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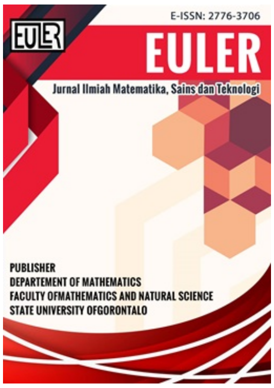

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Research Article

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Time Series Modeling with Intervention Analysis to Evaluate of COVID-19 Impact on the Stock Markets in Indonesia and Global

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ABSTRACT. *The COVID-19 pandemic began in December 2019 and led to significant disruptions in global financial markets. This study investigates the impact of the pandemic on stock indices in Indonesia (IHSG), the United States (DJI), and South Korea (KOSPI) using intervention analysis with a step function, which is designed to model permanent shifts in time series data following external shocks. Unlike traditional models such as ARIMA that assume data continuity, intervention models, particularly those using step functions, are highly suitable for assessing long-term economic disruptions and structural breaks caused by pandemics. This research uses daily stock price index data from January 10, 2019, to May 8, 2020, obtained from Yahoo Finance. The step function identifies the point of sustained change triggered by the initial COVID-19 outbreak and subsequent market reactions. The analysis shows that the pandemic caused significant and persistent declines across all observed indices. IHSG recorded its sharpest drop on March 26, 2020, while DJI and KOSPI experienced similar downward trends from March to April 2020. The forecasting performance of the intervention model was excellent, with Mean Absolute Percentage Error (MAPE) values of 0.72% for IHSG, 0.87% for DJI, and 0.82% for KOSPI, demonstrating high accuracy in modeling stock market behavior during crisis conditions.*

1. Introduction

The COVID-19 pandemic began in December 2019 in Wuhan, Hubei Province, China, and has had profound global economic implications [1, 2]. Initially identified as a mysterious pneumonia, the virus quickly spread to over 216 countries, prompting the World Health Organization (WHO) to declare COVID-19 a pandemic on March 11, 2020 [3, 4]. The pandemic triggered significant economic disruptions, particularly in the stock markets, as investors reacted to the rapid spread of the virus and the uncertainty surrounding its long-term effects on global financial stability [5, 6]. By March 17, 2020, the Indonesian Stock Exchange's Composite Stock Price Index (IHSG) had dropped by nearly 30% from the start of the year following the announcement of Indonesia's first confirmed COVID-19 cases. Similarly, other global stock exchanges, including the Dow Jones and the Nikkei Index, experienced sharp declines, highlighting the widespread impact of the pandemic on financial markets worldwide [6, 7].

In econometric analysis, understanding the effects of external shocks, like the COVID-19 outbreak, is critical for predicting and mitigating economic losses [8]. Time series data refers to a sequence of data points measured at successive, equally spaced points in time [9, 10]. These data are typically used to identify patterns, trends, and cycles over time, and can exhibit features such as trends, seasonality, and random variations [11, 12]. However, time series data can be disrupted by shocks that cause structural changes in these patterns. Traditional time series models, such as ARIMA or smoothing techniques, are designed to predict based on historical data trends and assume that the future will resemble the past [13–15]. However, these models are often ineffective in capturing the impacts of sudden, unprecedented events like the COVID-19 pandemic, which leads to significant structural breaks and alters the underlying data patterns. In such cases, intervention analysis offers a practical statistical approach to model these disruptions by quantifying the impact of external events (such as a pandemic) on time series data [16, 17].

Specifically, intervention models use step and pulse functions to model long-term or short-term disruptions [18]. The step function represents a sustained shift in data following an intervention, while the pulse function captures transient changes occurring at a particular point in time [16, 19]. Intervention analysis is, therefore, particularly well-suited for capturing the profound effects of COVID-19 on stock prices, as it allows for identifying and measuring both immediate and lasting impacts. This study explores the application of intervention models to assess the effect of COVID-19 on stock market indices across several countries. By identifying and measuring the magnitude and duration of the pandemic's impact, this research aims to provide a clearer understanding of how such global crises affect financial market behavior and offer a modeling framework for future eco-

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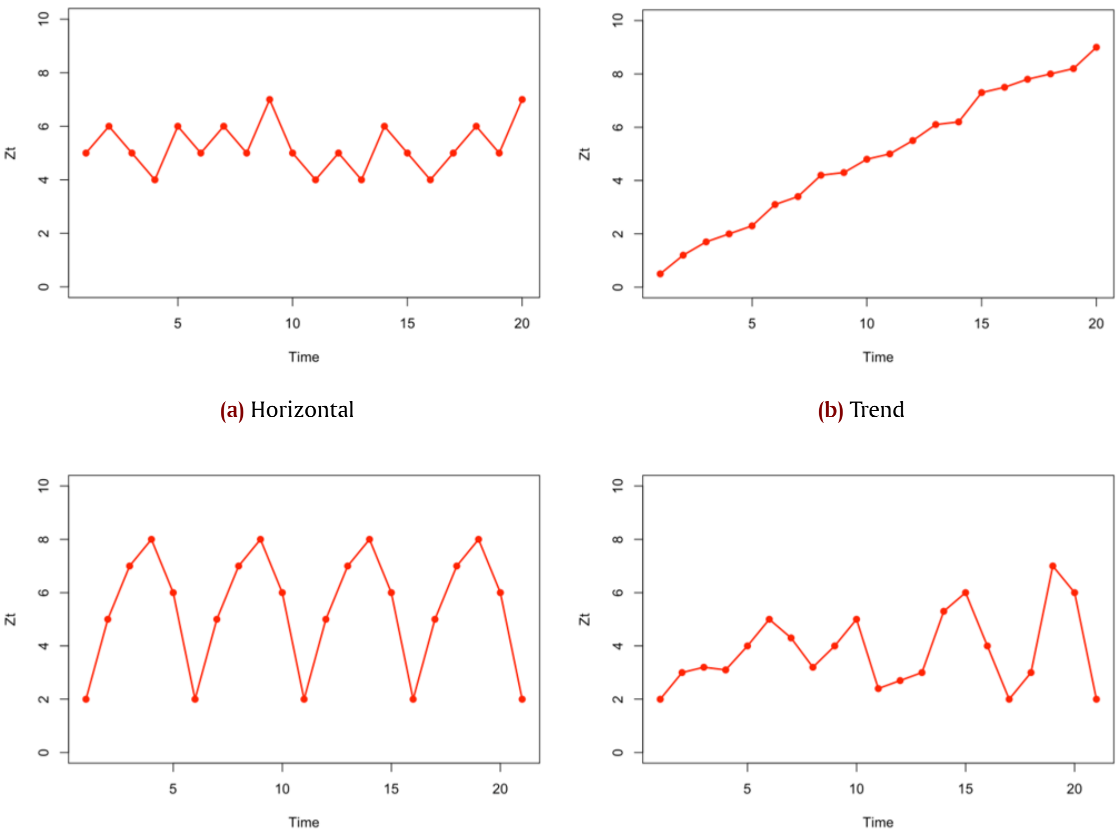


(a) Horizontal **(b)** Trend

(c) Seasonal **(d)** Cyclic

Figure 1. Time series data patterns

nomic disruptions. By isolating the impact of the pandemic on these indices, the research aims to provide insights into how such global crises affect financial market behavior, offering a statistical framework for future economic disruptions.

2. Methods

2.1. Time Series Data

An essential step in choosing an appropriate forecasting method in time series analysis is to consider the type of data pattern so that the most suitable method for that data pattern can be tested and analyzed [20]. According to, time series data patterns can be divided into four types, visualized in Figure 1.

1. Figure 1a visualizes data fluctuating around a fixed average without showing a significant uptrend or downtrend over some time.
2. Figure 1b visualizes data showing a long-term increase or decrease over some time.
3. Figure 1c visualizes data influenced by seasonal factors, with fluctuations occurring periodically over some time (e.g., monthly, yearly).
4. Figure 1d The movement of data swings around a trendline, with cycles repeating over some time.

