The Modelling of Heteroscedastics IDR-USD Exchange Rate with Intervention and Outlier Factors

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Abstract. The nonstationary in time series data may be caused by the existence of intervention, outliers, and heteroscedastic effects. The outliers can represent an intervention so that it creates a heteroscedastic process. This research investigates the involvements of these three factors in time series data modelling. It is also reviewed how long the effects of the intervention and outliers factors will last. The weekly IDR-USD exchange rate in period of May 2015 to April 2020 be evaluated. It is obtained that ARIMA model with the intervention factor gives the best re-estimation result, with smallest average of errors squared. Meanwhile for prediction, the heteroscedastic effect combined with outlier factors gives better results with the lowest percentage of errors. One of the phenomenal interventions in this data is the Covid-19 pandemic, which was started in Indonesia on March 2020. It is found that the effect of the intervention lasts less than five months and the prediction shows that the volatility of IDR-USD exchange rate starts to decline. This shows the stability of the process is starting to be maintained.

Keywords: Covid-19, exchange rate, heteroscedastic, interventions, outliers, volatility

1. Introduction
There are many purposes for studying time series. Time series is usually used to extrapolate data by making forecasts from the obtained model. As for the assumption that the model is said to be feasible to describe the data is to have a model error that is not correlated with each other and a constant mean and variance [1]. However, these two assumptions are sometimes not met. This can be caused by other factors causing the two assumptions unaccomplished. Often, the time series model ignores factors such as outliers or other events that affect the time series for example interventions. Although, these factors can make sudden change of the process. Based on these things, it is interesting to observe a heteroscedastic time series (non-constant variance) with intervention and outlier factors. Both factors can be considered as exogenous or external factors.
Many research regarding heteroscedasticity effect and external factors had been investigated. A non-stationary model with heteroscedasticity effect is used to evaluate the rice prices [2], ARCH model was applied to electric power of extra high voltage [3], a multiplicative component GARCH be evaluated to forecast the intraday volatility in the US Equity Market [4], and a fractionally integrated Generalized ARCH model was analyzed [5]. In term of outlier, [6] analyzed the outlier detection in time series, meanwhile [7] combine the Autoregressive Distributive Lag (ADL) model with outliers to model the dengue fever case. By involving many locations simultaneously, the prediction of the dengue cases was executed using GSTAR model with outlier factor [8] and be continued by involving exogenous variable to enrich the model [9]. Considering the effect of intervention or outliers which can stimulate the sudden change of the process, [10] explored the Gaussian process to accommodate it. The uncertainty that is possible happen should be considered. A quantitative structural analysis for economic policy uncertainty was explored by [11], meanwhile [12] modelled and explored the sudden change pattern in order to give an early warning of Mount Merapi Eruptions. All of those studies discussed time series modelling with heteroscedastic, intervention and outliers effects separately. Although it could all happen at the same time. There are not many studies have considered these effects simultaneously. Some of them are [13] which analysed the outliers effect in GARCH models, [14] which investigated the outlier detection in intervention effects of panel data, and [15] which evaluated how the intervention reduce the increasing volatility of observations. The last researches used the autoregressive distributed lag model to find that the interest rate policy and foreign exchange intervention fail to reduce the exchange rates volatility.

Here, the research is aimed to evaluate the effect of the intervention and outlier effect on the time series categorized as heteroscedastic. The problem limitation are the factors that cause heteroscedasticity are reviewed, namely intervention and outliers, the events that are categorized as interventions only occur once, that is, only events that are considered to have a major influence on the time series, and the seasonal factor is ignored, so the data used as much as possible does not contain this factor. For study case the IDR-USD exchange rate data at week-19th of 2015 until week-14th of 2020 be used. The intervention and outliers happened were considered as the impact of the Covid-19 pandemic. This pandemic had given big influences in many areas, thus, it is interesting to explore it from many point of views, especially in economic sector. The Covid-19 cases in Java Island by considering the people mobility among provinces which is in line with the movement of the Indonesia’s economy was modeled by [16], meanwhile [17] evaluated how much is this pandemic affecting the USD/IDR exchange rate by using multivariate transfer function model. The effect of gold exchange prices and exchange rate on CSPI and stock volatility on COVID-19 pandemic periods using GARCH model was tested by [18] while [19] found that the Covid-19 pandemic causes different impacts of particular monetary policy instruments on Indonesia’s financial markets by using regression analysis.

