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## **Determination of Stock Investment Risk Using the Multivariate Time Series Approach**

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### **Abstract**

Stock investment is putting money in stocks carried out in the long term with the hope of getting profits in the future. Investors make investments to get returns. Return is the result obtained from investment activities within a certain period. The higher the profits, the greater the risks faced by investors. To overcome the chance, it is possible to estimate the return in the future and calculate the risk that investors will likely obtain. The return includes time series data so that estimates can be made to determine its future value. One model that can be used to estimate stock returns is the transfer function. The transfer function combines ARIMA and regression analysis that can be applied to time series related to other variables. This study found that the daily stock return of PT. Cisadane Sawit Raya Tbk (CSRA) has a cross-correlation with Jakarta Composite Indeks (JKSE) during the daily stock return of PT. Salim Ivomas Pratama Tbk (SIMP) has a cross-correlation with JKSE and the exchange rate. The transfer function estimation results show that the RMSE value for CSRA is 0.24%. This value is greater than the RMSE value for SIMP, which is 0.01%. Meanwhile, from the results of risk testing on stock assets, it is found that the greater the level of trust used, the greater the risk of loss.

**Keywords:** risk; value at risk; investment; transfer function; ARIMA.

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## **1. Introduction**

Stock investment is investing money or funds in purchasing securities in the form of shares to obtain additional benefits or certain benefits in the future [1]. The risks will also be greater if an investor wants high returns. According to the Big Indonesian Dictionary (KBBI), risk is the possibility of an event that could harm an individual or group (company). Measuring the risk of an asset or portfolio is very important because it will be a consideration for investors in making decisions to get optimal profit. Value at Risk (VaR) is a measure of risk that is often used in measuring the risk of assets [2]. According to [2], VaR can provide information regarding the maximum loss with a certain confidence level. Measurement of risk requires the distribution of returns in its calculations. Therefore it is necessary to estimate returns before measuring risk.

According to [3], return results from investment activities within a certain period. Return or rate of return is a function of the natural logarithm of price changes [4]. An investor generally hopes to get a high return when buying or selling stocks, but the right time to sell and buy these shares is challenging for an investor. Thus, the ability to predict return is an important factor in financial markets. One of the models that can be used for estimating returns is the transfer function. The transfer function combines the Autoregressive Integrated Moving Average (ARIMA) method and regression analysis. It can be applied to time series cases with causal properties with other variables. The transfer function is one of the multivariate time series analysis models. In time series analysis, other input variables often influence output variables. The transfer function is the model that can analyze the effect of the input series on the time series data. In this study, the output series to be examined is PT. Cisadane Sawit Raya Tbk (CSRA) and PT. Salim Ivomas Pratama Tbk (SIMP). Factors influencing the two stock returns are the Jakarta Composite Index (JKSE), the USD exchange rate against the rupiah, and crude palm oil [5]. CSRA and SIMP are companies engaged in the palm oil commodity. The palm oil commodity is one of the country's major foreign exchange earners from the non-oil and gas sector. The Investment Coordinating Board (BKPM) prioritizes the agricultural sector in terms of investment [6]. Investing in palm oil commodities is hoped to increase the country's foreign exchange. JKSE is a joint stock, one of the determining indicators for investors to invest in the Indonesia Stock Exchange (IDX) [7]. Reference [8] stated that the USD exchange rate significantly affected the JKSE movement. The USD exchange rate against the rupiah is also one-factor affecting stock returns. This is because companies use US dollars for business transactions [9]. In previous research, [10] compared the transfer function and artificial neural network to analyze the cash flow of Bank Rakyat Indonesia. [11] estimated the composite stock price index with only one input series. Reference [12] modeled five foreign currency exchange rates using a univariate time series model and calculated ES values to see the risk of each exchange rate used. Reference [13] estimated VaR values using the GARCH model. This research was conducted with one audible input variable based on the description above. This research hopes to provide good prediction results for company shares for the next period and also know the estimated risks that must be borne when investing in stocks.