2.2. ARIMA Box-Jenkins

The ARIMA model combines two models, namely the autoregressive (AR) model, which is then integrated with the moving average (MA) model [21]. The ARIMA model is generally written in ARIMA notation (*p, d, q*), where *p* is the degree of the AR process, *d* is the differencing order, and *q* is the degree of the MA process [22]. The ARIMA model, mathematically, can be written in eq. (1).

$$\phi_p(B)\left(1-B\right)^d Y_t = \theta_q\left(B\right) a_t, \tag{1}$$

with

$$\phi_p\left(B\right) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,$$
$$\theta_q\left(B\right) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q.$$

Furthermore, eq. (1) can be explained into eq. (2).

$$\begin{aligned}\left(1-\phi_1 B-\phi_2 B^2 - \cdots - \phi_p B^p\right)\left(1-B\right)^d Y_t \\ = \left(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q\right) a_t.\end{aligned} \tag{2}$$

2.3. Intervention Analysis

According to [17], time series data influenced by several external or internal events may exhibit changes in the data pattern at a specific time t. To evaluate the impact of such events, a modeling approach known as intervention analysis can be applied [19]. This technique is used to measure both the magnitude and duration of the intervention effect occurring at time t. Novianti and Suhartono [23] presents the general form of the model in eq. (3).

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)} B^b X_t + \frac{\theta_q(B)}{\phi_p\left(B\right)\left(1-B\right)^d} a_t, \tag{3}$$

where Y_t is the response variable at time t, and X_t is the intervention variable, which shows whether or not there is an impact of an intervention at time T. In general, there are two types of intervention variables, namely step and pulse functions. Intervention events from time T onwards over a long period are called step functions. Mathematically, the step function intervention is represented in eq. (4).

$$X_t = S_t = \begin{cases} 0 & ;\ \text{for } t < T \\ 1 & ;\ \text{for } t \geq T \end{cases}. \tag{4}$$

Meanwhile, in the pulse function, the intervention event only occurs at time T and does not continue at subsequent times. Mathematically, the form of pulse function intervention is represented in eq. (5).

$$X_t = P_t = \begin{cases} 0 & ;\ \text{for } t \neq T \\ 1 & ;\ \text{for } t = T \end{cases}, \tag{5}$$

with,

$$\omega_s(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s,$$
$$\delta_r(B) = 1 - \delta_1 B - \delta_2 B^2 - \ldots, \delta_r B^r.$$

Eq. (3) shows that the orders b, r, and s indicate the magnitude and period of the impact of the intervention. The border shows the delay time, the s order shows the length of time an intervention affects the data after a certain b period, and the r order shows the pattern of the impact of the intervention. The effect of the intervention model on the Y_t^* is represented in eq. (6).

$$Y_t^* = Y_t - \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t = \frac{\omega_s(B)}{\delta_r(B)} B^b X_t. \tag{6}$$

The b, r and s orders are important in intervention modeling [16].

2.4. Accuracy of Forecasting Results

According to [24], in modeling time series data, there is the possibility that there are several suitable models, namely that all the parameters are significant, meet the assumptions of white noise, and the residuals are normally distributed. Selecting the best model using several criteria for model goodness is necessary. In this study, the author used the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) criteria. The MSE criteria in eq. (7).

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \widehat{Y}_t\right)^2, \tag{7}$$

and the MAPE criteria in eq. (8).

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \widehat{Y}_t}{Y_t}\right| \times 100. \tag{8}$$

The smaller the MSE and MAPE values, it means that the estimated values are closer to the actual values, or in other words the model chosen is the best model [25].

2.5. Data Sources

The data used in this research is secondary data on stock price indices in several countries and specific sectors in Indonesia, which are accessed via the official website (https://finance.yahoo.com/). The data taken is daily stock price index data recorded from 10 January 2019 to 08 May 2020. The research variables are time series data for each stock index which are written in Table 1.

Table 1. Research variable

Variable	Variable Name	Operational Definition
$Y_{1,t}$	IHSG	The Composite Stock Price Index (IHSG) is the average value of composite shares on the Indonesian Stock Exchange.
$Y_{2,t}$	INDEXDJX: DJI	One of the stock market indexes established to measure the performance of the industrial components of the American stock market.
$Y_{3,t}$	KS11: KOSPI Composite Index	The Korean Composite Stock Price Indexes (KOSPI) is a series of indices that track the entire South Korean Stock Exchange and its components.

The intervention variable used in this study is a step function taken based on the first confirmation of COVID-19 in the country, which is presented in Table 2.

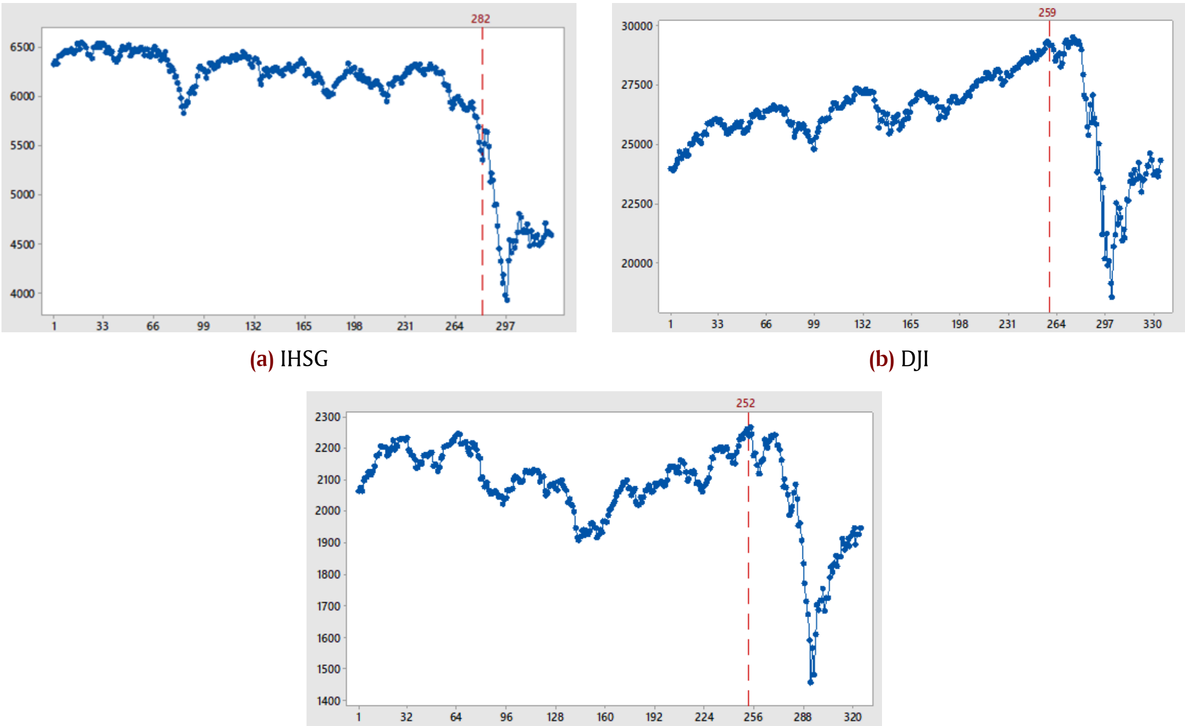
Table 2. Intervention research variables

For IHSG $X_{(1,t)}$ that is on 02 March 2020
$X_{(1,t)} = S_{(1,t)} = \begin{cases} 0 & \text{for } t < 282 \\ 1 & \text{for } t \geq 282 \end{cases}$
For DJI $X_{(2,t)}$ that is on 21 January 2020
$X_{(2,t)} = S_{(2,t)} = \begin{cases} 0 & \text{for } t < 259 \\ 1 & \text{for } t \geq 259 \end{cases}$
For KS11 $X_{(3,t)}$ that is on 20 January 2020
$X_{(3,t)} = S_{(3,t)} = \begin{cases} 0 & \text{for } t < 252 \\ 1 & \text{for } t \geq 252 \end{cases}$

2.6. Data Analysis Techniques

The intervention variable used is a step function because the impact of COVID-19 is not yet known how long it will end, so it will affect the stock price index in the long term. The analysis steps carried out are:

1. *Preliminary Analysis*
   (a) Collect stock price index data, including the Indonesian Composite Index (IHSG) and selected global indices such as the Dow Jones Index, and KOSPI (KS11).
   (b) Construct time series plots to observe data fluctuation patterns, identify potential responses to interventions, and estimate the timing of the intervention event.
2. *ARIMA Modeling for Pre-Intervention Data*
   (a) Divide data based on the time when the intervention occurred. Data before intervention was then modeled using ARIMA. Stages of checking stationarity, stationary in the variance using Box-Cox Transformation, and stationary in the average using the ACF graph.
   (b) Carrying out a differencing process if the data before the intervention does not meet the stationary assumption on the mean.



