Forecasting the Performance of Volatility of Share Prices with the Application of ARIMA Model

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ABSTRACT: The global decrease in the price of Crude Palm Oil (CPO) has affected the performance of share prices in Astra Agro Lestari, Tbk (Code: AALI). However, this financial series data is highly volatile in both mean and variance. Therefore, the ARIMA model is one of the ways to deal with this error. This study, therefore, aims to determine the best ARIMA model to forecast the series of AALI from August 2016 to August 2019. The findings suggest that ARIMA (1,1,1) is the best-selected model due to its very significant p-value (less than 0.0001), which showed that the model is best for forecasting. The model is then used to establish the prediction of AALI share prices for the next 30 days.

# INTRODUCTION

In 2018 the price of Crude Palm Oil (CPO) dropped significantly, thereby affecting the performance of the national palm oil industry as well as Astra Agro Lestari, Tbk (PT Astra Agro Lestari Tbk, 2018). The uncertainty of its price was linked to the share price of the company, which is the largest agricultural capital market in Indonesia (IDX Statistic, 2018).

Conversely, financial data such as daily shire prices have been widely used to predict future volatility. Furthermore, the high volatility and varying heterogeneity, with financial time series, are capable of affecting its asymmetric and leverage, which tends to increase/decrease prices (Barusman et al., 2018). One way to analyze the data series is through the autoregressive integrated moving average (ARIMA) model in which a large range of the forecasted issues are coped (Newbold, 1983). Therefore, the ups and downs of the share prices need to be forecasted in order to assist the investors with their funds, particularly in the Agricultural Sector.

Therefore, this study aims to predict the volatility share prices of a CPO company in Indonesia to determine the estimated parameters and forecast its ARIMA model.

# METHODS

Wei (2006) stated that the sequence of observations over some interval is known as time series, which are either stationary or non-stationary and analyzed using the ARIMA model (Barusman et al. 2018, Tsay, 2005). According to Sampson (2001), the first step in ARIMA modeling is to station the series, which is a fundamental concept. Therefore, it is a necessity to check the stationary of the series that uses the Augmented Dickey-Fuller (ADF) unit-root test by conducting the hypothesis where H0 equals zero (Barusman et al., 2018). This is mathematically equated as follows:

ADF Test: (1)

H0 is rejected assuming t and the p-value are less than -2.57 and 0.05, respectively, at 95% confidence (Brockwell and Davis, 2002).

In addition to ADF test, autocorrelation function (ACF) and partial autocorrelation function (PACF) are exhibited to have a clear picture of the stationary series. It is also used to determine the data, which is a fundamental tool in identifying the ARIMA model for forecasting (Montgomery et al., 2008). Brockwell and Davis (2002) analyzed the equation of ARIMA model as follows:

(2)

Where,

; ; is differencing of order d; is Constanta; is residuals; and L is the notational device for lags.

However, equation (2) is simplified as follows:

(3)

# RESULT AND DISCUSSION

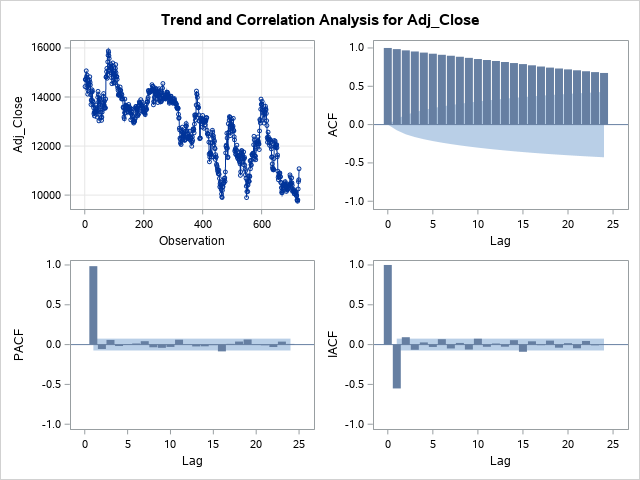
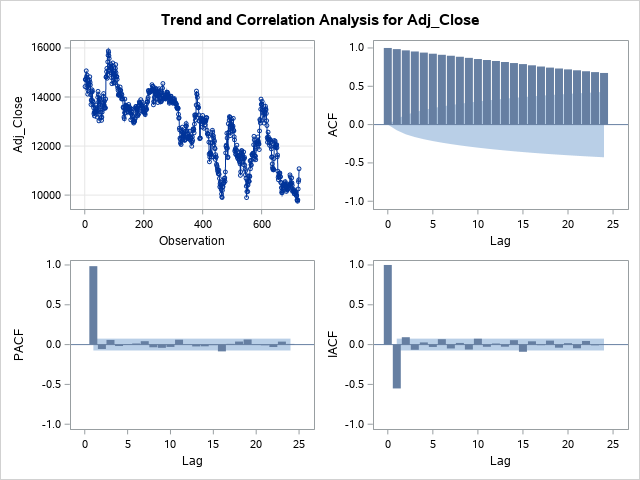
The data used in this study were obtained three years ago from the daily stock prices of Astra Agro Lestari, Tbk (Code: AALI) listed at Jakarta Composite Index (IHSG). It is the biggest market capitalization in the agriculture industry, Indonesia (IDX Annual Statistic, 2018).

