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SARIMAX–GARCH Model to Forecast Composite Index with Inflation Rate and Exchange Rate Factors

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Abstract

Investors should consider the Indonesia Composite Index (ICI) as a key indicator before making investment decisions, as it reflects the performance of industries and the broader economic growth. In Indonesia, the ICI exhibits fluctuating movements, making accurate forecasting essential for understanding the country's economic conditions, which are closely tied to capital flows, growth, and tax revenues. This study aims to forecast the ICI using the SARIMAX-GARCH model, incorporating macroeconomic factors such as the inflation rate and exchange rate. The findings reveal that both variables significantly impact the ICI, with the model achieving a Mean Absolute Percentage Error (MAPE) of 0.952% for training data and 5.233% for test data. The model's performance is supported by an R^2 value of 0.9782 and a Mean Squared Error (MSE) of 0.0003. This research not only improves the accuracy of ICI forecasts but also supports Indonesia's 8th Sustainable Development Goal (SDG) for decent work and economic growth.

Keywords: Indonesia Composite Index; SARIMAX-GARCH; Inflation Rate;, Exchange Rate; Sustainable Development Goals.

1. Introduction

1.1. Indonesia Composite Index

The Indonesia Composite Index (ICI) is a statistical measurement used to determine changes in the share prices of all companies listed in the capital market at a certain time compared to the base year [1]. The development of the ICI not only reflects the performance of a country's companies or industries but can also be considered a broader fundamental indicator of national economic health [2]. The movement of the ICI in Indonesia tends to fluctuate. In 2022, the ICI closed down 0.14% to 6,850.61 in the last trade. However, on a year-to-date (YTD) basis, the index increased by 4.09% throughout 2022, though this growth was not as high as in the previous period [3]. The volatile movement of the ICI is closely related to macroeconomic conditions. Macroeconomic factors are elements outside the company that can affect performance, either directly or indirectly. Inflation and exchange rates are macroeconomic variables that are known to affect the capital market [4].

1.2. Inflation Rate

Inflation is generally defined as a continuous increase in prices that applies broadly or impacts other goods and services [5]. As a key macroeconomic indicator, inflation significantly influences various aspects of the economy,

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including the stock market. Understanding the relationship between inflation and the ICI on the Indonesia Stock Exchange (IDX) is crucial for assessing its implications for the wider economy [6]. Studies such as Amalia (2016) show that inflation has a significant positive effect on the composite stock price index [7]. However, this finding contrasts with research conducted by Yudha (2016), which suggests that inflation has a significant negative effect on the composite stock price index [8]. Typically, a stable or low inflation rate reflects a healthy economy, boosting investor confidence. Conversely, high inflation can raise concerns about the government's ability to maintain economic stability, potentially reducing the ICI [9].

1.3. Exchange Rate

The exchange rate, specifically the comparison of the value of the rupiah with foreign currencies, is a crucial factor in determining the cost of goods and services across borders [10]. Research by Tampubolon (2021) indicates that the exchange rate has a significant negative effect on the ICI [11]. This study explains that if the rupiah depreciates, it can increase operational costs, thereby reducing company profits and affecting the ICI negatively. In contrast, Hasanudin (2021) demonstrates that a stronger rupiah can lead to better ICI performance [12]. The exchange rate used is the middle rate of the rupiah against the US dollar. A weakening dollar against the rupiah, coupled with less promising alternative investments, might lead investors to prefer holding dollars, further influencing the ICI [13].

1.4. Vision Statement

The urgency of this research lies in the need to improve the accuracy of ICI forecasts, an essential indicator of Indonesia's economic health. The SARIMAX-GARCH method, which extends the basic ARIMA model by including exogenous variables such as inflation and exchange rates while accounting for seasonal effects, offers a significant advancement. The SARIMAX model provides the ability to predict time-series observations and incorporate the influence of exogenous variables on the response variable. However, when applied to economic data, the SARIMAX model can encounter issues with non-constant variance. The GARCH model addresses this by managing variance non-uniformity in time series data, resulting in a robust prediction model [14]. Given the global economic uncertainties, such as those caused by the COVID-19 pandemic, this research is particularly urgent as it aims to provide more accurate forecasts of the ICI. This enhanced predictive capability supports better investment decisions and policymaking, directly contributing to the achievement of Indonesia's 8th Sustainable Development Goal (SDG), which targets decent work and economic growth.

2. Research Methodology

2.1. Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) method, also known as the Box-Jenkins method, was introduced by George Box and Gwilym Jenkins in 1970 [15]. ARIMA represents an Autoregressive Moving Average (ARMA) model that lacks stationarity. While the ARIMA method excels in short-term forecasting, its accuracy diminishes for long-term projections, often resulting in forecasted values remaining relatively constant over extended periods.

The ARIMA model comprises three processes: autoregressive, integration, and moving average, represented by the order autoregre. An essential assumption of ARIMA is the requirement of stationarity in variation. To address non-stationarity in the data, a differencing process is employed to make the data stationary, with the number of differencing steps denoted as (d). The fundamental principle of time series posits that the current observation (z_t). is influenced by one or more preceding observations (z_t). The general expression for the autoregressive integrated moving average model is denoted as ARIMA(p, d, q) [16].

$$\varphi_p(B)(1-B)^d Z_t = \theta_q(B)\varepsilon_t \tag{1}$$

where, B is denoted as backshift operation and $\varphi_p(B)$ is denoted as autoregressive (AR) backshift that follows second equation below.

$$\varphi_p(B) = \left(1 - \varphi_1 B - \cdots - \varphi_p B^p\right) \tag{2}$$

while, $\theta_q(B)$ is denoted as moving average (MA) backshift operator as follows.

$$\theta_q(B) = (1 - \theta_1 B - \cdots - \theta_q B^q) \tag{3}$$

with $(1-B)^d Z_t$ as time series that is stationary at the d-th differencing. This process is denoted with ARIMA (p, d, q).

ARIMA is usually estimated with maximum likelihood (MLE) method or conditional sum squares (CSS) method to find the estimation of all parameters. However, the selection of the number of parameters p and q in the

ARIMA model is based on the patterns observed in the autocorrelation function (ACF) and the partial autocorrelation function (PACF) as referred to Table 1 [17].

