

# B29

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**Submission date:** 17-May-2022 09:21AM (UTC-0500)

**Submission ID:** 1838391996

**File name:** Lampiran\_B29.pdf (541.47K)

**Word count:** 2703



**Character count:** 13260

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To cite this article: R Utami *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1115** 012057

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## Intervention Model of IDX Finance Stock for the Period May 2010 – May 2020 Due to the Effects of the Corona Virus

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**Abstract.** This study aim to model IDX Finance data that was intervened by the corona virus. With the increasing spread of the corona virus, the consequence is that it is necessary to anticipate to prevent further losses. To model time series data that is intervened by an event, it is necessary to carry out intervention analysis to describe the changes that have occurred in the data and forecasting can be done for some future data. By looking at changes in patterns in IDX Finance data since January 2020 which are immediately felt and are prolonged in nature, it can be concluded that IDX Finance's stock closing price data has a permanent abrupt response pattern and intervention order  $b = 0$ ,  $s = 0$ ,  $r = 0$ . However, the final model that is produced does not have significant parameters that are generated by the maximum likelihood estimation method. Because there are several possibilities that the data does not contain intervention or data is used too little to identify the order of intervention.

### 1. Introduction

The term intervention is often found in various statistical analyzes, especially in data analysis related to time, also known as time series analysis. Intervention defined as the following, namely the act of interfering with the results or direction, especially of a condition or process (such as to prevent loss or increase function) or defined as the interference of a state in the affairs of another country to force it to take or refrain from taking specific actions. While the time series is a series of observations on a variable taken based on a fixed time sequence [1]. Time series data that are intervened by an event or certain events result in the data experiencing a changing pattern depending on the nature of the events that affect it, namely temporary (pulse) and prolonged (step) [2]. To describing the effect of an intervention that affects data, intervention analysis is used [3].

Since the coronavirus (covid-19) was declared a global pandemic by the WHO Direct-General. Covid-19 intervened in all fields, one of which was in the economic sector [4]-[7]. The quick spread of the coronavirus in China to various countries has sparked concern among market players. Indonesia as one of the affected countries feels the consequences. The domestic stock market has been hit by negative sentiment from the coronavirus (Corona effect), one of which is that the shares of the Indonesia Stock Exchange (IDX) in the financial sector have decreased.

So to describe the effect of the coronavirus intervening in IDX finance stock data, it is necessary to conduct an intervention analysis so that a model will obtain. The intervention model will be said to be



appropriate to describe the corona effect that occurs in the data if the parameters of the model are significant and meet the model's assumptions. The basic assumption is that the residual is white noise (identically-independent distributed) and normally distributed. To obtaining significant parameters, it is necessary to estimate the parameters. The method of parameter estimation often used is the maximum likelihood method. It is because that the maximum likelihood method is closely related to numerical ability, especially in producing a solution point in an equation [8]. Maximum likelihood is a parameter estimation method that maximizes the likelihood function [9]-[10]. This method can be used to estimate parameters simultaneously from several parameters from a specific population. In this case, the parameter estimate value maximizes its likelihood function.

## 2. Methodology

The data used is secondary data obtained from the Investing.id website regarding the latest price data (or closing price) of Idx finance shares from May 2010 - May 2020. The initial prediction of the intervention variable is the step function because the intervention affects the stock closing price in the long term. The intervention variables are defined as follows:

$$S_t^{(T)} = \begin{cases} 0 & , \quad t \neq T \text{ (before the decline in share prices due to the effects of the coronavirus)} \\ 1 & , \quad t \geq T \text{ (during and after the decline in share prices due to the effects of the coronavirus)} \end{cases} \quad (1)$$

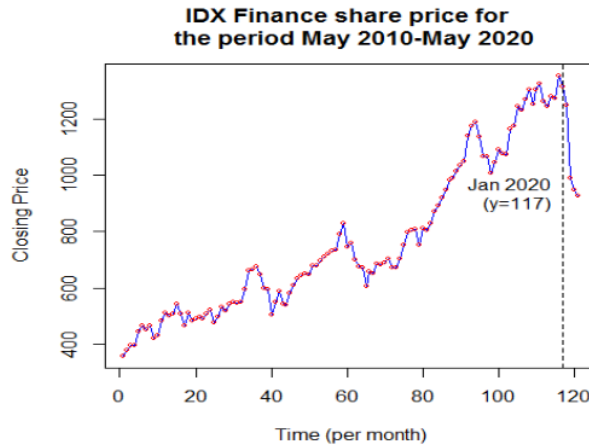
Where  $T$  is the time of intervention, which is the time when the effects of the coronavirus begin to affect the IDX finance stock data.