## **2. Methodology**

### **2.1. Data**

The data used in this study are daily stock return data for PT Cisadane Sawit Raya Tbk (CSRA), PT Salim Ivomas Pratama Tbk (SIMP), the Jakarta Composite Index (JKSE), world palm oil (CPO) and the USD exchange rate against the rupiah. The source data is obtained from the search results of historical data on daily stock prices on the yahoo finance website. Return data is obtained by calculating the natural logarithm of the stock price at time  $t$  divided by the stock price at time  $t - 1$ . The data from January 5, 2021, to December 30, 2021, is 246 trading days.

## 2.2. Data Analysis Procedures

This research begins by studying the ARIMA method, the transfer function, and the value at risk. The simulation studies were sourced from several journals, the internet, and library books. Data analysis was performed using R-Studio software and Statistical Analysis Software (SAS). The data is divided into two parts, namely training data for modeling and data testing as test data. The stages of the research to be carried out are as follows:

- a. It was calculating daily stock return data for PT Cisadane Sawit Raya Tbk and PT Salim Ivomas Pratama Tbk (SIMP) after this referred to as output series data, as well as the Jakarta Composite Index, world palm oil and the USD exchange rate against the rupiah after this referred to as input series data.
- b. Check the stationarity of the variance and mean of the training data for each input and output series.
- c. Modeling the transfer function on the input and output data series with the following algorithm:
  - 1) Modeling input and output series data using the ARIMA model using ACF and PACF plots.
  - 2) Simplify the input  $X_t(\alpha_t)$  and output  $Y_t(\beta_t)$  series.
  - 3) Calculate the Cross Correlation Function (CCF) for each input and output series that has undergone a prewhitening process ( $\alpha_t$  dan  $\beta_t$ ).
  - 4) Identify  $b, s$ , and  $r$  values based on CCF plots.
  - 5) Perform initial identification of the noise series ( $n_t$ ).
  - 6) Carry out a diagnostic test of the residuals of the transfer function model with the autocorrelation test of the residuals and the cross-correlation between  $X_t$  and  $\varepsilon_t$ .
  - 7) Estimating the transfer function model.
- d. Calculating the risk value of investment losses using value at risk with the following algorithm:
  - 1) Performing a normality test on the return value using the Kolmogorov-Smirnov test, if the return value data is normally distributed, then the next step is to look for parameter values, namely the average and variance of the return value data.
  - 2) Simulate the return value by randomly generating return assets based on the parameters obtained in step 1) for  $n$  values.
  - 3) Calculating the VaR value at the confidence level  $(1 - \alpha)$  in a period of  $t$  days using the formula