Table 1. Determine p and q in ARIMA Model

Model	ACF	PACF
ARIMA $(\boldsymbol{p}, \boldsymbol{d}, \mathbf{0})$	Dies down	Drop off after lag q
ARIMA $(\mathbf{0}, \boldsymbol{d}, \boldsymbol{q})$	Drop off after lag q	Dies down
ARIMA $(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$	Dies down (until lag q is still different from zero)	Dies down (until lag p is still different from zero)

2.2. Seasonal Autoregressive Integrated Moving Average (SARIMA)

A time series may occasionally exhibit seasonal phenomena that recur at specific intervals. The shortest time interval for these recurring phenomena is known as the seasonal period [18]. Seasonal periods commonly used include 1 month, 3 months, 4 months, 6 months, and 12 months or annually. In general, a seasonal ARIMA model is expressed as ARIMA$(p\ d\ q)(P\ D\ Q)^S$, where d is the nonseasonal differencing order, D is the seasonal differencing order, and S is the seasonal period. The general form of the seasonal ARIMA has been stated in Equation 4 as follows.

$$\emptyset_p(B)\ \Phi_P(B^S)(1-B)^d(1-B^S)^D\dot{Z}_t = \theta_q(B)\ \Theta_Q(B^S)\ a_t \tag{4}$$

where,

$\emptyset_p(B)$: $\left(1-\emptyset_1 B-\emptyset_2 B^2-\cdots-\emptyset_p B^p\right)$ polynomial of non seasonal AR(p)
$\theta_q(B)$: $\left(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q\right)$ polynomial of non seasonal MA(q)
$\Phi_P(B^S)$: $(1-\Phi_1 B^S-\Phi_2 B^{2S}\ldots-\Phi_P B^{PS})$ polynomial of seasonal AR(P)
$\Theta_Q(B^S)$: $\left(1-\Theta_1 B^S-\Theta_2 B^{2S}\ldots-\Theta_Q B^{QS}\right)$ polynomial of seasonal MA(Q)

2.3. Autoregressive Integrated Moving Average with Exogenous Variable (SARIMAX)

The ARIMAX model, an extension of the ARIMA model, incorporates additional or exogenous variables that are considered to have a significant impact on the data, thereby enhancing the accuracy of forecasting [19]. In the field of forecasting, there are other variables that are postulated to influence the model. The existence of these influential variables can lead to significant fluctuations in observation values, which recur over distinct time periods. As a result, a specialized model is necessary for forecasting under these conditions. The first step in ARIMAX modeling involves testing the stationarity of the exogenous variables [20]. According to Simms et al. (2022) [21], the general form of the ARIMAX $(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$ model can be expressed with the following equation.

$$Z_t = \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_p X_{p,t} + \frac{\theta_q(B)}{\varphi_p(B)(1-B)^d}\varepsilon_t \tag{5}$$

The exogenous variables $X_{i,t}$ $(i = 1,2,\ldots,t)$ in Equation 4 are presented under the condition of stationarity with each variable have their unknown parameter β. Extending this further, the ARIMAX model equation, when considering a stochastic trend and seasonality, is referred to as the SARIMAX model. The SARIMAX model represents an enhancement of the ARIMAX model, as it incorporates considerations for seasonal factors. The typical expression for the SARIMAX model is generally articulated as follows [22].

$$Z_t = \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots + \beta_p X_{p,t} + \frac{\theta_q(B)\Theta_Q(B^S)}{\varphi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D}\varepsilon_t \tag{6}$$

To determine the appropriateness of the obtained model, a diagnostic check is necessary. It is possible that the results of time series modeling may yield several models with all significant parameters. In such cases, the residuals should meet the white noise assumption and be normally distributed [23].

2.4. Generalized Autoregressive Conditional Heterocedasticity (GARCH)

The term 'volatility' is commonly used to describe the 'volatile' behavior observed in financial markets. Volatility has become significant in both financial theory and practice, playing a pivotal role in areas such as risk management and portfolio selection. In statistical analyses, volatility is typically quantified using variance or standard deviation. In 1982, Engle successfully introduced a volatility model for financial time series data, known as the Autoregressive Conditional Heteroscedasticity (ARCH) model. Furthermore, in 1986, Bollerslev developed a more adaptable volatility model, termed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) [24].

When the ARCH effect test indicates significance for a time series, it becomes feasible to estimate the ARCH model and concurrently derive an estimate of volatility, denoted as σ_t, based on historical information. In practical applications, the lag count, p, is often substantial, leading to a considerable number of parameters being estimated in the model. In 2002, Bollerslev, Zivot, and Wang introduced a more concise model, replacing the AR model with the subsequent formulation [25].

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{j-t}^2 \quad (7)$$

Ensuring that all coefficients $\alpha_i > 0\ (where\ i = 0,1,\dots,p)$ and $\beta_j > 0\ (where\ j = 1,\dots,p)$ are positive is necessary to maintain the positivity of the conditional variance σ_t^2. The equation presented above, coupled with the stationary time series equation (rt), is recognized as the Generalized Autoregressive Conditional Heteroscedasticity or GARCH(p, q) model. In the given equation, when $\beta_j > 0\ (where\ j = 1,\dots,p)$, the GARCH model transforms into an Autoregressive Conditional Heteroscedasticity or ARCH model.

2.5. Goodness of Fit Model

In modeling to generate predictions, goodness-of-fit measures are used to assess how accurately a model can estimate true values. The following are several techniques that can be employed to measure the goodness-of-fit of a model.

1) *Mean Absolute Percentage Error (MAPE)*

The Mean Absolute Percentage Error (MAPE) is a statistical measure employed in the evaluation of the accuracy of predictions or forecasts within a model. MAPE quantifies the average error in percentage terms between actual and predicted values [26], providing insight into the extent to which forecast errors compare to the actual data values. The statistical formula for MAPE is presented in Equation 8:

$$\text{MAPE} = \sum_{t=1}^{n} \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \times 100\% \quad (8)$$

Z_t indicates the actual value and $\hat{Z}_t$ indicates the predicted value. The smaller the percentage error value in MAPE, the higher the accuracy level of the forecasting results. Table 2 provides an interpretation of MAPE values [27].

Table 2. Interpretation of MAPE Values

MAPE Value Ranges	Interpretation
$< 10\%$	The ranges indicate that the model has a high degree of forecasting accuracy.
$10\% \leq MAPE \leq 20\%$	The ranges indicate that the model's forecasting accuracy is good.
$20\% < MAPE \leq 50\%$	The ranges indicate that the model has sufficient predictive power.
$> 50\%$	The ranges indicate that the model's predictive power is at its lowest.

2) *Mean Squared Error (MSE)*

The Root Mean Square Error (RMSE) serves as an error metric utilized to evaluate forecasting methods and measure the precision of a model's predictive outcomes. The Mean Squared Error (MSE), which is the average of squared errors, quantifies the extent of discrepancies between the model-predicted values and the actual values [28]. Consequently, a lower RMSE value signifies a higher level of accuracy in the model's predictions of actual values. The computation formula for RMSE is delineated in Equation 9 (n indicates sum of data).

$$\text{MSE} = \frac{\sum_{t=1}^{n} \left(Z_t - \hat{Z}_t\right)^2}{n} \quad (9)$$

3) *R Squared (R^2) – Coefficients of Determination*

According to Ghozali [29], a low coefficient of determination indicates a limited capacity of independent variables to explain the dependent variable. Conversely, a value approaching 1, distinct from 0, suggests that the independent variables have the potential to provide all the necessary information for predicting the dependent variable. The formula for calculating this coefficient is outlined below.

$$\text{R}^2 = 1 - \frac{\sum_{t=1}^{n} \left(Z_t - \hat{Z}_t\right)^2}{\sum_{t=1}^{n} (Z_t - \bar{Z})^2} \quad (10)$$

The larger the value of the coefficient of determination, the better the estimation results for the model. However, a coefficient value very close to 1 can lead to overfitting in the estimation results. Therefore, additional evaluations such as MSE and MAPE, as explained earlier, are needed.

