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ARIMA Models For Kijang Emas Price Forecasting: Pre- and Post-COVID Analysis

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Abstract

Gold has significant economic value in a country's economic landscape, serving as a hedge against inflation, particularly during financial turmoil. In Malaysia, gold is known as Kijang Emas and serves as the official bullion gold coin. The price of gold also impacts stock market dynamics, making understanding its fluctuations essential for risk-averse investors. However, the credibility of gold as an investment has been called into question due to price volatility caused by various factors, including the recent upheaval caused by the COVID-19 pandemic. The goal of this study is to explore the effectiveness of the ARIMA model in modelling and forecasting daily Kijang Emas prices in Malaysia from 2012 to 2022, divided into two phases: pre-COVID-19 and post-COVID-19. Model performance was assessed using metrics such as AIC, MAE, and MAPE. The results that the ARIMA model can analyse and forecast Kijang Emas prices, particularly on post-COVID-19 data with high volatility and uncertainty. This insight is valuable for investors seeking to understand market trends and develop future strategies.

Keywords: ARIMA; COVID-19; kijang emas; volatility.

1 Introduction

Time series analysis is a powerful tool for understanding and forecasting sequential data. The observations collected at fixed time intervals aid in the identification of patterns and trends in various fields, including economics, finance, ecology, and environment. The primary goals of time series analysis are to explain and summarise data as well as forecast future values. To achieve these goals, one must identify and interpret data patterns, which can be classified into two main components: trend and seasonality.

In this study, time series modelling and forecasting techniques were applied to analyse uncertain data in financial markets, specifically gold prices. Volatility, or the variance between high and low data values, is a critical aspect of time series analysis in finance. According to Miswan [8], price volatility in financial markets is often measured using conditional return variance as a proxy for asset risk. By accurately understanding and forecasting volatile values, researchers can better assess and manage financial risk.

Our focus is on Kijang Emas, also known as "Malaysian Gold", a valuable commodity introduced by Bank Negara Malaysia (BNM) on July 17, 2001. Kijang Emas has a long history of trading and mining in Malaysia and was once an important medium of exchange before being replaced by paper money and coins. Sukri et al. [12] stated that gold is a valuable investment for both the short and long term and is considered valuable worldwide. Gold is also a liquid asset that can be easily converted into paper money. Due to unpredictable economic instability, investors often use gold as a hedge against risk and as a means of storing wealth.

The COVID-19 pandemic has had a significant impact on global markets, including Malaysia. On March 18, 2020, the Malaysian government implemented the movement control order to curb the spread of the virus. The country's economy was further affected by the declaration of emergency throughout the country by Yang Di-Pertuan Agong on January 12, 2021. These events caused gold prices to fluctuate unevenly over time [1]. Accurate gold price forecasting is critical for understanding international monetary policy. With a thorough understanding of this variable, economists can more effectively navigate the challenges of promoting economic development in the post-COVID-19 era [9].

This study aims to investigate Kijang Emas price trends by determining an appropriate time series model and evaluating its performance in forecasting. The modelling of Kijang Emas prices was evaluated over three phases: the overall time span, pre-COVID-19, and post-COVID-19. The ultimate goal was to identify the appropriate ARIMA model in providing reliable forecasts for this uncertain dataset.

2 Related Works

The COVID-19 pandemic has presented unprecedented challenges to financial and commodity markets, inspiring a growing body of research [15]. In Malaysia, the government implemented the Movement Control Order (MCO) on 18th March 2020, extending it subsequently to the Recovery Movement Control Order (RMCO) until 31st December 2020 [7]. These measures were enacted to mitigate the spread of the disease. The period before the first MCO declaration represents the pre-COVID-19 phase, while the initiation of the MCO signifies the inception of the new norm practices or the post-COVID-19 phases. The pandemic has placed immense stress on all aspects of the economy, not just agriculture and food. However, the impact of the crisis on commodity markets remains underexplored.

Gold prices in Malaysia are influenced by global market demand but are regulated by the BNM. According to Khamis and Awang [6], Gold prices vary by country and currency, and a country's economic development success can influence its value. Gold prices are denominated in US dollars, and as such, they are closely linked to fluctuations in the value of the US dollar.

The uncertain nature of gold prices during pre-COVID-19 attracted attention from many researchers and analysts to develop forecasting models due to gold being seen as an inflation hedge and a proven store of value. According to Rahmadia and Febriyani [17], the gold market is one of the three sectors most affected by the COVID-19 pandemic due to the uncertain global situation, and its price cannot be forecast with previous forecasting models. Due to a lack of research and literature following COVID-19, investors and investment institutions were unable to make accurate decisions in forecasting gold prices [1]. Therefore, this study aims to contribute to the current literature and assist researchers in making informed decisions based on current gold price trends.