This paper is consisted of six sections, which is started with Introduction. The second section briefly explained the intervention and outlier factor in time series, which followed by heteroscedasticity in third section. The stages of modelling is presented in Section 4, and be applied in Section 5 as data analysis. Some conclusions are reported in the last section.

2. Time Series with Intervention and Outlier Factors

2.1. Intervention

Intervention is one of the factors that causes a time series to be non-stationary. An intervention is an unexpected event in a process that usually causes a change in the mean or variance of the process [20]. Interventions are divided into two categories, namely neutral and non-neutral intervention, which are differed by the cause. The non-neutral intervention happens based on human willingness. For example, the government issued a policy to carry out large-scale restrictions on Covid-19 cases, resulting in a decline in public transportation passengers after the policy was implemented.

The time series modelling with intervention factor consist of two functions, which are Step and Pulse function. Both functions are defined, consecutively as:
\[ S_t^{(T)} = \{1, \quad t \geq T \}, \quad t < T \]
and
\[ p_t^{(T)} = S_t^{(T)} - S_{t-1}^{(T)} = \{1, \quad t = T \}, \quad t \neq T \]
The step function, \( S_t^{(T)} \), means that the intervention occurring at time \( T \) and the effect remains thereafter, meanwhile the pulse function, \( p_t^{(T)} \), means that the intervention happens at only one time period.

In addition to these two functions, there is the term intervention effect. The intervention effect is the effect given by an intervention in the time series process [20]. There are several important things contained in the effect of the intervention, including the magnitude, the determinant of the motion, and the changes in the mean function of intervention effect.

The time series model with intervention factors is formulated as follows:
\[ Z_t = m_t + N_t \]
which \( N_t = \frac{\theta(B)}{\phi(B)} \alpha(t) \) is a white noise and \( m_t = \frac{\omega(B)}{\delta(B)} I_t^{(T)} \) is representing the mean changing in a process.

The \( \alpha \) represents the magnitude of intervention effect, meanwhile \( \delta \) as the determinant of the motion.
It is assumed that there will only be one intervention happen, which has formula as in equation (1),

\[ Z_t = \mu + \frac{\omega(B)}{\delta(B)} I_t^{(T)} + \frac{\theta(B)}{\phi(B)} \alpha(t) \]  

(1)

2.2. Outlier
Outliers are types of observations that increase or decrease at a certain time due to several factors such as errors in data input, or because of other things in a time series process [21]. Outliers are often neglected in forecasting and fitting time series models. In fact, outliers have an effect that can affect a process.

Based on the duration of the effect, outliers in the time series are divided into two types of outliers, namely:

2.2.1 Additive outlier (AO). AO is a type of outlier that only has an effect when the outlier occurs, that is \( t = T \). The general form of the equation of the time series model with the AO factor is:
\[ Z_t = \frac{\theta(B)}{\phi(B)} \alpha(t) + \omega I_t^{(T)} \]  

(2)

where \( I_t^{(T)} \) has role as pulse function, that is \( I_t^{(T)} = \{1, \; for \; t = T \}, \; otherwise \).

2.2.2 Innovational outlier (IO). IO is a type of outlier that affects all observations after \( t = T \). The general form of the equation of the time series model with IO is:
\[ Z_t = \frac{\theta(B)}{\phi(B)} \alpha(t) + \frac{\theta(B)}{\phi(B)} \omega I_t^{(T)} \]  

(3)

with \( I_t^{(T)} \) is the pulse function.

3. Heteroscedastic Time Series
A heteroscedastic time series has a conditional variance that is not constant, which is changes with time \( t \). Consider a regression model \( Z_t = \chi_t \beta + e_t \). Define \( e_t = r_t \), which \( \{r_t\} \) are mutually correlated and have conditional variance that changes over time \( t \) say \( \sigma^2_{t|t-1} \). Choose an unbiased estimator for \( \sigma^2_{t|t-1} \) which is \( \hat{\sigma}^2_{t|t-1} \). Then write,

\[ r_t = \sigma_{t|t-1} e_t \]
\[ \hat{\sigma}^2_{t|t-1} = \omega_0 + \alpha_1 r^2_{t-1} \]  

(4)

with \( e_t \) are uncorrelated and have identical standardized normal distribution. This model is named as first order of Autoregressive Conditional Heteroscedasticity or ARCH (1).