The analysis steps that will be carried out are:

1. Create a time series plot to see patterns of intervention responses and predict possible intervention variables.
2. Dividing the data into two groups of data, namely the pre-intervention data group and the post-intervention data group.
3. Create the ARIMA model from the pre-intervention data group so that an ARIMA model is produced with all significant parameters and fulfilling the residual assumptions, namely white noise (identical-independent) and normally distributed.
4. Predict several post-intervention data groups using the ARIMA model that is obtained from the pre-intervention data group.
5. Calculating the response residuals between the post-intervention data and the forecast results from the pre-intervention data.
6. Identifying patterns of intervention response through residual graphs of response to forecasting results, and identifying intervention orders, namely,  $b$ ,  $s$ , and  $r$ .
7. Create an intervention model to produce a model with all significant parameters and satisfying the residual assumptions.
8. Make forecasts using the best intervention model.

## 3. Results and Discussion

To get an intervention model from the IDX stock closing price data, the first step that needs to be done is to create a time series plot to see changes in patterns that occur in data due to the impact of the coronavirus. The following is the result of the time series plot from the IDX Finance data in Figure 1.



**Figure 1.** Time series plot of IDX Finance Period May 2010 - May 2020

Based on Figure 1, that can be concluded that from January 2020 to May 2020 the closing price of IDX shares has decreased, inversely proportional to the data in the period May 2010 to December 2019 which tends to increase every month. This decrease was due to intervention by the increasingly rapid spread of the coronavirus which resulted in many changes in all fields. This decline was seen in the 117th series.

### 3.1 Formation of ARIMA Model from Pre-Intervention Data Group

By looking at the pattern of changes in the time series plot in Figure 1, IDX Finance data is dividing into two data groups, namely the pre-intervention data group (pre-intervention) and the data group during and after the intervention (post-intervention). After obtaining the pre-intervention data group, namely the stock data from May 2010 to December 2019, the next step is to create an ARIMA model from the pre-intervention data group.

To create an ARIMA model, the data must first meet the stationary data, namely stationary to variance and average. By looking at the Box-Cox graph, a  $\lambda$  value is  $-0.35$  which means that the data needs to be transformed by the transfer function used, namely:

$$Z_t = \frac{Z_t^\lambda - 1}{\lambda} \quad (2)$$

Then the differencing is made once. After generating the stationary data, to identify the ARIMA model can use ACF and PACF plot.

The best ARIMA model chosen is ARIMA (2,1,2) because its parameters are significant, satisfied all residual assumptions, and have the smallest RMSE, AICc, and AIC values compared to other ARIMA models as in Table 1.

