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The Modeling of Jakarta Composite Index Data Before and During COVID-19 Pandemic and its Alignment into Government Policy in Energy Sector

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Abstract: The COVID-19 pandemic brings significant effects to the global stock market, including Indonesia. This study investigates the behavior and fluctuation of Jakarta Composite Index (JKSE) before the COVID-19 pandemic arises (2018–2019) and 2 years during the COVID-19 pandemic (2020–2021) and its alignment with the government policy in the energy sector. This study will use the JKSE data before and during the Covid-19 pandemic. The study showed that before COVID-19 pandemic, the JKSE was in normal conditions and showed an increasing trend. However, the study found anomalies in the JKSE volatility when COVID-19 pandemic was officially announced in Indonesia during 1st quarter 2020. This study is able to find the forecasted next 30 days best models that can describe the pattern of JKSE data are AR (2)–GARCH (1,1) models for the closing price of JKSE data before the COVID-19 pandemic and AR (5)–GARCH (1,1) models for the closing price of JKSE data during the COVID-19 pandemic. With the government economic recovery program related to the energy sector, this study was able to forecast the next 30 days for the closing price of JKSE during COVID-19, which showed the improvement of JKSE into the small increasing trend. These findings are expected to increase public investor trust, especially foreign investors investing their money in the JKSE. The positive trend in JKSE will ensure the government continues its economic policy recovery plan.

Key-Words: - Jakarta Composite Index, Auto regression, GARCH model, Forecasting

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1 Introduction

The GDP of Indonesia was still dominated by the commodity and power sectors. The government royalties from these two sectors reached IDR 121.1 trillion. Budget deficit balance as the key indicator showed significant improvement from −2.59% in 2015 to −1.82% in 2019. The Indonesia crude price was growing at 30% yearly, which reached at US$70 per barrel in the end year 2019. Meanwhile, the rise of fuel and gas subsidies that has been triggered by the upward trend of international oil and gas prices reached 69.605 billion Rupiah for the gas subsidy and 59.300 billion Rupiah for the electricity subsidy. Coal as one source of commodity export significantly contributes to Indonesia's balance of trade. Coal exports before the pandemic occurred reached 73.57 million tons, [1]. The strong performance of exports and the stability of the Rupiah exchange rate gave the positive contribution of macroeconomic performance and were shown by the increasing trend of JKSE index. Indonesia is ranked the highest investment destination especially in the stock and bond market and is the most promising country among the other 32 emerging market countries for 2019 based on the survey conducted by Bloomberg on 57 global investors, [2].

The condition changed when COVID-19 virus spread all over the world. The first positive COVID-19 case in Indonesia was officially announced on March 2, 2020, and on March 31, 2020; the Indonesian government declared large-scale social distancing to minimize the spread of the virus. The pandemic is having a major impact on economic activity in Indonesia. COVID-19 pandemic caused the Indonesia government to widen the deficit level of −6.34% in 2020. In 2020, the government revenue from two main energy sectors (oil and gas) decreased to IDR 53.3 trillion. Subsidies for transport fuel fell 41%, while the LPG subsidy fell 56%. Fuel sales and power sector dropped due to the travel restrictions, physical distancing policies as well as economic slowdown. Electricity usage for the commercial sector in Jakarta has decreased by 11.38%, the industrial sector has decreased by 15.81%, and the residential sector has increased by 4.73%, [3]. On the contrary, there is an increase in LPG subsidy since there is increasing consumption of food and homemade cooking, [4]. This subsidy burdens the country’s budget since 70% of Indonesia’s LPG supply is imported, [5]. Coal industries also experienced the same significant drops in volumes and prices and affected Indonesia’s exports due to lower coal demand in some countries and coal oversupply globally. During the pandemic, the coal exports have decreased by 44.35% from the same period last year, [1].

Stock market investors respond to this changing situation and their reactions have an impact on the volatility of stock markets in Indonesia, [6]. The JKSE reached its lowest level and fell by 38% from the year 2020 due to negative sentiment from the major global financial market and COVID-19 outbreak in Indonesia, [7]. In addition, the fear of COVID-19 outbreak had caused capital outflow of foreign investors from the Jakarta Stock Market. Some previous studies have examined the impact of the COVID-19 pandemic on financial market performance, in which the market had a negative reaction in response to the virus spreading, [8] which pushed higher volatility in the stock market, [9].

However, this condition was only temporary and showed improvement when the Indonesia government started to take precautionary action to stabilize the economic condition. [10] suggested that government policy stimulus packages would restore overall investor confidence by boosting stock prices. The Indonesian government launched the National Economic Recovery Program (PEN) containing specific programs to revive the economy. The government started to launch the National Economic Recovery along with the healthcare program as a response to minimize the impact of COVID-19 pandemic. The following economic stimulus programs in macro and micro economics were implemented: the restructuring program or relaxation program for the SME’s customers, giving capital assistance for SMEs, vaccination programs all across the country, social distancing, working from home activities, and various programs to the most impacted industries such as tourism and services.