Statistical analysis of time series data has a long history, with forecasting being a primary objective in many cases. Although the specific goals of time series analysis may vary, forecasting is often a major component of such studies. One popular time series model is the Box-Jenkins autoregressive integrated moving average (ARIMA) model, which was first proposed by George Box and Gwilym Jenkins in 1970. The ARIMA model has been widely used in practical applications due to its ability to handle non-stationary data. Gold prices have been shown to follow random movements and exhibit non-stationary characteristics, making ARIMA a potentially useful forecasting model [18]. The ARIMA model has become popular in financial market forecasting due to its statistical nature in providing accurate short-term forecasts and ease of application [6].

The Box-Jenkins ARIMA model has not only been applied in financial and economic markets but also in social and environmental sectors. For instance, Swain et al. [14] applied this model to forecast monthly rainfall in the Khordha district of Odisha from 1901 to 2002. The result demonstrates that ARIMA(1,2,1)(1,0,1)[12] outperforms others. Forecasts from the model were found to be in excellent agreement with observed monthly rainfall data, confirming its potential for future applications in the study area. Abhilash et al. [2] used the ARIMA model on pollution data such as NO2, PM10, and SO2. The results show that the data for PM10 and NO2 were stationary, resulting in a suitable forecasting model with the actual plot, while the remaining plots were analysed using non-stationary data. PM10 was identified as the dominant pollutant, while SO2 contributed the least.

Didiharyono and Syukri [3] conducted a social study using the ARIMA model to forecast open unemployment rates in South Sulawesi. The unemployment rate is one of the socio-economic issues that need to be addressed in all developing countries, including Indonesia. The ARIMA(1,2,1) model was discovered to be the best time series model for forecasting. In the healthcare setting, the ARIMA model was applied by Zheng et al. [19] to forecast infectious disease morbidity because it can consider trend changes, periodic changes, and random disturbances in time series. The ARIMA-ARCH hybridization model was used and the comparative analysis showed that the combined ARIMA(1,1,2)(1,1,1)[12]-ARCH(1) model was more effective in forecasting tuberculosis morbidity.

In financial applications, several researchers [13, 16, 5] found that the ARIMA model was able to capture the patterns and trends of each financial price movement and predict its future values during the COVID-19 pandemic. Nonetheless, despite the outstanding results, few studies have examined the performance of the ARIMA model during the pre- and post-COVID-19 phases, owing to the massive impact of the pandemic on the financial market [17].

According to the literature review, the Box-Jenkins ARIMA model has been widely used and has always been the underlying model in many areas of time series analysis. Therefore, the focus of this study will be on the application of the ARIMA model in modelling and forecasting Kijang Emas prices pre- and post-COVID-19.

3 Materials and Methods

Figure 1 depicts the overall research framework, which began with data collection. Only stationary data was considered during the ARIMA model development process. As a result, stationarity testing was performed, followed by model identification, model diagnostics, and, finally, model forecasting.

