3years)	ARIMA(0,1,2)	ma1= -0.0046 ; ma2=-0.0781
	GGRM (4years)	ARIMA(0,1,2)	ma1= -0.0195 ; ma2=-0.0765
	GGRM (5years)	ARIMA(1,1,1)	ar1= 0.7585 ; ma1=-0.7998

No.	Stock Code	ARIMA Model	ARIMA Coefficient
18.	HMSP (1 years)	ARIMA(0,1,0)	
	HMSP (2 years)	ARIMA(0,1,0) with drift	Drift=-1.0073
	HMSP (3 years)	ARIMA(1,1,1) with drift	ar1= 0.8579 ; ma1=-0.9020 ; drift=-0.0185
	HMSP (4 years)	ARIMA(0,1,2)	ma1= -0.0297 ; ma2=-0.0936
	HMSP (5 years)	ARIMA(1,1,2)	ar1= 0.5183 ; ma1= -0.5639 ; ma2=-0.0673
19.	ICBP (1 years)	ARIMA(2,1,3)	ar1= -1.4991 ; ar2=-0.9375 ; ma1=1.5457 ; ma2= 0.9119 ; ma3=-0.0155
	ICBP (2 years)	ARIMA(2,1,2)	ar1= -0.0049 ; ar2=-0.8951 ; ma1= -0.0651 ; ma2=0.8921
	ICBP (3years)	ARIMA(1,1,4)	ar1= 0.6700 ;ma1= -0.7311 ;ma2= -0.0511 ;ma3 = 0.1058 ; ma4=-0.0935
	ICBP (4 years)	ARIMA(1,1,1)	ar1= 0.7891 ; ma1=-0.8618
	ICBP (5 years)	ARIMA(2,1,1)	ar1= 0.7754 ; ar2= -0.0401 ; ma1=-0.8298
20.	INCO (1 years)	ARIMA(0,1,0)	
	INCO (2 years)	ARIMA(2,1,2) with drift	ar1= -1.5096 ; ar2=-0.9098 ; ma1=1.5361 ; ma2=0.8973 ; drift=1.8374
	INCO (3 years)	ARIMA(1,1,1)	ar1= -0.5306 ; ma1=0.5953
	INCO (4 years)	ARIMA(2,1,2)	ar1= -1.4329 ; ar2= -0.6757 ; ma1=1.5052 ; ma2=0.7195
	INCO (5 years)	ARIMA(0,1,2)	ma1= 0.0824 ma2=-0.0444
21.	INDF (1 years)	ARIMA(0,1,2)	ma1= -0.0070 ; ma2=-0.2571
	INDF (2 years)	ARIMA(1,1,3)	ar1= -0.9884 ; ma1= 0.9502 ; ma2= -0.2309 ; ma3=-0.2026
	INDF (3 years)	ARIMA(4,1,0)	ar1=-0.0318 ; ar2=-0.1406 ; ar3= -0.0600 ; ar4=-0.0817
	INDF (4 years)	ARIMA(4,1,0)	ar1=-0.0419 ; ar2=-0.1199 ; ar3=-0.0635 ; ar4=-0.0798
	INDF (5 years)	ARIMA(0,1,3)	ma1=-0.0678 ; ma2= -0.0540 ; ma3=-0.0956
22.	INKP (1 years)	ARIMA(0,1,0)	
	INKP (2 years)	ARIMA(0,1,0)	
	INKP (3 years)	ARIMA(0,1,0)	
	INKP (4 years)	ARIMA(5,2,0)	ar1=-0.8048 ; ar2=-0.6712 ; ar3=-0.5057 ; ar4= -0.3518 ; ar5=-0.2074
	INKP (5 years)	ARIMA(0,1,0) with drift	Drift=0.0014
23.	INTP (1 years)	ARIMA(0,1,0)	
	INTP (2 years)	ARIMA(0,1,0)	