(a) IHSG

(b) DJI

(c) KS11

Figure 2. Time series data patterns of several stock price indices

  (c) Identify all temporary ARIMA models based on ACF and PACF graphs from data before the stationary intervention.
  (d) Perform parameter estimation and parameter significance testing of all temporary ARIMA models.
  (e) Check the significant residual assumptions of the temporary ARIMA model. The ARIMA model meets the assumptions of white noise and residuals following a normal distribution.
  (f) Select the best ARIMA model based on the criteria for the smallest MSE and MAPE values.
  (g) Select the best ARIMA model based on the criteria for the smallest MSE and MAPE values.
  (h) Carry out forecasts for data before the intervention occurs to data after the intervention occurs based on the best ARIMA model.
3. *Intervention Analysis*
  (a) Calculate the response function, namely the residual of the data after intervention with forecasting results obtained from the best ARIMA model. Next, residual standardization is carried out, where the residual obtained is divided by the root of the MSE value obtained from the best ARIMA model.
  (b) Identify intervention response patterns and form intervention models based on graphs of standardized residual values to determine the order of b, r, and s.
  (c) Carrying out parameter estimation and testing the significance of parameters from the intervention model formed.
  (d) Check the residual assumptions of the intervention model. The intervention model meets the white noise assumptions, and the residuals follow a normal distribution.
  (e) Carry out forecasts using the best intervention model.

3. Results and Discussion

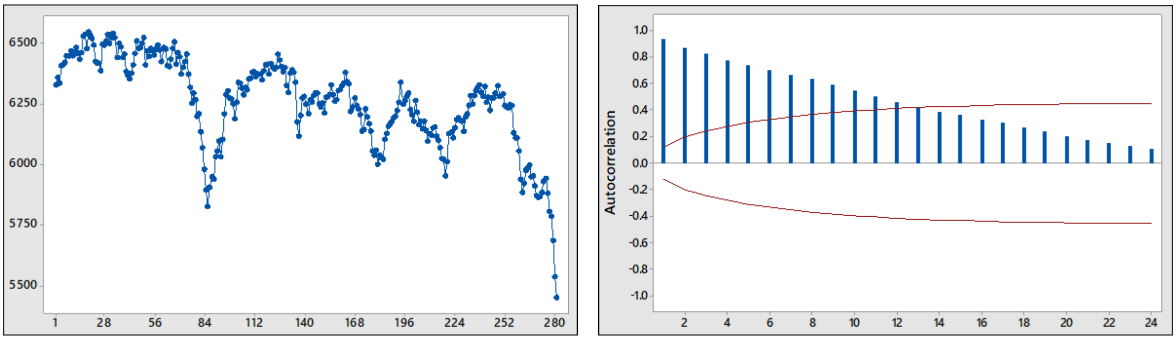
To evaluate the impact of the COVID-19 pandemic on stock market performance, this study applies intervention analysis to several major stock indices, namely the Indonesia Composite Index (IHSG), the Dow Jones Industrial Average (DJIA), and the Korea Composite Stock Price Index (KOSPI/KS11).

3.1. Exploration Data

Descriptive statistics are first presented through time series graphs to provide an overview of pattern changes and data fluctuations, identify potential intervention response patterns, and estimate the timing of the intervention event.

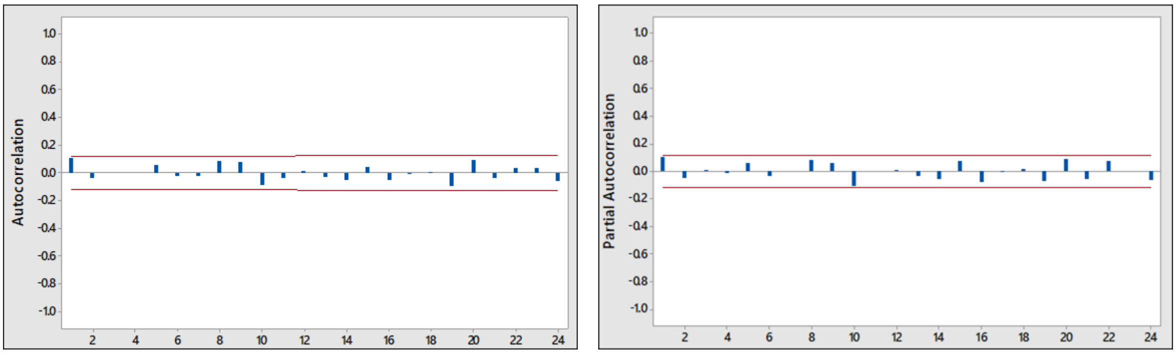
Figure 2 presents the time series plots of three major stock indices, each marked with a vertical red dashed line indicating the intervention point. These structural changes are likely associated with the initial announcements of confirmed COVID-19 cases, which triggered increased market uncertainty:

1. IHSG (Indonesia Composite Index) shows a significant structural break around 02 March 2020, following relatively stable fluctuations. This shift coincides with the announcement of Indonesia's first confirmed COVID-19 cases, which may have affected investor sentiment.
2. DJI (Dow Jones Industrial Average) exhibits a sharp decline beginning around 21 January 2020, after a steady upward trend. This period aligns with the first confirmed COVID-19 case in the United States, leading to heightened market concern.



(a) Time series graph pre-intervention **(b)** ACF pre-intervention

Figure 3. Time series graph and ACF pre-intervention for IHSG



(a) ACF pre-intervention **(b)** PACF pre-intervention

Figure 4. Graph of ACF and PACF data before intervention after differencing

3. KS11 (KOSPI Index) reveals a structural change around 20 January 2020, corresponding with South Korea's first reported COVID-19 case, followed by a notable drop in market performance.

3.2. Modeling the Indonesian IHSG

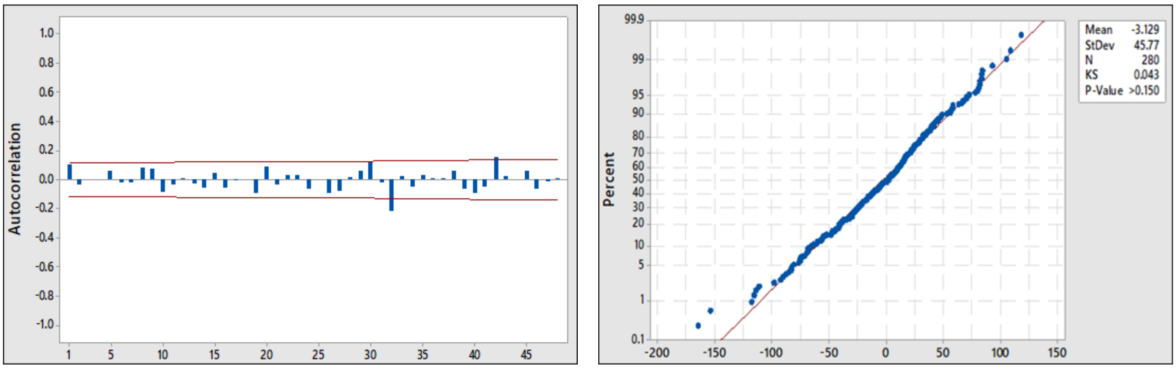
3.2.1. ARIMA Modeling of the Indonesia IHSG Prior to Intervention

To initiate the construction of the intervention model, an ARIMA model is first developed using data from the period preceding the intervention. For the Indonesian IHSG, the timeframe from 10 January 2019 to 28 February 2020 is selected as the pre-intervention phase. This period was chosen because it ended just before the official announcement of the first confirmed COVID-19 cases in Indonesia on 2 March 2020, a critical event believed to have triggered substantial structural changes in the market. As such, this data segment is assumed to represent the natural behavior of the IHSG under normal conditions unaffected by pandemic-related shocks. An appropriate ARIMA model is identified exclusively using this pre-intervention dataset.

Based on Figure 3a, the Indonesian IHSG data exhibits a downward trend, indicating that the series is non-stationary in the mean, as the average level of the data changes over time. This condition is further supported by Figure 3b, where the Autocorrelation Function (ACF) decays slowly, suggesting the presence of persistent correlation over time and reinforcing the need for differencing. Consequently, first-order differencing is applied to achieve stationarity in the mean. It is important to note that a Box-Cox transformation was not performed in this study. The ACF and PACF plots of the differenced data are presented below to assist in identifying the appropriate ARIMA model in Figure 4.