In addition, some strategy initiated was lowering the energy subsidy allocation for fiscal year 2020 from IDR 31.044 billion to IDR 19,900 billion, [11]. Through the Ministry of Energy and Mineral Resources Regulation No. 7/2020 in March 2020, the Indonesia government expanded the coal mining industries that are eligible to receive fiscal incentives in terms of reduced royalties. Through fiscal stimulus package II, the government offered four types of incentives for the 6 months, including free import tax, 30% deduction of income tax, and personal income tax borne by the government, and accelerated restitution with the limit raised to IDR 5 billion, [12]. The government also issued financial regulation to stimulate the business sector by allowing deferment of loan installments, a lower increase rate for specific projects, and exemption from penalties, [13].

This research used modeling time series data in analyzing the stock market behavior before and during COVID-19 pandemic and can be used for forecasting and prediction of future values. The autoregressive conditional heteroscedasticity (ARCH) or generalized autoregressive conditional heteroscedasticity (GARCH) model can be used to forecast stock volatility as suggested by [14] in his previous study. Meanwhile, the application of this model in the Indonesia stock market can be found in the research of, [15]. The study will use the Jakarta Composite Index (JKSE) over 2 years before the COVID-19 pandemic rises in Indonesia (2018–2019) and during the COVID-19 pandemic (2020–2021). This study aims to find the best model for JKSE data before and during COVID-19 pandemic and its alignment with the government policy in energy sectors that was already covered in the economic recovery plan.

2 Statistical Modeling

In this study, the closing price of Jakarta Composite Index (JKSE) shares from January 2018 to October 2021 will be discussed using time series modeling. The closing price of JKSE data will be divided into two categories, namely, data before (BPC) and during the COVID-19 pandemic (DPC), and each data will be modeled using time series modeling. In the JKSE data study, both data sets will be analyzed using time series model analysis methods, parameter estimation, hypothesis testing, and further analysis. Before constructing the best model for both data sets (BPC and DPC), the assumption of stationary data will be checked. Stationary assumption checks will be carried out by looking at data trend patterns in the 2018–2019 (BPC) and 2020–2021 (DPC). In addition, it will also be examined whether the data has an ARCH effect. There are two approaches to examining the stationary data used: to examine the behavior of the data plot and to examine the results of the stationary test using the augmented Dickey–Fuller (ADF) test with the null hypothesis that the data is not stationary, [16], [17], [18], [19]. If the data is not stationary, then the data is transformed using a differencing process, so that the data becomes stationary, [17], [20]. To test the effect of ARCH, the Portmanteau Q test and the Lagrange multiplier (LM) test were used. If there is an ARCH effect on the data before the COVID-19 pandemic (BPC) and during the COVID-19 pandemic (DPC), then the GARCH model will be used to model the residual BPC and DPC data. To estimate the order of the autoregressive (AR) model, the corrected Akaike information criterion (AICC) will be used. The AR process provides a class of models that are very useful in univariate time series to describe the dynamics of individual time series. The order pth AR, AR(p), is formulated as follows: for example, for JKSE closing price data before the COVID-19 pandemic (BPC):

$$BPC_t = \gamma_0 + \gamma_1 BPC_{t-1} + \gamma_2 BPC_{t-2} + \dots + \gamma_p BPC_{t-p} + \varepsilon_t, \quad (1)$$

where BPC_t is a closing price of JKSE at time t before COVID-19 pandemic, γ_0 is a constant, $\gamma_1, \gamma_2, \dots, \gamma_p$ are the coefficient parameters for BPC_{t-1}, BPC_{t-2}, …, BPC_{t-p}, respectively, and ε_t is the white noise.

Similar for data closing price JKSE during COVID-19 pandemic (DPC), the order qth AR, AR(q), is:

$$DPC_t = \delta_0 + \delta_1 DPC_{t-1} + \delta_2 DPC_{t-2} + \dots + \delta_q DPC_{t-q} + \xi_t, \quad (2)$$

where DPC_t is a closing price of JKSE at time t during COVID-19 pandemic, δ_0 is a constant, $\delta_1, \delta_2, \dots, \delta_q$ are the coefficient parameters for DPC_{t-1}, DPC_{t-2}, …, DPC_{t-q}, respectively, and ξ_t is the white noise.

Augmented Dickey–Fuller (ADF) Test

The ADF test is used to check the stationary data BPC and DPC with the null hypothesis that the data BPC and DPC are non-stationary, [16], [17], [19]. The ADF test with lag-p is formulated as follows, [21], [16], for data BPC and DPC can be conducted the same way.

$$BPC_t = \alpha_t + \eta BPC_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta BPC_{t-i} + \varepsilon_t, \quad (3)$$

where α_t is a constant function at time t, $\Delta BPC_t = BPC_t - BPC_{t-1}$ is the difference of a series of BPC_t, and ε_t is the white noise. The ADF test (or tau test) statistic is formulated as follows:

$$\tau\text{-test (ADF test)} = \frac{\hat{\eta} - 1}{std(\hat{\eta})} \quad (4)$$

and the null hypothesis is rejected if the P-value is <0.05, [16], [22].