2.6. Data Sources and Research Variables

This research employs a quantitative approach, focusing on the analysis of time series data using SARIMAX-GARCH methods. The data for the Indonesia Composite Index (ICI) was sourced from the Yahoo Finance website, while the data for Inflation and Exchange Rate was obtained from the Bank Indonesia website. The study utilizes monthly data spanning from January 2015 to March 2023. The research data is bifurcated into two segments: training data and testing data. The training data, which is used to construct the model, comprises data from January 2015 to September 2022. Conversely, the testing data, used to gauge the accuracy of the model, includes data from October 2022 to March 2023. In this context, the t index on each variable signifies time, and the significance level of α is set at 0.1. The variables employed in this research are delineated in Table 3. As an additional note, the analysis will be conducted in RStudio for model analysis and Minitab for visualization.

Table 3. Research Variables

Variable	Description
Z_t	Indonesia Composite Index
X_{1t}	Inflation Rate
X_{2t}	Exchange Rate (Dollars to Rupiah)

2.7. Data Analysis Stages

The procedure or stages of the analysis method in this study are systematically presented in the flow chart of Figure 1 as follows.

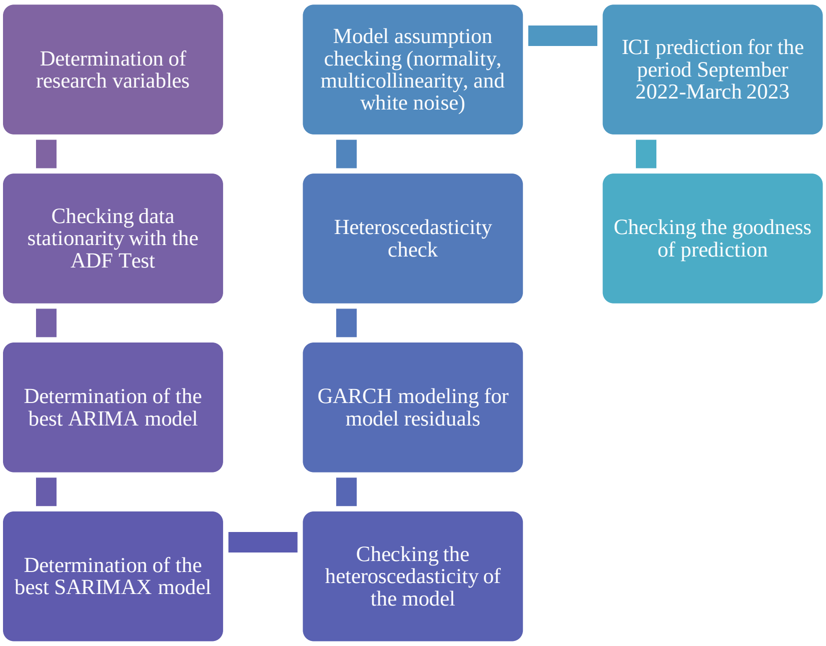


Figure 1. Data Analysis Stages Chart

3. Results and Discussion

3.1. Time Series Plots and Descriptive Statistics

Descriptive statistics serve as the initial observation to examine the characteristics of each variable, namely the Indonesia Composite Index (ICI), inflation rate, and the dollar-to-rupiah exchange rate. Figure 2 presents the time series plots of the ICI, inflation rate, and the Indonesian dollar-to-rupiah exchange rate on a monthly basis from January 2015 to September 2022.

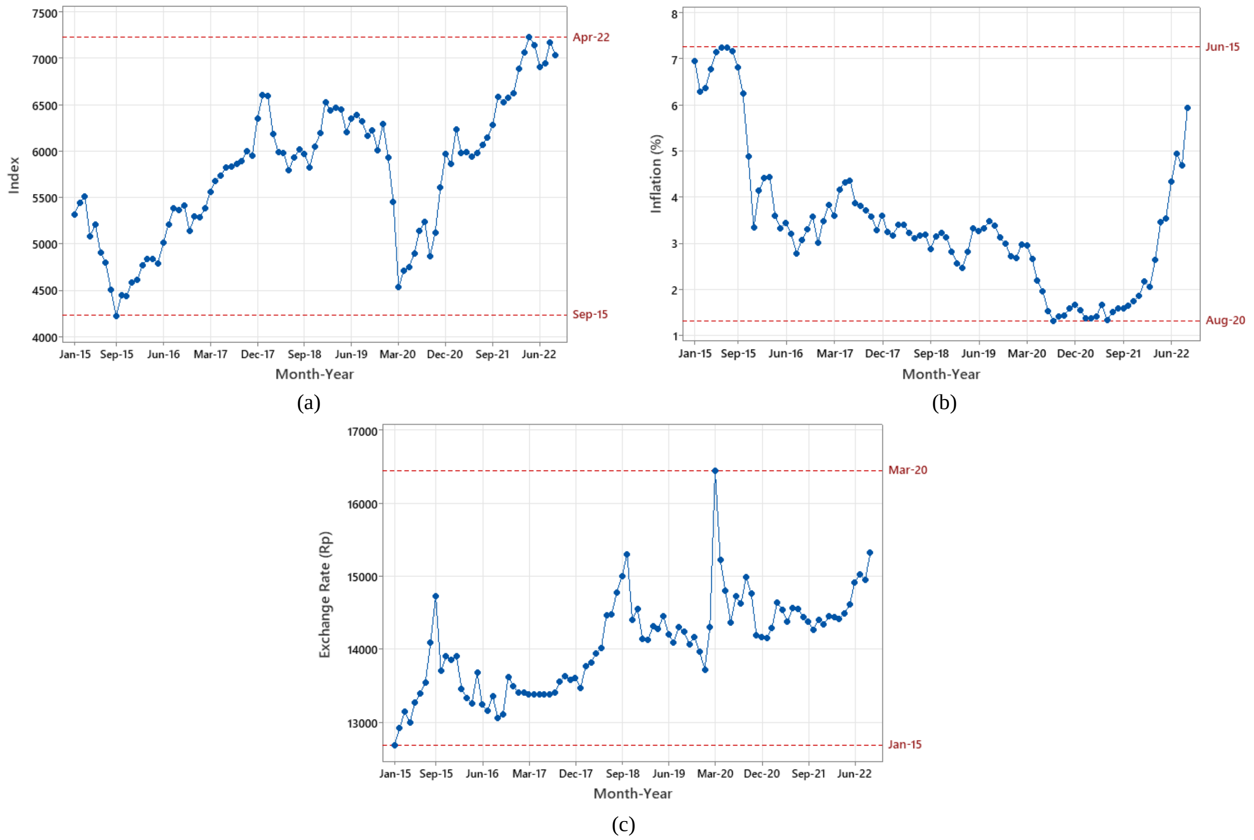


Figure 2. (a) Time Series of ICI, (b) Time Series of Inflation, (c) Time Series of Exchange Rate

The observation plot reveals fluctuations in the ICI, inflation rate, and dollar-to-rupiah exchange rate. The plot of the dollar-to-rupiah exchange rate exhibits an upward trend, beginning in January 2015 at Rp 12,688.00 (also the minimum value) and ending at Rp 15,323.00. Similarly, the ICI plot demonstrates an upward trend amidst the fluctuating curve. The minimum ICI was 4223.91 in September 2015, and the maximum value of ICI was 7228.91, which occurred in April 2022. However, the year-on-year inflation rate in Indonesia displayed a downward trend, starting at 6.96% and ending at 5.95% in September 2022. Table 4 provides a summary of the data in the form of descriptive statistics for each variable.