	INTP (3 years)	ARIMA(0,1,0)	
	INTP (4 years)	ARIMA(0,1,0)	
	INTP (5 years)	ARIMA(0,1,1)	ma1=-0.0449
24.	ITMG (1 years)	ARIMA(0,2,4)	ma1 = -0.9516 ; ma2= 0.0739 ; ma3= 0.1043 ; ma4=-0.2082
	ITMG (2 years)	ARIMA(0,1,3)	ma1= 0.0724 ; ma2= 0.1102 ; ma3=0.1110
	ITMG (3 years)	ARIMA(0,1,3)	ma1= 0.0636 ; ma2=0.0691 ; ma3=0.1145
	ITMG (4 years)	ARIMA(3,1,0)	ar1=0.0715 ; ar2=0.0307 ; ar3=0.0825
	ITMG (5 years)	ARIMA(3,1,0)	ar1= 0.0856 ; ar2= -0.0114 ; ar3=0.0872
25.	JPFA (1 years)	ARIMA(2,1,3)	ar1= 0.0852 ; ar2=-0.6484 ; ma1=-0.0480 ; ma2= 0.7303 ; ma3=0.2002
	JPFA (2 years)	ARIMA(3,1,2)	ar1= 0.0569 ; ar2= -0.8035 ; ar3=0.1714 ; ma1=0.0587 ; ma2=0.8398
	JPFA (3 years)	ARIMA(2,1,3)	ar1= -0.1402 ; ar2=-0.8495 ; ma1= 0.2053 ; ma2=0.8661 ; ma3=0.1176
	JPFA (4 years)	ARIMA(2,1,3)	ar1= -0.1951; ar2=-0.8889 ; ma1=0.2562 ; ma2=0.8979 ; ma3=0.1052
	JPFA (5 years)	ARIMA(1,1,1)	ar1= -0.8876 ; ma1=0.9154

No.	Stock Code	ARIMA Model	ARIMA Coefficient
26.	JSMR (1 years)	ARIMA(2,1,3)	ar1=1.6006 ; ar2=-0.7678 ; ma1=-1.5471 ; ma2= 0.6459 ; ma3=0.1421
	JSMR (2 years)	ARIMA(2,1,3)	ar1=1.6625 ; ar2=-0.8357 ; ma1= -1.6353 ; ma2= 0.7329 ; ma3=0.1091
	JSMR (3 years)	ARIMA(0,1,0)	
	JSMR (4 years)	ARIMA(0,1,2)	ma1= 0.0471; ma2=-0.0591
	JSMR (5 years)	ARIMA(0,1,2)	ma1=0.0449 ; ma2=-0.0689
27.	KLBF (1 years)	ARIMA(0,1,0)	
	KLBF (2 years)	ARIMA(0,1,1)	ma1=-0.1160
	KLBF (3 years)	ARIMA(1,0,1) with non-zero mean	ar1= 0.9813 ; ma1=-0.0764 ; mean=1096.71779
	KLBF (4 years)	ARIMA(0,1,3)	ma1= -0.1083 ; ma2=-0.0285 ; ma3=-0.0714
	KLBF (5 years)	ARIMA(1,1,1)	ar1= 0.5008 ; ma1=-0.5871
28.	MDKA (1years)	ARIMA(0,1,2) with drift	ma1=0.0786 ; ma2=-0.1410 ; drift=0.0944
	MDKA (2years)	ARIMA(2,1,0) with drift	ar1= 0.0450 ; ar2= -0.0947 ; drift=4e-04
	MDKA (3years)	ARIMA(0,1,5) with drift	ma1= -0.0585 ; ma2= -0.0531 ; ma3=0.0056 ; ma4= 0.0362 ; ma5= -0.0983 ; drift=5e-04
	MDKA (4years)	ARIMA(1,1,1) with drift	ar1= 0.3851 ; ma1=-0.5068 ; drift=0.0021