The equation (4) can be generalized into ARCH(q), as follows:
\[ \hat{\sigma}^2_{t|t-1} = \omega_0 + \alpha_1 r^2_{t-1} + \alpha_2 r^2_{t-2} + \cdots + \alpha_q r^2_{t-q} \]  

(5)
The equation (5) means that the conditional variance of future events is influenced by a linear combination of square past errors [22]. It is necessary to pay attention to the non-negativity condition of the variance, so that $\omega_i > 0$ and $\alpha_i > 0$ for every $i = 1, 2, \ldots, q$.

It turns out that the future conditional variance is not only influenced by the square past error 2, but is also influenced by the previous variances or known as Generalized Autoregressive Conditional Heteroscedasticity (GARCH). It was introduced by [23]. The GARCH model can be expressed as:

$$\sigma^2_{t|t-1} = \omega + \beta_1 \sigma^2_{t-1} + \cdots + \beta_p \sigma^2_{t-p} + \alpha_1 r^2_{t-1} + \alpha_2 r^2_{t-2} + \cdots + \alpha_q r^2_{t-q}$$  \hspace{1cm} (6)

Choose an unbiased estimator of $\sigma^2_{t|t-1}$, that is $r^2_t$. Notice that Equation (6) follows ARMA($r$, $p$) of $r^2_t$, which $r = \max (p, q)$. Thus, it is obtained the Equation (7):

$$r^2_t = \omega + \sum_{i=1}^{\max (p, q)} (\alpha_i + \beta_i) r^2_{t-i} + a_t - \sum_{j=1}^{p} \beta_i a_{t-j}$$  \hspace{1cm} (7)

### 3.1. Best model selection

Here are some criteria for choosing the best model [20]:

#### 3.1.1 Akaike Info Criterion (AIC)

AIC is a measure of information developed by Hirotsugu Akaike in 1971 regarding the best measure of the feasibility of measuring model estimates. AIC is a test between models or as a measuring tool to choose the right model. The smaller the AIC value, the better the model in 1971 regarding the best measure of the feasibility of measuring model estimates. AIC is a test between used. The AIC formula is

$$AIC = 2k - 2ln(L)$$

where $k$ is number of involved parameters and $L$ is the maximum likelihood of the estimated model [24].

#### 3.1.2 Mean Square Error (MSE)

MSE is a measure of the model goodness by calculating the average of the difference between the squares of the actual value and the estimated value of the resulting model. The smaller the value of MSE, the better the model will be. The MSE can be calculated as:

$$MSE = \frac{\sum_{t=1}^{N} (z_t - \hat{z}_t)^2}{N}$$  \hspace{1cm} (8)

where $N$ is number of observations [20].

### 3.2 Prediction accuracy

One way to measure the accuracy of predictions is to measure the Mean Absolute Percentage Error (MAPE). According to Makridaki [25], the calculation of MAPE is formulated as follows:

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{z_t - \hat{z}_t}{z_t} \right| \times 100\%$$  \hspace{1cm} (9)

with criteria is classified as “very good” for MAPE is less than 10%, “well” for MAPE between 10% and 20%, “feasible” for MAPE between 20% and 50%, and “poor” for MAPE is more than 50% [26].

### 4. Time Series Modelling

#### 4.1 Modelling with intervention

In general, there are several factors that affect the time series which causes the time series to not meet the white noise assumption. One of them is an event that occurs unplanned or will be planned. These events are usually referred to as interventions [20]. The time series modelling stages with intervention is summarized by flowchart in figure 1.

Suppose a time series data follows the ($p, d, q$) model and is not white noise. It is suspected that the model contains an unexpected event such as an intervention. There are several ways to be able to determine the time of an intervention including: 1) view the data table directly, and 2) observe the data plot. The first way can be executed by observing the sudden change of the values, then in that time, the intervention has happened. The similar way is applied to the data plot. The sign of a data having intervention is that an increasing or decreasing pattern occurs and then stabilizes for some time lag.