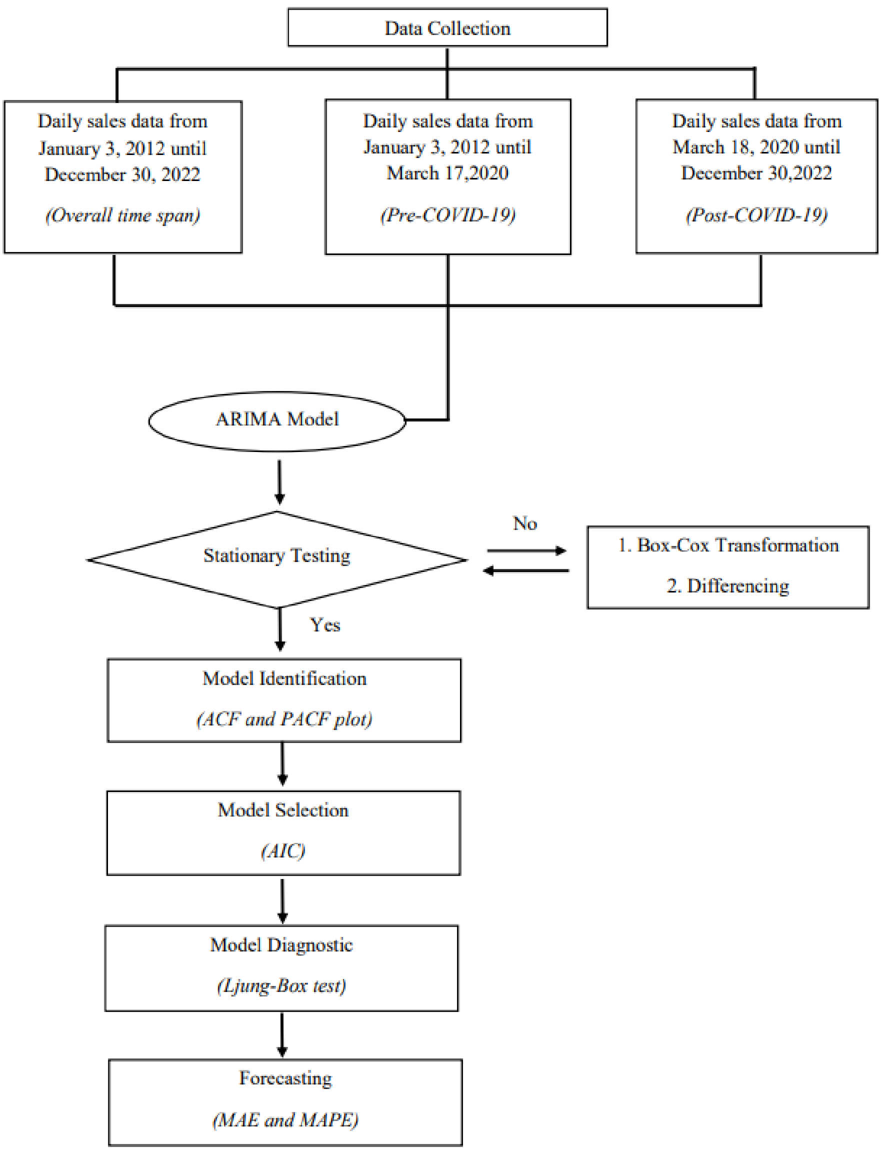

Figure 1: The overall research framework in forecasting Kijang Emas prices using ARIMA model.

3.1 Stationary Testing

Stationarity is a key concept in time series analysis, and Box-Jenkins models such as the ARIMA employ it before analysis and model building. Stationary data refers to data that has a constant mean, variance, and autocorrelation structure over time. Non-stationary data is data that decreases and increases at different rates over different time intervals, and some modifications can be made to achieve stationarity.

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was conducted to determine data stationarity. Consider the time series model as defined in Equation (1),

$$\Delta y_t = \mu D_t + \phi_t + \epsilon_t, \tag{1}$$

where $\phi_t = \phi_{t-1} + u_t$ and D_t is the determinant component, $u_t \sim I.I.D(0, \sigma^2)$, and $\epsilon_t \sim I.I.D(0, \sigma_u^2)$. The hypothesis test for the KPSS test against equation (1) is $H_0 : \sigma_u^2 = 0$ and $H_1 : \sigma_u^2 > 0$ with statistical tests of $KPSS = \frac{T^{-2}\sum_{t=1}^{T}\hat{S}_t^2}{\hat{\lambda}^2}$, with $\hat{S}_t = \sum_{j=1}^{t}\hat{u}_j$ is the cumulative error function and $\hat{\lambda}^2$ is the variance of the error ϵ_t. Under the null hypothesis, if the p-value of the KPSS test is less than a certain level of significance, such as 0.05, there is sufficient evidence that the data trend is constant. If the null hypothesis is rejected, the data must be modified using techniques such as differentiation and Box-Cox transformation.

Differencing can be used to reduce a nonhomogeneous stationary time series process to a stationary time series process. In general, the difference is expressed in Equation (2),

$$\Delta^d y_t = (1 - B)^d + y_t, \tag{2}$$

where y_t is the value of y at time t, B is for the backward shift operator, and d is the difference level. The differencing level on the original data series is called the order of integration, denoted by d. Generally, first- and second-order differences can produce stationary data.

The Box-Cox transformation is commonly used to stabilise the variance of a non-stationary time series process [4]. The Box-Cox transformation represents a family of power transformations that combine and extend the transformation options to find the optimal normalising transformation for each variable. The Box-Cox transformation is defined in Equation (3),

$$y_t^{(\lambda)} = \begin{cases} \frac{y_t^{\lambda} - 1}{\lambda}; \lambda \neq 0 \\ \log(y_t); \lambda = 0 \end{cases}, \tag{3}$$

where y_t is the variable for transformation and λ is the transformation parameter.

3.2 Volatility Testing

Volatility is a phenomenon characterized by the dynamic variation of the conditional variance in a time series. In essence, it denotes that the variance of the time series is not constant across different time periods. An effective method for quantifying the volatility of data involves the application of a Jarque-Bera (JB) test, where the measurement of kurtosis serves as a key descriptive statistic associated with the JB test. Kurtosis, in this context, gauges the peakedness of the distribution of the series. For data conforming to a normal distribution, the kurtosis value is expected to be three. However, in instances of heightened volatility, signifying a more pronounced peak, the kurtosis value often exceeds three. This condition is commonly referred to as leptokurtosis or being leptokurtic. The null hypothesis for JB test is written as H_0 : normally distributed versus its alternative hypothesis H_1 : non-normally distributed. The sample kurtosis and JB test statistics can be defined as in Equation (4) and Equation (5),

$$K = \frac{1}{n}\left(\frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^2}\right), \tag{4}$$

$$JB = \frac{n}{6}\left(S^2 + \frac{(EK)^2}{4}\right), \tag{5}$$

where $S = \frac{1}{n}\left(\frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{3/2}}\right)$ is the sample skewness and $EK = K - 3$ is the excess kurtosis of the data. Under the null hypothesis, the test statistics is distributed as chi-squared distribution, χ^2 with two degrees of freedom.

