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# Comparison of Forecasting Transfer Function Methods and ARIMA-GARCH on Daily Stock Data in the Agribusiness and Trade Sector

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**Abstract**

Shares are one of the long-term financial instruments traded in the capital market and are one of the popular investment alternatives for investors in Indonesia. One of the goals of investors investing in a company is to get a profit (return). The higher the stock's selling price is above the purchase price, the higher the return that investors will get. Stock data is time-series data. Therefore, time-series data modeling is needed to determine when investors will get returns shared. One of the models used for time-series data is the ARIMA model. This model assumes that the data's volatility (rate of fluctuation) is constant. In financial data, there are many cases of data with non-constant volatility. This non-constant volatility will cause heteroscedastic problems in the data. Therefore we need a model that can accommodate heteroscedastic problems in the data. One model used is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. This study also examines the effect of independent variables ( input series ), namely world crude oil prices, the positive number of Covid-19, the dollar exchange rate against the rupiah, and the Shanghai composite index on stock return time-series data ( output series ) in the agribusiness and trade sectors. One of the models used to analyze the effect of input series variables on time series data is the transfer function model. The data used is from March 2, 2020, to June 30, 2021. These two models are compared to find out which time series forecast is better. The results showed that the transfer function method is a better method used for forecasting the next seven days on the stock return data of PT. Sawit Sumber Mas Sarana Tbk and PT. Astra Internasional Tbk compared to the ARIMA-GARCH model.

***Keywords:*** ARIMA; GARCH; return; transfer function.

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## 1. Introduction

Shares are long-term financial instruments traded in the capital market and are popular investment alternatives for investors in Indonesia. Shares are proof of equity participation in a company or are proof of company ownership. One of the goals of investors investing in a company is to get a return. Return or rate of return is the difference between the amount received and the amount invested, divided by the amount invested. The higher the stock's selling price is above the purchase price, the higher the investors' return. If an investor wants a high return, he must be willing to bear higher risk, and vice versa; the chance is also common if he wants a low return. There are several factors that every investor must be aware of, consisting of macro and micro factors. Some of the factors used are the exchange rate [16], world crude oil prices [12], the Shanghai composite index [11], and the daily number of positive cases of Covid-19 [10]. According to Bank Indonesia [1], some of the impacts of Covid-19 on the global economy are the trade sector, the tourism sector, and the financial sector. Meanwhile, the agribusiness sector, namely agriculture, forestry, and fisheries, still grew by 2.19%. The growth of the food crops sub-sector and the plantation sub-sector supports the positive development of the agribusiness sector, especially oil palm [19]. Therefore, it is necessary to model time series data on stock returns to determine conditions and prepare strategies to deal with a decline or spike in stock returns for some time during the Covid-19 pandemic.

In time-series data modeling can use the ARIMA model. This model requires the assumption that the volatility (fluctuation) of the data is constant. There are many cases of data with non-constant changes in financial data, causing the problem of heterogeneity of variance errors (heteroscedastic) in the data; one of the models can use the GARCH model. The GARCH model has a symmetrical characteristic of the volatility response to positive (good) and adverse (lousy news) shocks. Therefore, by considering the flexibility and simplicity of the ARIMA model and the ability of the GARCH model to capture the volatility of financial time series data, in this study, stock returns are modeled using ARIMA combined with GARCH called ARIMA-GARCH.

Several studies in predicting stock data use ARIMA-GARCH modeling, including research that applies the ARIMA-GARCH model to rubber price volatility data [9]. Furthermore, the GARCH model is used to model the Rupee exchange rate against five foreign currencies, namely USD, S.F., JPY, GBP, and EURO [13]. A study using the ARMA-GARCH model to forecast Guaranty Trust Bank Nigeria Plc stock returns concluded that the ARMA-GARCH model is suitable [6].

In time-series analysis, input variables often affect output variables determined outside the model. One of the models used to analyze the effect of input series variables on time series data is the transfer function model. The ARIMA-ARCH/GARCH model compared with the transfer function on the input series of West Texas Intermediate (WTI) world crude oil prices and the JCI as the output series, resulting in the conclusion that the transfer function with ARCH/GARCH is better [8]. Also, the ARIMA compared with the transfer function model in stock price forecasting shows that the transfer function method better explains the relationship between variables. On the other hand, the results of the accuracy comparison show that the transfer function method does not always produce better accuracy than the ARIMA method [18].