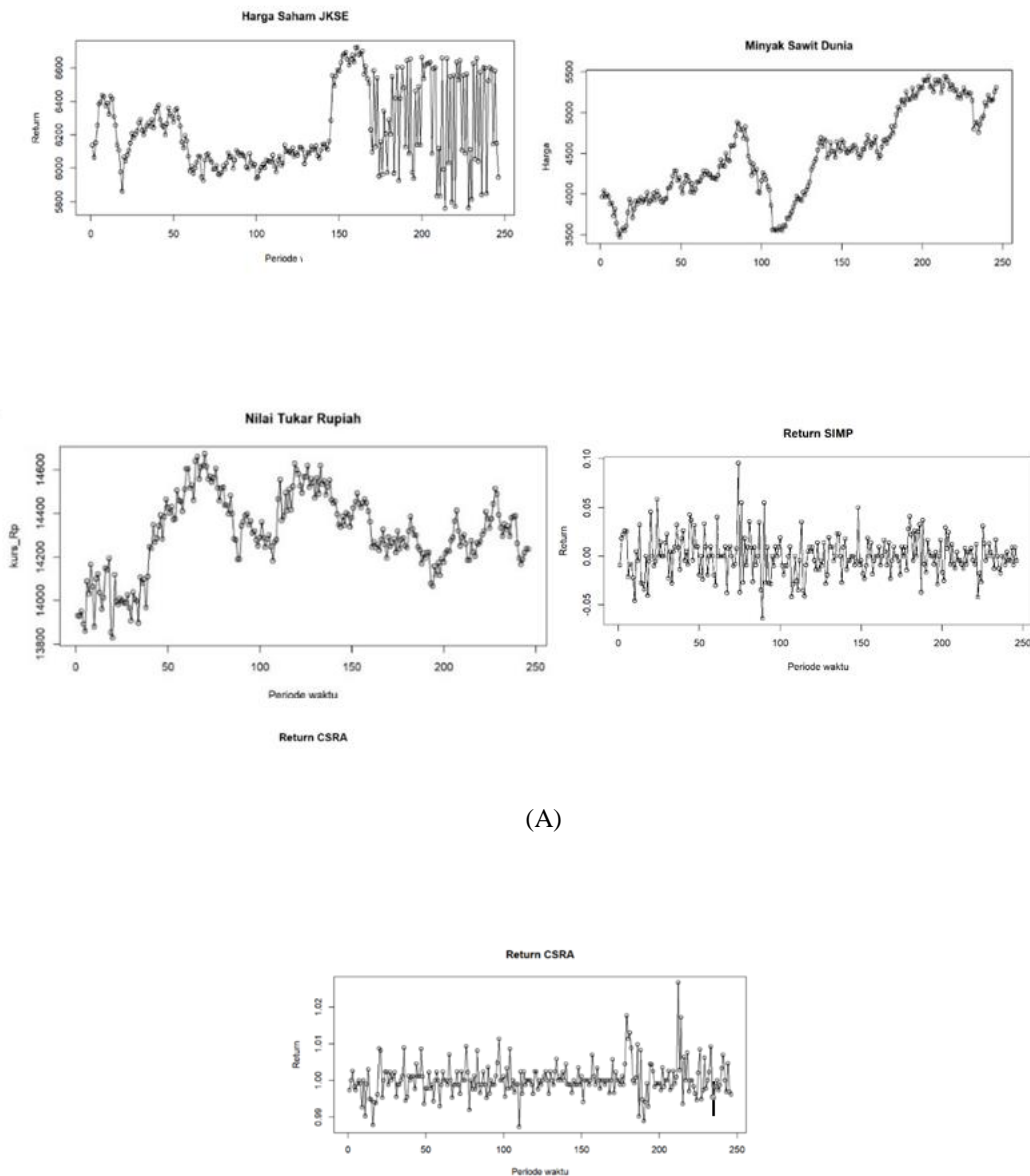
$$VaR_{(1-\alpha)} = W_0 R^* \sqrt{t}$$

- 4) Iterates  $m$  times to produce various possible VaR values, namely  $VaR_1, VaR_2, \dots, VaR_m$ .
- 5) Calculate the average VaR value from  $m$  iterations.

### 3. Result and Discussion

This section will discuss the analysis and development of a transfer function model for estimating CSRA and SIMP stock returns. In addition, the calculation of investment risk will be carried out on the results of the second prediction of stock returns.

#### 3.1. Data Exploration for Output and Input Series



(A)

(B)

**Figure 1:** (a) Plot of input and (b) output series

Data exploration is an overview of the data used in this study. The downloaded input and output series data are

on stock price returns for CSRA, SIMP, JKSE, CPO, and the USD exchange rate against the rupiah. Data exploration is done by graphing the input and output series data to see the movement pattern of each data from time to time.

Based on the input series data plot in Figure 1(a), it can be seen that each data has relatively high fluctuations. The three input series data appear non-stationary, while in Figure 1(b), the output series data tends to be stationary.

### **3.2. Stationarity of Output and Input Series Data**

The stationarity of the data is seen through the mean and variance. Testing for stationarity in the mean was carried out using the Augmented Dickey-Fuller (ADF) test. In contrast, testing for stationarity in the mean was carried out using the Lagrange multiplier test. If the data is not stationary in the range, a transformation can be carried out, while the differencing process can be carried out if it is not stationary in the average.