AICC

In time series modeling, several model selection criteria are available, such as AICC, HQC, AIC, and BSC. The best model is selected from several models with the smallest criterion value. Basically, AICC is an estimate of the quality of the statistical model. In this study, the AICC will be used in an effort to select the best model. The calculation process is as follows: let a linear model with p coefficient of parameters and let $\hat{\sigma}_p^2$ be the likelihood estimator of variance. Therefore,

$$\hat{\sigma}_p^2 = \frac{RSS_p}{T}, \tag{5}$$

where $RSS_p = \sum_{t=1}^{p}(BPC_t - \overline{BPC})^2$, for data before COVID-19 pandemic, is the residual sum of squares under the model with p coefficients of parameters. The AICC is defined as follows:

$$AICC = \ln \hat{\sigma}_p^2 + \frac{T+p}{T-p-2}, \tag{6}$$

where T is the sample size, [16], [23].

Testing for White Noise

To check whether errors (residuals) are white noise, Q-statistic (or Box–Pierce test) or Ljung–Box test will be used, [23]. The Q-statistic (Q_{BP}) tests the null hypothesis that the errors (residuals) are white noise. The Q-statistic is calculated as follows:

$$Q_{BP} = T \sum_{j=1}^{p} \hat{\rho}_j^2, \tag{7}$$

where $\hat{\rho}_j$ is the estimate of autocorrelation at lag j and T is the sample size. Under the null hypothesis, the Q_{BP} statistic is asymptotically the Chi-square distribution with k degrees of freedom, $\chi^2(p)$.

Test for Normality Distribution

There are some methods available to check the normality of the errors (residuals). Some methods are commonly used to check whether the errors (residuals) are normally distributed: (1) check the histogram of the residuals, (2) check the Q–Q plot of the data or error (residuals), and (3) use the statistical test, the Jarque–Bera (JB) test, with the null hypothesis that the data are normally distributed, [22], [16]. The JB test is calculated as follows:

$$JB = \frac{T}{6}\left[S^2 + \frac{(K-3)^2}{4}\right], \tag{8}$$

where T is the sample size, S is the expected skewness, and K is the expected excess kurtosis.

Testing for ARCH Effect

The ARCH was introduced by [23] and later developed further by [14] who expanded the ARCH concept into GARCH. The GARCH model was developed based on the assumption that the variance is not constant or heteroscedastic. Before we apply the ARCH or GARCH model to the JKSE BPC and JKSE DPC data, it must be tested whether the data has an ARCH effect on the residual (error). If there is an ARCH effect, then the ARCH or GARCH model will be used in modeling for the JKSE BPC data and JKSE DPC data. To test the ARCH effect, we used the LM test with the null hypothesis that there is no ARCH effect. The null hypothesis is rejected if the P-value <0.05. To perform the LM test, the residual model is built as follows:

$$\varepsilon_t^2 = \gamma_o + \gamma_1 \varepsilon_{t-1}^2 + \ldots + \gamma_p \varepsilon_{t-p}^2 + u_t \tag{9}$$

From model (9), R-square (R^2) value can be calculated, and then calculate the LM test. The LM test is defined as follows:

$$LM = T.\ R^2, \tag{10}$$

where T is the sample size and R^2 is the R-square computed from model (9). Under the null hypothesis, the LM test approximately has a Chi-square distribution with p degrees of freedom, $\chi^2(p)$, [17].

AR(p)–GARCH (k, l) Model

In the AR(p) model, it is assumed that error ε_t is independent and identically distributed (white noise). However, in practice, this assumption is sometimes violated. Let the observations for data JKSE before the pandemic COVID-19 are: BPC_1, BPC_2, …, BPC_n be generated by the AR(p) model, and then the residuals are generated by the GARCH (k, l) process as follows:

$$BPC_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i BPC_{t-i} + \varepsilon_t \tag{11}$$

and

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \phi_i \varepsilon_{t-i}^2 + \sum_{i=1}^{l} \mu_i \sigma_{t-i}^2 \tag{12}$$

Models (11) and (12) are called the AR(p)–GARCH (k, l) model. Under the GARCH (k, l) model, the conditional variance depends on the squares error (residual) in the previous k periods and the conditional variance in the previous l periods. Usually, a GARCH (1,1) model is adequate to obtain a good model fit for share price time series data, [21].

Forecasting

Forecasting will perform after obtaining the best model for both data JKSE before COVID-19 pandemic and data closing price of JKSE during COVID-19 pandemic. By using the best model that fits the data, forecasting is carried out directly for the next 30 periods.

3 Result and Discussion

The data used in this study is the closing price of the JKSE from January 2018 to October 2021, where in January 2018 to December 2019, there were 485 data before the COVID-19 pandemic, and the price January 2020 to October 2021 is data at the time of the COVID-19 pandemic as many as 448 data with an average of 20 trading days in each month.