The parameter estimation is executed by using the least squares method. First, generalize the intervention formula in equation (1) to be:
\[ Z_t = \frac{\omega(B)}{\delta(B)} B^\beta I_t^{(T)} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} \alpha(t) \]

by cross multiplying after equalizing the denominator, it is obtained,
\[ \phi_p(B)(1-B)^d \delta(B)Z_t = \omega(B)I_t^{(T)} + \delta(B)\theta_q(B)\alpha(t) \]

Consider \( \nu(B, \phi, \delta) = \phi_p(B)(1-B)^d \delta(B) \), \( \nu(B, \phi, \omega) = \omega(B)\phi_p(B)(1-B)^d \), and \( u(B, \phi, \omega) = \delta(B)\theta_q(B) \), then the residual is obtained as
\[ \alpha(t) = \frac{\nu(B,\phi,\delta)Z_t-\nu(B,\phi,\omega)I_t^{(T)}}{u(B,\phi,\omega)} \]

**Figure 1.** Flowchart of time series modelling with intervention factor.

To test the parameter significance, the Wald test is applied, with null hypotheses is the parameter is not significance. The statistics test be used is standardized normal distributed. For obtaining the final model, the diagnostic checking is executed. The residual assumptions, those are normality and uncorrelated are tested consecutively by Kolmogorov-Smirnov and Ljung-Box test. Furthermore, consider \( \delta(t) \) is the effect of intervention, then the model prediction for \( l \)-step ahead be,
\[ \hat{Z}_n(l) = \sum_{j=1}^{\infty} \pi_j^{(l)} Z_{t-j+1} + \hat{m}_{t+l} \]

and the \((1-\alpha) \times 100\%\) of prediction interval is \( \hat{Z}_n(l) \pm z\sqrt{\text{Var}(\alpha_{t+1})} \), with \( z \) is the realization of standardized normal distributed statistics [27].

### 4.2. Modelling with outlier

Most of the times, outliers existence in the time series modelling are ignored or replaced with mean of process. Whereas the outliers can have a significant effect in the model. The procedure of time series modelling which considering the outliers existence, is presented in figure 2.

Basically, the outliers can be detected using box-plot diagram. In time series data, the problem is not only detecting this extreme value but also the time when this outlier is exist. The flowchart of outliers detection is presented in figure 3.
After finding the time of the outliers, then the parameters of model be estimated. Let all parameters of $Z_t = \frac{\theta_t(B)}{\phi_t(B)} \alpha_t$ are known and the outlier $k$-th happen at time $T = t$. Define, $e_t = \pi(B) Z_t$, with
\[ \pi(B) = \frac{\theta(B)}{\phi(B)} = (1 - \pi B - \pi B^2 - \ldots). \] Thus, the residual for AO and IO, consecutively are
\[ e_t = \omega \pi(B) l_t(T) + a_t \]
and
\[ e_t = \omega l_t(T) + a_t. \]

Consider \( \hat{\omega}_{AT} \) is the least squares estimator of \( \omega \) for AO. Since the \( \{a_t\} \) is white noise, thus
\[ \hat{\omega}_{AT} = \frac{\phi - \sum_{j=1}^{T} \pi_j e_{t+j}}{\sum_{j=0}^{T-1} \pi_j^2} \]
with \( \pi^*(F) = (1 - \pi_1 F - \ldots - \pi_{n-T} F^{n-T}) \), and the variance is
\[ \text{Var}(\hat{\omega}_{AT}) = \text{Var}(\pi^*(F) e_T) \]
\[ = \frac{1}{T^2} \text{Var}(\pi^*(F) a_T) = \frac{\sigma_a^2}{T^2} \]

Similar with AO, for IO is obtained that, \( \hat{\omega}_{IT} = e_T \) with variance is
\[ \text{Var}(\hat{\omega}_{IT}) = \text{Var}(e_T) = \text{Var}(\omega l_t(T) + a_T) = \sigma_a^2 \]
The residual \( a_T \) which is assumed as white noise should be tested its uncorrelated and normal distribution as explained in Subsection 4.2. Furthermore, consider \( \hat{\rho}_{t+l} \) is the effect of outlier, then the model prediction for \( l \)-step ahead be,
\[ \hat{Z}_n(l) = \sum_{j=1}^{\infty} \pi_{(l)}^j X_{t-j+1} + \hat{\rho}_{t+l} \]

4.3. Modelling with heteroscedastic
A heteroscedastic time series has a variance that changes over time. Interventions and outliers can cause this. However, if the time series residue with one of both factors contains a heteroscedastic effect, it can be suspected that the model is a strong heteroscedastic model. The flowchart of the modelling and the parameter estimation with iteration method consecutively be presented in figure 4 and figure 5.

