Forecasting LQ45 Shares Using ARIMA Method aim the COVID-19 Pandemic in Indonesia

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Abstract. The purpose of this study was to study Covid-19's thoughts on the LQ45 stock price. Stock price fluctuations by investors, where investor behaviour will also be influenced by external factors such as global economic developments. The pandemic caused by Covid-19 forced investors to wait and see. How much influence Covid-19 on the LQ-45 stock price is interesting to investigate. This study relies on secondary data to analyze share price movements. Secondary data needed for analysis is the LQ-45 stock price daily data in January, February, and March 2020. The data was be analyzed with a quantitative approach, namely the Autoregressive Integrated Moving Average (ARIMA), to produce a three-month stock price forecast model. ARIMA has the advantage of being used as a method to obtain an estimation model by relying on the stock price data itself. The results showed that the estimation model with ARIMA obtained the best model for IHSG LQ 45 was DLQ45 AR (2) d (1) MA (1) or ARIMA (2,1,1). This model supports it, adding to the LQ45 share price every day because of the Covid-19 period. If the Covid-19 pandemic emergency period is not ended in Indonesia and the world, there will be a threatening crisis in Indonesia.

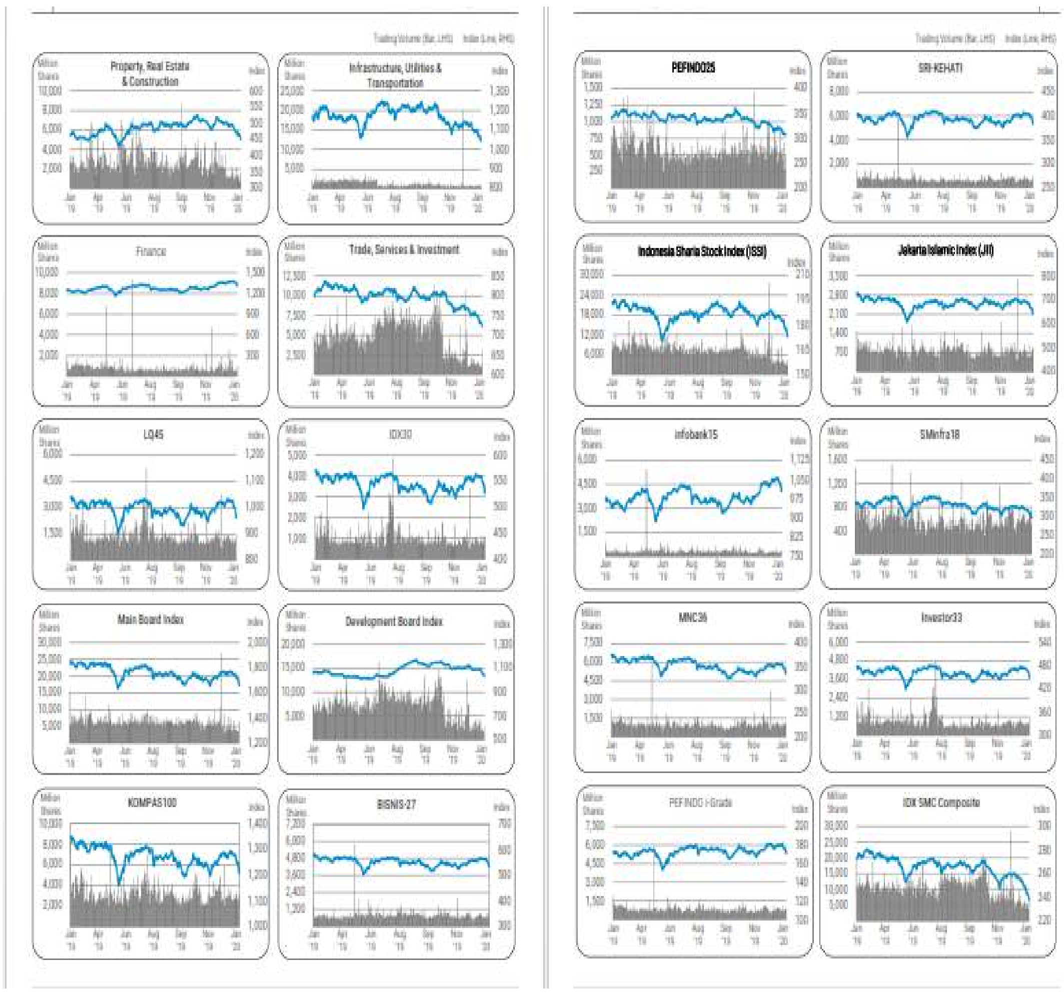
Keywords: IHSG, LQ45, ARIMA, DLQ45.