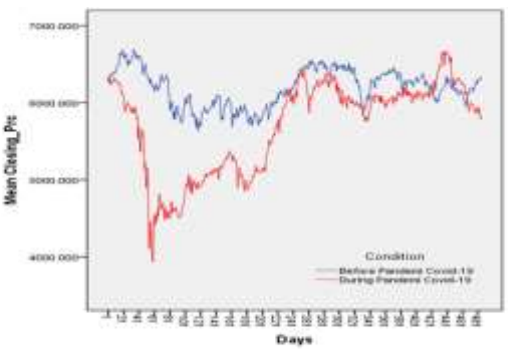


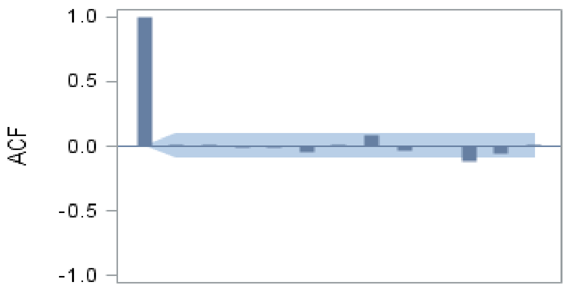
Fig. 3: Plot data for the closing price of the JKSE before the COVID-19 pandemic (blue line) and during the COVID-19 pandemic (red line)

Figure 3 shows that the closing price JKSE before the COVID-19 pandemic (2018–2019), namely, the blue line, shows that the fluctuations are relatively not too extreme. From January 2018 to April 2018, the trend decreased; from April 2018 to October 2018, the trend was horizontal; from October 2018 to January 2019, the trend was increased; and from January 2019 to December 2019, the trend was flat and fluctuating. During the COVID-19 pandemic, the red line indicates that the stock price has fallen quite deep, from around 6300 at the beginning of January 2020 to around 4000 at the end of March 2020; from April 2020 to December 2020, the closing price JKSE trend increased, and throughout the year 2021, the closing price of JKSE is relatively stable, but the price is still below the JKSE price in 2019 before the COVID-19 pandemic. Figure 3 shows a significant downward price change during the COVID-19 pandemic throughout 2020. Figure 4 also shows that the JKSE data both before and after COVID-19 showed non-stationary data.

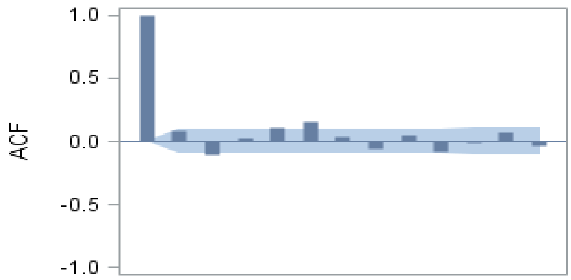
Since the data is not stationary, data differencing is carried out so that the data meets the stationary assumption, [17]. To check the stationary of the data, we can use analytical approaches such as the ADF (augmented Dickey–Fuller) test, the ACF test, and also other suitable tools to test the stationary of the data, [18].

Table 2. ADF test of JKSE closing price before and during the COVID-19 pandemic after differencing with lag = 1 (d = 1)

Type	Data	ADF Test	P-value
Mean	Before the COVID-19 pandemic	−16.67	<0.0001
	During the COVID-19 pandemic	−19.50	<0.0001



(a)



(b)

Fig. 4: ACF plotting after differencing with d = 1 for (a) closing price of JKSE before the COVID-19 pandemic and (b) during the COVID-19 pandemic

Due to the closing price of JKSE data before and during the COVID-19 pandemic, it was not stationary; the next step is to transform the data so that the data becomes stationary, namely, by differencing the data with lag = 1 (d = 1). After the data is differencing, the closing price of JKSE data before and during the COVID-19 pandemic became stationary. By using the ADF test (Table 2), it was significantly rejected because the P-value (<0.0001) was smaller than the value of = 0.05. Furthermore, this result is also reinforced by the ACF (Fig. 4 (a) and (b)) for the closing price of JKSE data before and during the COVID-19 pandemic; it decreases very quickly, indicating that both data were stationary. Thus, after the data is stationary, we need to know whether this research requires autocorrelation modeling using autoregression (AR) or moving average or a combination of the two, namely, the ARMA model using the AICC criteria.

Model Determination by Using AICC Criteria

AICC is one of the criteria used to determine the optimum lag in this study, [17]. Based on the results of the AICC analysis (Table 3), the AR(P) model with the optimum lag for the closing price of JKSE data before the COVID-19 pandemic is AR(2) and the best AR(p) model for the closing price of JKSE data during the COVID-19 pandemic is AR(5) because it has the smallest value compared to other values.