	MDKA (5years)	ARIMA(1,1,1) with drift	ar1= 0.3798 ; ma1= -0.5105 ; drift=0.0048
29.	MIKA (1 years)	ARIMA(2,1,2)	ar1= -1.3847 ; ar2= -0.8463 ; ma1=1.3530 ; ma2=0.7495
	MIKA (2 years)	ARIMA(2,1,2)	ar1= -1.3761 ; ar2= -0.8535 ; ma1=1.3546 ; ma2=0.7746
	MIKA (3 years)	ARIMA(2,1,2)	ar1=-1.3533 ; ar2= -0.8544 ; ma1=1.3166 ; ma2=0.7843
	MIKA (4 years)	ARIMA(2,1,2)	ar1= -1.3460 ; ar2= -0.8442 ; ma1=1.3140 ; ma2=0.7807
	MIKA (5 years)	ARIMA(0,1,1)	ma1=-0.1093
30.	MNCN (1years)	ARIMA(0,1,0)	
	MNCN (2years)	ARIMA(2,1,0)	ar1= -0.0629 ; ar2=0.0851
	MNCN (3years)	ARIMA(0,1,2)	ma1= -0.0709 ; ma2=0.0660
	MNCN (4years)	ARIMA(2,1,0)	ar1= -0.0501 ; ar2=0.0552
	MNCN (5years)	ARIMA(0,1,0)	
31.	PGAS (1 years)	ARIMA(1,2,2)	ar1= -0.7228 ; ma1= -0.1275 ; ma2=-0.8025
	PGAS (2 years)	ARIMA(2,1,3)	ar1=1.5264 ; ar2=-0.8157 ; ma1=-1.4604 ; ma2= 0.6449 ; ma3=0.1764
	PGAS (3 years)	ARIMA(2,1,3)	ar1= 1.5227 ; ar2= -0.8610 ; ma1=-1.5413 ; ma2= 0.8610 ; ma3=0.0419
	PGAS (4 years)	ARIMA(2,1,3)	ar1=1.4801 ; ar2= -0.7985 ; ma1= -1.5053 ; ma2= 0.8068 ; ma3=0.0340
	PGAS (5 years)	ARIMA(0,1,0)	
32.	PTBA (1 years)	ARIMA(1,1,4)	ar1=-0.8320 ; ma1=0.8496 ; ma2= -0.0568 ; ma3= 0.0516 ; ma4=0.2232
	PTBA (2 years)	ARIMA(1,1,4)	ar1= -0.8320 ; ma1= 0.8707 ; ma2=-0.0065 ; ma3= 0.0527 ; ma4=0.1708
	PTBA (3 years)	ARIMA(2,1,2)	ar1= -0.1597 ; ar2= -0.9496 ; ma1= 0.1476 ; ma2=0.9082
	PTBA (4 years)	ARIMA(2,1,2)	ar1= -0.1549 ; ar2= -0.9431 ; ma1= 0.1381 ; ma2=0.9071
	PTBA (5 years)	ARIMA(2,1,2)	ar1= -0.0946 ; ar2=-0.8834 ; ma1= 0.0610 ; ma2=0.8366
33.	PTPP (1 years)	ARIMA(0,2,2)	ma1= -0.8221 ; ma2=-0.1288
	PTPP (2 years)	ARIMA(2,1,3)	ar1= 1.3990 ; ar2= -0.5877 ; ma1= -1.2451 ; ma2= 0.3445 ; ma3=0.1805
	PTPP (3 years)	ARIMA(3,1,2)	ar1=1.6027 ; ar2=-0.9938 ; ar3=0.1605 ; ma1=-1.4910 ; ma2=0.7966
	PTPP (4 years)	ARIMA(4,1,1)	ar1= 0.7878 ; ar2=-0.1131 ; ar3=-0.0140 ; ar4= 0.0809 ; ma1=-0.6515

No.	Stock Code	ARIMA Model	ARIMA Coefficient