1. Introduction

The Covid-19 outbreak has infected more than 200 countries in the world. Most of the countries allocate additional budgets as countermeasures. However, per May 2020, the development of countermeasures could not be considered a positive movement. The spread of Covid-19 in Indonesia has surpassed 240,000 positive confirmed cases with the curve remaining sharp. Obviously, this condition is not favourable for economic activity. Investors opt to hold back and observe while waiting for better conditions.

The movement of world share prices simultaneously reflects investor behaviour. Data released from February 24 to March 24, 2020, there were 22 days of trading and price spikes were recorded. According to [1], share price fluctuations move extremely and there has never been a case of virus infection with the impact as great as the Covid-19.

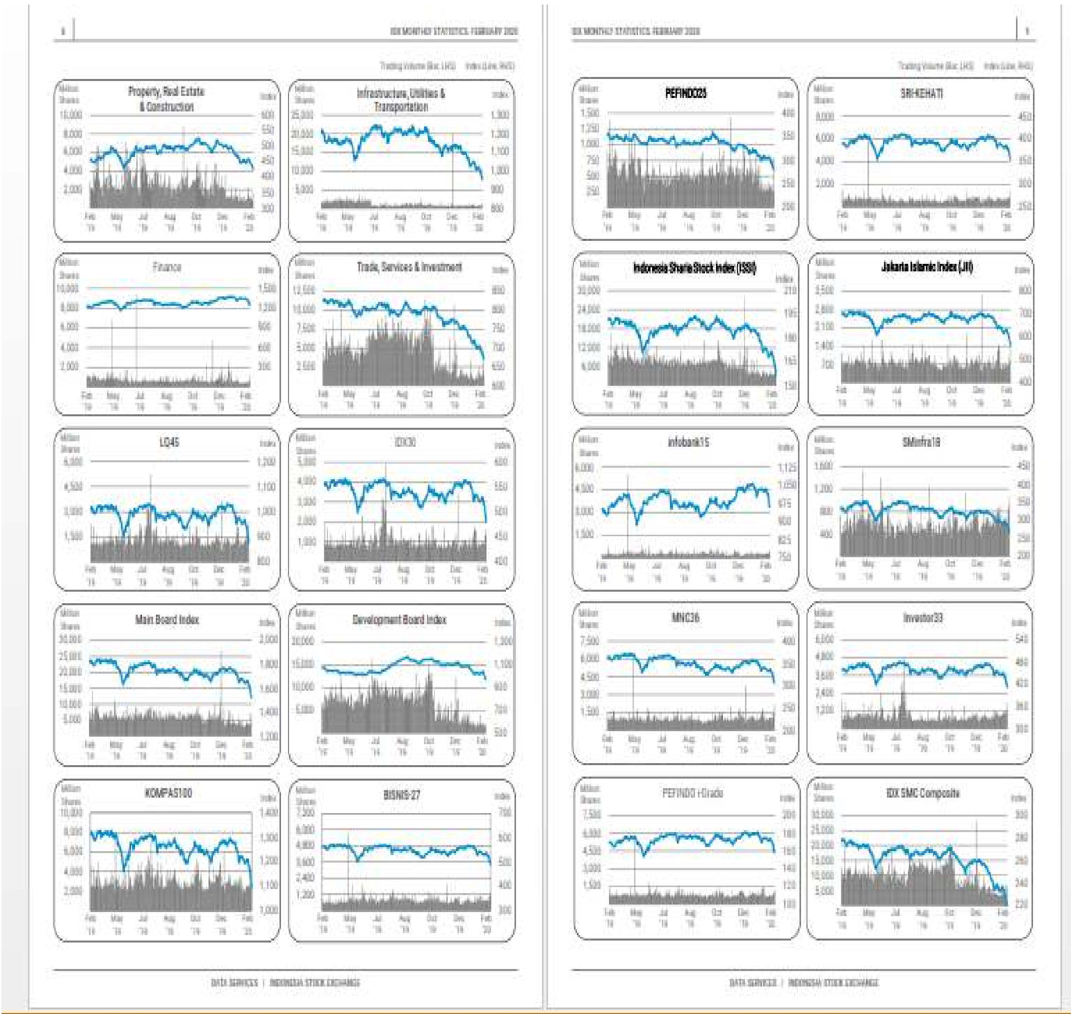
Negative sentiment related to Covid-19 profoundly affects the capital market including the Indonesia Stock Exchange (IDX). The transmission of Covid-19 in Indonesia brings impacts on various sectors including the capital market. It is shown from the movement of the Jakarta Composite Index (IHSG). IHSG reflects the movement of all common stocks and preferred stocks listed on the Indonesia Stock Exchange (IDX). IHSG has approximately 34 index names, among them are JCI, LQ 45, IDX 30, JII, Kompas100, Bisnis-27, PERINDO25, Sri-Kehati, ISSI, and others. Based on graphic movement, the IHSG movement tends to decline (fluctuate) in January and February 2020 (source idx.co.id). Several IHSG movements are displayed in the following charts:



Source: IDX Monthly Statistics, January 2020, Vol. 29 No.1

Figure 1. IHSG January 2020

Based on Figure 1, in general, the stock movements experiencing fluctuation trend are LQ45 stocks; Infrastructure, Utilities, Transportation; IDX SMC Company; Properties and Real Estates; and Kompas100 which declines sharply. Meanwhile, Finance shares remain stable.



Source: IDX Monthly Statistics February 2020, Vol. 29 No. 02

Figure 2. IHSG February 2020

If compared to Figure 1 showing the decline in share prices, Figure 2 shows that the decline is sharper. Especially LQ45 stocks, the downward trend is more visible. LQ45 is the 45 most liquid companies with the largest market capitalization and the highest transaction value in the last twelve months. Stocks incorporated in LQ45 are also known as blue-chip stock since the companies of LQ45 stocks are dynamic. Once every six months, the IDX will evaluate the performance of LQ45 stocks. Those with poor performance will be excluded from the LQ45 list.

Based on the dynamic characteristics of the LQ45, share price movements in LQ45 can be used as an economic benchmark. If LQ45 stocks decline sharply, it may indicate that the transaction value has decreased and the capital market has also decreased.

Problem Formulation

Investor behaviour in investment decisions is influenced some factors, such as by company and market information. The current Covid-19 pandemic has affected capital market investment. It can be observed based on the movement of IHSG which reflects the stock movement traded on the IDX. Data obtained from the Indonesia Stock Exchange have shown that the trend of IHSG declined since January 2020. This trend is following the Covid-19 pandemic which has been widely transmitted across countries in the world.

Indonesia IHSG is prone to a downward trend, including the LQ45. The LQ45 movement fluctuates and decreases every day. It indicates that transactions on the capital market are influenced by prior trading day. Investors will find safe points in investment so that decisions are not only influenced by information but also forecast related to conditions in the capital market. Based on the explanation, this study estimates and forecasts the LQ45 movement amid the widespread Covid-19.