3.3 Box-Jenkins ARIMA Model

After achieving data stationarity in the previous step, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were used to determine the parameters for moving average (MA), q and autoregressive (AR), p. The Box-Jenkins ARIMA model, generally written as ARIMA (p, d, q) can be defined as in Equation (6),

$$(1 - \phi_1 B - ... - \phi_p B^p)(1 - B)^d y_t = \vartheta + (1 - \theta_1 B - ... - \theta_q B^q)\epsilon_t, \tag{6}$$

where ϑ is a constant coefficient, ϕ_p is the parameter coefficient of AR and θ_q is the parameter coefficient of MA. The adequacy of these ARIMA models is then evaluated.

3.4 Model Diagnostic

Model diagnostic analysis evaluates the adequacy of the model during the construction of a time series model. Model diagnostics were conducted to determine whether the model is suitable for the data. Adjustments or alternative time series models may be required if the model does not accurately represent the entire dataset. The Ljung-Box test is one of the statistical tests used in model diagnostic analysis. This test examines sample errors using an ACF plot to determine the null hypothesis that the data is independently distributed, as well as whether the chosen time series model is appropriate for the data being analysed and makes necessary adjustments to improve forecast accuracy. The null hypothesis is written as $H_0 : r_1 = r_2 = ... = r_n$, whereas the alternative hypothesis is written as $H_0 : r_i \neq 0$ for at least one i, where $i = 1, 2, ..., n$. The Ljung-Box test can be represented as Equation (7),

$$Q = n(n + 2)\sum_{i=1}^{r}\frac{r_i^2}{n - i}, \tag{7}$$

where r_i^2 is the sample autocorrelation of residual at i and n represents the number of observations. Under the null hypothesis, the distribution of the Ljung-Box test statistic is skewed against the chi-squared distribution, χ^2 with $(k - p - q)$ degrees of freedom.

3.5 Forecasting

Forecasting is essential for operational control and planning in many areas, including quality control, investment analysis, financial planning, and production management. Certain criteria must be met to select the best model based on forecast values. Before forecasting, the best model based on model values must be selected. Modelling was done with in-sample (training) data, while forecasting was done with out-of-sample (testing) data. The Akaike information criterion (AIC) is one of the model evaluation criteria used in determining the goodness of fit of the model. The AIC can be expressed using Equation (8),

$$AIC = 2k - 2\ln(\hat{L}), \tag{8}$$

where k is the number of model parameters and $\hat{L}$ is the maximum likelihood of the model. The model with the lowest AIC is regarded as having the best fit for the data.

Following that, the model evaluation criteria for forecasting against test data was tested using evaluation values such as mean absolute error (MAE) and mean absolute percentage error (MAPE) [11]. These evaluation metrics determine the accuracy of the time series model in forecasting out-of-sample data. MAE is a measure of the error between the observed true value and the predicted value in pairs, while MAPE is a measure in percentage terms and can be calculated as the average absolute per cent error divided by the actual value at each time period. MAE and MAPE are expressed in Equation (9) and Equation (10), respectively.

$$MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n}, \tag{9}$$

$$MAPE = \left(\frac{\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} \right) \times 100, \tag{10}$$

where y_t is the actual value at time t, $\hat{y}_t$ is the predicted value at time t, and n is the number of observations. The best model for forecasting data is one with the lowest MAE and MAPE.

4 Results and Discussion

The Kijang Emas price dataset for this study is shown in Table 1, which was obtained from the BNM website. The dataset contains 2685 data points representing the selling price of 1 ounce of Kijang Emas in Malaysian Ringgit (MYR) from January 3, 2012, to December 30, 2022.

Table 1: Partial Kijang Emas price dataset in MYR.

Weight (Oz)	1		0.5		0.25	
Date	Selling	Buying	Selling	Buying	Selling	Buying
3/1/2012	5,283	5,078	2,691	2,539	1,370	1,270
4/1/2012	5,346	5,139	2,723	2,570	1,387	1,285
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
30/12/2022	8,506	8,166	4,333	4,083	2,207	2,042

*Reference : *https://www.bnm.gov.my/kijang-emas-prices*

The data was divided into three phases: pre-COVID-19, post-COVID-19, and the overall time span. Figure 2 depicts the Kijang Emas selling price from the dataset plotted against the time index for three phases: (a) the pre-COVID-19 phase, (b) the post-COVID-19 phase, and (c) the overall time span.