Table 3. Determination of candidate models based on the minimum AICC for the closing price of JKSE data before and during the COVID-19 pandemic

Minimum information criterion based on AICC for JKSE Closing Price before the COVID-19 Pandemic						
Lag	**MA 0**	**MA 1**	**MA 2**	**MA 3**	**MA 4**	**MA 5**
AR 0	7.957	7.960	7.958	7.961	7.965	7.965
AR 1	7.957	7.964	7.962	7.965	7.970	7.969
AR 2	7.954	7.961	7.964	7.969	7.969	7.966
AR 3	7.958	7.965	7.968	7.971	7.968	7.970
AR 4	7.963	7.969	7.968	7.967	7.972	7.974
AR 5	7.967	7.969	7.967	7.970	7.975	7.963

Minimum information criterion based on AICC for JKSE Closing Price during the COVID-19 Pandemic						
Lag	**MA 0**	**MA 1**	**MA 2**	**MA 3**	**MA 4**	**MA 5**
AR 0	8.958	8.965	8.938	8.933	8.893	8.888
AR 1	8.958	8.963	8.941	8.927	8.897	8.890
AR 2	8.910	8.921	8.914	8.909	8.898	8.889
AR 3	8.916	8.919	8.913	8.912	8.902	8.893
AR 4	8.895	8.897	8.902	8.901	8.905	8.897
AR 5	8.881	8.892	8.896	8.901	8.904	8.901

Test for ARCH Effect

The problem arises that causes an estimation measurement in time series data to be inefficient due to heteroscedasticity, so we need to apply an adequate method such as the GARCH model. Therefore, we need to confirm whether there is a heteroscedasticity problem in the data using the ARCH effect test.

Table 4. ARCH effect of the closing price of JKSE data before and during the COVID-19 pandemic

Data	Test	P-value
The closing price of JKSE data before the COVID-19 pandemic	ARCH effect	0.0022
	Normality	<0.0001
The closing price of JKSE data during the COVID-19 pandemic	ARCH effect	<0.0001
	Normality	<0.0001

ARCH effect test with the null hypothesis there is no ARCH effect and the alternative hypothesis is there is an ARCH effect. Judging from the information contained in Table 4, from the test results for the closing price of JKSE data before the COVID-19 pandemic, it can be concluded that the null hypothesis is rejected so that there is an ARCH effect that is indicated by a P-value of less than 0.05, which is 0.0022, so it is necessary to model the variance, namely, GARCH modeling for the residue. For data on the closing price of the JKSE during the COVID-19 pandemic, the null hypothesis was also rejected, so it is necessary to model GARCH for the residual, which is indicated by a P-value (<0.0001) less than 0.05.

Model AR (p)–GARCH (p, q) Data Closing Price of JKSE Data Before and During the COVID-19 Pandemic

The following is the best model for parameter estimation for AR(p) and GARCH (p, q) for JKSE closing price data before and during the COVID-19 pandemic.

Table 5. Parameter estimation model AR(2)-GARCH (1,1) for the closing price of JKSE data before the COVID-19 pandemic

Model parameter estimates the closing price of JKSE data before the COVID-19 pandemic					
Parameter	**Estimate**	**Std error**	**t-value**	**P-value**	**Variable**
CONST1	1.09601	2.35321	0.47	0.6416	1
AR1_1_1	0.01269	0.05122	0.25	0.8044	BPC_{t-1}
AR2_1_1	−0.10055	0.04448	−2.26	0.0242	BPC_{t-2}
GCHC1_1	2386.51187	201.37416	11.85	0.0001	
ACH1_1_1	0.39061	0.08135	4.80	0.0001	
GCH1_1_1	−0.00006	0.48511	−0.00	0.9999	

Based on the results of the analysis in Table 5, the best model for the closing price of JKSE data before the COVID-19 pandemic is AR(2)–GARCH(1,1), so the best model estimation is:

Mean Model AR(2):

$$\mathrm{BPC_t} = 1.09601 + 0.01269\mathrm{BPC_{t-1}} - 0.10055\mathrm{BPC_{t-2}} + \varepsilon_\mathrm{t}$$

and the variance model, GARCH(1,1):

$$\sigma_t^2 = 2386.5118 + 0.3906\varepsilon_{t-1}^2 - 0.00006\sigma_{t-1}^2$$

where BPC_t is the closing price of JKSE data before the COVID-19 pandemic, ε_t is the residual at time t, and σ_t^2 is variance at time t. The AR(2) model for the closing price of JKSE data before the COVID-19 pandemic was chosen as the best model based on the optimum AICC. AR(2) means that the current price is influenced by the price of the previous 2 days. The constant value of the JKSE closing price before the COVID-19 pandemic was 1.09601, which means that if the other variables are fixed, the closing price of JKSE data before the COVID-19 pandemic is 1.09601. If the closing price of the JKSE before the COVID-19 pandemic at time t-1 (BPC_{t-1}) increases by 1 unit and other variables are held constant, then the closing price of the JKSE before the COVID-19 pandemic will increase by 0.01269. If the closing price of the JKSE data before the COVID-19 pandemic at time t-2 (BPC_{t-2}) increases by 1 unit and other variables are held constant, then the closing price of the JKSE before the COVID-19 pandemic will decrease by 0.10055.