Research Objectives

Based on the background and problem formulations above, the objectives of this study are:

1. To obtain the best projection results for IHSG LQ45
2. To create the best projection model for IHSG LQ45.

2. Literature Review

The decision making by investors in the financial sector cannot be released by the information obtained. There is a group of researchers who concludes that decision making is influenced by the behaviour of historical data and there are also those who believe that investors' decisions are based on sentiment or psychological factors.

Some researchers have concluded that decision making is based on the behaviour of past variables, for example, [2]; [3]; and [4]. According to [5] who conducted literature research by reviewing 52 articles conclude that the most popular source of information used to forecast the capital market was using technical indicators, namely the trend of price or index movements in the previous period. The study was also examined by [2] developed a stock return prediction model in developing country markets that transitioned to developed countries using the Markov Regime Switching (MRS) method. The results show that the MRS model with data analysis of the past period had consistency in predicting the level of stock returns during times of low volatility compared to times of high volatility.

[6] performed short-term forecasting of the Covid-19 case on the Spain stock market IBEX using the SutteARIMA model. Research data were obtained from Worldmeter and Spain stock market (IBEX 35) data with observation periods from 12 February 2020 to 9 April 2020 and 03 April 2020 to 9 April 2020. Short-term forecasts were employed to make a short estimation for the coming period (10 April-12 April 2020; 14 April – 16 April 2020). The forecasting method applied forecasting measure with the mean absolute percentage error (MAPE). Based on forecasting results, SutteeARIMA was more suitable than ARIMA for calculating daily stock market forecasts of Covid-19 cases in the Spain stock market IBEX.

Meanwhile, [3] compared the decisions due to sentiment or psychological factors. The results of research by [3] are similar to the research by [7] and [5]. The results show that incorporating technical variables into the autoregression benchmark could produce a more accurate forecast. Technical indicators provide useful information regarding future volatility. The pattern is consistent with the fact that share prices are much more volatile when the economy is down, then predictability emerged. Technical indicators and macroeconomic variables provide complementary information relevant to estimating stock volatility. Incorporating economic variables and technical information produces the most reliable estimate than combining the two types of information alone.

Other researches by [8]; [9] [10] and [11] show that the behaviour of stock price reflects psychological decisions. The information signal obtained by professionals is based on the representation of all groups of information subjects.

Psychological factors are also significant in decision making. Research by [8] probed investment decisions related to investor behaviour in the form of anchoring and adjustments. The analysis was carried out on the stock market ratios traded on several capital markets in NYSE, Amex, and Nasdaq in the period 1983 – 2005. Based on research conducted by [8] it can be determined that investor behaviour was influenced by psychology - investment is influenced by over-optimistic or over-pessimistic feelings in predicting the expected return. Optimistic or pessimistic occurs when the EPS ratio is compared (higher or lower) to the average EPS value of similar industries. Investor behaviour is influenced by situations/circumstances/phenomena experienced by the investor based on experience patterns in the previous period (Perceptual framework).

[12] and [13] conclude more or less similar results of the study. Decision making is influenced by the sentiment factor of investors. [12] conducted forecasting of exchange rates which is an important aspect of business investment plans. High profits are often associated with high risk due to

the nonlinear feature of the data. The stock market is often volatile and changes immediately due to economic situations, political situations, and major events in a country. Researchers examined four countries, namely The United States, Hong Kong, Turkey, and Pakistan in the period 2012-2016. Data sources were obtained from the Twitter Dataset to calculate the sentiment analysis of each event. Regression analysis and evaluation with Root Mean Square (RMSE) and Mean Absolute Error (MAE) were simultaneously conducted.

In another research, [14] attempted to include historical variables as well as psychological variables. [15] carried out projections with multiple regression that included return and interest rate variables. Research results by [14] predicted stock returns using predictors selected based on a multivariate regression model. The data analyzed are the short interest index (SII) proposed by [16] and investor sentiment (AIS) proposed by [17] with the observation period from January 1973 to December 2014. The empirical results show an estimation strategy with a standard value model of a historical average, univariate regression model based on individual predictions. A simple method can extract more complementary information to predict stock returns related to AIS and SII.