In this study, the researcher compares the transfer function model with the ARIMA-GARCH model for the output return series for the agribusiness and trade sectors. In the transfer function, the input series used are world crude oil prices, the number of positive COVID-19 cases in Indonesia, the dollar exchange rate against the rupiah, and the Shanghai composite index. The ARIMA-GARCH model is used to model the variance of the remainder of the output series that is not homogeneous (heteroscedastic). Through this study, the researcher hopes that the prediction results obtained can predict well the stock prices of the two companies in the future so that the public, especially investors, can plan and make the right decisions in making investments. Furthermore, it can facilitate the government in taking appropriate policies in the economic sector, especially in the subsector of agribusiness and trade. The purpose of this study was to compare which forecasting results are better used between the transfer function model and ARIMA-GARCH on daily stock return data in the agribusiness and trading sectors.

## 2. Data and Method

### *2.1. Data*

The data used in this research is secondary data accessed on finance.yahoo.com, bi.go.id, investing.com, and covid19.go.id websites. The data taken is daily data from March 2, 2020, to June 30, 2021. The research variables used in this study are as follows:

**Table 1:** Research variables.

| Number | Series | Variable Name | Data Type | Unit |
|---|---|---|---|---|
| 1 | Output | Stock price return PT. Sawit Sumber Mas Sarana Tbk ($Y_1$) | Numerical | fold |
| 2 | | Stock price return P.T. Astra International Tbk ($Y_2$) | Numerical | fold |
| 3 | Input | World crude oil price (WTI) ($X_1$) | Numerical | USD |
| 4 | | Number of positive cases of Covid-19 ($X_2$) | Numerical | case |
| 5 | | Exchange Rate USD against Rupiah ($X_3$) | Numerical | Rupiah |
| 6 | | Shanghai Composite Index (SSEC) ($X_4$) | Numerical | USD |

### *2.2. Methodology*

In the study, data analysis used SAS and R-Studio software. Before conducting data analysis, research data is divided into two parts, namely training data for modeling and testing data as test data. Tests were carried out on three split scenarios, namely 313 training data and 7 testing data, 306 training data and 14 testing data, 299 training data, and 21 testing data. The stages of data analysis are as follows:

1. Data exploration aims to see the distribution pattern of the input and output series data.
2. Check the stationarity of the training data for the input and output series against the mean using the ADF test and perform the transformation if the data is not stationary.
3. Performing transfer function modeling on input and output data series with the following algorithm:

    a. identify the input data and model the two series with the ARIMA model $X_t$ using ACF and PACF plots and pre-whitening the input $X_t$ ($\alpha_t$) and output $Y_t$ ($\beta_t$)series,
    b. calculates the cross-correlation of each input and output series that has gone through the pre-whitening

process ($\alpha_t$ and $\beta_t$),

c. perform initial identification of the transfer function by determining the values of b, r, and s and identify the noise model ($N_t$),
d. perform a diagnostic test of the remainder of the transfer function model with residual autocorrelation and cross-correlation tests between $X_t$ with $\varepsilon_t$ (whether natural or not until the specified lag), and
e. forecast the transfer function model.

4. Perform ARIMA-GARCH modeling with the following algorithm:

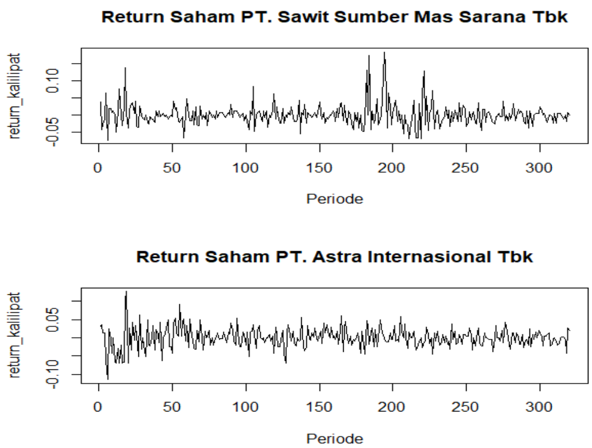
   a. perform ARIMA modeling on the data for each output series (stock returns of PT. Sawit Sumber Mas Sarana Tbk and PT. Astra International Tbk),
   b. testing the effect of ARCH/GARCH on the output series by examining heteroscedasticity,
   c. identify the GARCH model if it meets the assumption of heteroscedasticity,
   d. perform a diagnostic test of the rest of the model, and
   e. forecast using the GARCH model.