The results of the stationary test for a variance on the input series data using the Lagrange multiplier test show that the p-value for JKSE, CPO, and the exchange rate is 1. The p-value  $> \lambda$ , so it can be concluded that the data is stationary to variance. Furthermore, the ADF test was carried out to test the stationarity in the mean of the input series data. The results of the ADF test show that the p-values for JKSE, CPO, and the exchange rate are 0.0620, 0.3057, and 0.4812, respectively. The values of the ADF test results on the input series data indicate that the data are not stationary to the mean, so it is necessary to make differences. Using the help of R software, the differencing process is only done once until the input series data is stationary to the mean.

Testing for stationarity in the variance of the output series data is also carried out using the Lagrange multiplier test. The results of the Lagrange multiplier test on CSRA and SIMP stock return data show that the p-value is  $2.2e - 16$ , so it is necessary to transform the output series data because the p-value  $< \lambda$ . The transformation performed is the natural logarithmic transformation of the data. The results of the ADF test show that the output series data are stationary in the mean because the p-value is less than the 5% significance level, which is 0.01.

### **3.3. Transfer Function Models**

The transfer function model combines the univariate ARIMA model and multiple regression analysis. The transfer function is one way to estimate the value of  $Y_t$ , which is thought to be affected by  $X_t$  and a combination of other influences called noise. This study involved three input series variables, so it was called the multivariate transfer function model. The following are the stages of forming the transfer function:

#### **a. Forming Input Series ARIMA Model**

The ARIMA model is identified through the ACF and PACF plots of the stationary input series. On the JKSE stock returns, the ACF plot cuts off at lags 1,2,3, and 4, and the PACF plot cuts off at lags 1,2, and 3. The ACF and PACF plots on the price of crude palm oil tail off, so the data is unsuitable for analysis using ARIMA. At the exchange rate, the ACF plot cuts off at lags 1 and 2, while the PACF plot cuts off at lags

1,2,3,4, and 5. So the best model candidates obtained are as follows:

**Table 1:** Candidate ARIMA model input series

Input Series	Model	AIC
$X_1$	ARIMA(3,1,0)	3262.28
	ARIMA(1,1,1)	3267.22
	ARIMA(0,1,2)	3270.42
$X_3$	ARIMA(0,1,2)	2782.24
	ARIMA(3,1,0)	2783.80
	ARIMA(4,1,0)	2780.82

Some of the best model candidates will be obtained based on identifying the ARIMA model using the ACF and PACF plots. Then overfitting will be done to get the best model by selecting the smallest AIC model. The smaller the AIC value, the better the resulting model. Based on Table 1, the best model for JKSE is ARIMA (3,1,0). ARIMA is the best model for the USD exchange rate against the rupiah (4,1,0).

The next step is to estimate the model obtained by examining the model residuals. The ARIMA model is said to be good if there is no autocorrelation, which means that the residuals from the ARIMA model do not have a specific pattern. Examination of the residual model can be tested using the L-Jung Box statistical test. The results of the L-Jung Box test for the residual ARIMA model are presented in the following table:

**Table 2:** The results of checking the autocorrelation of the input series model residuals

Series	Model	<i>p-value</i>
$X_1$	ARIMA(3,1,0)	0.2438
$X_3$	ARIMA(4,1,0)	0.2100

Based on the L-Jung Box test results, all ARIMA models have p-values of more than 5%, so these models do not have autocorrelation, and the model can be used for the subsequent modeling stage.

b. Prewhitening the input and output series

In the transfer function, the steps taken in the input series are also applied to the output series. The process of prewhitening the input and output series is carried out to obtain a series of noise or residuals in the transfer function. The following is a prewhitening input and output series model.