Table 4. Summary Results of Descriptive Statistics

Variables	Average	Variance	Standard Deviation	Median	*Range*	Minimum	Maximum
ICI	5777.7	530225.4	728.2	5936.4	3005	4223.9	7228.9
Inflation Rate	3402	2.336	1.529	3.23	5.94	1.32	7.26
Exchange Rate	14077	421791	649	14154	3761	12688	16449

Descriptive statistics yield seven indicator values derived from measures of data centering and deviation. The standard deviation of the ICI is 728.2, indicating that, on average, the ICI deviates from its parameters by 728.2. The inflation rate has a unit value compared to the other two variables, the ICI and the dollar-to-rupiah exchange rate, which are in the thousands. This suggests an imbalance in the variance of all variables. Additionally, the selling exchange rate has a high standard deviation of 649. Based on the descriptive statistical analysis, a logarithmic transformation is performed to minimize the range of variation of the three variables [30]. As a result, variables with a large variance are drastically reduced. The results of the descriptive statistics can be seen in Table 5.

Table 5. Summary Results of Descriptive Statistics (Logarithm Transformation)

Variables	Average	Variance	Standard Deviation	Median	*Range*	Minimum	Maximum
ICI	8.65	0.0166	0.1287	8.35	0.5373	8.35	8.89
Inflation Rate	1.13	0.2001	0.4473	0.28	1.7047	0.28	1.98
Exchange Rate	9.55	0.0021	0.0459	9.45	0.2596	9.45	9.71

3.2. Data Stationarity

Stationarity is a prerequisite in classical time series modeling, such as ARIMA, ARIMAX, or SARIMAX. Stationarity in data implies stability over time, with a constant mean and covariance. Graphically, data with fluctuations typically does not yield stationary data, as it often lacks a constant mean or covariance. The Augmented Dickey-Fuller (ADF) Test is the statistical test used to assess the stationarity of time series data [31]. The null hypothesis for the test posits that the data is not stationary, while the alternative hypothesis asserts stationarity. Stationarity is achieved if the ADF test yields a probability value (p-value) less than the specified significance level ($\alpha = 0.1$). Table 6 presents the ADF test results for all the variables.

Regrettably, the initial trial did not satisfy the stationarity condition. To address the issue of data non-stationarity, a transformation in the form of differencing the data is required. As an experiment, differencing was performed with a lag of 1 on each data point. Subsequently, the transformed data was retested with the ADF test. The results of this test are displayed in Table 6.

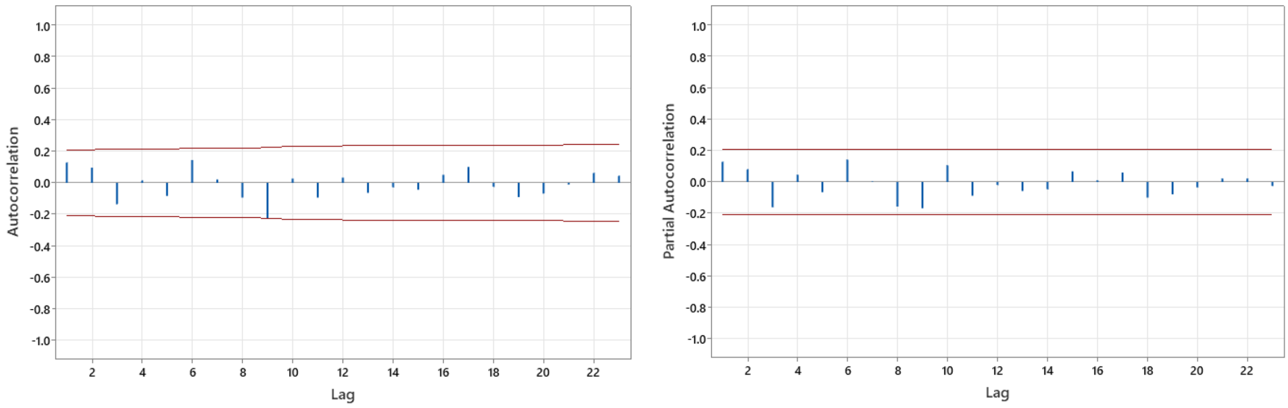
Table 6. ADF Test Results

Transformation	Variables	P-value	Decision
Not transformed with first differencing	Indonesia Composite Index	0.4573	Data is not stationary
	Inflation Rate	0.9683	Data is not stationary
	Exchange Rate	0.1157	Data is not stationary
Transformed with first differencing	Indonesia Composite Index	0.000	Data is stationary
	Inflation Rate	0.041	Data is stationary
	Exchange Rate	0.000	Data is stationary

The ADF test results indicate that the ICI, inflation rate, and dollar-to-rupiah exchange rate are stationary following logarithmic transformation and first differencing. Consequently, modeling with ARIMAX can proceed, as the data has fulfilled the stationarity assumption.

3.3. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

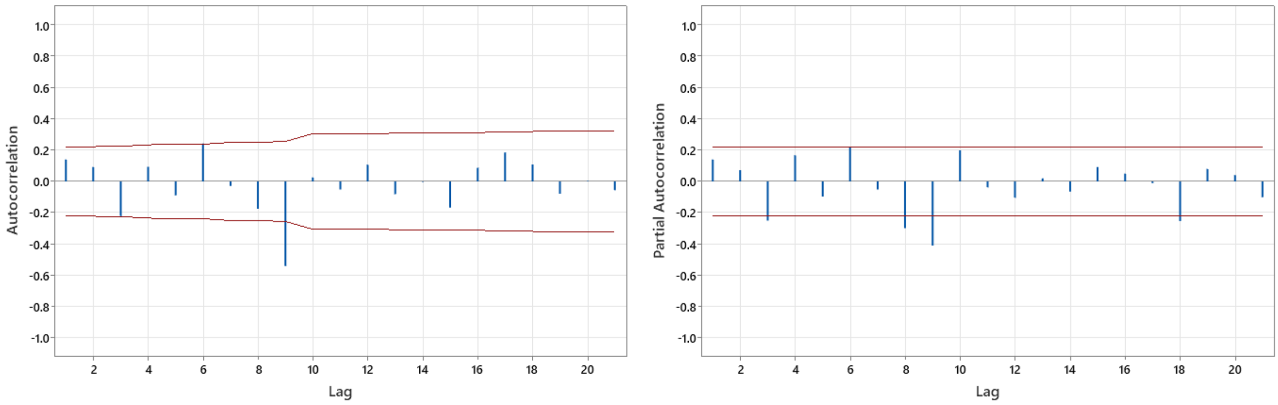
ACF and PACF are two primary indicators that describe how the data is correlated with time. ACF is used to measure the correlation between the previous observation and the current observation in the time series data (for MA order determination), while PACF measures the direct correlation between two observations in the time series after accounting for the influence between them (for AR order determination) [32]. Figure 3 illustrates the ACF and PACF plots of the ICI data that has been transformed to stationarity by differencing.