An opposite opinion is expressed by [18]; [19] who conducted an analysis of share prices using technical analysis. However, the principle shares similarities because [18] and [20] believe that the same price behaviour already includes macro variables. Thus, it is sufficient to analyze price trend patterns to predict the stock market.

3. Hypothesis

The investor behaviour in the capital market, especially LQ45 stocks based on behaviour theory, is influenced by the behaviour of the stock prices and psychological variables. The behaviour of stock prices is already examined by researchers, among them are [3]; Li et al. and [5] and psychological variables as probed by [21] [8]; [22] and [6]. Based on these studies, the hypothesis of this study is: The IHSG LQ45 projection model can be predicted using the behaviour of stock price in the past period and its psychological variables.

4. Research Methodology

This type of research is to compile the best estimation model that will be used for forecasting based on the IHSG LQ45 daily data in the period January and February 2020. The estimation method used the Autoregressive Integrated Moving Average (ARIMA).

The data used in this estimation are the time-series data from the daily IHSG LQ45 from January 2020 to March 2020. During those periods, 63 observations were conducted (based on effective trading days on the Indonesia Stock Exchange). Data sources were obtained from IDX monthly reports for the January period (Volume 29 No.02), IDX monthly reports for the period February 2020 (Volume 29 No.02), and IDX monthly reports for the period March 2020 (Volume 29 No.03). The reports were obtained online through the IDX website http://idx.co.id.

Data Analysis Stage

The ARIMA method used in estimating the IHSG LQ45 model comprises four stages; (1) Identification; (2) Estimation; (3) Diagnostic Checking, and (4) Forecasting.

(1) Identification Stage

This first stage is used to determine whether the data that will be estimated are already qualified for stationary requirements. It is necessary because time series data for forecasting identify stationarity. The identification stage in this study used the Correlogram and Augmented Dickey-Fuller (ADF) test.

a. Correlogram

This test is based on the ACF and PACF autocorrelation values. The results of the IHSG LQ45 Corelogram testing using the eviews.8 program. Based on the Correlogram results above, ACF and PACF autocorrelation values from lag 1 to lag 3 using α = 5% exceed the interval limit of ± 0,302435 (±1,96 ($\frac{1}{\sqrt{63}}$), which implies that the data are not stationary.

b. Augmented Dickey-Fuller (ADF) Test

Based on the ADF test, the t statistical value was 0.005575, the value is smaller than the critical value level of 1% (3.540198); 5% (2,909206); and 10% (2,592215) so that the data are not stationary. Based on the Correlogram and ADF values, it can be determined that the data are not stationary so those do not meet the estimation requirements for forecasting. Thus, the degree of integration testing will be carried out along with differentiation to fulfill the stationary requirements.

(2) Estimation

The model estimation stage is an attempt to estimate the model according to the characteristics of the data following analysis, which is integrated into the first degree (d (1)). The estimation model must contain Autoregressive (AR) and Moving Average (MA) elements. The determination of AR and MA values uses the following approach [23]:

Table 1. Typical patterns of ACF and PACF

Model Type	Typical Pattern of ACF	Typical Pattern of PACF
AR (p)	Decrease exponentially towards zero	Significant in all lag q
MA (q)	Significant in all lag q	Decrease exponentially towards zero
ARMA (p,q)	Decrease exponentially towards zero	Decrease exponentially towards zero

Source: Gujarati, 2009

The determination of AR and MA values was also performed by trial tests from AR (1), AR (2), AR (3); MA (1), MA (2), and MA (3). Based on the comparison of the values of Akaike Info Criterion (AIC) and Schwarz Criterion from DLQ45 AR (1), AR (2), and AR (3), the smallest value is the DLQ45 AR (1).