5. Compare the best forecasting results between the transfer function model and ARIMA-GARCH based on the RMSE and MAPE values.

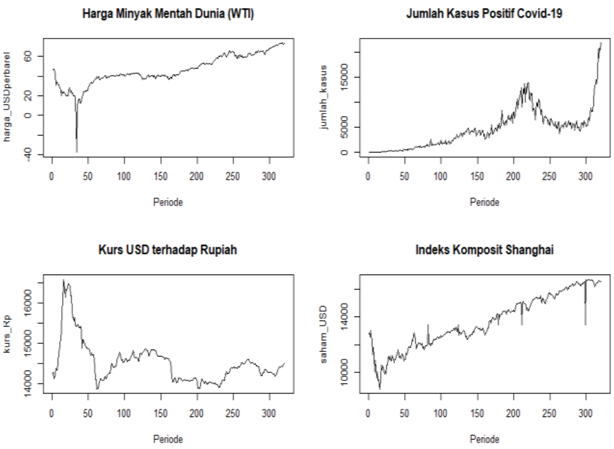
## 3. Result and Discussion

### *3.1. Data Exploration*

Presented in figure 1 are the the training data plot for the input and output series. As shown, the output series of return for each stock price shows a relatively high data fluctuation at one time, and the same trend occurs next over time. PT. Astra International Tbk and PT. Sumber Mas Sarana Tbk daily tend to be stationary. The input series of world crude oil, the positive number of Covid-19 in Indonesia, the dollar exchange rate against the rupiah and the Shanghai Composite Index (SSEC) do not look stationary.




(a)




(b)

**Figure 1:** (a) Plot of the Output Series and (b) Input.

Figure 1(a) shows the SSMS return has a minimum value of -0.0727 times, meaning that ASII's return experienced a maximum loss of 7.27% on March 9, 2020, and experienced a maximum profit of 18.33% on December 18, 2020. In return, Astra International experienced a total loss of 11.45% on March 9, 2020, and experienced a maximum profit of 12.72% on March 27, 2020. It shows that on March 9, 2020, both share prices fell March 9, 2020.

In Figure 1(b), the world crude oil (WTI) price fell to its lowest point of 37.63 USD per barrel on April 20, 2020, and rose to a maximum level of 66.96 USD per barrel on May 31, 2021. The number of positive Covid-19 in Indonesia the lowest was 0 cases at the beginning of March 2020, namely the beginning of the pandemic entering Indonesia, while the highest number was 13802 cases on January 29, 2021. The dollar exchange rate against the rupiah showed that the rupiah exchange rate weakened to a low of 13870/USD on June 5, 2020, and strengthened to a high of 16575/USD on March 23, 2020. The Shanghai Composite Index (SSEC) experienced a low of 8777 USD on March 23, 2020, and a high of 13010 USD on March 4, 2021. It concludes that the four variables experienced their lowest point at the beginning of the Covid-19 pandemic entering Indonesia, from early March 2020 to April 2020.

### *3.2. Data Stationary Check*

The ADF test of the Sawit Sumber Mas Sarana and Astra International output return series data is obtained ADF with a p-value=0.01. So, the output return series is stationary. Meanwhile, based on the ADF test of the four input series variables, it shows that the data is not stationary concerning the mean (p-value> 0.05). The next step is to transform the input series variables through differencing, namely, calculating the difference between the data ($Y_t$) and the previous data ($Y_{t-1}$). Each input series variable has stationary after the first differencing, the input series data is stationary concerning variance, so there is no need to perform Box-Cox transformation.