Table 6. Parameter estimation model AR(5)-GARCH (1,1) for the closing price of JKSE data during the COVID-19 pandemic

Model parameter estimates the closing price of JKSE data during the COVID-19 pandemic					
Parameter	Estimate	Std error	t-value	P-value	Variable
CONST1	4.0686	3.0234	1.35	0.1791	1
AR1_1_1	−0.2081	0.0553	−3.76	0.0002	DPC_{t-1}
AR2_1_1	−0.1107	0.0531	−2.08	0.0377	DPC_{t-2}
AR3_1_1	0.0195	0.0524	0.37	0.7106	DPC_{t-3}
AR4_1_1	0.1160	0.0505	2.29	0.0222	DPC_{t-4}
AR5_1_1	0.0662	0.0485	1.37	0.1726	DPC_{t-5}
GCHC1_1	592.9424	174.3579	3.40	0.0007	
ACH1_1_1	0.4468	0.0565	7.91	0.0001	
GCH1_1_1	−0.8378	0.0359	−23.33	0.0001	

From Table 6, the model chosen for the closing price of JKSE data during the COVID-19 pandemic is AR(5)–GARCH(1,1), so the best estimated model is:

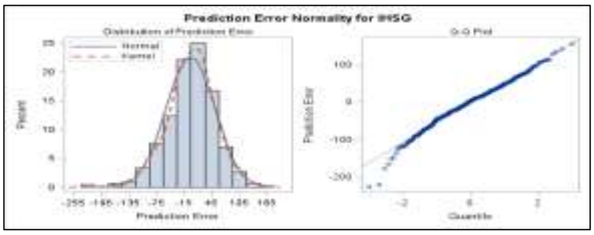
Mean Model AR(5):

$$DPC_t = 4.0686 - 0.2081\,DPC_{t-1} - 0.1107DPC_{t-2} + 0.0195DPC_{t-3} + 0.1160DPC_{t-4} + 0.0662DPC_{t-5} + \xi_t$$

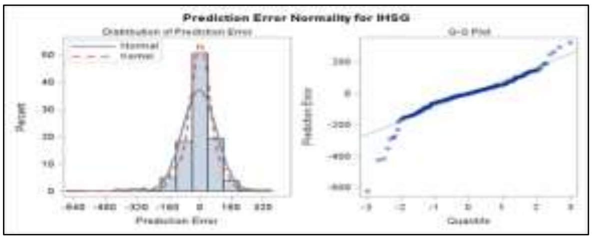
And the variance model, GARCH(1,1):

$$\sigma_t^2 = 592.9424 + 0.4468\xi_{t-1}^2 - 0.8378\sigma_{t-1}^2.$$

Here, DPC_t is the closing price of JKSE data during the COVID-19 pandemic, ξ_t is residual at time t, and σ_t^2 is the variance at time t. For the closing price of JKSE data during the COVID-19 pandemic based on the optimum AICC, the AR(5) model is the best model. AR(5) means that the current price is influenced by the price of the previous 5 days. The constant value of the closing price of JKSE data during the COVID-19 pandemic was 40,686, which means if the other variable is zero (0), then the closing price of JKSE data before the COVID-19 pandemic is 4,0686. If the closing price of JKSE data during the COVID-19 pandemic at time t-1, DPC_{t-1}, increases by 1 unit and other variables are held constant, then the closing price of JKSE data during the COVID-19 pandemic will decrease by 0.0662. If the closing price of JKSE data during the COVID-19 pandemic at time t-5, DPC_{t-5}, increases by 1 unit and other variables are held constant, then the closing price of JKSE data during the COVID-19 pandemic will decrease by 0.1005.



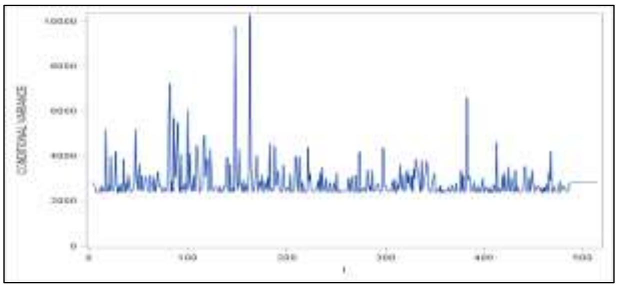
(a)



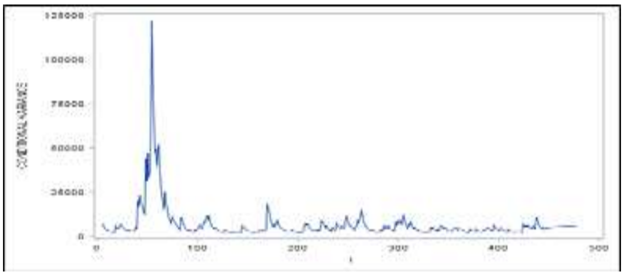
(b)

Fig. 5: Distribution of error predictions and Q-Q plots for data (a) JKSE closing price before and (b) during the COVID-19 pandemic

From the results of the normality test of the closing price of JKSE data before and during the COVID-19 pandemic, the residual value of the data is not normally distributed because the P-value is smaller than 0.05. However, the error distribution and the Q-Q plot for the closing price of JKSE before (Fig. 5a) and during the COVID-19 pandemic in Fig. 5b shows that there is a deviation that is not too far from the normal distribution although statistically the null hypothesis is rejected, but the error distribution graph is close to normal.