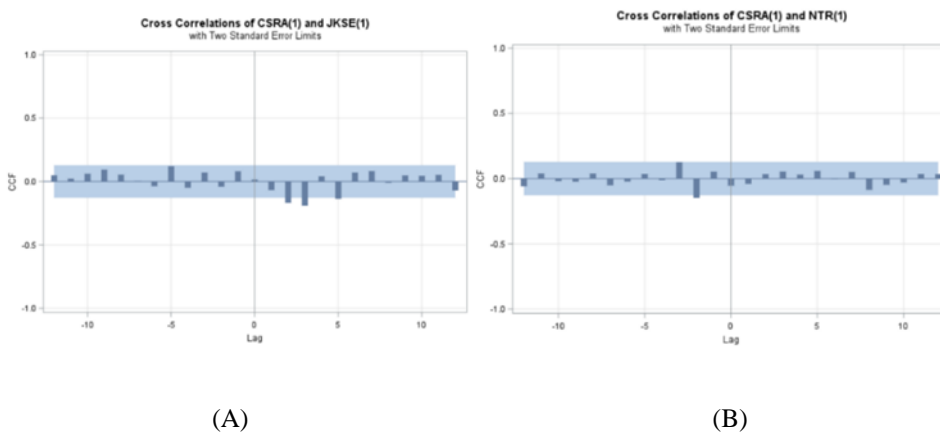
**Table 3:** Prewhitening input and output series model

Input Series	Initial Model	Prewhitening Model	Input Series Model	
			CSRA	SIMP
$X_1$	$X_{1t}$ $= 0.06459X_{1t-1}$ $+ 0.45378X_{1t-2}$ $+ 0.21084X_{1t-3}$ $+ 0.27079X_{1t-4}$ $+ \alpha_t$	$x_{1t} = X_{1t}$ $- 0.06459X_{1t-1}$ $- 0.45378X_{1t-2}$ $- 0.21084X_{1t-3}$ $- 0.27079X_{1t-4}$	$\beta_{1t} = Y_{csra_{1t}}$ $- 0.06459Y_{csra_{1t-1}}$ $- 0.45378Y_{csra_{1t-2}}$ $- 0.21084Y_{csra_{1t-3}}$ $- 0.27079Y_{csra_{1t-4}}$	$1_t = Y_{simp_{1t}}$ $\cdot 0.06459Y_{simp_{1t-1}}$ $\cdot 0.45378Y_{simp_{1t-2}}$ $\cdot 0.21084Y_{simp_{1t-3}}$ $\cdot 0.27079Y_{simp_{1t-4}}$
$X_3$	$X_{3t}$ $= 0.69536X_{3t-1}$ $- 0.01741X_{3t-2}$ $+ 0.14211X_{3t-3}$ $+ 0.03928X_{3t-4}$ $+ 0.14066X_{3t-5}$ $+ \alpha_{3t}$	$\alpha_{3t} = X_{3t}$ $- 0.69536X_{3t-1}$ $+ 0.01741X_{3t-2}$ $- 0.14211X_{3t-3}$ $- 0.03928X_{3t-4}$ $- 0.14066X_{3t-5}$	$\beta_{3t} = Y_{csra_{3t}}$ $- 0.69536Y_{csra_{3t-1}}$ $+ 0.01741Y_{csra_{3t-2}}$ $- 0.14211Y_{csra_{3t-3}}$ $- 0.03928Y_{csra_{3t-4}}$ $- 0.14066Y_{csra_{3t-5}}$	$\beta_{3t} = Y_{simp_{3t}}$ $- 0.69536Y_{simp_{3t-1}}$ $+ 0.01741Y_{simp_{3t-2}}$ $- 0.14211Y_{simp_{3t-3}}$ $- 0.03928Y_{simp_{3t-4}}$ $- 0.14066Y_{simp_{3t-5}}$

It can be seen in Table 3 above the remaining two input series variables used are significant. From the initial model for each variable, after simplification, we get an output series model where  $X_t$  changes to  $\alpha_t$  and  $Y_t$  changes to  $\beta_t$ . Whatever model is obtained on the input variable is transformed into the output series variable to simplify the output series.

c. Cross-Correlation Function (CCF)

CCF or their cross-correlation calculates simplified input and output series data. The CCF plot is used to identify the initial model of the transfer function by finding  $b, r,$  and  $s$  values. The following is the result of the CCF plot obtained with the help of SAS software.



**Figure 2:** CCF plot between (a) CSRA and JKSE (b) CSRA and exchange rates

Figure 2(a) shows a natural lag in the positive lag, so it can be concluded that there is a cross-correlation between CSRA and JKSE. In Figure 2(b), it can be seen that the overall positive lag has no discernible lag, so there is no cross-correlation between CSRA and the exchange rate. It can be concluded that exchange rate

data cannot be used for further analysis of the CSRA output series.