Table 1: ADF unit-root test of AALI with lag = 2

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Type | Lags | Rho | Pr < Rho | Tau | Pr < Tau | F | Pr > F |
| Zero Mean | 2 | -0.3850 | 0.5954 | -0.86 | 0.3437 |  |  |
| Single Mean | 2 | -8.8799 | 0.1756 | -2.12 | 0.2352 | 2.46 | 0.4402 |
| Trend | 2 | -27.0281 | 0.0151 | -3.63 | 0.0285 | 6.58 | 0.0411 |

Figure 1: Plotting of Daily Share Prices of AALI

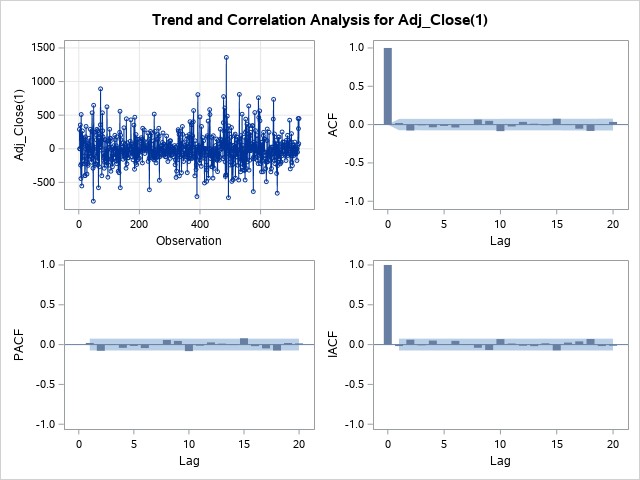
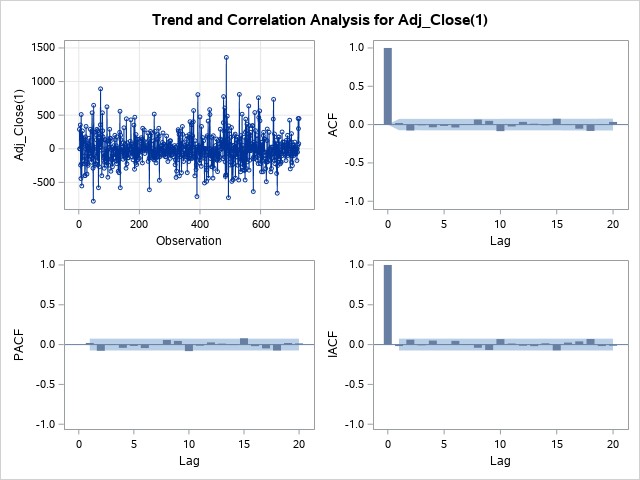
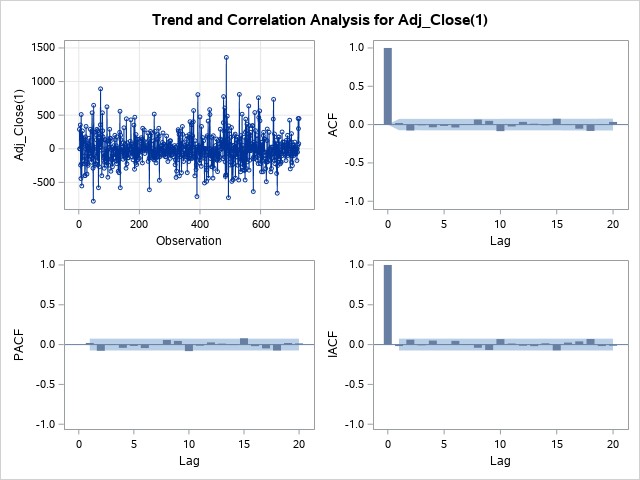
Overall, AALI has experienced a downward trend since mid-2016 until the end of 2017 with a fluctuated volatile downward data. However, the remaining data showed high volatility, which means that the share prices are very unstable and decreased a high-risk investment. Furthermore, not all plotted data of AALI is stationary as the behaviour of the series is not constant.