### *3.3. Transfer Function Model*

### *3.3.1. ARIMA Model Identification*

The ARIMA model formation for each input series goes through the model identification stage in the transfer function. Identifying the ARIMA input series model is done by looking at the ACF and PACF plots.

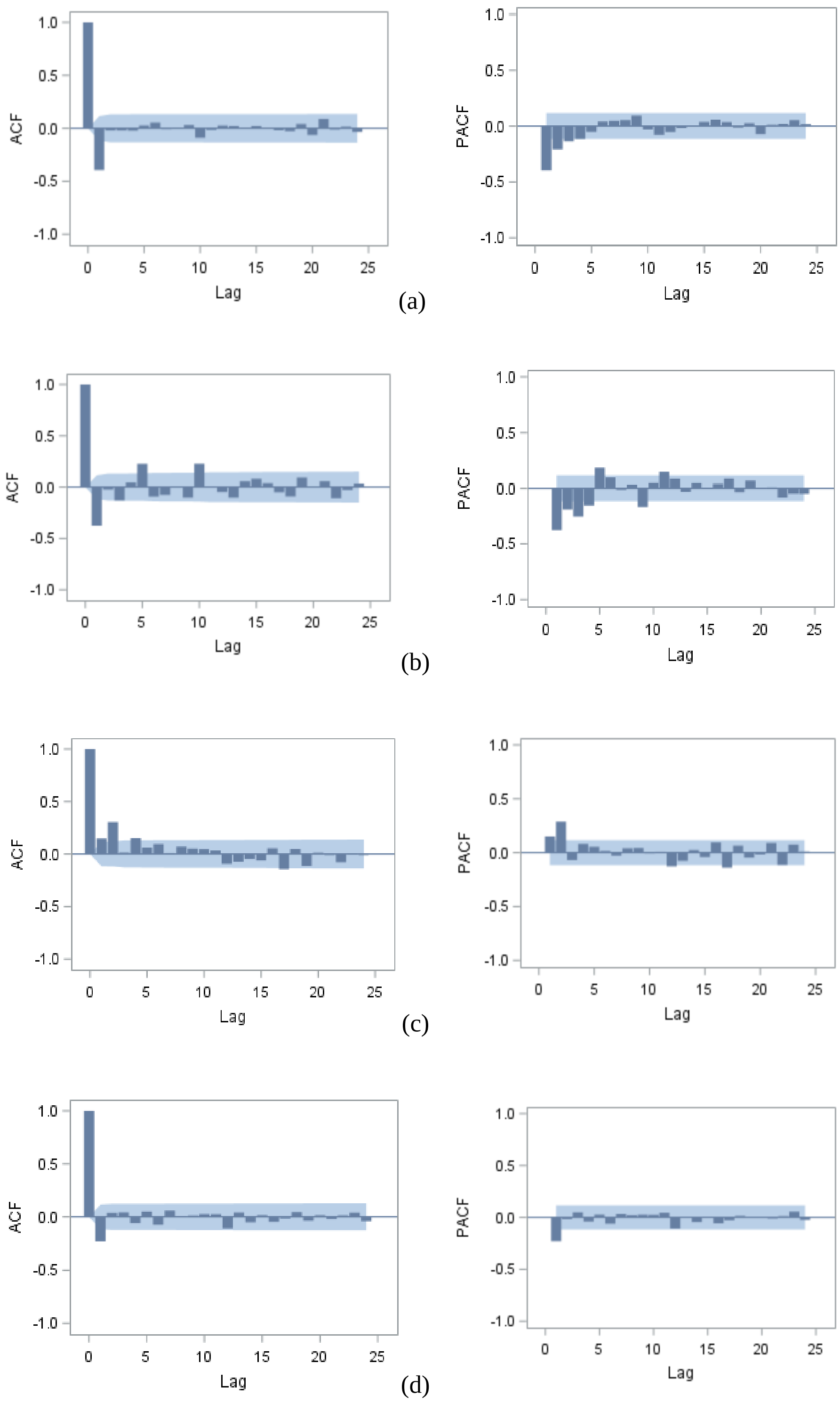



**Figure 2:** Plots of ACF and PACF (a) world crude oil prices $(X_1)$, (b) positive number of Covid-19 in Indonesia $(X_2)$, (c) dollar exchange rate against rupiah $(X_3)$, (d) Shanghai composite index $(X_4)$ after differencing at lag-1.