Based on Figure 4a and Figure 4b, which display the ACF and PACF plots of the differenced IHSG data, it is observed that no lag exceeds the significance bounds, indicating the absence of significant autocorrelation in the series. The ACF and PACF show a rapid decline to near-zero values, suggesting that the data behaves as a white noise process after first-order differencing. This pattern supports selecting an ARIMA(0,1,0) model for the IHSG data before the intervention. Although the ARIMA(0,1,0) model does not include autoregressive (AR) or moving average (MA) terms, it still possesses a structural component, namely, the integrated (I) part, which captures the change from one time point to the next. This model implies that the observation at time t equals that at time $t-1$, plus a random shock. Subsequently, diagnostic checking is performed to assess whether the residuals behave as white noise and whether they follow a normal distribution, ensuring the adequacy of the selected model in Figure 5.

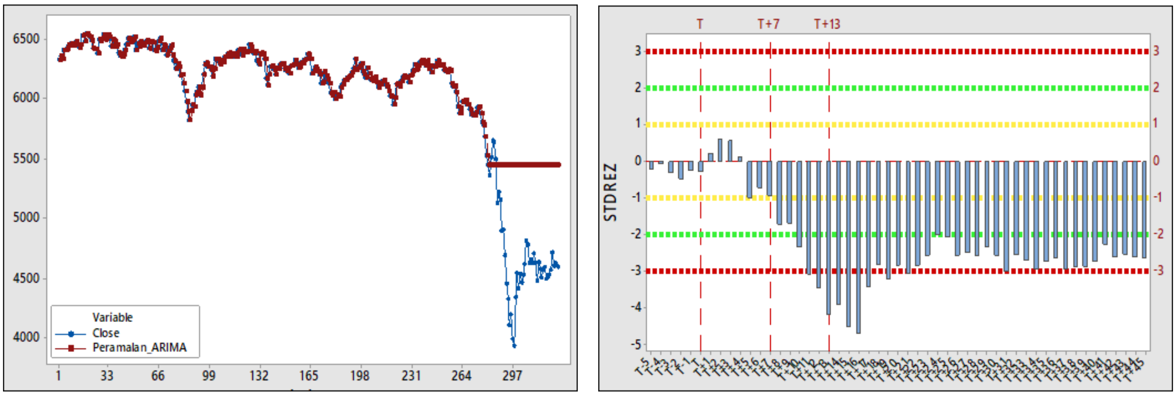
Based on Figure 5a, it is observed that all autocorrelations of the residuals from the ARIMA(0,1,0) model lie within the significance bounds. This indicates that the residuals behave as white noise, suggesting that the model has adequately captured the underlying structure of the time series data. In addition, Figure 5b shows the normal probability plot, accompanied by the Kolmogorov–Smirnov test result, which produces a pvalue greater than 0.150. This confirms that the residuals are approxi-



(a) ACF for residuals ARIMA (0,1,0)

(b) Normal probability plot

Figure 5. ACF graph of residuals and normal probability plot



(a) Actual vs Predicted ARIMA (0,1,0)

(b) Bar plot residual standardized value

Figure 6. Time series graph ARIMA(0,1,0) and residual standardized values

mately normally distributed, thus satisfying a key assumption of ARIMA modeling.

3.2.2. Modeling Indonesian IHSG Data using the Intervention Model

The first intervention event affecting the Indonesian IHSG is attributed to the COVID-19 pandemic, which is modeled using a step function to represent a permanent structural shift in the time series. After establishing the initial ARIMA model based on pre-intervention data, the model is extended to incorporate the intervention effect. A key component in developing the intervention model involves determining the appropriate values of b, r, and s, which characterize the timing and dynamic response of the intervention. These values are identified by analyzing the response function, constructed from the standardized residuals obtained after the intervention period. By examining the graphical pattern of these residuals, one can infer the suitable values of b, r, and s, which are essential for accurately capturing the nature and duration of the intervention effect on the time series.

Based on Figure 6, the initial estimated values for the intervention order are $b = 13$, $r = 0$, and $s = [1, 2, 4, 5, 6, 7, 8, 9, 13, 19, 20, 28, 29]$. Next, the ARIMA model was refined to ARIMA(0,1,[1,5]), guided by the results of the Ljung–Box test presented in Table 3. The parameter estimation and significance testing results for the ARIMA(0,1,[1,5]) model demonstrate that all estimated parameters are statistically significant, confirming their contribution to improving model adequacy.

Table 3. Examination of the intervention diagnostic model of IHSG data

Residual White Noise				Residual Normal
Lag 6	Lag 12	Lag 18	Lag 24	Kolmogorov-Smirnov
0.234	0.441	0.615	0.232	< 0.010

In addition, based on Table 3, the Kolmogorov–Smirnov test for normality produces a pvalue less than 0.010, indicating that the residuals deviate from a normal distribution. The intervention model can be written as:

$$Y_{1,t} = \left[\omega_0 - \omega_1 B - \omega_2 B^2 - \omega_4 B^4 - \cdots - \omega_{29} B^{29}\right] B^{13} S_{1,282(t)} + \frac{(1-\theta_1 B - \theta_5 B^5)}{(1-B)} a_{1,t},$$

$$Y_{1,t} = \left[\omega_0 S_{1,282(t-13)} - \omega_1 S_{1,282(t-14)} - \omega_2 S_{1,282(t-15)} - \cdots - \omega_4 S_{1,282(t-17)}\right] + \left[Y_{1,t-1} + a_{1,t} - \theta_1 q_{1,t-1} - \theta_5 q_{1,t-5}\right],$$

$$Y_{1,t} = -167.24 S_{1,282(t-13)} + 259.48 S_{1,282(t-14)} - 182.24\, S_{1,282(t-15)} + 487.08 S_{1,282(t-17)} - \cdots - 185.12\, S_{1,282(t-42)} + Y_{1,t-1} + a_{1,t} + 0.19 q_{1,t-1} + 0.19 q_{1,t-5}.$$

Based on the results of the intervention model, it is evident that the COVID-19 pandemic exerted a significantly negative

Table 4. Details of the impact of COVID-19 on the IHSG

Time (t)	Date	Magnitude of Impact	Extraordinary Event
T+13	19 March 2020	-167.24	BI decided to lower the BI 7-Day Reverse Repo Rate (BI7DRR).
T+14	20 March 2020	-426.73	The Minister of Foreign Affairs implemented a policy of restricting the movement of foreigners from all countries.
T+15 - T+16	23 – 24 March 2020	-244.49	President Joko Widodo launched an economic stimulus package which is thought to be able to ease the effects of COVID-19.
T+17	26 March 2020	-731.57	Indonesia repatriates Indonesian citizens stranded in Uzbekistan.
T+18	27 March 2020	-540.38	BI strengthens monetary and financial market stability together with the Government and OJK.
T+19	30 March 2020	-186.13	BI expands the incentive policy of easing daily GWM in Rupiah.
T+20	31 March 2020	-489.32	The government issues government regulations in lieu of law (Perpu) regarding state financial policy and financial system stability.
T+21	01 April 2020	-264.89	BI accelerates the implementation of provisions on the use of domestic Rupiah accounts (Vostro) for foreign investors as underlying transactions in DNDF.
T+22 - T+25	02 – 07 April 2020	-401.65	The Minister of Health approved the PSBB to be implemented in DKI Jakarta. The government provides motor vehicle credit relief for 1 year for online motorcycle taxi drivers, fishermen and taxi drivers.
T+26 - T+31	08 – 16 April 2020	-289.02	BI provides funds for economic activities to support handling the impact of COVID-19.
T+32	17 April 2020	-510.42	BI policy stance loosens, BI maintains the reference interest rate (BI-7DRRR) and PSBB begins to be implemented in several regions.
T+33 -T+40	20 – 29 April 2020	-325.06	The Ministry of Transportation has temporarily stopped air, sea and land transportation activities. The government issued a ban on returning home for Eid al-Fitr.
T+41	30 April 2020	-486.59	BI issues follow-up policy to deal with COVID-19.
T+42	04 May 2020	-301.64	BI made changes to the Macroprudential Intermediation Ratio (RIM) and Macroprudential Liquidity Buffer (PLM) for Banks.