The non-stationary data is statistically proven by testing an ADF unit-root. H0 is rejected when the P-value is lower than 0.05 significant confidences. Table 1 clearly shows that the p-value has a greater statistic number than the confidence interval. Therefore, H0 is rejected. Figures 2a and b support the non-stationary data, as the decay movement of ACF, which is very slow, while the PACF graph suggests an out-of-confidence-limit data.

1. (b)

Figure 2: Plot of ACF and PACF for AALI

1. *Differencing*

The data needs to be made stationary. Otherwise, it becomes less effective to model the forecasting setting. In this stage, the technique that also supports the model is conducted by differencing the data with some certain lag.

c

b

a

Figure 3a,b,c : Plot of Residuals after differencing (d=1), ACF and PACF

Figure 3a shows that after differencing d by 1, the plotting data becomes zero. The graph also demonstrates that the error predictions of the first four hundred data are homogenous. However, the last three hundred data tend to be larger, and some are beyond the two standard errors, which are confirmed in figure 1. Therefore, from 2018 to August 2019, the prices were highly volatile. The transformed stationary is also supported with the graphs of ACF (3b) and PACF (3c) as well as the ADF test table as follows:

Table 2: ADF unit-root test of AALI with lag = 2 after differencing (d=1)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Type | Lags | Rho | Pr < Rho | Tau | Pr < Tau | F | Pr > F |
| Zero Mean | 2 | -841.681 | 0.0001 | -16.19 | <.0001 |  |  |
| Single Mean | 2 | -844.947 | 0.0001 | -16.20 | <.0001 | 131.24 | 0.0010 |
| Trend | 2 | -844.855 | 0.0001 | -16.19 | <.0001 | 131.06 | 0.0010 |

Table 3: Autocorrelation Check for White Noise

| To Lag | Chi-Square | DF | Pr > ChiSq | Autocorrelations | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 6 | 6.88 | 6 | 0.3321 | 0.020 | -0.077 | -0.009 | -0.035 | -0.017 | -0.038 |
| 12 | 18.57 | 12 | 0.0995 | 0.004 | 0.066 | 0.049 | -0.086 | -0.024 | 0.035 |
| 18 | 30.33 | 18 | 0.0343 | 0.011 | -0.009 | 0.076 | -0.006 | -0.054 | -0.083 |
| 24 | 33.77 | 24 | 0.0888 | 0.007 | 0.035 | 0.010 | -0.045 | -0.017 | -0.031 |

1. *ARIMA Model*

The stationary stage is followed by designing the ARIMA model that fits the forecasting data set. Therefore, tables 3 and 4 presents the parameters of estimation for the ARIMA (1,1,1) model.

Table 3: Parameter Estimation Model ARIMA (1,1,1) Table 4: ARIMA Statistical Estimation

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Parameter | Estimate | Standard Error | t Value | Approx Pr > |t| | Lag |
| MU | -4.58037 | 8.47872 | -0.54 | 0.5892 | 0 |
| MA1,1 | -0.96537 | 0.03250 | -29.70 | <.0001 | 1 |
| AR1,1 | -0.93429 | 0.04380 | -21.33 | <.0001 | 1 |

|  |  |
| --- | --- |
| Constant Estimate | -8.85976 |
| Variance Estimate | 50555.19 |
| Std Error Estimate | 224.8448 |
| Number of Residuals | 726 |

According to the data analysis of ARIMA (p, d, q), the model estimation of autoregressive AR (1), differencing (1), and moving average MA(1), are exhibited as follows:

(4)

The model is confirmed to fit both the AR (p) and MA(q) parameters with a significant p-value of less than 0.0001. Equation (4) is further interpreted by holding all variables on a fixed average and forecasting that share prices are going to decrease by 8.86976. A decrease by 1 unit of AALIt-1 in AR(1) estimation tends to have an effect of 0.93429 on MA(1) and another variable constant on average. Conversely, when both AR(1) and constant estimates are fixed, AALIt decreases the average by 0.96537. Therefore, the model is used to predict the share prices volatility of AALI for the next 30 days, which is tabulated as follows:

Table 5. AALI Share Prices Prediction

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Obs** | **Forecast** | **Std Error** | **95% Confidence Limits** | |  | **Obs** | **Forecast** | **Std Error** | **95% Confidence Limits** | |
| **728** | 11083.53 | 224.8448 | 10642.84 | 11524.21 |  | **743** | 11006.21 | 913.5706 | 9215.64 | 12796.77 |
| **729** | 11066.7 | 322.9578 | 10433.71 | 11699.69 |  | **744** | 11006.04 | 941.4081 | 9160.917 | 12851.17 |
| **730** | 11073.56 | 393.7812 | 10301.76 | 11845.36 |  | **745** | 10997.34 | 969.0011 | 9098.128 | 12896.54 |
| **731** | 11058.29 | 456.74 | 10163.1 | 11953.49 |  | **746** | 10996.61 | 995.3248 | 9045.81 | 12947.41 |
| **732** | 11063.7 | 509.4645 | 10065.16 | 12062.23 |  | **747** | 10988.43 | 1021.43 | 8986.462 | 12990.39 |
| **733** | 11049.79 | 559.4003 | 9953.383 | 12146.19 |  | **748** | 10987.21 | 1046.465 | 8936.18 | 13038.25 |
| **734** | 11053.92 | 603.3485 | 9871.382 | 12236.46 |  | **749** | 10979.49 | 1071.298 | 8879.784 | 13079.19 |
| **735** | 11041.2 | 645.9513 | 9775.158 | 12307.24 |  | **750** | 10977.85 | 1095.218 | 8831.258 | 13124.43 |
| **736** | 11044.23 | 684.4648 | 9702.701 | 12385.75 |  | **751** | 10970.52 | 1118.947 | 8777.426 | 13163.62 |
| **737** | 11032.54 | 722.2078 | 9617.037 | 12448.04 |  | **752** | 10968.5 | 1141.89 | 8730.443 | 13206.57 |
| **738** | 11034.6 | 756.9305 | 9551.043 | 12518.16 |  | **753** | 10961.53 | 1164.649 | 8678.859 | 13244.2 |
| **739** | 11023.81 | 791.1518 | 9473.185 | 12574.44 |  | **754** | 10959.19 | 1186.726 | 8633.247 | 13285.13 |
| **740** | 11025.03 | 823.0348 | 9411.912 | 12638.15 |  | **755** | 10952.51 | 1208.625 | 8583.653 | 13321.38 |
| **741** | 11015.03 | 854.5547 | 9340.138 | 12689.93 |  | **756** | 10949.89 | 1229.928 | 8539.275 | 13360.5 |
| **742** | 11015.51 | 884.2065 | 9282.501 | 12748.53 |  | **757** | 10943.48 | 1251.057 | 8491.455 | 13395.51 |

Table 5 shows a downward trend for AALI share prices for the next 30 days. However, on the basis of statistics, the confidence interval is becoming wider over the forecasted dates. This means the volatility of prediction is quite high relative to the interval limits.

# CONCLUSION

In conclusion, the ARIMA model selected to forecast the series of data of AALI is ARIMA (1,1,1). However, before the analysis was conducted, the values of p, d, and q were first estimated to ensure the series' were stationary. The data obtained from August 2016 to August 2019 showed that they not stationary with a differencing value of 1.

The stationary model of ARIMA(1,1,1), is used to determine a well-behaved construct and share price volatility due to its significant level of confidence, which is low (<0.0001). Therefore, this model has a sound ability to forecast time series data for the following month.

# REFERENCES

Barusman, M. Yusuf., Usman, Mustafa., Ambarwati, Riyama., and Virginia, Erica. 2018. Application of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model for Forecasting. Journal of Engineering and Applied Sciences, 13(10), 3418-3422.

Brockwell, P.J., and R.A. Davis. 2002. Introduction to Time Series and Forecasting. 8th Edition. Springer. Berlin.

IDX Annual Statistic. 2018. Available from: <https://idx.co.id/media/4842/idx-annual-statistics-2018.pdf> [last retrieved on 20 August 2019].

Montgomery, D., Jennings, C., Kulachi, M. (2008). Introduction Time Series Analysis and Forecasting. Hoboken, New Jersey: John Wiley & Sons Inc.

Newbold, Paul. 1983. ARIMA Model Building and the Time Series Analysis Approach to Forecasting. Journal of Forecasting, 2, 23-35.

PT Astra Agro Lestari Tbk. (2018). Available from:

<https://finance.yahoo.com/quote/AALI.JK/history?p=AALI.JK> [last retrieved on 20 August 2019].

Sampson, M., 2001. Time Series Analysis. Loglinear Publishing, Montreal, Quebec, Canada.

Tsay, R.S. (2005), Analysis of Financial Time Series. Hoboken, New Jersey: John Wiley & Sons, Inc.

Wei, W.W. (2006). Time Series Analysis: Univariate and Multivariate Methods. 2nd ed. New York: Pearson.