Based on Figures 2 (a)-(d), the model identification results from significant lag in the ACF and PACF plots obtained ARIMA models for $X_1$ is ARIMA (0,1,1), for $X_2$ is ARIMA (5,1,1), for $X_3$ is ARIMA (1,1,0), and for $X_4$ is ARIMA (1,1,1). Then do overfitting and test the significance of the parameters to get the best model.

Based on the overfitting and autoarima, all candidate parameters of the input series model are significant, namely *p-value* < = 5%. So for the input data series of world crude oil prices, the best ARIMA model with the smallest AIC value is ARIMA (0,1,1). The best model for the daily number of positive cases of Covid-19 in Indonesia is ARIMA (4,1,0). The best model for the dollar exchange rate against the rupiah data is ARIMA (1,1,4) and for the Shanghai composite index is ARIMA (2,1,1). The next step is to transform the correlated series to white-noise behavior that is not correlated or pre-whitening. This pre-whitening process uses the ARIMA model for the input series. The transfer function is mapping the input series to the output series, so the pre-whitening process on the output series also uses a filter based on the ARIMA model of the input series. Applying this filter results $\alpha_t$ for the input series $(X_t)$ and $\beta_t$ for the output series $(Y_t)$.

### *3.3.2. Cross-Correlation Calculation*

The output and input variables have gone through a pre-whitening process to obtain $\alpha_t$ and $\beta_t$ to calculate their cross-correlation. Presented in table 2 are the Cross-correlation between input and output series. As shown, the sum of all the geometric mean or the sum of all the total rows is 10.9485. It shows that the SSMS output series shows a relationship (cross-correlation) between the Shanghai composite index $(X_4)$ and SSMS returns. Meanwhile, the ASII output series shows cross-correlation between world crude oil prices $(X_1)$, the dollar exchange rate against the rupiah $(X_3)$, and the Shanghai composite index $(X_4)$ with ASII returns. The cross-correlation pattern obtained will be used to identify the transfer function model (b,r,s).

**Table 2:** Cross-correlation between Input and Output Series.

| Output $(\beta_t)$ | Input $(\alpha_t)$ | P-value | | | | Result |
|---|---|---|---|---|---|---|
| | | Lag 6 | Lag 12 | Lag 18 | Lag 24 | |
| SSMS | $\alpha_1$ | 0.9410 | 0.9995 | 0.9979 | 0.9995 | No |
| | $\alpha_3$ | 0.5240 | 0.2478 | 0.4350 | 0.5455 | No |
| | $\alpha_4$ | 0.0225 | 0.0181 | 0.0521 | 0.0584 | Yes |
| ASII | $\alpha_1$ | 0.0075 | 0.0017 | 0.0004 | 0.0006 | Yes |
| | $\alpha_3$ | <0.0001 | <0.0001 | <0.0001 | <0.0001 | Yes |
| | $\alpha_4$ | 0.0137 | 0.0391 | 0.0054 | 0.0037 | Yes |

### *3.3.3. Early Identification of Transfer Function Model*

Initial identification of the model is made by looking at the cross-correlation pattern between and using the values of b, r, and s. The value of b is determined based on the first significant lag in the cross-correlation pattern, while the value of s based on the length of X affects Y after the first significant.