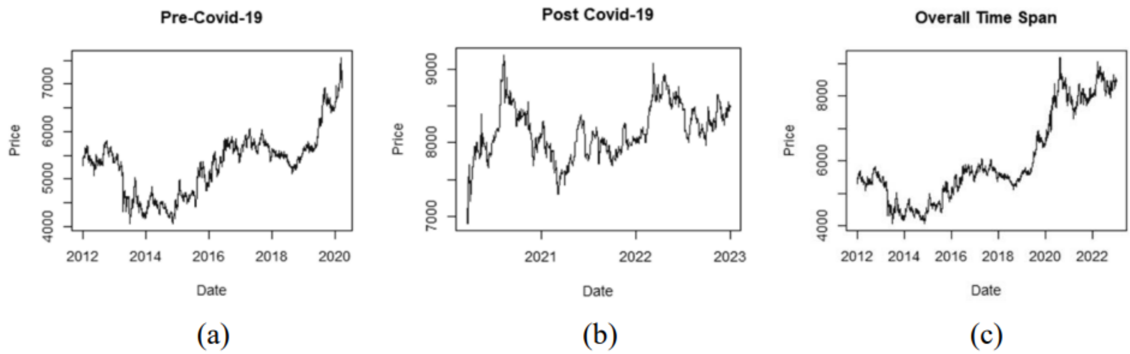

Figure 2: Kijang Emas 1oz selling price vs time (January 2012 - December 2022).

The analysis begins with the KPSS test for stationary testing. Figure 2 depicts the increasing trend across all three phases. The post-COVID-19 increase pattern is slower than the pre-COVID-19 timeline. The data was then transformed using the Box-Cox transformation and differencing to achieve stationary in the dataset. For the pre-COVID-19 phase, the KPSS test yielded a p-value of 0.0100, indicating that the time series is non-stationary. The value of lambda for the Box-Cox transformation is 1, indicating that no transformation is required. After the first-order differencing, the KPSS test yielded a p-value of 0.1000, which is greater than the 5% significant level, indicating that the time series has achieved stationarity.

For the post-COVID-19 phase, the KPSS test yielded a p-value of 0.0100, indicating that the time series is non-stationary. Table 2 shows the result of the KPSS test and the Box-Cox lambda. The value of lambda for the Box-Cox transformation is 1, indicating that no transformation is required. After the first-order differencing, the KPSS test yielded a p-value of 0.1000, which is greater than a 5% significant level, indicating that the time series has achieved stationarity. For the overall time span, the KPSS test yielded a p-value of 0.0100, indicating that the time series is non-stationary. The value of lambda for the Box-Cox transformation is 1, indicating that no transformation is required. After the first-order differencing, the KPSS test yielded a p-value of 0.1000, which is greater than a 5% significant level, indicating that the time series has achieved stationarity.

Table 2: The result of the KPSS test and box-cox transformation for the three phases.

		KPSS Test			
		Before differencing		After first differencing	
Phase	Box-Cox lambda	Test statistics	p-value	Test statistics	p-value
Pre-COVID-19	1	14.60943	0.0100	0.1789251	0.1000
Post-COVID-19	1	2.48916	0.0100	0.07820052	0.1000
Overall time span	1	28.93033	0.0100	0.1546622	0.1000

Figure 3 depicts the first-order differencing of the data for all three phases, where (a) is the first-order difference of the pre-COVID-19 phase, (b) is the first-order difference of the post-COVID-19 phase, and (c) is the first-order difference of the overall time span. As shown in Figure 3, the time series are stationary.

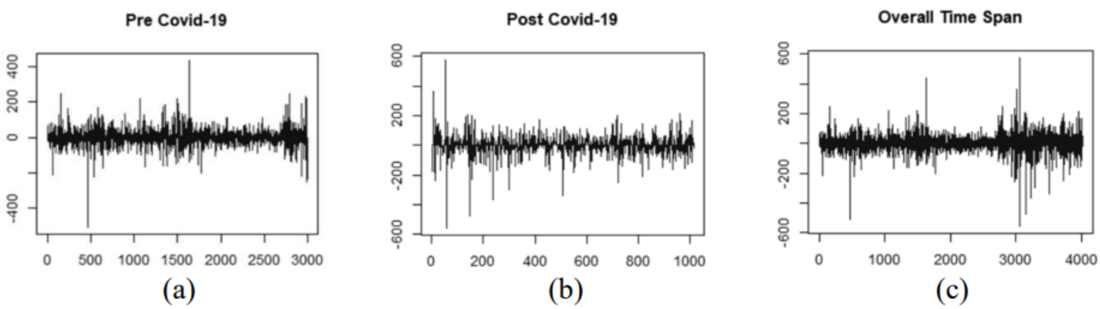

Figure 3: First-order difference of Kijang Emas prices data.

Upon achieving stationarity, the next step involves conducting volatility testing to quantify and assess the volatility of the data at various phases, subsequent to the first difference level as in Table 3. Across the pre-COVID-19, post-COVID-19, and the overall time span phases, the kurtosis values are observed to be 20.35421, 16.7131, and 22.74529, respectively. These values, surpassing the threshold of three, signify a pronounced peak and high volatility within each phase's distribution. The p-values resulting from the Jarque-Bera (JB) test for these three distinct phases are all less than 2.2e-16, falling below the 5% significance level. This suggests the rejection of the null hypothesis, indicating that the time series is non-normally distributed across the specified phases.