(a)



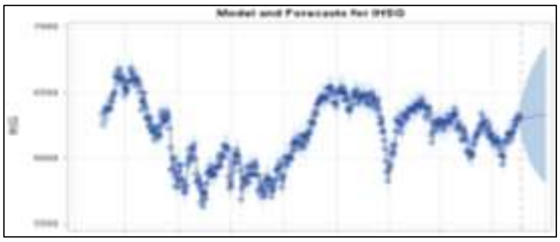
(b)

Fig. 6: Conditional variance (a) Model AR(2)-GARCH(1,1) for the closing price of JKSE data before the COVID-19 pandemic. (b) Model AR(5)-GARCH(1,1) for the closing price of JKSE data during the COVID-19 pandemic

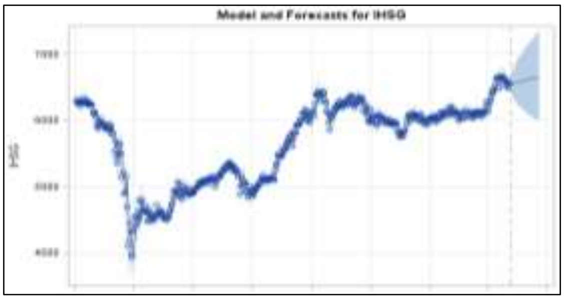
Figure 6(a) shows the ARCH effect model AR(2)-GARCH(1,1) for the closing price of JKSE data before the COVID-19 pandemic, from January 2018 to September 2018 the volatility was high, this condition showed that prices were very unstable and unpredictable. From October 2018 to December 2019, the volatility is relatively small; this shows that data changes in this time range are relatively stable in terms of not drastic ups and downs. Figure 6(b) is the conditional variance for the AR(5)-GARCH(1,1) model showing high volatility from January 2020 to April 2020; this shows that the closing price of JKSE data is very unstable, and this in line with Figure 3, indicating a very drastic decrease in the closing price and this situation also indicating that the prices were unpredictable in this time range. From May 2020 to December 2021, the volatility is relatively small, this shows that the price changes up and down are not drastic.

Forecasting

Forecasting is carried out for the next 30 days.



(a)



(b)

Fig. 7: (a) Plot of data and forecasting for the next 30 days for the closing prices of JKSE data before the COVID-19 pandemic and (b) data and forecasting for the closing prices of JKSE data during the COVID-19 pandemic

Table 7. Forecasting data for the next 30 days for the closing price of JKSE data before and during the COVID-19 pandemic

Forecasting the next 30 days for JKSE closing price data before COVID-19				
Obs	Forecast	Standard error	95% confidence limits	
486	6299.26	50.20	6200.87	6397.66
487	6303.35	73.18	6159.91	6446.79
488	6304.53	88.03	6131.99	6477.06
489	6305.23	100.44	6108.36	6502.09
490	6306.21	111.66	6087.37	6525.06
491	6307.25	121.86	6068.40	6546.10
492	6308.26	131.27	6050.98	6565.54
493	6309.27	140.04	6034.80	6583.73
494	6310.27	148.29	6019.63	6600.91
495	6311.28	156.11	6005.32	6617.24
496	6312.29	163.55	5991.73	6632.84
497	6313.30	170.67	5978.79	6647.81
498	6314.30	177.51	5966.40	6662.21
499	6315.31	184.09	5954.51	6676.11
500	6316.32	190.44	5943.06	6689.57
501	6317.33	196.59	5932.02	6702.63
502	6318.33	202.55	5921.34	6715.33
503	6319.34	208.34	5911.00	6727.68
504	6320.35	213.98	5900.96	6739.74
505	6321.36	219.47	5891.21	6751.50
506	6322.36	224.82	5881.72	6763.01
507	6323.37	230.05	5872.47	6774.27
508	6324.38	235.17	5863.45	6785.30
509	6325.39	240.18	5854.65	6796.12
510	6326.39	245.08	5846.05	6806.74
511	6327.40	249.89	5837.63	6817.17
512	6328.41	254.60	5829.39	6827.42
513	6329.42	259.24	5821.32	6837.51
514	6330.42	263.79	5813.41	6847.43
515	6331.43	268.26	5805.65	6857.21