**Table 3:** Identification of The Initial Model Order of The Transfer Function.

| Output | Orde (b,r,s) | Parameter | P-value | Result |
|---|---|---|---|---|
| SSMS | $X_4$ (b=0,r=1,s=1) | $\omega_0$<br>$\delta_1$ | 0.0004<br><0.001 | Significant<br>Significant |
| ASII | $X_1$ (b=9,r=0,s=0) | $\omega_0$ | 0.0017 | Significant |
| | $X_3$(b=0,r=0,s=1) | $\omega_0$<br>$\omega_1$ | <0.0001<br><0.0001 | Significant<br>Significant |
| | $X_4$(b=2,r=0,s=0) | $\omega_0$ | 0.0051 | Significant |

It can be seen in Table 3 that the results of the alleged transfer function model produce all fundamental components because p-value < $\alpha$ = 5%. In the SSMS output series, this indicates that the input series of Shanghai composite index ($X_4$) affects the SSMS output return series from day-0 (*b* = 0) until day-1 (*s* = 1). The ASII output series indicates that the input series of world crude oil prices ($X_1$) affects ASII's output return series on day-9 (*b* = *9*). In contrast, it did not act the last time and did not affect (*s=0*) stock returns on the following day.

Based on the identification results above, it is necessary to do ARIMA modeling of the noise series to get a white-noise residual. The transfer function model formed for the input and *output* series is as follows:

$$Y_{1_t} = \frac{\omega_{04}}{1+\delta_1 B} X_{4t-3} + \eta_{1_t} \tag{1}$$

$$Y_{2_t} = \omega_{01} X_{1t-9} + (\omega_{03} - \omega_{13} B) X_{3t} + \omega_0 X_{4t-2} + \eta_{2_t} \tag{2}$$

Identify ACF and PACF plots to form a noise model. In both output series, plot the ACF noise cut-off in the first lag and PACF tail-off so that the model for each noise is MA(1). Next, estimate and test the significance of the model parameters so that the noise series model formed is:

$$\eta_{1_t} = (1 - 0{,}85524 B^1) a_{1_t} \tag{3}$$

$$\eta_{2_t} = (1 - 0{,}98985 B^1) a_{2_t} \tag{4}$$

### *3.3.4. Model Residual Diagnosis*

The next stage is to check the feasibility of the model by testing the assumption of white noise from each of the resulting model residues. The ACF and PACF residual plots are not significantly different from zero, which indicates that the model residuals are independent. Based on the residual self-correlation value, the residual value of the two transfer function models is white-noise because the residual auto-correlation value is not significantly different from zero ($\alpha$ = 5%). The cross-correlation value between the input series and the model residuals is also not entirely different from zero. The model is good at separating the residuals. The transfer function model is feasible by considering parameter tests, residual self-correlation, and correlation between input series and residual.

### *3.3.5. Forecasting with Transfer Function Model*

The last stage is forecasting the data transfer function for the next 7, 14, and 21 days using the transfer function model. The comparison of the transfer function forecasting for the two stock returns is shown in Table 4.

**Table 4:** Comparison of Forecast Results for the Next 7, 14, and 21 Days.

| Accuracy | 7 Days | | 14 Days | | 21 Days | |
|---|---|---|---|---|---|---|
| | ASII | SSMS | ASII | SSMS | ASII | SSMS |
| RMSE | 0.015 | 0.009 | 0.019 | 0.011 | 0.019 | 0.013 |
| MAPE | 0.507 | 0.597 | 0.662 | 0.605 | 0.925 | 0.732 |

### *3.4. ARIMA-GARCH Model*

### *3.4.1. ARIMA Model Identification*

Similar to the steps of the transfer function model, the ARIMA-GARCH model must also meet data stationarity. The next step is to identify the model using ACF and PACF plots.