Table 2. Comparison of AIC and Schwarz Criterion values on MA

	Akaike Info Criterion	Schwarz Criterion
DLQ45 AR(1)	9,2041	9,2733
DLQ45 AR(2)	9,2465	9,3163
DLQ45 AR(3)	9,2364	9,3069
DLQ45 MA(1)	9,1776	9,2463
DLQ45 MA(2)	9,2178	9,2865
DLQ45 MA(3)	9,1885	9,2569

Source: Processed data

Based on the comparison of the values of Akaike Infor Criterion (AIC) and Schwarz Criterion from DLQ45 MA (1), MA (2), and MA (3), the smallest value is the DLQ45 MA (1).

The determination of AR and MA values was also administered by trial test from DLQ45 AR (1) MA (1), DLQ45 AR (1) MA (2), DLQ45 AR (1) MA (3), DLQ45 AR (2) MA (1), DLQ45 AR (2) MA (2), and DLQ45 AR (2) MA (3).

Table 3. Comparison of AIC and Schwarz Criterion ARIMA values

Model	*Akaike Info Creterion*	*Schwarz Criterion*
DLQ45 AR (1) d(1) MA(1) or ARIMA (1,1,1)	9,0677	9,1715
DLQ45 AR (1) d(1) MA(2) or ARIMA (1,1,2)	9,1622	9,2660
DLQ45 AR (1) d(1) MA(3) or ARIMA (1,1,3)	9,1725	9,2763
DLQ45 AR (2) d(1) MA(1) or ARIMA (2,1,1)	9,2152	9,3199
DLQ45 AR (2) d(1) MA(2) or ARIMA (2,1,2)	9,1721	9,2769
DLQ45 AR (2) d(1) MA(3) or ARIMA (2,1,3)	9,2212	9,3260

Source: Processed data

Based on the ARIMA model, the smallest AIC and Schwarz Criterion values are DLQ45 AR (1) MA (1)

(3) Diagnostic Checking

Table 4. Comparison of RMSE ARIMA values

Model	*Root Mean Square Error* (RMSE)
DLQ45 ARIMA (1,1,1)	23,59591
DLQ45 ARIMA (1,1,2)	23,61466
DLQ45 ARIMA (1,1,3)	23,59598
DLQ45 ARIMA (2,1,1)	23,59562
DLQ45 ARIMA (2,1,2)	23,74268
DLQ45 ARIMA (2,1,3)	23,59605

Source: Processed data

Based on the comparison, the smallest RMSE value is the DLQ45 AR (2) MA (1) or ARIMA (2,1,1) model, which is 23.59562.

(4) Forecasting

Based on the above tests, the best estimation model is DLQ45 AR (2) d (1) MA (1) or ARIMA (2,1,1) compared to the AR model or MA model which are:

DLQ45 = C + AR (2) + MA (1)

DLQ45 = -5.066946 - 0.136282 t-2 + 0.345647 µt-1

The ARIMA estimation model (2,1,1) produces the DLQ45 projection as in Figure 1. Based on Figure 1, it shows that there is no significant difference between the actual data and the forecasting results.