Forecasting the next 30 days for JKSE closing price data during COVID-19				
Obs	Forecast	Standard error	95% confidence limits	
449	6559.03	66.44	6428.80	6689.25
450	6558.76	86.08	6390.04	6727.48
451	6553.24	100.19	6356.88	6749.60
452	6565.20	114.20	6341.38	6789.02
453	6568.76	129.77	6314.42	6823.09
454	6571.30	142.74	6291.54	6851.06
455	6574.62	154.65	6271.51	6877.73
456	6579.60	166.16	6253.93	6905.27
457	6583.29	177.24	6235.90	6930.68
458	6586.96	187.65	6219.17	6954.75
459	6590.87	197.62	6203.54	6978.20
460	6594.89	207.24	6188.70	7001.08
461	6598.73	216.52	6174.35	7023.11
462	6602.60	225.47	6160.68	7044.52
463	6606.50	234.15	6147.59	7065.42
464	6610.41	242.56	6134.99	7085.82
465	6614.29	250.74	6122.84	7105.73
466	6618.18	258.70	6111.14	7125.22
467	6622.07	266.45	6099.84	7144.31
468	6625.97	274.02	6088.90	7163.03
469	6629.86	281.40	6078.32	7181.40
470	6633.75	288.62	6068.06	7199.44
471	6637.64	295.68	6058.11	7217.17
472	6641.53	302.60	6048.45	7234.62
473	6645.42	309.37	6039.06	7251.79
474	6649.32	316.02	6029.93	7268.70
475	6653.21	322.54	6021.05	7285.37
476	6657.10	328.93	6012.40	7301.80
477	6660.99	335.22	6003.97	7318.01
478	6664.88	341.40	5995.76	7334.01

From Table 7 and Figure 7(a), predictions for the next 30 days for the closing price of JKSE before the COVID-19 pandemic are as follows: to experience an increasing trend, assuming normal conditions or no COVID-19 pandemic. However, if we compare them with the closing price of JKSE data plot at the beginning of COVID-19 (Figure 7(b)) in the month of January 2020 to April 2020, the closing price of JKSE data has decreased drastically; this shows that the COVID-19 pandemic caused price chaos and the closing price of JKSE decreased drastically and unpredictable. This means that the COVID-19 pandemic has had a huge impact on changes in the closing price of JKSE. For forecasting when COVID-19 occurs (Table 7 and Figure 7(b)), it shows an increasing trend. The forecasting results obtained in this study can only be used for short-term periods because we can see that the risk for longer periods increases significantly over time. This can be seen from the value of the confidence interval for both the closing price of JKSE data before and during the COVID-19 pandemic, which shows that for a long forecast period, the predictive value is unstable (high standard error).

4 Conclusion

This study discusses the behaviour of the closing price of JKSE data 2 years before the COVID-19 pandemic (2018–2019) and 2 years during the COVID-19 pandemic (2020–2021).

The best model for the closing price of JKSE data before the COVID-19 pandemic is AR(2)-GARCH (1,1), while the best model for the closing price of JKSE data during the COVID-19 pandemic is AR(5)-GARCH(1,1).

The results of data forecasting for models before the COVID-19 pandemic describe an increasing trend, assuming normal conditions and no COVID-19 pandemic. However, in reality, there was a COVID-19 pandemic and the closing price of JKSE data experienced a very drastic decline in the period January 2020 to April 2020; this shows that the COVID-19 pandemic has had a very high impact on price changes, which decreased drastically from the closing price of the JKSE. This large and unstable price is also indicated by the high value of the volatility data in the range of January 2020 to April 2020. Forecasting for the next 30 days for the closing price of JKSE data during COVID-19 shows an increasing trend, although the increase is small.

The growing domestic demand in consumption and investment and the improvement of global economic conditions will speed up Indonesia's economic recovery into a better curve. The Indonesian government also actively participates in maintaining the financial market stability. There was a stock market anomaly during the COVID-19 pandemic in Indonesia in that the pandemic interacted positively with the Indonesian stock market.

The increasing trend of JKSE stock price showed the higher confidence and trust from investors to the government's commitment to achieve the target of the country's economic growth at 4.8% in the year 2022.

There is an urgency to continue in implementing new reform of energy subsidies as it has had an important impact on GDP growth by spending priorities in fuel consumption and reducing energy subsidy to boost economic development across the country.The non-tax state revenue from the oil and gas sector was expected to rebound aligned with the good performance of export commodities.

The results of this study have several practical implications. First, the existence of a stock market anomaly implies investors' confidence in future returns and in an eventual market recovery. Therefore, financial market authorities should implement strategies to maintain and even increase investors' confidence. In addition, the government should intervene by implementing stimulus packages to alleviate stock market panic and avoid capital outflow from the country.

The future research should be able to consider other variables that can influence the JKSE performance growth such as: the exchange rate; foreign capital outflow/inflow and other industries which had major contribution in JKSE, including: financial industries.

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-Florentina Kurniasari and Nurhuda Nizar carried out the modelling and statistical testing.
-Eko Endarto and Helena Dewi collecting the secondary data (JKSE stock price).
-Cynthia Sari Dewi responsible for collecting information of macro-economic especially in Indonesia policy in energy sector.

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Conflict of Interest
The authors have no conflicts of interest to declare that are relevant to the content of this article.