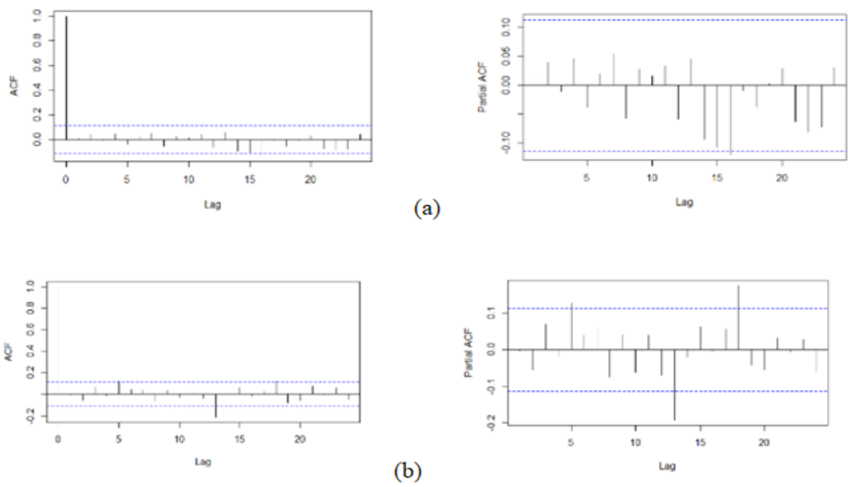



**Figure 4:** Plots of ACF and PACF (a) PT. Sawit Sumber Mas Sarana Tbk and (b) PT. Astra International Tbk.

According to Figure 4, the ARIMA(0,0,0) model for SSMS returns and ARIMA(0,0,0) model for ASII returns. After overfitting the initial model and testing the parameter significance of the candidate models, the best ARIMA model with the smallest AIC value is ARIMA (4,0,4) for SSMS stock returns and ARIMA (3,0,3) for ASII stock returns. Next, perform a diagnostic test of the residual model and the significance of the parameters as follows.

**Table 5:** Diagnostics of The Residual Model and The Significance of The Parameters.

| Stock Return | Model | P-value | | Parameter significance | |
|---|---|---|---|---|---|
| | | L-Jung Box | Jarque-Bera | Nilai L.M. | P-value |
| SSMS | ARIMA (4,0,4) | *0.989* | *< 2.2e-16* | 57.353 | 1.144316e-08 |
| ASIA | ARIMA (3,0,3) | 0.958 | < 2.2e-16 | 85.356 | 4.440892e-14 |

Based on Table 5, test L-Jung Box both data showed $a$ p-value > $\alpha$ = 5%, that is a remnant of independent and test Jarque-Bera both data showed $a$ p-value > $\alpha$ = 5%, meaning that a remnant does not meet the normality assumption. The parameter significance test shows a heteroscedasticity effect in the variance of the residuals of the ARIMA model. Therefore, it is necessary to conduct a test to see the effect of the ARCH effect on each stock return.

### *3.4.2. ARCH/GARCH Effect Testing*

Testing the effect of ARCH/GARCH is by looking at the heteroscedasticity of the rest of the average model using the ARCH Lagrange Multiplier (L.M.) test.

**Table 6:** The results of the p-value test for L.M. stock returns of SSMS and ASII.

| Return | P-value | | | |
|---|---|---|---|---|
| | Lag 1 | Lag 6 | Lag 12 | Lag 24 |
| SSMS | 0.0001 | 0.0009 | $3.74x10^{-6}$ | $5.4x10^{-5}$ |
| ASII | $6.35x10^{-12}$ | $2.12x10^{-11}$ | $6.49x10^{-12}$ | $6.8x10^{-9}$ |

Table 6 shows the L.M. test for both returns up to the 24th lag has a p-value < $\alpha$ = 5%. So it can be concluded that in the remainder, there is heteroscedasticity, which is a condition that the constant model cannot overcome. Heteroscedasticity in the residuals of these two models can be overcome using the ARCH model if the residuals of the mean model indicate a short memory process; only the squares of the latest residuals are used to estimate the change invariance. The short memory process is characterized by only significant p-values in the initial lags. However, if seen in Table 5, all p-values are significant until the 24th lag; this means that SSMS and ASII indicate a long memory process. The indication of this long memory process makes the use of the ARCH model less precise so that the modeling for conditional variance is GARCH modeling.

### *3.4.3. Identification of the GARCH Model*

Simultaneous identification of the GARCH model is carried out using the previously selected average model. Based on the p-value generated by each parameter estimate, there is a model with all significant parameters in the model. The best GARCH model for each SSMS and ASII stock is GARCH (1,1). The GARCH model formed can overcome the problem of heteroscedasticity in the data.

Based on the model identification results, the best model for SSMS stock is the ARIMA(4,0,4)-GARCH(1,1) model, meaning that today's SSMS stock return is influenced by the residual value in the same period. At the same time, the conditional variance is a function of the residual value and the conditional variance of the previous period. While the best model for ASII shares is the model ARIMA(3,0,3)-GARCH(1,1), meaning that the residual value influences ASII stock returns in the same period.