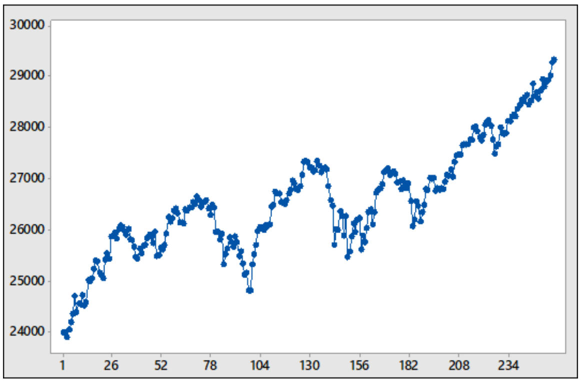
impact on the Indonesian IHSG. The estimated escalation effect, measured in terms of deviation from the projected trend, reached –167.24 points on the 13th day following the intervention. This adverse effect intensified further, with the impact deepening to –301.64 points by the 42nd day after the intervention event. These findings indicate a substantial and worsening market reaction in the weeks immediately following the announcement of the first confirmed COVID-19 cases in Indonesia. The details of the impact of COVID-19 on the Indonesian IHSG written in Table 4.

The dynamic impact of the COVID-19 intervention on the Indonesian IHSG, as outlined in the post-intervention escalation estimates, reveals a pattern of sharp initial decline, followed by fluctuating but gradually moderating effects. The maximum negative impact is observed on T+17 (26 March 2020), where the estimated escalation reached –731.57 points, indicating a peak in market stress. Before this peak, the magnitude of the impact increased significantly, most notably on T+14 (20 March 2020), with a sharp drop of –426.73 points, followed by a partial correction and a subsequent intensified decline. After reaching the lowest point on T+17, the magnitude of the impact began to exhibit signs of moderation, though still reflecting substantial volatility. From early April onward, the estimates suggest a reduction in the severity of the negative escalation, with values fluctuating between approximately –300 to –500 points. By T+42 (04 May 2020), the impact had lessened to –301.64 points, suggesting a partial market sentiment recovery or stabilization.

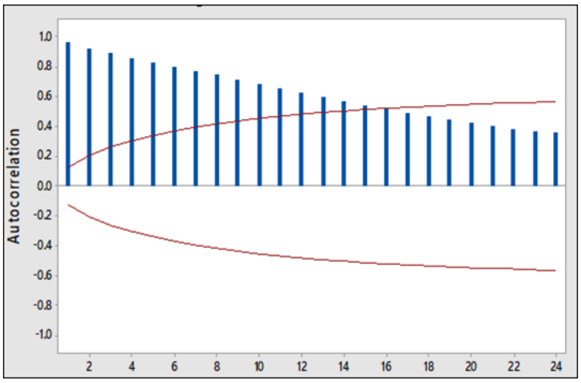
3.3. Modeling the INDEXDJX: DJI USA

3.3.1. ARIMA Modeling of the DJI United States Stock Prior to Intervention

The initial phase in constructing an intervention model involves identifying a baseline ARIMA model using data that reflects the natural behavior of the time series prior to any external disruption. For the Dow Jones Industrial Average (DJI) in the United States, the pre-intervention period is defined from 10 January 2019 to 20 January 2020. This timeframe is deliberately selected as it precedes the official confirmation of the first COVID-19 cases in the United States, an event that subsequently triggered widespread volatility in global financial markets. The identification of an appropriate ARIMA model is conducted exclusively on this pre-intervention dataset to ensure that the model captures the underlying dynamics of the series in the absence of pandemic-related shocks.

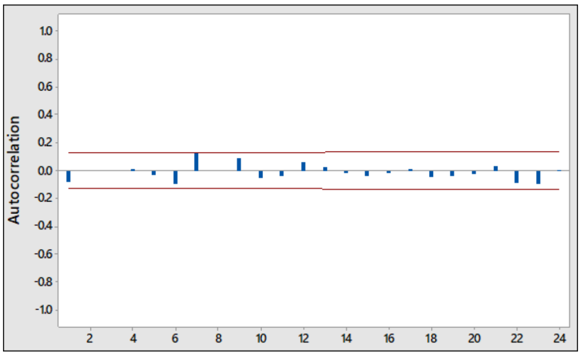


(a) Time series graph pre-intervention

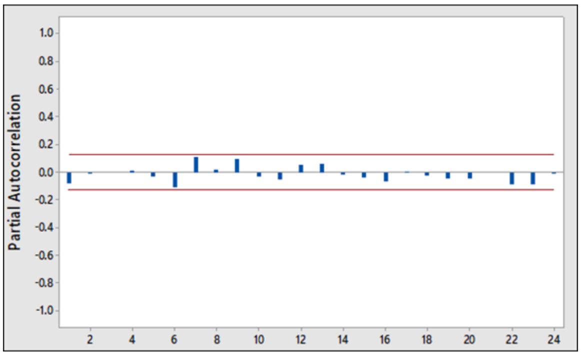


(b) ACF pre-intervention

Figure 7. Time series graph and ACF pre-intervention for DJI



(a) ACF pre-intervention



(b) PACF pre-intervention

Figure 8. Graph of ACF and PACF data before intervention after differencing

Based on Figure 7a, the DJI time series for the United States exhibits notable fluctuations accompanied by an upward trend over time. This indicates that the data is not stationary in terms of the mean, as the average level of the series changes with time. Further confirmation is provided by Figure 7b, where the ACF declines gradually rather than cutting off sharply, suggesting the presence of non-stationarity. To address this, first-order differencing is applied to stabilize the series mean. It is also noted that no Box-Cox transformation was performed in this study. After differencing, the ACF and PACF plots are presented in Figure 8.

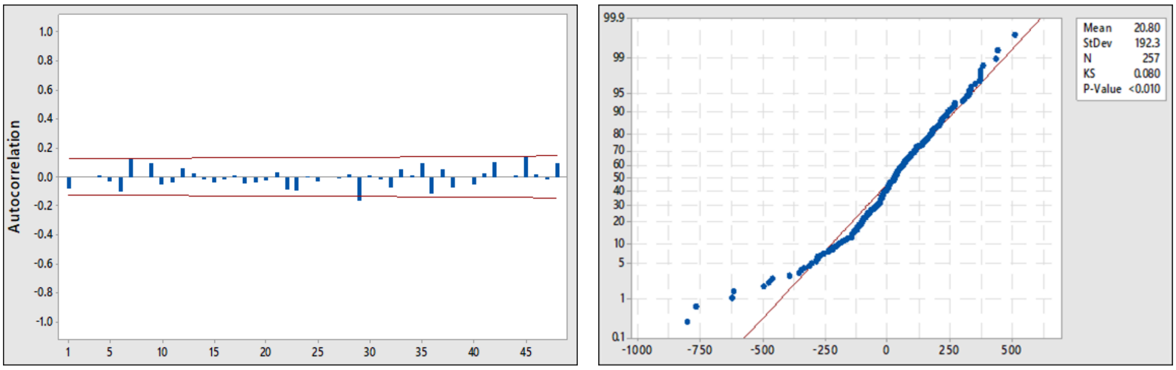
Based on Figure 8a-Figure 8b, which display the ACF and PACF plots of the differenced DJI data, it is observed that no lag exceeds the significance bounds, indicating the absence of significant autocorrelation in the series. The ACF and PACF show a rapid decline to near-zero values, suggesting that the data behaves as a white noise process after first-order differencing. This pattern supports selecting an ARIMA(0,1,0) model for the DJI data before the intervention. This model implies that the observation at time t equals that at time $t-1$, plus a random shock. Subsequently, diagnostic checking is performed to assess whether the residuals behave as white noise and whether they follow a normal distribution, ensuring the adequacy of the selected model in Figure 9.

Based on Figure 9a, the residuals from the ARIMA(0,1,0) model still exhibit patterns that deviate from the characteristics of white noise. This is indicated by the presence of autocorrelations that exceed the significance bounds, suggesting that the model does not fully capture the underlying structure of the time series. Furthermore, Figure 9b presents a Normal Probability Plot based on the Kolmogorov-Smirnov test. The resulting p-value of less than 0.010 indicates that the residuals deviate significantly from a normal distribution.