(a) (b)

Figure 3. (a) ACF Plot for Differencing 1, (b) PACF Plot for Differencing 1

The results reveal minimal lags in both the ACF and PACF. However, lag-9 on the ACF plot slightly crosses the red line of significance. This suggests that the ICI data is likely correlated with its own data every 9 periods. Additionally, the significant lag that is quite distant is indicative of the possibility that the ICI exhibits a seasonal trend every 9 periods or every 9 months. Figure 4 presents the ACF and PACF plot of the ICI data that has been differenced for 9 periods.



(a) (b)

Figure 4. (a) ACF Plot for Differencing 9, (b) PACF Plot for Differencing 9

Based on the results of the ACF and PACF plots with a seasonal trend every 9 periods, it is observed that the ACF plot increasingly shows its significance at lag-9 and several lags emerge in the PACF. Therefore, based on these plots, the potential SARIMAX models to be used are SARIMAX(0,1,0)$(1,1,0)^9$, SARIMAX(0,1,0)$(0,1,1)^9$, SARIMAX(0,1,0)$(1,1,1)^9$, SARIMAX(0,1,0)$(2,1,0)^9$, and SARIMAX(0,1,0)$(2,1,1)^9$.

3.4. SARIMAX Model Estimation

The ACF and PACF plots have suggested several potential SARIMAX models for estimation. In SARIMAX modeling, it is crucial that exogenous variables, which have achieved stationarity, do not exhibit multicollinearity [33]. Accordingly, Table 7 presents the results of the multicollinearity test, conducted using the Variance Inflation Factor (VIF) method, for each exogenous variable [33].

Table 7. Multicollinearity Test for Exogenous Variables

Variables	VIF	Conclusion
Difference 1 Inflation	1.00	There is no multicollinearity between the inflation rate and the exchange rate.
Difference 1 Exchange Rate	1.00	

The absence of multicollinearity suggests that the exogenous variables satisfy the assumptions and should be incorporated into the SARIMA model, thereby transforming it into a SARIMAX model. Table 8 provides details about the five potential SARIMAX models discussed earlier in the "ACF and PACF Plots" section. In addition to meeting the assumptions of the SARIMAX model, such as residual normality and white noise residual, the Shapiro-Wilk test will be used for normality testing, and the Ljung-Box Test will be employed for white noise testing [34].

Table 8. Summary of ICI Model Estimation with SARIMAX

SARIMAX Model Order	P-value Residual Normality Test	P-value Residual White Noise Test	Parameter Significance
(0,1,0)$(1,1,0)^9$	0.1286 (Normal)	0.1104 (White Noise)	All Parameters Significant
(0,1,0)$(0,1,1)^9$	0.0051 (Not Normal)	0.1602 (White Noise)	All Parameters Significant
(0,1,0)$(1,1,1)^9$	0.0013 (Not Normal)	0.1691 (White Noise)	All Parameters Significant
(0,1,0)$(2,1,0)^9$	0.0128 (Not Normal)	0.0071 (Not White Noise)	All Parameters Significant
(0,1,0)$(2,1,1)^9$	0.1502 (Normal)	0.0027 (Not White Noise)	SAR-18 Not Significant

Based on Table 8, the SARIMAX model that fulfills all assumptions is SARIMAX(0,1,0)$(1,1,0)^9$. Table 9 provides a more complete estimate of the SARIMAX(0,1,0)$(1,1,0)^9$ model with its estimated parameters.

Table 9. Summary of ICI Model Estimation with SARIMAX

Parameter Estimated	Coefficient	Standard Deviation of Coefficient	P-value
Seasonal AR ($\hat{\boldsymbol{\Phi}}_9$)	-0.556	0.0893	0.000
Difference 1 Inflation Rate ($\hat{\boldsymbol{\beta}}_1$)	-0.0089	0.0305	0.000
Difference 1 Exchange Rate ($\hat{\boldsymbol{\beta}}_2$)	-0.4053	0.1083	0.000

Thus, the estimated SARIMAX(0,1,0)(1,1,0)^9 model will be used in the SARIMAX-GARCH estimation. The mathematical equation of the logarithmically transformed ICI model estimation with SARIMAX(0,1,0)(1,1,0)^9 is as follows:

$$\widehat{Z_t}^* = -0.0089X_{1t}^* - 0.4053X_{2t}^* + \frac{\widehat{\varepsilon_t}}{[(1 + 0.556\,B^9)(1 - B^9)(1 - B)]} \tag{11}$$

With, $\widehat{Z_t}^* = ln(\hat{Z}_t)$, while X_{1t}^* is the first differentiation of the inflation rate and X_{2t}^* is the first differentiation of the exchange rate. Another interpretation is that all of the exogenous variables are exhibiting a significant negative effect on the ICI over time. The negative coefficient in the first differencing of the inflation rate suggests that a larger shock in uncertain inflation rates leads to a decrease in the performance of the ICI. Regrettably, this also applies to the exchange rate differences. The coefficient of the first difference exchange rate, which is larger in a negative sense compared to the inflation rate, indicates a greater decrease in the ICI due to the inconsistency of changes in the exchange rate. Therefore, both inflation rates and exchange rates have a significant impact and play important roles in the performance of the Indonesia Composite Index.

Based on the equation obtained, Figure 5 shows the comparison graph between the actual ICI's value with the ICI's estimated value with the SARIMAX(0,1,0)(1,1,0)^9 model. The red line shows the estimation of ICI with SARIMAX model and the blue line represents the actual ICI's values.