Table 3: The result of Jarque-Bera test for the three phases.

Phase	Kurtosis	Test statistics	p-value
Pre-COVID-19	20.35421	37605	2.2e-16
Post-COVID-19	16.7131	7999.4	2.2e-16
Overall time span	22.74529	65277	2.2e-16

Subsequently, the dataset corresponding to each phase will be partitioned into training and testing sets, maintaining an 80:20 ratio. This approach ensures that the model's efficacy is assessed through the training dataset, while the testing dataset remains independent for accurate forecasting evaluations. The model identification process began by computing the sample ACF and partial PACF. Figure 4 depicts the ACF and PACF correlograms for the first difference level of the time series for all three phases, where (a) is the residuals plot of first-order difference for the pre-COVID-19 phase, (b) is the residuals plot of first-order difference for the post-COVID-19 phase, and (c) is the residuals plot of first-order difference for the overall time span.

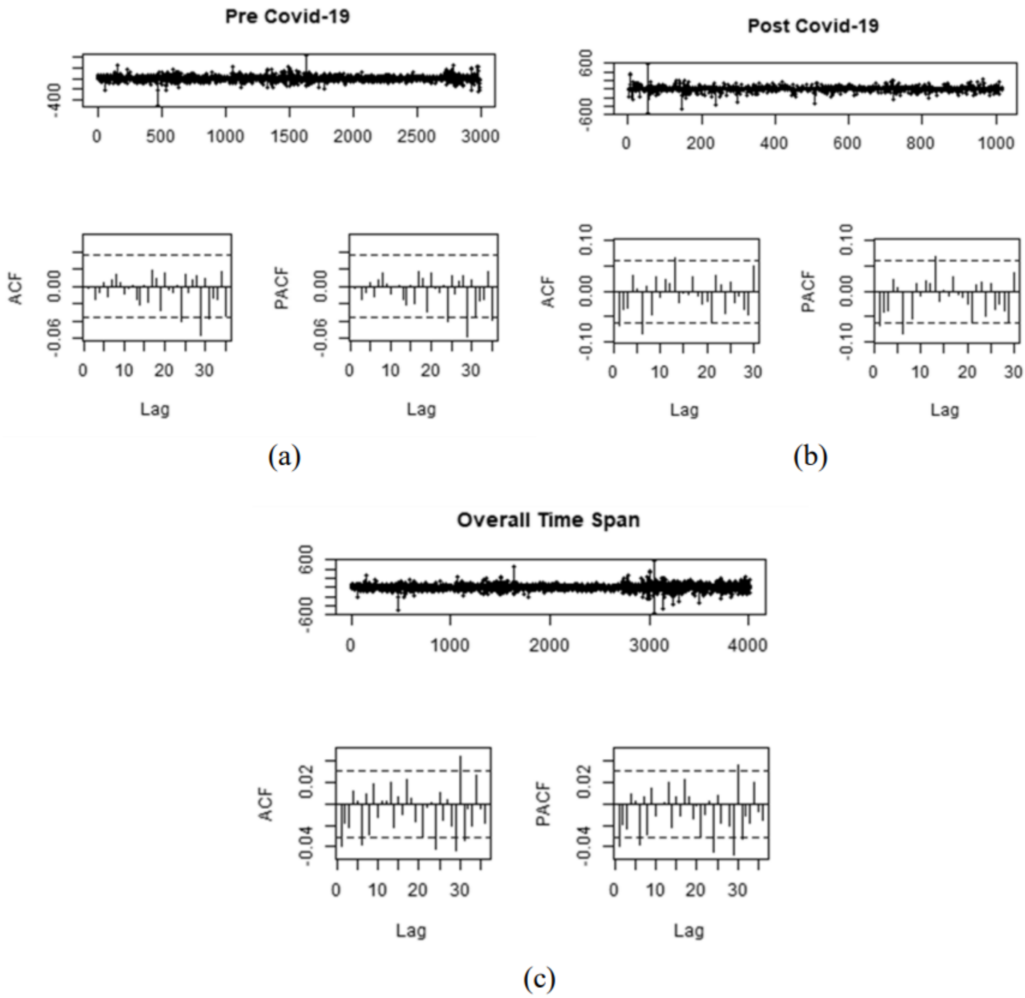

Figure 4: The residuals plots of the first-order difference of Kijang Emas price data.

