Available online at http://iorajournal.org/indx.php/orics /index

Operations Research: International Conference Series

e-ISSN: 2722-0974
p-ISSN: 2723-1739

Vol. 5, No. 3, pp. 99-104, 2024

Forecasting Indonesian Stock Index Using ARMA-GARCH Model

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Abstract

The stock market is an institution that provides a facility for buying and selling stocks. Covid-19 is an issue that has affected the stock markets of many countries, including Indonesia. Due to the pandemic, the condition of stocks before and during Covid-19 is certainly different. Stocks can be measured using stock indices. To predict future stock conditions, it is necessary to forecast the stock index. Therefore, this research aims to forecast the Indonesian stock index before and during Covid-19 using the ARMA-GARCH time series model. The results show that the best forecasting model for before Covid-19 data is ARMA (0,2) - GARCH (1,0), and for the data during Covid-19, it is ARMA (3,3)-GARCH (3,3). These findings can help investors make better investment decisions in the future.

Keywords: Stock index, Covid-19, ARMA-GARCH

1. Introduction

The stock market is an institution that provides a market facility to facilitate the buying and selling of securities between companies and individuals involved (Suhail *et al.*, 2021). Every country has its own stock market, including Indonesia, which has the Jakarta Stock Exchange Composite (JKSE). Stocks can be measured using stock indices. Stock indices show trends in investment patterns by providing useful information of the changes in investor behavior in a specific period, thereby giving an overall image of the market activity (Lim *et al.*, 2023). Changes in stock market indexes frequently reflect the general mood and market trends (Kapoor, 2023).

In 2019, the Covid-19 pandemic emerged, affecting all sectors. According to Narang, Pradhan and Singh (2023) the impact of Covid-19 affect a financial sector. The stock market, being part of the financial sector, was likely affected by Covid-19. There are significant differences in the stock market before and during the Covid-19 pandemic (Sholikhah, Darmayanti and Zulkarnaen, 2023). The differences can be due to various factors.

Covid-19 entered Indonesia in 2020 and certainly affected the stock market in the country. Even though this year can be considered the post-Covid-19 period, but there may be future pandemics or other challenges. Therefore, it is essential to forecast data to understand the future condition of Indonesian stocks. Forecasting the stock index accurately is of paramount importance for reducing risks in decision-making, by providing some important reference information (Lv *et al.*, 2022).

Based on the explanation above, this research uses Indonesian stock index data with the aim of forecasting the data before and during Covid-19. The data used is time series data, so the ARMA and GARCH time series models are applied. The ARMA is for mean equation and GARCH is for volatility modelling (Feng, 2023). The ARMA-GARCH model is a hybrid model that can detect heteroskedasticity effects in the stock index data. The results of this research can help investors make better stock investment decisions in the future.

2. Literature Review

2.1. Stock Return

Return refers to the earnings or profits derived from financial assets. Higher stock prices indicate higher output, then stock returns and inflation will also be negatively related (Azar, 2013). Equation (1) facilitates the calculation of stock return value.

$$R_t \tag{1}$$

R_t : Stock return at time t , $t = 1,2, ...,$
P_t : Closing stock price at time t,
P_{t-1} : Closing stock price at time $t - 1$.

2.2. Stationarity Test

In analyzing time series data, the data used must be stationary; hence, a stationarity test is conducted. Data is considered stationary if it has constant mean and variance (E.P.Box *et al*., 2004).

For testing the stationarity of data regarding the mean, a Unit Root Test is performed using the Augmented Dickey-Fuller Test (ADF Test). The hypotheses of the ADF test are outlined as follows:
H_0 : $\delta = 0$, indicating the presence of a unit root, and the data is non-stationary.
H_1 : $\delta < 0$, indicating the absence of a unit root, and the data is stationary.
Test statistic,

$$t = \frac{\hat{\delta}}{SE(\hat{\delta})}, \tag{2}$$

t : The ratio value between the estimated parameter and standard error,
$\hat{\delta}$: The estimated value of δ,
$SE(\hat{\delta})$: The standard error of $\hat{\delta}$.

The test criteria used at a significance level of 5% are as follows:
1. If $|t| > |t_{kritis}|$ or *p-value* $< \alpha = 0{,}05$, then H_0 is rejected.
2. If $|t| \leq |t_{kritis}|$ or *p-value* $\geq \alpha = 0{,}05$, then H_0 is not rejected.

Subsequently, for testing the stationarity of data concerning variance, the Box-Cox transformation can be applied. The Box-Cox transformation is formulated as follows (Osborne, 2010) :

$$Z_t(\lambda) = \begin{cases} Z_t^{\lambda} - 1, \lambda \neq 0 \\ \ln Z_t , \lambda = 0 \end{cases}, \tag{3}$$

λ: The transformation parameter.

The estimation of the λ parameter can be obtained using the Maximum Likelihood method, where the value of λ is chosen based on the minimum residual sum of squares. The transformation is performed if the value of $\lambda = 1$ is not yet obtained, indicating stationarity in variance.