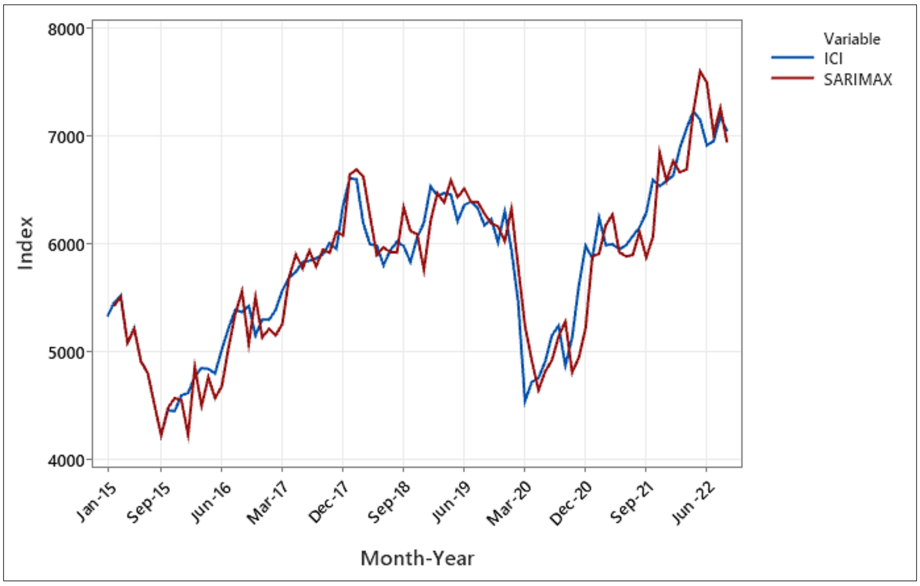


Figure 5. Indonesia Composite Index with SARIMAX Estimation

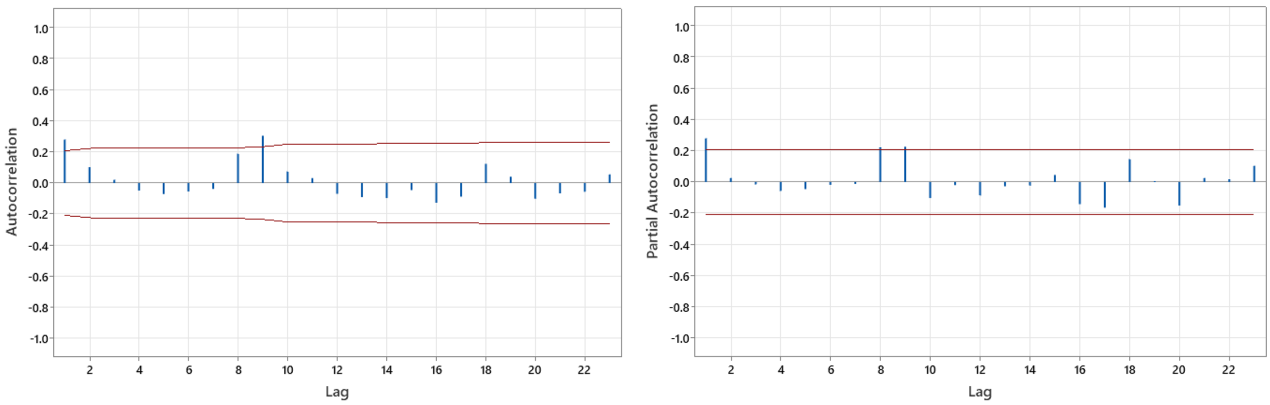
The plot of the estimation with the SARIMAX(0,1,0)(1,1,0)^9 model is approaching the pattern with very precise to the original data. To look how good is the estimation, Table 10 provides criteria for the goodness of the SARIMAX model in the form of the R^2 value, MSE, and the value of MAPE in sample.

Table 10. Summary of Goodnes of Fit from SARIMAX

Criteria	Value	Description
R^2	0.8785	Scores in the good category
MSE	0.0021	Small MSE value
MAPE in sample	3.265%	MAPE is in the excellent category

3.5. Heteroscedasticity Detection for SARIMAX Residuals

In the SARIMAX model, it is understood that the error follows a normal distribution with a mean of 0 and a homogeneous variance $\boldsymbol{\sigma^2}$. However, economic data generally exhibits high volatility, leading to a deviation from the assumption of homogeneous variance [35]. To detect heteroscedasticity, the squared error of the SARIMAX(0,1,0)(1,1,0)9 estimation is employed as a representative estimator of the residuals $\boldsymbol{\sigma^2}$ of the residuals [36]. So, in Figure 6 it will shows the ACF and PACF of the squared residual from SARIMAX(0,1,0)(1,1,0)^9.



(a) (b)

Figure 6. (a) ACF Plot for SARIMAX Squared Residuals, (b) PACF Plot for SARIMAX Squared Residuals

It can be observed that there is a lag out, indicating that the squared error has a correlation with its own data and previous residuals. This results in the variance of the error not being homogeneous. Therefore, the integration of the GARCH model into the SARIMAX model will address the issue of heteroscedasticity.

3.6. GARCH Estimation

Autoregressive Conditionally Heteroscedasticity (ARCH) is a model designed for the variance residuals of time series models that exhibit cases of heteroscedasticity. The ARCH model emphasizes that the variance of the error depends on the squared residual (variance estimator) of the preceding period. However, ARCH does not detect heteroscedasticity based solely on variability. The Generalized-ARCH (GARCH) model accommodates such variability. Thus, in addition to calculating the squared residuals from the previous period, GARCH enables the estimation of past variability.

In the preceding discussion, it was identified that the SARIMAX(0,1,0)(1,1,0)9 estimation exhibits heteroscedastic residuals. Consequently, ARCH/GARCH variance modeling is necessitated. Based on the ACF and PACF plots of squared residuals, the number of lags that emerge on the ACF determines the ARCH(p), and the number of lags that emerge on the PACF determines the GARCH(p, q) model [37]. Therefore, the potential variance model estimates, based on Figure 6, are ARCH(1) (equivalent to GARCH(1,0)) or GARCH(1,1). Table 11 presents the estimation results of both models using the residual data from SARIMAX(0,1,0)(1,1,0)^9.

Table 11. Summary of GARCH Model Estimation

Model	Parameter Significance
GARCH(1,0)	All Parameters Significant
GARCH(1,1)	Insignificant Variability Parameter

In Table 11, GARCH(1,0) has model simplicity and has parameters that are all significant to the model. Therefore, to overcome the case of heteroscedasticity, GARCH(1,0) will become addition in SARIMAX(0,1,0)(1,1,0)^9. Equation 12 shows the equation of residual variance as follows.

$$\widehat{\sigma_t}^2 = 0.0011983 + 0.4378342\hat{\varepsilon}_{t-1}^2 \tag{12}$$

with $\widehat{\sigma_t}^2$ is the estimated variance to solve the heteroscedasticity and $\hat{\varepsilon}_{t-1}^2$ is the estimated square residual 1 lag previous period from SARIMAX(0,1,0)(1,1,0)^9. Therefore, Equation 13 shows how to have the estimated residuals based on GARCH(1,0) model [38].

$$\hat{\varepsilon}_t = \hat{s}_t\hat{\sigma}_t \tag{13}$$

With, $\hat{s}_t$ is the standardization of the estimated SARIMAX(0,1,0)(1,1,0)^9 error and is assumed to be normally distributed with mean 0 and variance 1 and $\hat{\sigma}_t$ is the square root of estimated variance that was shown in Equation 12.

3.7. SARIMAX-GARCH Estimation

The combination of Equations 11 and 13 will be formed into SARIMAX(0,1,0)(1,1,0)^9-GARCH(1,0) which can be mathematically written as follows:

$$\widehat{Z_t}^* = -0.0089X_{1t}^* - 0.4053X_{2t}^* + \frac{\hat{s}_t\hat{\sigma}_t}{[(1+0.556\,B^9)(1-B^9)(1-B)]} \tag{14}$$

By changing the $\boldsymbol{\hat{\sigma}_t}$ with Equation 12 and returning $\boldsymbol{Z_t}$ to its original form (inverse of logarithmic transformation), it will have the final SARIMAX(0,1,0)(1,1,0)^9-GARCH(1,0) estimation as follows:

$$\hat{Z}_t = \exp\left[-0.0089X_{1t}^* - 0.4053X_{2t}^* + \frac{\hat{s}_t\sqrt{0.0011983 + 0.4378342\hat{\varepsilon}_{t-1}^2}}{[(1+0.556\,B^9)(1-B^9)(1-B)]}\right] \tag{15}$$

The results of this equation are remarkable, rendering the estimation of the Indonesia Composite Index highly similar to the original value, as depicted in Figure 7.