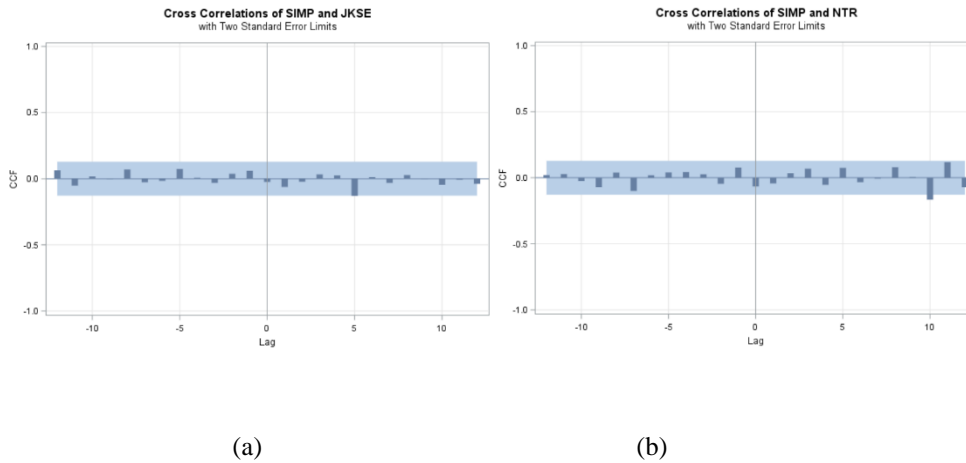


Figure 3: CCF plot between (a) SIMP and JKSE (b) SIMP and exchange rates

Based on Figure 3, it is found that there is a cross-correlation between SIMP and the two input series. Both input series data can be used for further analysis.

d. Identify the initial model of the transfer function.

The initial model of the transfer function is identified by determining the values of  $b, s,$  and  $r$ . The  $b, s,$  and  $r$  values are obtained by observing the CCF plot. The CCF CSRA plot in Figure 2(a) for JKSE is significant for the first time at lag 2 ( $b = 2$ ), and after that, there is only one considerable lag sequentially ( $s = 1$ ). The value of  $r$  is searched by testing using SAS software. SIMP CCF results can be seen in Figure 3. The importance of  $b, r, s$  The identification results of the initial model of the transfer function is as follows:

Table 4: Initial candidate model of the transfer function

Output Series	Input Series	Model	CCF Order	AIC
CSRA	$X_1$	ARIMA(3,1,0)	$b = 2, s = 1, r = 0$	-916.81
			$b = 2, s = 1, r = 1$	-921.06
			$b = 2, s = 1, r = 2^*$	-918.60
SIMP	$X_1$	ARIMA(3,1,0)	$b = 5, s = 0, r = 0^*$	-1190.16
			$b = 5, s = 0, r = 1$	-1184.85
			$b = 5, s = 0, r = 2$	-1177.41
	$X_3$	ARIMA(4,1,0)	$b = 10, s = 0, r = 0^*$	-980.18
			$b = 10, s = 0, r = 1^*$	-980.27
			$b = 10, s = 0, r = 2$	-980.27

Based on several experiments on the order  $r$  for the CSRA output series, it is known that  $r = 2$  produces a significant coefficient, so it can be concluded that orders  $b = 2, s = 1,$  and  $r = 2$  are the best order combinations in identifying the initial model of the transfer function for the CSRA output series. Identification of orders for the SIMP output series also uses the same method as identification of the CSRA



output series. The SIMP output series produces the best order for JKSE as order  $b = 5, s = 0, r = 0$ , and for the exchange rate, order  $b = 10, s = 0, r = 1$ . The initial model of the transfer function that is formed is as follows:

$$Y_{csra_t} = \frac{(\omega_{01} - \omega_{11}B)}{(1 - \delta_1 B)} X_{1t-2} + n_t$$

$$Y_{simp_t} = \omega_{01} X_{1t-5} + \frac{(\omega_{02})}{(1 - \delta_1 B)} X_{3t-10} + n_t$$

e. Identification of the Noise Series Model ( $n_t$ )

Estimating the transfer function model involves calculating the coefficient of the  $X$  and noise effect components. Noise is the result of the residual diagnosis of the  $b, r, s$  model using the results of the autocorrelation test of residuals and the ACF and PACF plots. Following are the results of the autocorrelation test of noise.