3.3.2. Modeling United States DJI Data using the Intervention Model

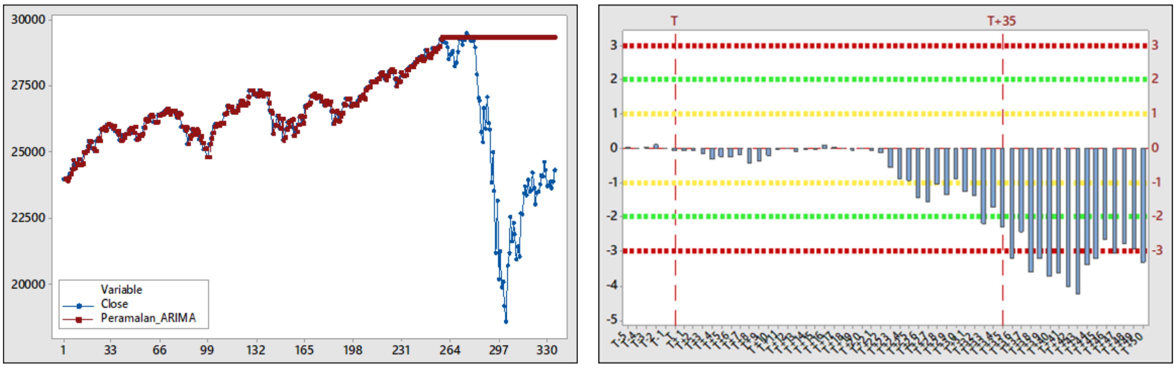
The initial intervention event influencing the Dow Jones Industrial Average (DJI) in the United States is associated with the onset of the COVID-19 pandemic. This event is represented using a step function to reflect a lasting structural change in the time series data. The ARIMA model previously constructed based on pre-intervention data is then expanded to incorporate this intervention effect. An important aspect of this modeling process involves identifying the values of b, r, and s, which define the lag, duration, and shape of the intervention's response. These parameters are estimated by analyzing the response function, derived from the standardized residuals observed after the intervention. By visualizing the pattern of these residuals in Figure 10, the appropriate values of b, r, and s can be determined, allowing the model to effectively capture the influence and dynamics of the intervention on the DJI index.

Based on Figure 10, the initial estimated values for the intervention order are $b = 35$, $r = 0$, and $s =$



(a) ACF for residuals ARIMA (0,1,0) **(b)** Normal probability plot

Figure 9. ACF graph of residuals and normal probability plot



(a) Actual vs Predicted ARIMA (0,1,0) **(b)** Bar plot residual standardized value

Figure 10. Time series graph ARIMA(0,1,0) and residual standardized values

[2, 3, 6, 7, 9, 12, 18]. Next, the ARIMA model was refined to ARIMA (0,1,[1,3,5,9,14,28]), guided by the results of the Ljung–Box test presented in Table 5. The parameter estimation and significance testing results for the ARIMA (0,1,[1,3,5,9,14,28]) model demonstrate that all estimated parameters are statistically significant, confirming their contribution to improving model adequacy.

Table 5. United states DJI data intervention model diagnostic check

Residual White Noise				Residual Normal
Lag 6	Lag 12	Lag 18	Lag 24	Kolmogorov-Smirnov
-	0.051	0.121	0.053	< 0.010

In addition, based on Table 5, the Kolmogorov–Smirnov test for normality produces a pvalue less than 0.010, indicating that the residuals deviate from a normal distribution. The intervention model can be written as:

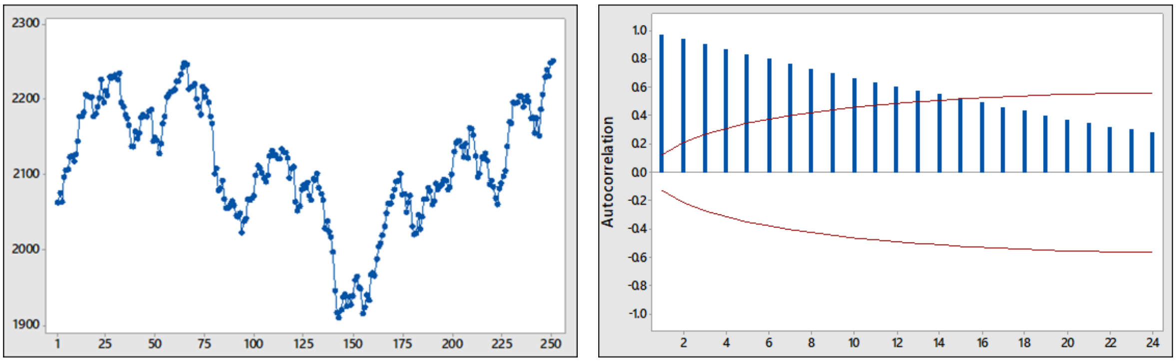
$$
\begin{aligned}
Y_{2,t} =\ & \left[\omega_0 - \omega_2 B^2 - \omega_3 B^3 - \omega_6 B^6 - \cdots - \omega_{18} B^{18}\right] B^{35} S_{2,259(t)} \\
& + \frac{(1 - \theta_1 B - \theta_3 B^3 - \cdots - \theta_{28} B^{28})}{(1 - B)} a_{2,t}, \\
Y_{2,t} =\ & \left[\omega_0 S_{2,259(t-35)} - \omega_2 S_{2,259(t-37)} - \omega_3 S_{2,259(t-38)} - \cdots \right. \\
& \left. - \omega_6 S_{2,259(t-41)} - \cdots - \omega_{18} S_{2,259(t-53)}\right] \\
& + \left[Y_{2,t-1} + a_{2,t} - \theta_1 a_{2,t-1} - \theta_3 a_{2,t-3} - \cdots \right. \\
& \left. - \theta_{28} a_{2,t-28}\right], \\
Y_{2,t} =\ & -1713.1 S_{2,259(t-35)} + 3387.7 S_{2,259(t-37)} - 2460.8 \\
& S_{2,259(t-38)} + 1138.7 S_{2,259(t-41)} - \cdots + 443.2 \\
& S_{2,259(t-53)} + Y_{2,t-1} + a_{2,t} - 0.13 a_{2,t-1} - 0.14 a_{2,t-3} \\
& - \cdots - 0.29 a_{2,t-28}.
\end{aligned}
$$

Based on the results of the intervention model, it is evident that the COVID-19 pandemic significantly negatively impacted the DJI United States. The estimated escalation effect, measured in terms of deviation from the projected trend, reached –1713.1 points on the 35th day following the intervention. This adverse effect intensified further, with the impact deepening to –3579.8 points by the 53rd day after the intervention event. These findings indicate a substantial and worsening market reaction in the weeks immediately following the announcement of the first confirmed COVID-19 cases in the United States. The details of the impact of COVID-19 on the DJI United States are written in Table 6.

The COVID-19 pandemic triggered a series of extraordinary events that significantly impacted the Dow Jones Industrial Average (DJI) in the United States. Between March 11 and April 6, 2020, the DJI experienced sharp declines in response to various developments, including the WHO's declaration of a global pandemic, the U.S. government's designation of a national emergency, and aggressive policy actions by the Federal Reserve. Additional volatility arose from international travel restrictions, tar-

Table 6. Details of the impact of COVID-19 on DJI United States stock

Time (*t*)	Date	Magnitude of Impact	Extraordinary Event
T+35 – T+36	11 – 12 March 2020	-1713.1	WHO declared COVID-19 a global pandemic.
T+37	13 March 2020	-5100.8	Trump declared his country in the category of a national emergency regarding COVID-19.
T+38 – T+40	16 – 18 March 2020	-2640	The United States (US) Federal Reserve lowered its benchmark interest rate.
T+41	19 March 2020	-3778.7	Trump announced a ban on travel to and from Europe, but the US trade representative allowed tariffs on imported Airbus planes to increase.
T+42 – T+43	20 – 23 March 2020	-2538.7	Trump reduces tariffs on medical imports from China. The US government is preparing additional stimulus to minimize the impact of COVID-19.
T+44 – T+46	24 – 26 March 2020	-4500.7	The US goes into debt by selling government bonds. Rumors have emerged that there is a fight between the US and China amid the COVID-19 pandemic.
T+47 – T+52	27 March 2020 – 03 April 2020	-3136.5	Trump announced WFH that 26.5 million US citizens applied for unemployment benefits. The US has become the new epicenter of the pandemic.
T+53	06 April 2020	-3579.8	Trump stops funding to WHO. Trump is blocking goods from China by imposing more import tariffs. There was a trade war between America and China.