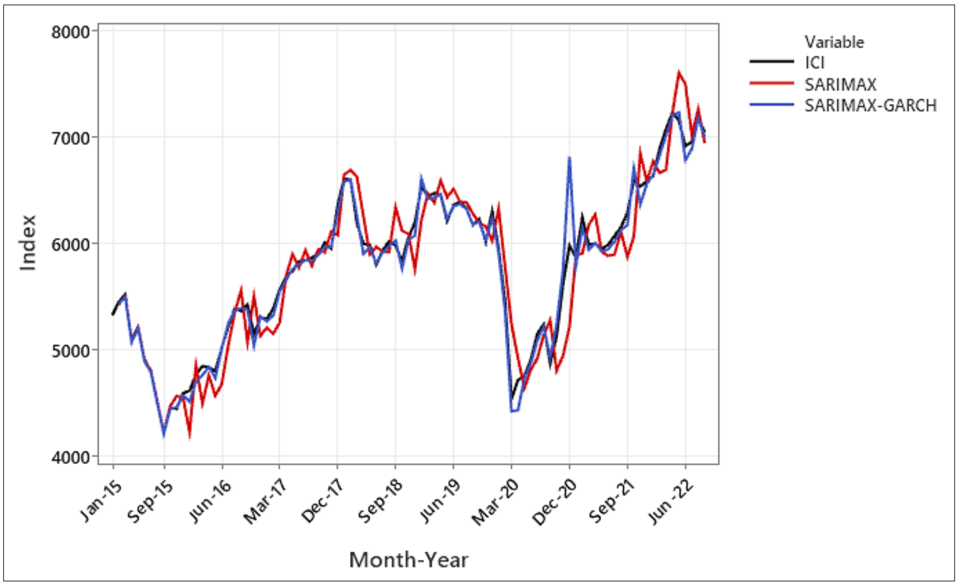


Figure 7. Indonesia Composite Index with SARIMAX-GARCH Estimation

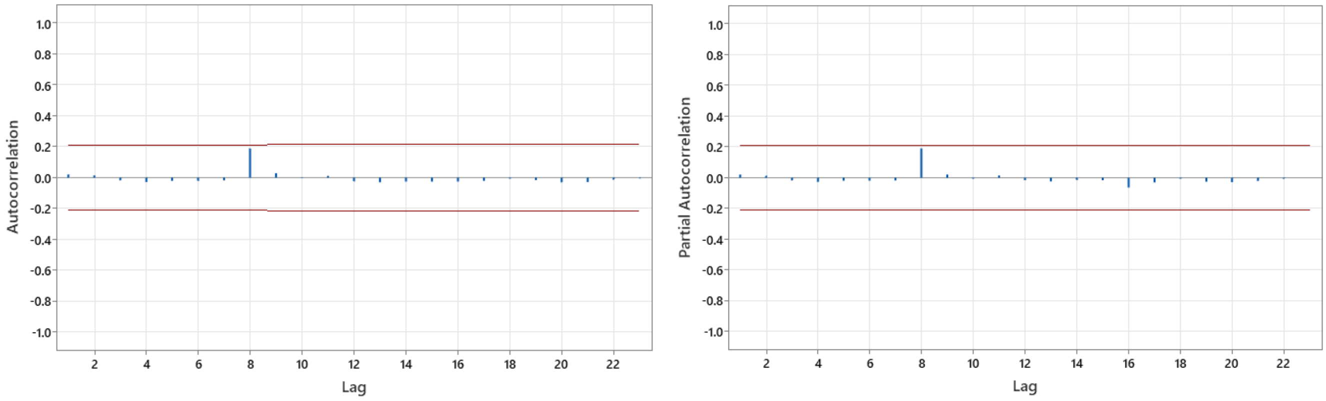
Based on the plot with SARIMAX(0,1,0)(1,1,0)^9 - GARCH(1,0) in blue, it appears to closely match the black graph (actual ICI value) and provides a better fit than the red line (SARIMAX(0,1,0)(1,1,0)^9 model without the GARCH model). This is because the residual variance does not fluctuate, resulting in a smaller and more precise residual value for estimation. Table 12 presents the goodness of fit from the SARIMAX-GARCH model.

Table 12. Summary of Goodness of Fit from SARIMAX-GARCH

Criteria	Value	Description
$\mathbf{R^2}$	0.9782	Scores in the excellent category
MSE	0.0003	MSE Value Very Small
MAPE in sample	0.952%	MAPE is in the excellent category

The results given by SARIMAX(0,1,0)(1,1,0)^9-GARCH(1,0) compared to only SARIMAX(0,1,0)(1,1,0)^9 in Table 10 have better criteria, such as R^2 higher, smaller MSE, and very small MAPE. The purpose of incorporating the GARCH model into SARIMAX is to eliminate heteroscedastic effects in the errors or residuals. Figure 8 displays the heteroscedasticity test results of the SARIMAX(0,1,0)(1,1,0)^9-GARCH(1,0) model, with the ACF and PACF plot once again.

The results from Figure 8 reveals that there are no lags outside of the ACF or PACF plots. This indicates that the squared errors (variance estimators) are independent and have no correlation with their variance or variability. Thus, the heteroscedasticity of errors in the SARIMAX(0,1,0)(1,1,0)^9 model has been addressed by incorporating the GARCH(1,0) model.



(a) (b)

Figure 8. (a) ACF for SARIMAX-GARCH Squared Residuals, (b) PACF for SARIMAX-GARCH Squared Residuals

3.8. Forecasting Indonesia Composite Index

Forecasting has the purpose of knowing the prediction of an event over the next few periods. In Table 13, we present the forecast data of Indonesia Composite Index for the next 6 month periods (October 2022 - March 2023) and compare it with actual values by using SARIMAX$(0,1,0)(1,1,0)^9$ - GARCH(1,0) estimation.

Table 13. Summary of ICI Prediction with SARIMAX$(0,1,0)(1,1,0)^9$-GARCH(1,0)

Period	Actual ICI	Predicted Lower Limit	Average Prediction	Predicted Upper Limit
October 2022	7098.89	6270.19	7444.60	8838.98
November 2022	7081.31	6121.24	7412.32	8975.72
December 2022	6850.62	5929.73	7289.77	8961.75
January 2023	6839.34	5833.37	7263.27	9043.67
February 2023	6843.24	5733.58	7219.61	9090.79
March 2023	6708.93	5471.73	6960.18	8853.52

The results of the ICI prediction tend to exhibit a decreasing trend, which is consistent with the actual ICI data. Although the ICI prediction slightly deviates on a monthly average, it remains within the permissible prediction interval. The Mean Absolute Percentage Error (MAPE) for the prediction is 5.233%, attesting to its exceptional predictive accuracy. Therefore, it can be concluded that the Indonesia Composite Index (ICI) can be effectively predicted using time series SARIMAX-GARCH models, with inflation rate and exchange rate as its exogenous variables. Figure 9, derived from Table 13, illustrates the time series plot and demonstrates the model's proficiency in predicting highly uncertain and fluctuating data, such as the Indonesia Composite Index.