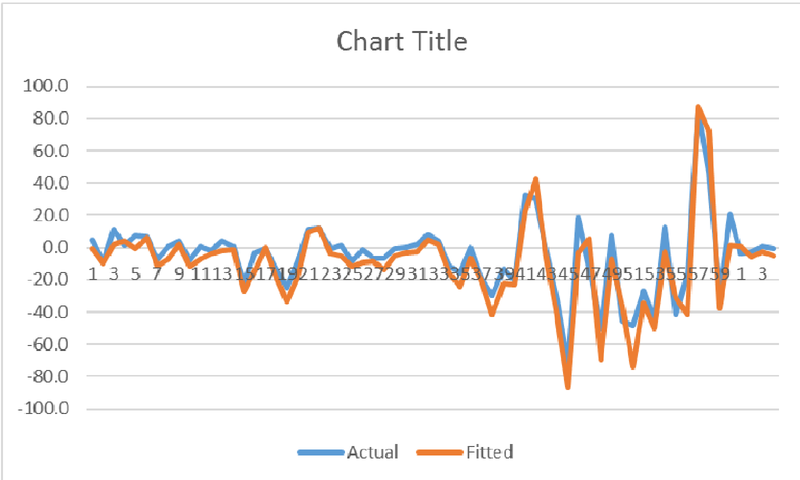


Figure 3. DLQ45 Forecasting Results

Figure 3 is showing the forecasting of LQ45 stocks in Indonesia using DLQ45 data. After transforming the DLQ45 data, forecasting data for LQ45 were obtained. During the pandemic, the price of LQ45 shares experienced a decline though it was predicted that for some time it would be stagnant. The aspect that needs to be considered is the level of success of the Indonesian Government in dealing with Covid-19. If the level of Covid-19 control is deemed successful, investors who are more likely to wait and see will return to stock market trading. Conversely, if the government is deemed unsuccessful, the decline in share prices will continue to decrease.

Questions about forecasting LQ45 share prices during a pandemic can also be explained by the theory of the behaviour of stock price. [3], for example, state that share prices that are forecasted using technical and economic approaches will provide better forecasting results. In fact, it has taken into account the factors that influence the share price.

Forecasting results in Figure 4 can be explained using investors' psychological factors. In Figure 4, there is a tendency after declining and flattening, it means that investors tend to hold back to see the government's actions for handling Corona. If the government is deemed successful, the price will soar.

In investor behaviour, investors will tend to take actions that minimize losses. Attitudes towards risk also influence investors' decisions. If macroeconomic conditions resemble today's situation, investors' behaviours who tend to hold back can be understandable. Examples of actions to avoid losses are selling stocks that have a profit margin. According to [24], they called this event "selling winner too early and riding losers too long" as an influence of disposition.

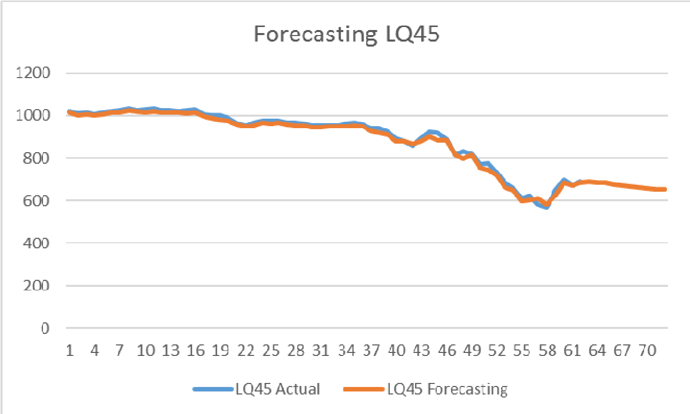


Figure 4. LQ45 Forecasting Results

Conclusion

The estimation model with the Autoregresive Integrated Moving Average (ARIMA) obtained the best model for the IHSG LQ45, which is DLQ45 AR (2) d (1) MA (1) or ARIMA (2,1,1):

DLQ45 = C + AR (2) + MA (1)

DLQ45 = -5.066946 - 0.136282 t-2 + 0.345647 μt-1

Based on the results of ARIMA testing, the hypothesis proposed in this study is accepted (the IHSG LQ45 projection model can be predicted using the behaviour of stock price in the past period and its psychological variables).

Suggestions

Suggestions for future researchers are:

1. IHSG estimation can be performed on IHSG excluding LQ 45 which also experiences a downward trend, such as IHSG, LQ 45, IDX 30, JII, Kompas100, Bisnis-27, PERINDO25, Sri-Kehati, ISSI, etc.
2. The estimation approach can use other models, such as the Vector Autoregressive (VAR). The VAR model can be used to model several endogenous variables simultaneously, each of variable is explained by lag or past period of its own values and other endogenous variables within the model so that the estimation results are more comprehensive.

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