(a) Time series graph pre-intervention

(b) ACF pre-intervention

Figure 11. Time series graph and ACF pre-intervention for KS11: KOSPI composite index

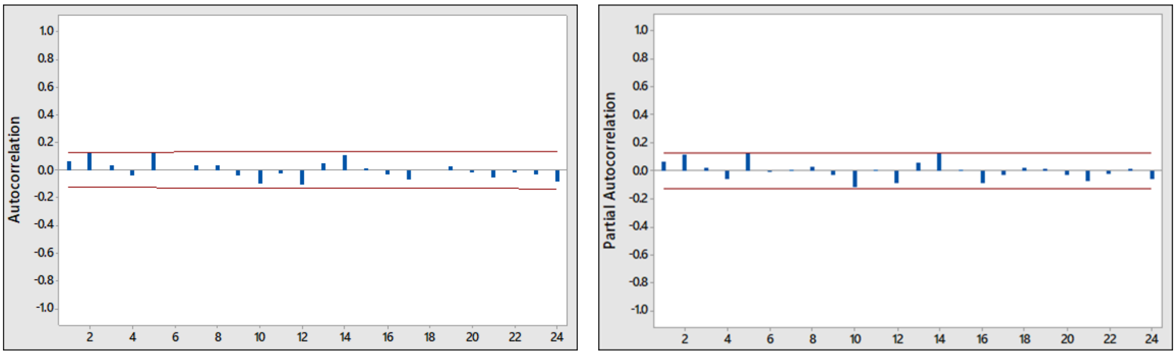
iff adjustments, and fiscal stimulus announcements. Tensions between the United States and China and domestic challenges such as rising unemployment and shifting public health strategies amplified market uncertainty. These events collectively reflect how the pandemic generated widespread fear among investors and disrupted the stability of financial markets, particularly affecting the performance of DJI stocks.

3.4. Modeling the KS11: KOSPI Composite Index

3.4.1. ARIMA Modeling of the South Korean KS11 Stock Prior to Intervention

The initial step in constructing an intervention model involves developing an ARIMA model based on pre-intervention data unaffected by the intervention event. For the KS11 index in South Korea, the pre-intervention period spans from January 10, 2019, to January 17, 2020. During this phase, the primary objective is to identify the appropriate ARIMA specification that best captures the underlying time series dynamics before the occurrence of the intervention. Figure 11a illustrates that the KS11 index data for South Korea exhibits noticeable fluctuations, along with visible upward and downward trend patterns over time. This behavior suggests that the series is non-stationary in the mean, as the average level of the data changes over time and is influenced by temporal dynamics. This indication is further supported by the ACF plot in Figure 11b, which shows a slow decay pattern characteristic of a non-stationary time series. Therefore, differencing is required to stabilize the mean and achieve stationarity. It is important to note that the Box-Cox transformation was not applied in this study. The ACF and PACF after differencing shown in Figure 12.

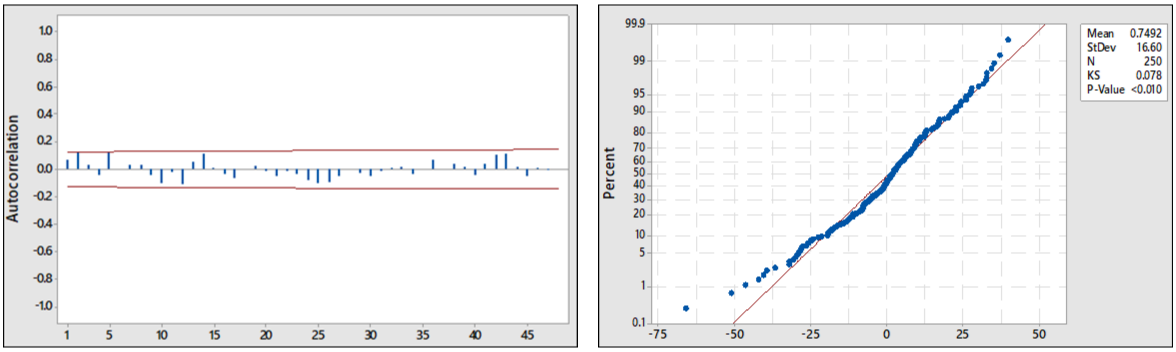
Based on Figure 12a-Figure 12b, which display the ACF and PACF plots of the differenced South Korean KS11 data before intervention, it is observed that no lag exceeds the significance bounds, indicating the absence of significant autocorrelation in the series. The ACF and PACF show a rapid decline to near-zero values, suggesting that the data behaves as a white noise process after first-order differencing. This pattern supports selecting an ARIMA(0,1,0) model. Subsequently, diagnostic checking is performed to assess whether the residuals behave as white noise and whether they follow a normal distribution, ensuring the ad-



(a) ACF pre-intervention

(b) PACF pre-intervention

Figure 12. Graph of ACF and PACF data before intervention after differencing



(a) ACF for residuals ARIMA (0,1,0)

(b) Normal probability plot

Figure 13. ACF graph of residuals and normal probability plot

equacy of the selected model in Figure 13.

Figure 13a indicates that the residuals from the ARIMA(0,1,0) model do not exhibit the characteristics of white noise, suggesting potential inadequacies in model specification. Furthermore, Figure 13b presents the Normal Probability Plot used in conjunction with the Kolmogorov–Smirnov test to assess the normality of residuals. The resulting p-value of less than 0.010 provides statistical evidence to reject the null hypothesis of normality by confirming that the residuals do not follow a normal distribution.

3.4.2. Modeling South Korean KS11 Stock Data using the Intervention Model

The initial intervention event influencing South Korea's KS11 index is associated with the onset of the COVID-19 pandemic. This event is represented using a step function to reflect a lasting structural change in the time series data. The ARIMA model previously constructed based on pre-intervention data is then expanded to incorporate the intervention effect. A critical component of this modeling process involves identifying the parameters b, r, and s, which represent the lag, duration, and shape of the intervention's response, respectively. These parameters are estimated by analyzing the response function, which is derived from the standardized residuals observed after the intervention. By examining the residual pattern presented in Figure 14, the appropriate values of b, r, and s can be determined, enabling the model to accurately capture the impact and dynamics of the intervention on the KS11 index.

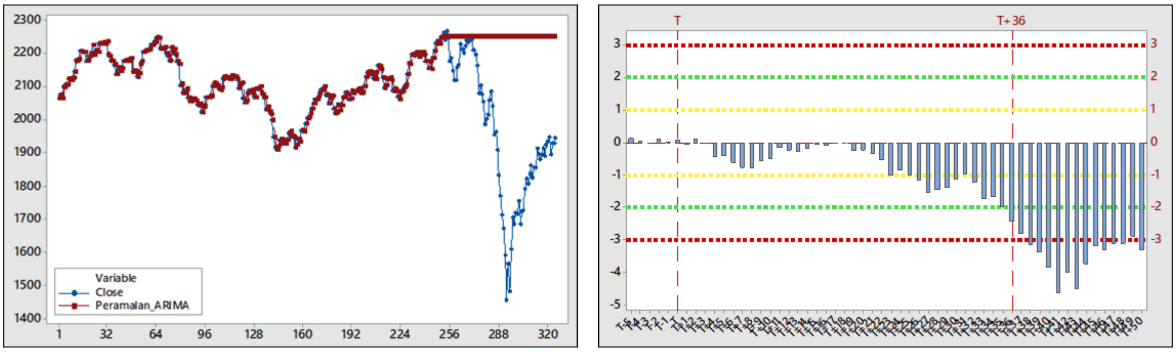
Based on Figure 14, the initial estimated values for the intervention order are $b = 36$, $r = 0$, and $s = [5, 7, 8, 10, 14, 15, 19]$. The parameter estimation and significance testing results show that all parameters are significant.

Table 7. Diagnostic examination intervention model South Korea KS11 data

Residual White Noise				Residual Normal
Lag 6	Lag 12	Lag 18	Lag 24	Kolmogorov-Smirnov
0.661	0.578	0.279	0.095	< 0.010

In addition, based on Table 7, the Kolmogorov–Smirnov test for normality produces a pvalue less than 0.010, indicating that the residuals deviate from a normal distribution. The intervention model can be written as:

$$
\begin{aligned}
Y_{3,t} = &\left[\omega_0 - \omega_5 B^5 - \omega_7 B^7 - \omega_8 B^8 - \cdots - \omega_{19} B^{19}\right] \\
& B^{36} S_{3,252(t)} + \frac{a_{3,t}}{(1-B)}, \\
Y_{3,t} = &\left[\omega_0 S_{3,252(t-36)} - \omega_5 S_{3,252(t-41)} - \omega_7 S_{3,252(t-43)} - \right. \\
& \left. \omega_8 S_{3,252(t-41)} - \cdots - \omega_{19} S_{3,252(t-55)}\right] \\
& + \left[Y_{3,t-1} + a_{3,t}\right], \\
Y_{3,t} = &- 63.41 S_{3,252(t-36)} + 50.88 S_{3,252(t-41)} - 71.16 \\
& S_{3,252(t-41)} + 194.84 S_{3,252(t-44)} - \cdots - 28.10 \\
& S_{3,252(t-55)} + Y_{3,t-1} + a_{3,t}.
\end{aligned}
$$