	PTPP (5 years)	ARIMA(0,1,1)	ma1 =0.1229
34.	PWON (1 years)	ARIMA(3,1,0)	ar1= 0.1106 ; ar2=-0.1057 ; ar3=0.1254
	PWON (2 years)	ARIMA(0,1,0)	
	PWON (3 years)	ARIMA(0,1,2)	ma1= -0.0286 ; ma2=-0.0769
	PWON (4 years)	ARIMA(0,1,2)	ma1=-0.0358 ; ma2=-0.0896
	PWON (5 years)	ARIMA(0,1,2)	ma1= -0.0367; ma2=-0.0912
35.	SCMA (1 years)	ARIMA(1,2,1)	ar1= -0.1525 ; ma1=-0.9319
	SCMA (2 years)	ARIMA(0,2,1)	ma1=-0.9799
	SCMA (3 years)	ARIMA(0,1,0)	
	SCMA (4 years)	ARIMA(0,1,0)	
	SCMA (5 years)	ARIMA(0,1,0)	
36.	SMGR (1 years)	ARIMA(0,1,0)	
	SMGR (2 years)	ARIMA(2,1,2)	ar1= -1.4649 ; ar2= -0.9127 ; ma1= 1.4735 ; ma2=0.8823
	SMGR (3 years)	ARIMA(2,1,2)	ar1= -1.4521 ; ar2=-0.9106 ; ma1=1.4511 ; ma2= 0.8741
	SMGR (4 years)	ARIMA(3,1,2)	ar1= -1.5107 ; ar2= -0.9759 ; ar3=-0.0462 ; ma1= 1.4807 ; ma2=0.8828
	SMGR (5 years)	ARIMA(2,1,2)	ar1= -1.4452 ; ar2= -0.9056 ; ma1=1.4512 ; ma2=0.8760
37.	SMRA (1 years)	ARIMA(0,2,2)	ma1= -0.8535 ; ma2=-0.1260
	SMRA (2 years)	ARIMA(0,1,2)	ma1= 0.1014 ; ma2=-0.0852
	SMRA (3 years)	ARIMA(0,1,1)	ma1 =0.1066
	SMRA (4 years)	ARIMA(2,1,0)	ar1= 0.0909 ; ar2=-0.0717
	SMRA (5 years)	ARIMA(0,1,1)	ma1 = 0.0644
38.	SRIL (1 years)	ARIMA(1,1,0)	ar1=0.1208
	SRIL (2 years)	ARIMA(0,1,0)	
	SRIL (3 years)	ARIMA(2,1,2)	ar1=0.1334 ; ar2= 0.5267 ; ma1=-0.0839 ; ma2=-0.6450
	SRIL (4 years)	ARIMA(3,1,1)	ar1= 0.9267 ; ar2= 0.0070 ; ar3= -0.0937 ; ma1=-0.8738
	SRIL (5 years)	ARIMA(2,1,3)	ar1=1.7583 ; ar2=-0.9660 ; ma1= -1.7093 ; ma2= 0.9043 ; ma3=0.0314
39.	TBIG (1 years)	ARIMA(1,1,0)	ar1=-0.1659
	TBIG (2 years)	ARIMA(1,1,0)	ar1=-0.0893
	TBIG (3 years)	ARIMA(3,1,2)	ar1=-1.6732 ; ar2=-1.0630 ; ar3=-0.0751 ; ma1=1.5908 ; ma2=0.9114
	TBIG (4 years)	ARIMA(3,1,2) with drift	ar1= -0.5324 ; ar2=-0.9901 ; ar3= -0.1380 ; ma1=0.4198 ; ma2=0.9227 ; drift = 0.0047
	TBIG (5 years)	ARIMA(3,1,2) with drift	ar1=-0.5662 ; ar2= -1.0176 ; ar3= -0.1556 ; ma1= 0.433 ; ma2= 0.9497 ; drift= 0.0058
40.	TKIM (1 years)	ARIMA(0,1,1)	ma1=0.1887