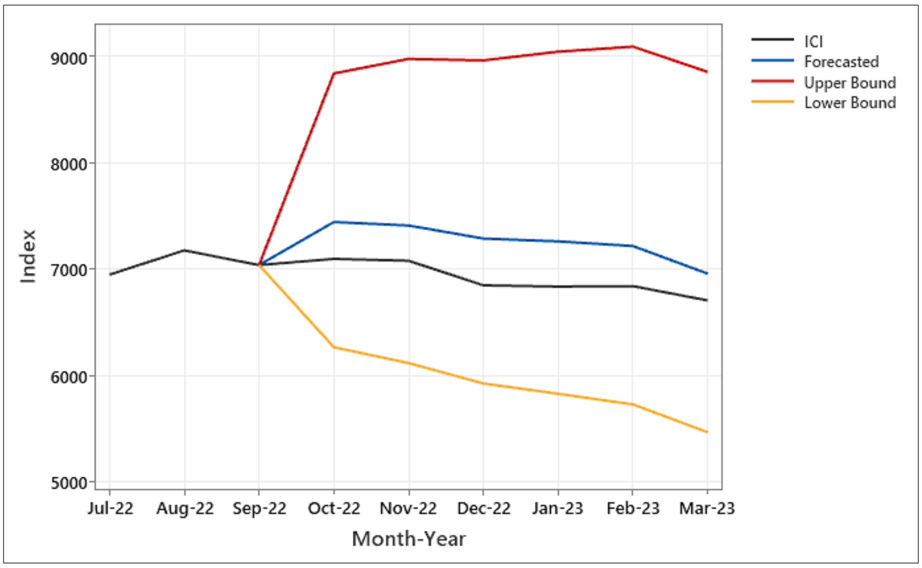


Figure 9. Indonesia Composite Index Prediction with SARIMAX-GARCH Estimation

3.9. A Brief of Discussion

This research focuses on predicting the Indonesia Composite Index (ICI), a vital indicator for investors and a broader measure of economic growth in Indonesia. The ICI mirrors the performance of the country's industries and is closely linked to capital flows, economic growth, and state tax revenues. Accurate forecasting of the ICI is crucial for understanding the country's economic conditions, particularly during periods of economic instability such as the COVID-19 pandemic and recent global economic disruptions. The significance of the Composite Stock Price Index has been explored by Rosyadi et al. (2020), who examined the relationship between the Jakarta Composite Index (JCI) and Indonesia's economic growth. Their findings indicated a positive relationship and significant feedback in the long run [39]. Other analyses, including recent studies by Haryanto et al. (2023) and Sutrisno (2024), underscore the importance of predicting the JCI given its reflection of the Exchange Market Index in Indonesia [40, 41]. While numerous studies have focused on ICI prediction, many overlook critical macroeconomic factors. For instance, Devianto et al. (2020) used artificial neural networks and nonparametric MARS models to predict the ICI, achieving commendable results with a Mean Absolute Percentage Error (MAPE) below 10% [42]. However, these models did not account for the volatile economic conditions that can drastically influence the ICI, such as significant policy changes or global economic shocks.

This research introduces the SARIMAX-GARCH model, which incorporates macroeconomic factors as exogenous variables, specifically the inflation rate and exchange rate. Based on Equations 14 and 15, the negative coefficients for both first order of difference in inflation rate and exchange rate were indicating that increases in either the inflation rate or exchange rate lead to a decrease in the Composite Index. Specifically, the inflation rate has a coefficient of -0.0089, suggesting that changes (differences) in the inflation rate have a smaller impact on the Composite Index, while the exchange rate, with a coefficient of -0.4053, exerts a more significant negative influence. This emphasizes that fluctuations in the exchange rate are more strongly correlated with movements in the Composite Index than inflation.

Recent studies, such as Wijaya et al. (2023) and Pratama (2024), have also highlighted the importance of these variables in predicting financial indices [43, 44]. The SARIMAX-GARCH model's ability to account for these factors provides a more accurate forecasting model for the ICI, enabling more informed decision-making in both the public and private sectors. This can potentially foster more stable economic growth and job creation, particularly in times of economic uncertainty.

Given the economic context of the period studied, characterized by fluctuating global markets and domestic policy shifts, the SARIMAX-GARCH model's robustness in capturing these dynamics is critical. The model's accuracy and its ability to incorporate significant macroeconomic factors make it a valuable tool for investors and policymakers alike. Policymakers can use this model to anticipate market movements, design responsive economic policies, and enhance overall economic stability. For future research, the VAR-GARCH model could be explored as an alternative approach. The VAR-GARCH model offers the advantage of capturing the dynamic interrelationships between multiple time series and accounting for volatility clustering across different variables, making it particularly useful for studying the interconnectedness of macroeconomic factors and financial markets. This approach could provide deeper insights into the systemic risks and spillover effects in emerging markets, where economic conditions are highly variable.

4. Conclusion

Based on the analysis, it can be concluded that both the inflation rate and the exchange rate against the US dollar significantly influence the Indonesia Composite Index (ICI). The negative coefficients found in the first differencing of these macroeconomic factors indicate that an increase in uncertainty surrounding inflation and exchange rates tends to reduce the ICI's performance. Specifically, a larger spike in inflation or a depreciation of the rupiah against the dollar is associated with a decrease in the ICI. The SARIMAX-GARCH model used in this study has shown a high level of accuracy, as evidenced by an in-sample Mean Absolute Percentage Error (MAPE) of 0.952%, a relatively low Mean Squared Error (MSE) of 0.0003, and a high R^2 value of 0.9782. For out-of-sample data, the MAPE was 5.233%, demonstrating the model's robustness in capturing the dynamics of the ICI. This model not only improves predictive accuracy but also offers a deeper understanding of the intricate relationships between these critical economic indicators.

Given these findings, it is imperative that investors in Indonesia closely monitor inflation rates and exchange rates, as these factors have proven to be crucial determinants of market performance. For policymakers, this study highlights the need to refine monetary policies that address macroeconomic variables, particularly inflation and exchange rates, to ensure economic stability. The significant correlations identified between the ICI, inflation, and exchange rates suggest that macroeconomic management is essential for sustaining market confidence and growth.

Moreover, this research contributes to the broader goal of achieving the 8th Sustainable Development Goal (SDG), which focuses on promoting decent work and economic growth. By providing a more accurate and reliable forecasting model for the ICI, this study supports informed decision-making across both public and private sectors. This, in turn, could foster a more stable economic environment in Indonesia, facilitating job creation and sustainable growth in the long term.

5. Declarations

5.1. Author Contributions

Conceptualization, M.M., E.P., and I.P.; methodology, R.R.; software, I.P. and D.U.; validation, M.M. and E.P.; formal analysis, I.P., D.U., and R.R.; investigation, M.M. and E.P.; resources, D.U.; data curation, R.R.; writing—original draft preparation, I.P. and E.P.; writing—review and editing, M.M., D.U., and R.R.; visualization, I.P. and D.U.; supervision, M.M. and E.P.; project administration, R.R.; funding acquisition, M.M. and E.P. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in:

- Indonesia Composite Index Data: https://finance.yahoo.com;
- Inflation Rate Data: https://www.bi.go.id/id/statistik/indikator/data-inflasi.aspx;
- Exchange Rate Data: https://www.bi.go.id/id/statistik/informasi-kurs/transaksi-bi/default.aspx.

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5.5. Institutional Review Board Statement

Not applicable.

5.6. Informed Consent Statement

Not applicable.

5.7. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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