**Figure 4.** The stage of heteroscedastic time series modeling.
5. Data Analysis and Discussion
The weekly IDR-USD exchange rate data is used for case study. The period of observations is since the week 19-th of 2015 until week 19-th of 2020. The data is divided into two, both are for training and testing data. The plot of data is presented in figure 6.

From figure 6, the process is non-stationary. There is a spike in some time lags. However, the use of graph is not very accurate to conclude non-stationary process. The stationarity test is carried out using the Augmented Dickey-Fuller Test (ADF Test), which null hypotheses says that process is non-stationary. It is obtained that p-value is equal to 0.304, then it is concluded that the process is non-stationary for any level of significance, $1\% \leq \alpha \leq 10\%$. Thus, the first difference is observed (figure 6(b)). From figure 6(b), the process is stationary from mean point of view.
5.1. Intervention model

In early March 2020, the Indonesian government announced the first Covid-19 case after it was discovered that two women from Depok, West Java, were positive for corona after having direct contact with a Japanese citizen who was also infected with the virus. This has not been taken seriously by the government. However, after cases began to increase, the Indonesian government finally issued a recommendation to work from home (WFH) since mid-March 2020. This incident will be reviewed as an intervention factor that is expected to affect the IDR-USD exchange rate.

By evaluating the AIC values for various order, the ARIMA (0,1,1) is selected with residual has met the uncorrelated and normal distribution assumption. The uncorrelated assumptions is tested using Ljung-Box test and it is obtained that $p$-value is equal to 0.306. Meanwhile the normality assumption is met with $p$-value is equal to 0.150. After parameter estimation, the obtained intervention model is

$$Z_t = \frac{(1-0.187B)(1-B)}{1-0.544B} a_t + \frac{735.476}{p_t^{(T)}}$$

with $p_t^{(T)}$ is a pulse function. The residual of this model is examined and it is found that the white noise assumption is met. Furthermore, the effect of intervention is evaluated, and it is obtained that $m_t = \frac{735.476}{1-0.544} p_t^{(T)}$ and illustrated in figure 7.

**Figure 7.** The intervention effect (in percent). The red line marked the significance of intervention effect.

Based on figure 7, the government intervention will give significance impact until 19 weeks after the intervention happened, since the value $|m_t|$ is already less than 1% after those weeks.

5.2. Outliers model

As obtained in the intervention modelling, the original process follows ARIMA(0,1,1) model. The outlier detection is executed based on figure 3, and it is obtained for outliers which consist of two AO ($T = 21$) and two IO ($T = 252$ and $T = 253$). Thus the ARIMA(0,1,1) model with outlier factors is:

$$Z_t = (1-0.209B)a_t - 646.021 t_t^{(21)} + 344.174 t_t^{(250)} + \frac{502.249}{1-B} t_t^{(252)} + \frac{1.505.192}{1-B} t_t^{(253)}$$

For $T = 21$, the effect occurred in the 2nd week of November 2015. At this time the Indonesian exchange rate strengthened against the dollar. This happened because the President and the Minister of Finance issued an economic package that attracted new foreign investors to invest. However, this effect only had an effect at that time, as evidenced in the following weeks the rupiah weakened against the dollar.

For $T = 250$, which happened in 4th week of February 2020. At this time the Indonesian exchange rate weakened against the dollar. This happened because the case of the Covid-19 pandemic caused
trade relations with superpowers like China to stop temporarily due to the lockdown in China. The China was started the lockdown on January 23, 2020. However, this effect only had an effect at that time, as evidenced in the following weeks the rupiah strengthened again.

The excitement after the rupiah had strengthened again had to run aground because on the 2nd Sunday of March 2020 (T =252) the rupiah weakened greatly to reach Rp. 15,912.00 per 1 US dollar. This is because the ongoing Covid-19 case has caused financial market uncertainty. In addition, many workers were laid off which resulted in an increasing unemployment rate. This effect continues in the following week (T=253), and it would be continued if there is no policy from the relevant government to stop it.