**Table 5:** Initial model autocorrelation test of the transfer function

Output Series	Input Series	CCF Order	Lag 6	Lag 12	Lag 18	Lag 24
CSRA	$X_1$	$b = 2, s = 1, r = 2$	< .0001	< .0001	< .0001	< .0001
	$X_1$	$b = 5, s = 0, r = 0$	< .0001	< .0001	< .0001	< .0001
SIMP	$X_3$	$b = 10, s = 0, r = 1$	< .0001	< .0001	< .0001	< .0001

Table 5 shows that there are several p-values less than 0.05, which means that the residuals (noise) experience autocorrelation of residuals. ARIMA modeling needs to be done again on the residual series. ARIMA modeling for the residual series is carried out the same way as for the input series ARIMA modeling, namely by analyzing the ACF and PACF plots. The best model obtained for the CSRA output series is ARIMA(1,1,1), while the SIMP output series is ARIMA(0,1,1).

f. Final Model Estimation of the Transfer Function

Estimation of the final model of the transfer function is carried out by combining the initial model of the transfer function and ARIMA in the residual series. Following are the results of the significance test of the final model parameter of the transfer function.

**Table 6:** Test the significance of the final model parameters of the transfer function

Output Series	Model	Parameter	Coefficient	p-value	
CSRA	ARIMA(1,1,1)	$\theta_1$	0.65311	0.00400	
		$\phi_1$	0.76582	< .00010	
		$b = 2, s = 1, r = 2$	$\omega_{01}$	-0.00002	0.01060
		$\omega_{11}$	0.00003	0.00020	
		$\delta_{11}$	-0.97998	< .00010	
		$\delta_{21}$	-0.50071	0.01340	
SIMP	ARIMA(0,1,1)	$\theta_1$	0.94830	< .00010	
		$b = 5, s = 0, r = 0$	$\omega_{01}$	-0.00002	0.00800
		$b = 10, s = 0, r = 1$	$\omega_{02}$	-0.00003	0.02050
		$\delta_{12}$	-0.80584	< .00010	

Table 6 shows that all the parameters of the final model of the transfer function are significant with a p-value < 0.05 so that the model can be used to make predictions. The final noise series model that is formed is as follows:

$$n_{csra}_t = \frac{(1 - 0.65311B)\alpha_t}{(1 - 0.76582)}$$

$$n_{simp}_t = (1 - 0.94830B^1)\alpha_t$$

Based on the results of the modeling that has been done, the final model for the transfer function is as follows:

$$Y_{csra}_t = \frac{(\omega_{01} - \omega_{11}B)}{(1 - \delta_{11}B - \delta_{21}B^2)} X_{1t-2} + \frac{(1 - 0.65311B)\alpha_t}{(1 - 0.76582)}$$

$$Y_{simp}_t = \omega_{01}X_{1t-5} + \frac{(\omega_{02})}{(1 - \delta_{12}B)} X_{3t-10} + (1 - 0.94830B^1)\alpha_t$$