Figure 4(a) shows that the values of p and q are both 24 for the pre-COVID-19 phase. Because these values are too large to compute, $p = 1$ and $q = 2$ were used instead. Therefore, the following ARIMA models were considered: ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,1), ARIMA(2,1,0), ARIMA(0,1,2), ARIMA(2,1,1), ARIMA(1,1,2), and ARIMA(2,1,2). In both Figure 4(b) and Figure 4(c), the values of p and q are 1 and 6, respectively. Consequently, eight models were evaluated with the same specifications for both the post-COVID-19 phase and the overall time span: ARIMA(1,1,1), ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,6), ARIMA(6,1,0), ARIMA(0,1,6), and ARIMA(6,1,6).

After identifying potential models, the parameters of the ARIMA models were estimated using R software. The parameters of the ARIMA models were estimated using maximum likelihood estimation. AIC determined the best model for fitting the training dataset, while MAE and MAPE determined the best model for forecasting the testing dataset. The model with the lowest value of the given criteria was chosen as the best model. Next, Ljung-Box test will be conducted. Table 4 compares the criterion and diagnostic values of the ARIMA models for each of the three phases.

Table 4: The Result of AIC, MAE, MAPE and Ljung-Box test Values of ARIMA Models.

		Training	Testing		Ljung-Box test	
Phase	Model	AIC	MAE	MAPE	χ^2 value	p-value
Pre-COVID-19	ARIMA(1,1,0)	24529.9	24.4113	0.38996	0.01635	0.898
	ARIMA(0,1,1)	24530.9	24.4430	0.39047	0.02128	0.884
	ARIMA(1,1,1)	24531.9	24.4282	0.39023	0.01037	0.919
	ARIMA(2,1,0)	24531.9	24.4313	0.39028	0.01399	0.906
	ARIMA(0,1,2)	24531.9	24.4523	0.39064	0.01097	0.917
	ARIMA(2,1,1)	24533.9	24.4176	0.39006	0.01569	0.900
	ARIMA(1,1,2)	24533.9	24.6867	0.39449	0.00188	0.965
	ARIMA(2,1,2)	24534.9	25.7314	0.41234	0.25333	0.615
Post-COVID-19	ARIMA(1,1,1)	9253.7	37.5821	0.45076	0.00075	0.978
	ARIMA(1,1,0)	9254.6	37.4037	0.44861	0.00143	0.969
	ARIMA(0,1,1)	9254.3	37.4469	0.44912	0.00068	0.979
	ARIMA(1,1,6)	9255.3	38.7209	0.46487	0.00209	0.964
	ARIMA(6,1,1)	9256.5	38.4588	0.46130	5.07e-05	0.994
	ARIMA(6,1,0)	9254.7	38.4568	0.46127	1.27e-05	0.997
	ARIMA(0,1,6)	9254.9	38.5195	0.46202	5.52e-06	0.998
	ARIMA(6,1,6)	9254.7	38.1086	0.45733	0.00238	0.961
Overall time span	ARIMA(1,1,1)	33925.8	36.1390	0.44293	0.00972	0.922
	ARIMA(1,1,0)	33925.9	35.9054	0.44004	0.00051	0.982
	ARIMA(0,1,1)	33925.7	35.9250	0.44029	0.00043	0.983
	ARIMA(1,1,6)	33930.6	36.8869	0.45214	1.12e-06	0.999
	ARIMA(6,1,1)	33930.5	36.9119	0.45245	1.51e-05	0.997
	ARIMA(6,1,0)	33928.4	36.5968	0.44856	0.00024	0.988
	ARIMA(0,1,6)	33928.7	36.6719	0.44948	0.00027	0.987
	ARIMA(6,1,6)	33934.1	37.9066	0.46456	0.80288	0.370

According to Table 4, ARIMA(1,1,0) has the lowest AIC, MAE, and MAPE values of 24529.9, 24.4113and 0.38996, respectively. As a result, ARIMA(1,1,0) is the best model for fitting the Kijang Emas price data and forecasting the price for the pre-COVID-19 phase. ARIMA(1,1,1) has the lowest AIC for the post-COVID-19 phase, which is 9253.7 while ARIMA(1,1,0) has the lowest MAE and MAPE values which are 37.4037 and 0.44861 respectively. This means that ARIMA(1,1,1) is the best model for modelling Kijang Emas prices, whereas ARIMA(1,1,0) is the best model for forecasting. For overall time span phase, ARIMA(0,1,1) has the lowest AIC which is 33925.7 while ARIMA(1,1,0) has the lowest MAE and MAPE values which are 35.9054 and 0.44004 respectively. This means that ARIMA(0,1,1) is the best model for modelling Kijang Emas prices, whereas ARIMA(1,1,0) is the best model for forecasting. Since the difference in modelling and forecasting performance between the two models is less than 1%, it can be concluded that the simplest model, ARIMA(1,1,0), is the best model for both the post-COVID-19 and overall time span phases.

Model diagnostics uphold the ARIMA model's assumption that there is no correlation between past errors and independently distributed errors. The Ljung-Box testing revealed that the best model chosen for each of the three phases resulted in p-values greater than the critical value at the 5% significant level of 0.898, 0.969, and 0.982, respectively. As a result, the data is distributed independently, and the model fits the data provided. The Ljung-Box test value for each best model in each phase is also shown in Table 4.