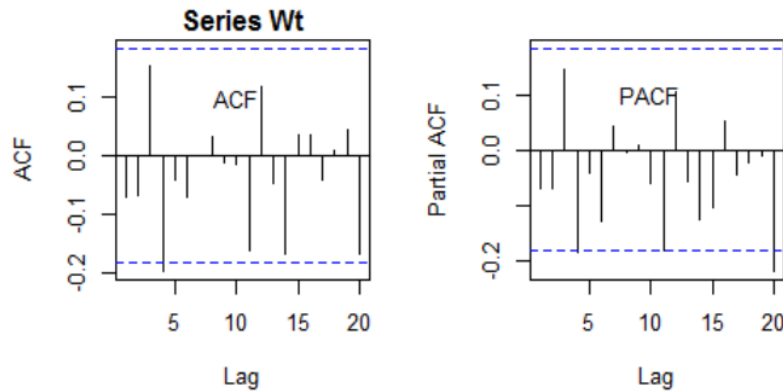


Figure 2. ACF and PACF plot of a pre-intervention data set

Table 1 Comparative analysis

| d=1 | MA(q)           |                 |                           |                 |
|-----|-----------------|-----------------|---------------------------|-----------------|
|     | 0               | 1               | 2                         | 3               |
| 0   | ARIMA(0,1,0)    | ARIMA(0,1,1)    | ARIMA(0,1,2)              | ARIMA(0,1,3)    |
|     | AICC = -1161.56 | AICC = -1159.56 | AICC = -1157.5            | AICC = -1160.25 |
|     | AIC = -1161.59  | AIC = -1159.66  | AIC = -1157.72            | AIC = -1160.61  |
|     | BIC = -1158.85  | BIC = -1154.17  | BIC = -1149.48            | BIC = -1149.63  |
| 1   | ARIMA(1,1,0)    | ARIMA(1,1,1)    | ARIMA(1,1,2)              | ARIMA(1,1,3)    |
|     | AICC = -1159.55 | AICC = -1157.45 | AICC = -1158.58           | AICC = -1159.61 |
|     | AIC = -1159.66  | AIC = -1157.66  | AIC = -1158.95            | AIC = -1160.16  |
|     | BIC = -1154.17  | BIC = -1149.43  | BIC = -1147.97            | BIC = -1146.44  |
| 2   | ARIMA(2,1,0)    | ARIMA(2,1,1)    | ARIMA(2,1,2) <sup>a</sup> | ARIMA(2,1,3)    |
|     | AICC = -1157.52 | AICC = -1159.19 | AICC = -1161.96           | AICC = -1157.99 |
|     | AIC = -1157.74  | AIC = -1159.55  | AIC = -1162.51            | AIC = -1158.77  |
|     | BIC = -1149.5   | BIC = -1148.57  | BIC = -1148.79            | BIC = -1142.3   |
| 3   | ARIMA(3,1,0)    | ARIMA(3,1,1)    | ARIMA(3,1,2)              | ARIMA(3,1,3)    |
|     | AICC = -1159.6  | AICC = -1160.03 | AICC = -1157.85           | AICC = -1159.44 |
|     | AIC = -1159.96  | AIC = -1160.58  | AIC = -1158.63            | AIC = -1160.49  |
|     | BIC = -1148.98  | BIC = -1146.85  | BIC = -1142.16            | BIC = -1141.27  |
|     | RMSE = 0.00542  | RMSE = 0.00542  | RMSE = 0.00542            | RMSE = 0.00530  |
|     | RMSE = 0.00542  | RMSE = 0.00542  | RMSE = 0.00534            | RMSE = 0.00527  |
|     | RMSE = 0.00542  | RMSE = 0.00533  | RMSE = 0.00519            | RMSE = 0.00525  |
|     | RMSE = 0.00532  | RMSE = 0.00526  | RMSE = 0.00526            | RMSE = 0.00515  |

<sup>a</sup>model has a significant parameters obtained from the maximum likelihood estimation method and satisfied the residual assumptions

The ARIMA (2,1,2) model generated above can be defined as follows:

$$(1 - \hat{\phi}_1 B - \hat{\phi}_2 B^2) (1 - B) Z_t = (1 - \hat{\theta}_1 B - \hat{\theta}_2 B^2) a_t$$

$$(1 + 1.717584 B + 0.873211 B^2) (1 - B) Z_t = (1 + 1.836051 B + 0.950613 B^2) a_t$$

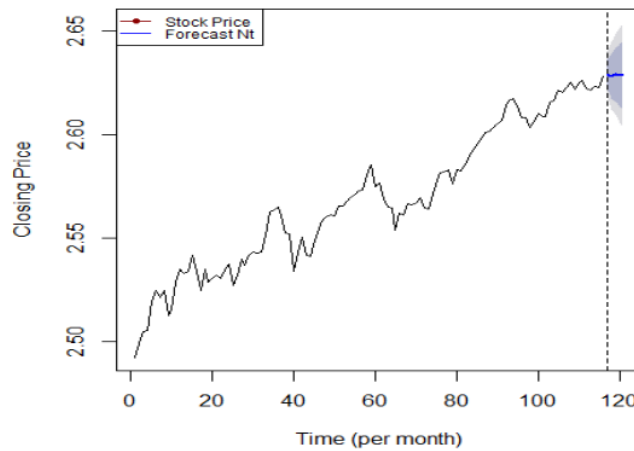
or,

$$Z_t = Z_{t-1} - 1.717584Z_{t-1} + 1.717584Z_{t-2} - 0.873211Z_{t-2} + 0.873211Z_{t-3} + a_t + 1.836051a_{t-1} + 0.950613a_{t-2} \quad (3)$$