### *3.4.4. Best Model Residual Diagnosis*

Having chosen the best model for each return stock, further diagnostic tests remnant GARCH (1,1) for each return to see if the model is formed has been unfit for use. The residual diagnostics performed were residual autocorrelation test, ARCH LM test, and residual normality test using the Jarque-fallow test. The residual to be tested is the standardized residual. The ARCH LM test for all lags that were tested had a p-value > $\alpha$ = 5%, so there is no effect of ARCH / GARCH. The Jarque-Bera test produces a p-value < $\alpha$= 5% for both stocks with the best model for each stock, so it can be concluded that the assumption of normality has not been met. The existence of deviations from the assumption of normality of this residual indicates that the data has very random volatility and extreme values.

#### *3.4.5. Forecasting with the GARCH Model*

The next stage is forecasting the second ARIMA-GARCH model of stock returns for the next 7, 14, and 21 days. ARIMA (4,0,4)-GARCH(1,1) forecast results for SSMS and ASII stock returns using testing data (actual) are shown in Table 7.

**Table 7:** Comparison of Forecast Results for the Next 7, 14, and 21 Days.

| Method | Accuracy | 7 Days | | 14 Days | | 21 Days | |
|---|---|---|---|---|---|---|---|
| | Return | ASII | SSMS | ASII | SSMS | ASII | SSMS |
| Transfer Function | RMSE | 0.015 | 0.009 | 0.019 | 0.011 | 0.019 | 0.013 |
| | MAPE | 0.507 | 0.597 | 0.662 | 0.605 | 0.925 | 0.732 |
| ARIMA-GARCH | RMSE | 0.012 | 0.006 | 0.016 | 0.011 | 0.017 | 0.019 |
| | MAPE | 0.847 | 0.706 | 1.177 | 0.855 | 0.875 | 1.167 |

### 3.5. Comparison of Forecasting Result

After forecasting for both methods, the next step is to compare the two ways to see the best model in predicting SSMS and ASII stock return data. Table 8 shows that the model with a higher level of accuracy that can be used for SSMS returns is the ARIMA-GARCH model and the transfer function model for ASII returns.

**Table 8:** Comparison of RMSE and MAPE Values Forecasting Results.

| *Return* | Transfer Function | | ARIMA-GARCH | |
|---|---|---|---|---|
| | RMSE | MAPE | RMSE | MAPE |
| SSMS | 0.029 | 108.294 | 0.019 | 106.612 |
| ASII | 0.016 | 106.204 | 0.021 | 117.679 |

The RMSE and MAPE comparison table above shows that forecasting results for the next seven days for stock returns of PT. Astra International Tbk and PT. Sawit Sumber Mas Sarana Tbk produces minimum RMSE and MAPE values so that the prediction results for the next seven days are more accurate in predicting the stock returns obtained. It is because stock data is volatile so that short-term forecasting is better.

## 4. Conclusion

In studying the forecasting model of time series data with the addition of a series input or a variable that can affect the data series output, it can be done using a transfer function. Furthermore, in financial data, especially stock data, heteroscedasticity problems can be overcome using ARCH/GARCH. In this study, the input series variables in the transfer function modeling significantly affect the output return series of PT. Sawit Sumber Mas Sarana Tbk is the Shanghai composite index. While on the variable output return of PT. Astra Internasional Tbk, several influencing factors include:

- World crude oil (WTI) prices.
- The decline in the USD against the rupiah.
- The Shanghai composite index.

Based on the analysis in determining/choosing the forecasting method that is considered appropriate to be used in forecasting stock returns of PT. Sawit Sumber Mas Sarana Tbk and PT. Astra Internasional Tbk from the two ways (transfer function and ARIMA-GARCH), it can be concluded that the transfer function method is better than the ARIMA-GARCH method.

## 5. **Suggestion**

It is hoped that further research will compare the transfer function method and the ARIMA-GARCH method to use case studies with other input series data that affect the stock return. Furthermore, for the ARIMA-GARCH model, asymmetric checks on the GARCH model can be carried out to improve the forecasting results.

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