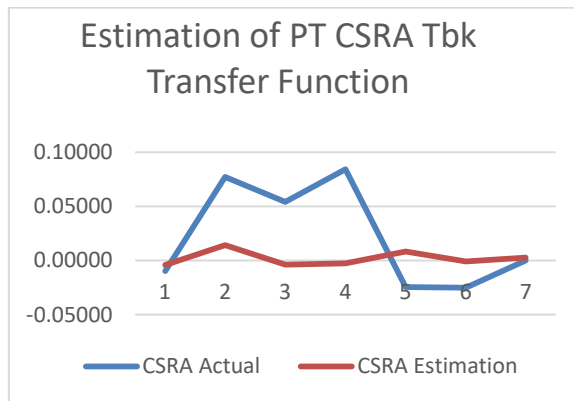
Then a diagnostic test was performed on the transfer function model to determine the feasibility of the model by testing the assumptions of white noise and normality on the residual model obtained. The test results show that the autocorrelation of the residuals is not significant, with a p-value > 0.05 for all lags, meaning that it meets the assumption of white noise. The ACF and PACF plots also show no significant or systematic

residual autocorrelation. For the residual normality test, it can be seen that there are still data that are not in the regular line, so it can be concluded that the transfer function model residuals are not normally distributed. This is due to the presence of outliers.

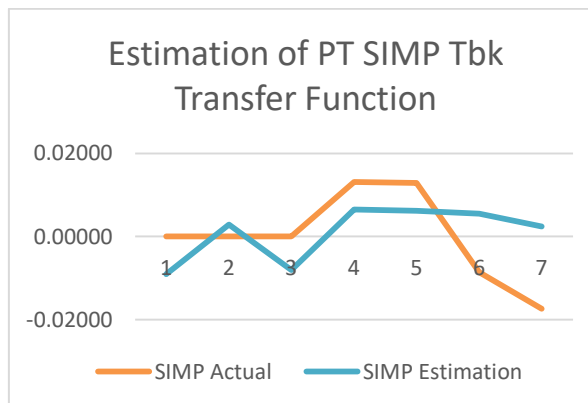
The cross-correlation test between the input and residual series of the CSRA and SIMP transfer function models was not significant for all lags, so it can be concluded that the model is good at separating the residuals. Based on these examinations, the transfer function model obtained is likely feasible.

g. Return Estimation Using Transfer Function

The results of the estimation of the transfer function at PT. Cisadane Sawit Raya Tbk and PT Salim Ivomas Pratama Tbk for the next twenty days can be seen in Figure 4. The following is the result of the estimation for the next seven days.



(A)



(B)

**Figure 4:** Graph of the transfer function estimation of PT CSRA Tbk and PT SIMP Tbk

Based on Figure 4, the estimation chart does not follow the actual data. To determine how good the model is at estimating, it will be tested using the RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) methods. The RMSE and MAE values for estimating the transfer function of PT CSRA Tbk are 0.24% and 3.90%. The transfer function estimation for PT SIMP Tbk has RMSE and MAE values of 0.01% and 0.96%.

### 3.4. Calculating Investment Risk

Before investing, an investor should know the alleged risks involved when investing. This study calculates investment risk using Value at Risk (VaR) with monte Carlo simulation. The VaR value obtained is an estimate for one day after the observation period. The following is the average VaR value obtained by calculating using excel.

**Table 7:** Average estimated VaR value

Saham	Value at Risk		
	90%	95%	99%
CSRA	-0.00692	-0.00938	-0.01399
SIMP	-0.00765	-0.01009	-0.01455

Based on Table 7, it is known that a greater level of confidence will result in a larger VaR value. If the initial investment fund opens  $W_0$  is \$ 100000, then investing in CSRA shares with 95% trust is expected to experience a maximum loss of \$ 938.

### 4. Conclusion and Suggestion

This study has formulated a transfer function model to estimate CSRA stock returns and SIMP. Modeling the transfer function that has been formed shows that JKSE shares influence CSRA's stock returns, while JKSE and the USD exchange rate against the rupiah influence SIMP's stock returns. The model validation results show that the RMSE and MAE values from the SIMP estimation results are smaller than those of CSRA. Both models produce inaccurate forecasts for some observations where these observations are outliers in the actual data. Meanwhile, from the results of risk measurement on stock assets, it is found that shares of CSRA produce a maximum risk of -0.00692, -0.00938, and -0.01399, respectively, at the confidence level of 90%, 95%, and 99%. The risk estimate for the shares of SIMP yields maximum risk at 90%, 95%, and 99% trust, respectively, of -0.00765, -0.01009, and -0.01455.

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