2.3. Autoregressive Moving Average (ARMA) Model

The autoregressive moving average model is a combined model consisting of the Autoregressive (AR) model and the Moving Average (MA) model. The Autoregressive (AR) model is a stationary model that utilizes time series data, where the observed value at time t is influenced by the observed value at the previous time. Meanwhile, the Moving Average (MA) model is a stationary model that utilizes time series data, depending on the previous residuals. The ARMA model of order p, q is symbolized as ARMA (p, q) and is represented by the following equation (4).

$$Z_t = c + \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}, \tag{4}$$

Z_t : The value of the variable at time t,
c : Intercept,
ϕ_i : Autoregressive (AR) model parameter, $i = 1,2, ... , p$,
Z_{t-p} : The value of the variable at the previous time,
ε_t : Residual at time t,
θ_i : Moving Average (MA) model parameter, $i = 1,2, ... , q$,
ε_{t-q} : Residual at the previous time,
p : Autoregressive order,
q : Moving average order.

2.4. Generalized Autoregressive Conditional heteroscedasticity (GARCH) Model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is a model that depends on previous time variances (order q), not just on previous time residuals alone (order p). According to Wei (2006) the GARCH(p,q) model has the following equation.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2, \tag{5}$$

σ_t^2 : The residual variance at time t,
ω : Intercept,
α_i : Model parameter, $i = 1,2,\dots,p$,
ε_{t-p}^2 : The square of residual at previous time,
β_i : Model parameter, $i = 1,2,\dots,q$,
σ_{t-q}^2 : The square of residual variance at previous time.

2.5. Mean Absolute Error (MAE)

The MAE value is used to evaluate the model, whether the obtained model is accurate or not. According to (Hodson, 2022), the formula to calculate MAE is as follows:

$$MAE = \frac{\sum_{t=1}^{n} \left| Z_t - \widehat{Z}_t \right|}{n}, \tag{6}$$

Z_t : The value of the variable at time t,
$\widehat{Z}_t$: The forecast value of the variable at time t,
n : The number of observations.

3. Materials and Methods

3.1. Materials

The data used is secondary data, indeks stock closing data every day of Indonesia from www.investing.com. The period of data is during Januari 2018 – December 2021. The applications used are R Studio and Microsoft Excel.

3.2. Methods

a) Calculating stock returns using equation (1) and conducting stationarity tests.
b) Creating an ARMA (p, q) model based on equation (4).
c) Creating an GARCH (p, q) model according to equation (5).
d) Forecast stock index and calculating MAPE value according to equation (6).

4. Results and Discussion

a) Stationarity tests

The stock index return data is calculated using equation (1) and then this data is tested for stationarity against the mean and variance. Testing the stationarity of data against the mean is conducted using the ADF test, and the results can be seen in Table 1.

Table 1: ADF test results of the Indonesian stock index returns

ADF Test	
Data	*p-value*
Before Covid-19	0.01
During Covid-19	0.01

Based on Table 1, a p-value of 0.01 is obtained, indicating the absence of a unit root, thus the data is stationary regarding the mean. Subsequently, the data is tested for stationarity against variance using the Box-Cox Transformation, and the results can be seen in Table 2.

Table 2: Box-Cox Transformation results of the ASEAN stock index returns

Box-Cox Transformation	
Data	λ value
Before Covid-19	1
During Covid-19	1

Based on Table 2, the Box-Cox lambda value obtained is 1. Therefore, it can be concluded that the data is stationary concerning variance.

b) Creating ARMA (p, q) model

The next step is create ARMA models for each dataset and later the residual of the ARMA models will be used to build GARCH models. The ARMA models for each dataset are obtained as shown in Table 3.

Table 3: ARMA model of the Indonesian stock index

Data	Model	Parameter	Estimation
Before Covid-19	ARMA (0,2)	θ_2	-0.092803
During Covid-19	ARMA (3,3)	ϕ_1	-0.782887
		ϕ_3	0.440282
		θ_1	0.879021
		θ_3	-0.364401

c) Creating GARCH (p, q) model

After obtaining the ARMA model, the residuals from that model are used to form the GARCH model. The GARCH models for each dataset are presented in Table 4.

Table 4: GARCH model of the Indonesian stock index

Data	Model	Parameter	Estimation
Before Covid-19	ARMA (0,2) – GARCH (1,0)	μ	0.000064
		θ_1	0.932411
		θ_2	0.349582
		α_1	0.869961
During Covid-19	ARMA (3,3) – GARCH (3,3)	μ	0.000065
		ϕ_1	2.149572
		ϕ_2	-1.876381
		ϕ_3	0.567677
		θ_1	-2.310482
		θ_2	2.130973
		θ_3	-0.689756
		ω	0.000018
		α_1	0.152952
		α_2	0.218873
		β_2	0.492901

d) Forecast stock index and calculate MAPE

After obtaining the best model, the next step is to evaluate the model using the MAE value. If the MAE value approaches zero, the model is considered more accurate.The MAE value are presented in Table 5.

Table 5: MAE value of Indonesian stock index

	Actual Data	Forecast Data	MAE Value
Before Covid-19	-0.002533	0.001847	0.00276895

	0.006348	0.0001351	
	−0.010448	0.00006388	
	0.003507	0.00006388	
	−0.008545	0.00006388	
During Covid-19	0.011681	−0.0011669	
	−0.0017	−0.0009369	
	0.000137	−0.0003109	0.0038215
	0.006491	0.0004376	
	0.001524	0.0010026	

Based on Table 5, the MAE value for the data before Covid-19 is 0.00276895, and for the data during Covid-19, it is 0.0038215.

5. Conclussion

The results of this study conclude that the best model for forecasting the stock index before Covid-19 is ARMA (0,2)-GARCH (1,0), and for during Covid-19, it is ARMA (3,3)-GARCH (3,3) because the MAE value is close to zero, indicating that the model is quite accurate.

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