(a) Actual vs Predicted ARIMA (0,1,0)

(b) Bar plot residual standardized value

Figure 14. Time series graph ARIMA(0,1,0) and residual standardized values

Table 8. Details of the impact of COVID-19 on South Korean KS11 stocks

Time (*t*)	Date	Magnitude of Impact	Extraordinary Event
T+36 – T+40	12 – 18 March 2020	-63.41	The day after WHO declared COVID-19 a global pandemic. There is a social distancing policy from the government and quarantine at home.
T+41 – T+42	19 – 20 March 2020	-114.30	Educational institutions are temporarily closed, workers are sent home to avoid the spread of the virus. The government provides masks for the public
T+43	23 March 2020	-43.14	Today, there were only 64 new cases, which is the lowest since COVID-19 broke out.
T+44 – T+45	24 – 25 March 2020	-237.97	The Shincheonji Church Cluster emerged, which is thought to be the second wave of COVID-19 in South Korea. Bringing instability back to several sectors
T+46 – T+49	26 – 31 March 2020	-139.29	The government carried out mass inspections, designating the city southeast of Daegu as a Special Disaster Area.
T+50	01 April 2020	-57.65	In early April, the South Korean government provided financial assistance to residents affected by COVID-19, to facilitate economic stability in society.
T+51 – T+54	02 – 07 April 2020	-161.36	There was a trade war between America and China which had an impact on the global economy.
T+55	08 April 2020	-133.26	The South Korean government is preparing an additional budget to stimulate the stock market into the green zone. The government extends the policy of limiting activities.

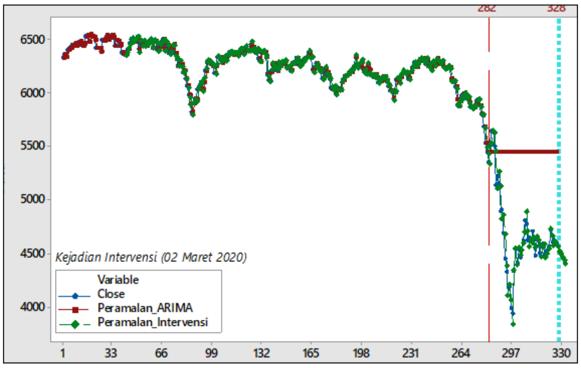
Based on the estimated intervention model, it can be concluded that the COVID-19 pandemic had a progressively worsening impact on South Korea's KS11 index. Thirty-six days after the intervention event, the index experienced a decline of -63.41 points, indicating the early stage of a negative market response. This adverse effect continued to escalate, with the magnitude of the deterioration increasing to -133.26 points by the 55th day. These findings highlight the prolonged and intensifying nature of the market disruption caused by the pandemic. Further details regarding the impact are presented in Table 8.

Table 8 highlights the significant and escalating impact of COVID-19 on South Korea's KS11 index. The initial decline began after the WHO's pandemic declaration, coinciding with domestic measures such as social distancing and school closures. Market instability deepened with the emergence of the Shincheonji Church Cluster, leading to the most significant drop during the observed period. Although some government interventions aimed to stabilize the economy, additional shocks, including the U.S.–China trade tensions, sustained the downward pressure. By April 8, 2020, the index had fallen by -133.26 points, reflecting internal and global uncertainties.

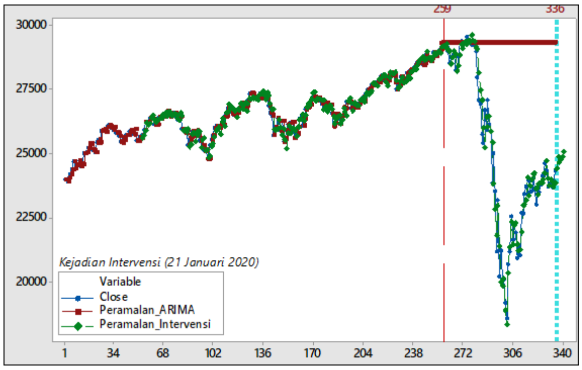
3.5. Comparison dan Discussion

The prediction results for the stock price indices, including IHSG Indonesia, and those for specific countries, such as the Dow Jones Index and KS11, are presented using the intervention model. These results, shown in Figure 18, highlight the model's ability to capture the dynamics and fluctuations of the stock indices in response to various external factors. The intervention model provides valuable insights into the behavior of these markets, offering a clearer understanding of how specific events and policies can impact stock price movements across different countries.

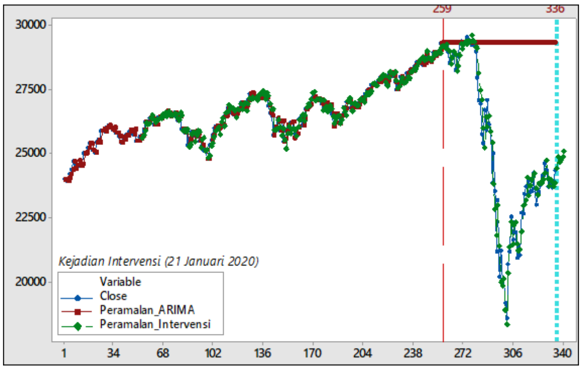
The results of the time series graphs displayed in Figure 15a Figure 15b, and Figure 15c, reveal that the stock price index predictions derived from the intervention model closely align with the actual observed data patterns. This suggests that the intervention model exhibits high forecasting accuracy, effectively



(a) IHSG



(b) DJI



(c) KS11

Figure 15. Graph of actual vs forecast results using intervention model

capturing the dynamics of the stock indices in question. The intervention at key dates, such as 2nd March 2020 for IHSG, 21st January 2020 for DJI, and 20th January 2020 for KS11, provides a robust framework for understanding the impact of external events on stock market behavior. This accuracy underscores the model's effectiveness in predicting market responses to significant changes.

Table 9. Details of forecasting result accuracy measurement

Variable	Stock Price Index	Accuracy of Forecasting Results	
		MSE	MAPE
Y_1, t	IHSG	3400.79	0.72%
Y_2, t	INDEXDJX: DJI	112674.80	0.87%
Y_3, t	KS11: KOSPI Composite Index	558.97	0.82%

The evaluation of forecast accuracy using MAPE (Mean Absolute Percentage Error) clearly indicates how well the intervention model predicts stock price indices (refer to Figure 15 and Table 9). IHSG (Y_1, t) demonstrated the lowest MAPE of 0.72%, indicating that the model was highly accurate in capturing the dynamics of the Indonesian stock market with minimal error.

In contrast, DJI (Y_2, t) had a slightly higher MAPE of 0.87%, which still reflects good accuracy. This could be attributed to differences in global economic conditions. As represented by the DJI, the U.S. stock market exhibits distinct fluctuations and characteristics compared to Asian markets. Although the absolute errors were larger, the relatively low MAPE suggests that the intervention model effectively handled these differences in market dynamics, maintaining strong forecasting accuracy.

The KOSPI Composite Index (Y_3, t) had a MAPE of 0.82%, indicating good accuracy, albeit slightly higher than IHSG. This might reflect the model's challenges in capturing the movements of the KOSPI index, which is influenced by distinct global economic factors. However, the error remains low, demonstrating the model's ability to predict reasonably.

4. Conclusion

This study concludes that the COVID-19 pandemic significantly disrupted stock price indices in Indonesia, the United States, and South Korea, with substantial declines observed across all three markets. For IHSG, the sharpest decline occurred on 26 March 2020, with a peak drop of 731.57 points, followed by a gradual recovery. DJI experienced similar volatility from March to April 2020, while KOSPI also saw a significant drop in early April, influenced by domestic and global uncertainties. Despite these disruptions, the forecasting accuracy of the intervention model was strong. IHSG achieved the best accuracy with a MAPE of 0.72%, indicating excellent precision. DJI and KOSPI had MAPEs of 0.87% and 0.82%, respectively, reflecting good accuracy despite market volatility. All MAPE values below 1% demonstrate that the intervention model was highly effective in forecasting stock price indices during the pandemic, showcasing its reliability in modeling market behavior under such volatile conditions.

Author Contributions. **Andrea Tri Rian Dani**: Conceptualization, Methodology, Validity tests, Writing-Preparation of the first draft, and Supervision. **Fachrian Bimantoro Putra**: Analysis, Visualization, Editing

Draft, and writing original draft. All authors discussed the results and contributed to the final manuscript.

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