The values of MAE and MAPE for the pre-COVID-19 phase were lower than for the post-COVID-19 and overall time span phases based on the forecasting performance of the ARIMA models. This could be due to the stability of gold prices before the pandemic, as opposed to the volatility of prices during and after the pandemic. The post-COVID-19 phase has the highest MAE and MAPE values, which is consistent with the findings of a study by Rosli et al. [10], which examined the forecasting performance of the Malaysian stock market during the COVID-19 pandemic, during which prices were highly fluctuating, indicating that the stock price rapidly increased and fell in a short period of time.

The coefficients of parameters for each model were estimated using R software, and the equations of the models are shown in Table 5 by substituting the given coefficients into Equation (6). ARIMA(1,1,0) for the pre-COVID-19 phase, ARIMA(1,1,0) for the post-COVID-19 phase, and ARIMA(1,1,0) for the overall time span phase are given in Equation (11) to Equation (13).

$$y_t = 0.9195y_{t-1} + 0.0669y_{t-2} + \epsilon_t, \tag{11}$$
$$y_t = 0.9341y_{t-1} + 0.0659y_{t-2} + \epsilon_t, \tag{12}$$
$$y_t = 0.9670y_{t-1} + 0.0321y_{t-2} + \epsilon_t. \tag{13}$$

Table 5: The result of the KPSS test and box-cox transformation for the three phases.

Phase	Model	Equation
Pre-COVID-19	ARIMA(1,1,0)	$(1+0.0805B)(1\text{-}B)y_t = \epsilon_t$
Post-COVID-19	ARIMA(1,1,0)	$(1+0.0659B)(1\text{-}B)y_t = \epsilon_t$
Overall time span	ARIMA(1,1,0)	$(1+0.0321B)(1\text{-}B)y_t = \epsilon_t$

Figure 5 shows the forecasting results for each model in each phase one year or 365 days ahead: (a) ARIMA(1,1,0) for the pre-COVID-19 phase, (b) ARIMA(1,1,0) for the post-COVID-19 phase, and (c) ARIMA(1,1,0) for the overall time span phase. The figures demonstrate the ARIMA models' promising performance in forecasting daily Kijang Emas prices, with the trend in Figure 5(a) closely following the actual prices in Figure 2(c), and both Figures 5(b) and Figure 5(c) forecasting the same trend.

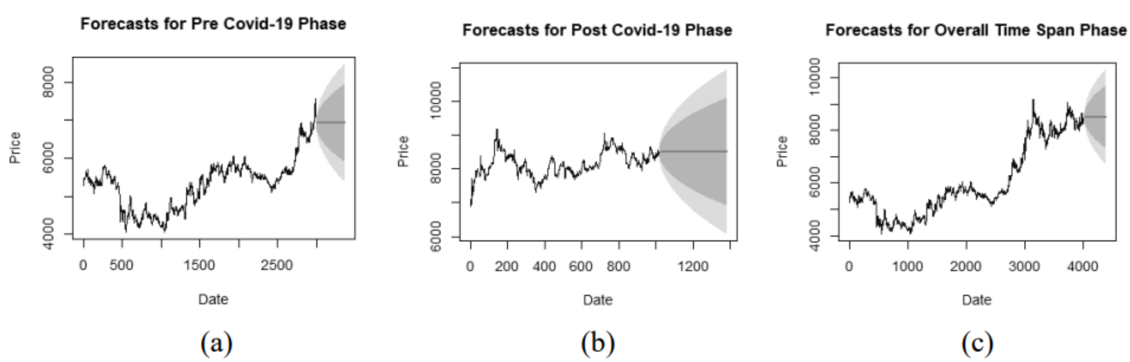

Figure 5: Kijang Emas price forecasting results for the 365 days ahead.

5 Conclusions

The performance of the ARIMA models used in modelling and forecasting the daily Kijang Emas price data series has been investigated in three phases: pre-COVID-19, post-COVID-19, and the overall time span. The dataset was subjected to differencing to address the non-stationary nature of the time series. According to the empirical results of the 2685-day Kijang Emas price data series, the ARIMA models produce optimal results and are suitable for forecasting the time series for each phase, specifically ARIMA(1,1,0) for all three different phases, pre-COVID-19, post-COVID-19 and the overall time span phases. In short, the Box-Jenkins ARIMA model is suitable for analysing and forecasting daily Kijang Emas prices. The ARIMA model, despite its strength and flexibility, cannot handle the volatility and nonlinearity found in many data series. The gold market, for example, has been volatile since it began actively trading on international markets in 1967. As a result, other forecasting models, such as generalised autoregressive conditional heteroscedasticity (GARCH) or long short-term memory (LSTM), may be used in future studies.

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Conflicts of Interest The authors declare no conflict of interest.

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