With the ARIMA model above, several post-intervention data groups that predicted to produce the following:

**Table 2.** Forecasting results of ARIMA (2,1,2)

| Month         | Forecast |
|---------------|----------|
| January 2020  | 2.629425 |
| February 2020 | 2.628386 |
| March 2020    | 2.629071 |
| April 2020    | 2.628801 |
| May 2020      | 2.628667 |



**Figure 3.** Comparison of Actual Value and Forecast Data of IDX Finance

### 3.2 Formation of an intervention model

Figure 4 is a residual graph obtained from the difference between the actual values from June 2019 - May 2020 that was used to identify the intervention orders, namely  $b$ ,  $s$  and  $r$ . Order  $b$  represents the starting time of the impact of the intervention, order  $s$  represented the delay time the data starts to stabilize calculated from the time the intervention occurs, and order  $r$  represents the next time-lag after  $b$  and  $s$  when the data forms have a clear pattern.

Based on Figure 4, it is found that the residuals exceed the significance limit, which is three times the RMSE of the ARIMA (2,1,2) model, which is  $0.0051897B$ . So it can be concluded that there are several intervention models with various possible intervention orders. With the initial assumption that the data was intervened by the coronavirus for a long term (step function), and by looking at Figure 1 it can be concluded that the coronavirus directly affects the data permanently, it can be concluded that the intervention response pattern is abrupt permanent. The abrupt permanent pattern is defined as follows:

$$\omega B^b S_i^{(T)} \tag{4}$$

Because the effect of direct intervention is immediate, the order  $b=0$ . Several possible intervention orders include  $b=0, s=0, r=0$ ;  $b=0, s=1, r=0$ ;  $Z$ ;  $b=0, s=2, r=0$ ;  $b=0, s=3, r=0$  and  $b=0, s=4, r=0$ . From the several possible orders above, it is found that none of the intervention models with the intervention order has a significant parameter. And for the intervention model with order  $s > 1$ , there are obstacles in running the R program, namely that the intervention model is not produced. So that the intervention model that is finally used is an intervention model with the order  $b=0, s=0, r=0$  which is defined as follows:

$$Z_t = \hat{\omega}_0 S_i^{(T)} + \frac{(1 - \hat{\theta}_1 B - \hat{\theta}_2 B^2)}{(1 - \hat{\phi}_1 B - \hat{\phi}_2 B^2)(1 - B)} a_t \tag{5}$$

$$Z_t = (-0.0048753) S_i^{(T)} + \frac{(1 + 0.0021066B - 0.9785980B^2)}{(1 - 0.0936719B - 0.8995401B^2)(1 - B)} a_t \tag{6}$$

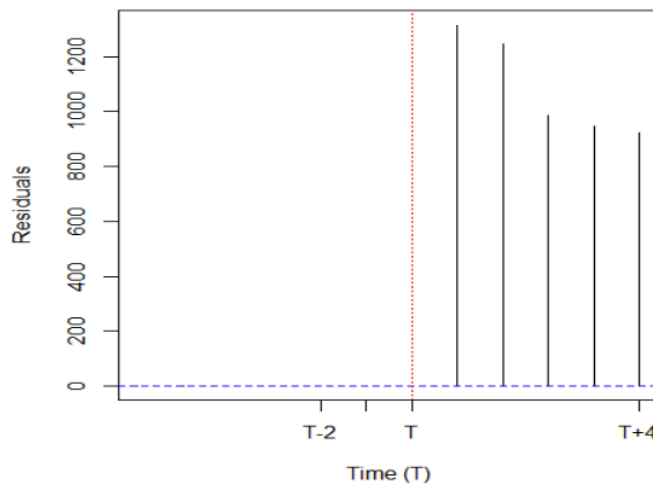


Figure 4. Residual Graph

**4. Conclusion**

By looking at the results of the intervention model obtained, namely the model that is not significant to the parameters. So it can be concluded that several possibilities resulted in this, including that there was no intervention in IDX Finance data or other words changes in IDX Finance data were not caused by the intervention of the coronavirus, and the data is used too little to identify the order of intervention.

**Acknowledgments**

Special thanks to KPBI Statistika of Universitas Mataram for their support.



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