5.3. Heteroscedasticity model
The residual of ARIMA(0,1,1) be tested for its heteroscedasticity existence using LM test. The null hypotheses said that the residual has no heteroscedasticity effect. The p-value obtained is 0.025, then null hypotheses is rejected, means that the heteroscedasticity is exist. Following the modelling stages in figure 4 and 5, the obtained model is

\[ \sigma^2_{it} = 24,587.001 + 0.143r^2_{t-1} + \alpha_t \]

Then

\[ \sigma^2_{it-1} = 24,587.001 + 0.143r^2_{t-1} \]

This model is ARCH (1) with \( \hat{\sigma} = 24,587.001 \) and \( \hat{\alpha} = 0.143 \). The diagnostic checking results uncorrelated and non-normal distributed of residuals. Nevertheless, using the data test, this model gives a good prediction with MAPE is 5.473% which is less than 10%. Based [27], if MAPE is less than 10% then the model has excellent ability in predicting. Furthermore, while five-steps ahead of conditional variances are predicted, it is obtained that the volatility of the IDR-USD exchange rate is decreasing slowly. The future variance is affected by the square of the errors from the previous one-time lag.

Suppose the results of this variance prediction are used to build a prediction interval. Then the first two predicted values are very close with the real values and the next three are quite different as can be seen in figure 7.

**Figure 8.** The five-step ahead of prediction. The predicted values (red line) which lie inside the interval (blue line) are slightly increasing, meanwhile the real values (black line) are decreasing after two weeks.

Based on figure 8, the obtained prediction results are over-estimate in last three observations. This is because there had been policies from the Government, especially the Minister of Finance and Bank of Indonesia in responding to the Covid-19 pandemic. According to the news, both parties intervened in spot market trading, Domestic Non-Deliverable Forward (DNDF), and bought Government Securities (SBN) released by foreigners. Thus, the IDR had begun to strengthen again.

Beside three above models, the combination of heteroscedasticity and outlier model is executed. The obtained model is ARCH (1) for the errors of ARIMA(0,1,1) model, and with outliers as follows:

\[ \sigma^2_{it-1} = 14,906.8 + 0.455r^2_{t-1} \]

It means that the variance is influenced by the squared residual of one previous lag time.
As the comparison, the summary of all models are presented in table 1. From table 1, it is obtained the most appropriate model is ARIMA (0,1,1) with intervention factor, followed by the combination model of ARCH(1) and outliers. The best model is obtained by evaluating the MSE, MAPE and the fulfilment of white noise assumption.

Table 1. The comparison of modelling. Based on MSE, MAPE, and white noise assumption then ARIMA(0,1,1) model with intervention be the most appropriate model to this IDR-USD exchange rate data.

| Model ARIMA(0,1,1) with … | MSE      | MAPE   | White noise |
|--------------------------|----------|--------|-------------|
| Intervention             | 596.698  | 2.160% | Yes         |
| Outliers                 | 10,730.060 | 6.413% | No          |
| ARCH(1)                  | 20,218.150 | 5.473% | No          |
| ARCH(1) and outliers     | 23,130.110 | 2.099% | Yes         |

All obtained models show that the covid pandemic had influences to the economic sector in Indonesia. This is in line with the previous results of researches with different point of views. For example in [19] which analysed the impacts of Covid-19 pandemic to the five types of Indonesia’s financial markets. It is found that the pandemic causes different impacts to Indonesia’s financial markets during the pandemic compared to those in the non-pandemic period. Further, the Bank of Indonesia (BI) intervention made some changes to the IDR-USD exchange rate. Here, the pandemic could be considered as intervention which impact to the existence of heteroscedastic and outliers. By using the ARIMA (0,1,1) with the pandemic covid as the intervention, the IDR-USD exchange rate can be well predicted.

6. Conclusion
In the IDR-USD exchange rate data, the effect of Work From Home (WFH) intervention in the 3rd week of March 2020 is estimated to end in the 3rd week of July 2020. The AO-type of outlier affect on the 2nd week of November 2015 and the 4th week of February 2020 only affects on that week. Meanwhile for the IO type of outlier, which are occurring in the 3rd and 4th week of March 2020, gave the permanent effect. In other words, this IO effect will continue with assumption that there are no other interventions that will stop this effect. It means that the government interventions have a big influence to stabilize the economy during pandemic. Thus, the right policies should be implemented to give the good impacts.

The heteroscedastic time series model has the less performance in terms of fitting but has the best performance for the IDR-USD exchange rate data at week-19th of 2015 until week-14th of 2020 in prediction when combined with outlier factors so that it has white noise errors with smaller values than pure outliers and heteroscedastic model. The combination of both models will give a better model in prediction. In addition to using a heteroscedastic time series model with an outlier factor, this IDR-USD exchange rate data is also suitable for using model with an intervention factor for data containing extreme outliers. In other words, the outlier considered as or can replace the intervention factor in the model.

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