	TKIM (2 years)	ARIMA(0,1,1)	ma1 =0.1521
	TKIM (3 years)	ARIMA(0,1,1)	ma1=0.1814
	TKIM (4 years)	ARIMA(2,1,1) with drift	ar1= -0.7916 ; ar2= 0.1238 ; ma1= 0.9632 ; drift=0.0030
	TKIM (5 years)	ARIMA(0,1,1) with drift	ma1= 0.1267 ; drift=0.0011
41.	TLKM (1 years)	ARIMA(2,1,2)	ar1=-1.4765 ; ar2= -0.8043 ; ma1=1.6368 ; ma2=0.8895
	TLKM (2 years)	ARIMA(0,1,2)	ma1= -0.0119 ; ma2=-0.1539
	TLKM (3 years)	ARIMA(0,1,2)	ma1= 0.0072 ; ma2=-0.1598
	TLKM (4 years)	ARIMA(0,1,2)	ma1= -0.0170 ; ma2=-0.1562
	TLKM (5 years)	ARIMA(0,1,2)	ma1= -0.0495 ; ma2=-0.1253
42.	TOWR (1 years)	ARIMA(0,1,0)	
	TOWR (2 years)	ARIMA(0,1,1)	ma1=-0.0725
	TOWR (3 years)	ARIMA(1,1,1)	ar1=-0.6136 ; ma1=0.2856

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	TOWR (4 years)	ARIMA(0,1,4)	ma1= -0.3225 ; ma2= 0.1603 ; ma3= -0.1595 ; ma4=0.0732
	TOWR (5 years)	ARIMA(0,1,4)	ma1= -0.3230 ; ma2= 0.1361 ; ma3=-0.1429 ; ma4=0.0658
43.	UNTR (1 years)	ARIMA(0,1,0)	
	UNTR (2 years)	ARIMA(0,1,0)	
	UNTR (3 years)	ARIMA(0,1,1)	ma1=-0.0778
	UNTR (4 years)	ARIMA(2,1,2)	ar1=1.7103 ; ar2= -0.8736 ; ma1= -1.7744 ; ma2= 0.941
	UNTR (5 years)	ARIMA(0,1,2)	ma1= -0.0773 ; ma2=-0.0648
44.	UNVR (1 years)	ARIMA(2,1,2)	ar1= -0.1600 ; ar2= -0.8235 ; ma1= 0.0333 ; ma2=0.7261
	UNVR (2 years)	ARIMA(2,1,0)	ar1= -0.1416 ; ar2=-0.1433
	UNVR (3 years)	ARIMA(1,1,1)	ar1= 0.6374 ; ma1=-0.7401
	UNVR (4 years)	ARIMA(1,1,1)	ar1= 0.6163 ; ma1=-0.7199
	UNVR (5 years)	ARIMA(1,1,1)	ar1= 0.6487 ; ma1=-0.7439
45.	WIKA (1 years)	ARIMA(3,1,2)	ar1= 1.6290 ; ar2=-0.9472 ; ar3= 0.1329 ; ma1=-1.5792 ; ma2=0.8648
	WIKA (2 years)	ARIMA(1,1,3)	ar1=0.7141 ; ma1=-0.6707 ; ma2= -0.0276 ; ma3=0.1009
	WIKA (3 years)	ARIMA(3,1,2)	ar1=1.5643 ; ar2= -0.9088 ; ar3= 0.0875 ; ma1= -1.5189 ; ma2=0.8453
	WIKA (4 years)	ARIMA(0,1,5)	ma1= 0.0409 ; ma2=0.0107 ; ma3= 0.0468 ; ma4= 0.0388 ; ma5=0.1011
	WIKA (5 years)	ARIMA(2,1,3)	ar1=1.4656 ; ar2=-0.6759 ; ma1= -1.3997 ; ma2= 0.5677 ; ma3 = 0.0900