PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 04 No. 2, August 2025
Pages 249-260

Hybrid ARIMA-GARCH Model with Walk-Forward Method On LQ45 Stock Price Forecasting

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Abstract

Stock investment offers returns but also risks, such as potential capital losses due to declining stock prices. To mitigate these risks, investors use forecasting models, and one common approach is time series forecasting. The ARIMA model captures linear patterns in data, while the GARCH model handles time-varying volatility. This study uses a hybrid ARIMA-GARCH model with the Walk-Forward method to predict the daily closing prices of LQ45 index stocks from January 2022 to May 2024, utilizing data from Yahoo Finance. The Walk-Forward approach divides the data into 80% training and 20% testing, ensuring the model is tested on unseen data for more realistic evaluation. The process includes fitting the ARIMA model to stock return data, testing for heteroscedasticity, and building the hybrid ARIMA-GARCH model. The best model, ARIMA(1,0,0) – GARCH(1,1), was selected based on the lowest AIC value of -3004.88 for ARIMA and -6.83 (AIC) and -6.78 (BIC) for GARCH. This research contributes to stock forecasting by applying high-frequency data and the Walk-Forward validation method, offering a more accurate assessment of the model's performance. It also enriches time series analysis methodology in the Indonesian stock market by combining ARIMA and GARCH models, optimizing model parameters using AIC and BIC criteria for stock price prediction.

Keywords: *ARIMA-GARCH, forecasting, return, stocks, time series.*

: https://doi.org/10.30598/parameterv4i1pp249-260

Submitted: May 2025
Accepted: August 2025

1. INTRODUCTION

Forecasting plays a critical role in financial markets, especially in predicting stock prices, as it helps investors anticipate market fluctuations and make informed decisions. As financial markets become increasingly complex and dynamic, the need for accurate forecasting continues to grow. Forecasting is the activity of estimating future events based on past data[1]. In finance, the need for forecasting is growing due to increased awareness of how crucial it is to anticipate future developments. The accuracy of forecasting depends significantly on the method chosen, as not all predictions yield satisfactory results due to various influencing factors.

One of the most common challenges is the presence of high or unstable variance in the data, often referred to as volatility. In statistics, this condition is known as heteroskedasticity, especially prevalent in financial or economic data such as stock prices[2], [3]. Investment offers many advantages, but it inherently comes with risks. One such risk is the potential drop in stock prices, which can cause investors to suffer capital losses[4]. To anticipate this, investors usually apply forecasting models to help predict future stock prices more effectively[5].

Time series analysis is frequently used in this context. A time series is a sequence of data collected over time at regular intervals[1], [6], [7]. In this field, technological advancements have led to the emergence of various models for predicting future trends and behavior. Among these, the Autoregressive Integrated Moving Average (ARIMA) model is widely used. For example, research by Jarrett and Kyper showed how ARIMA was applied to predict the Chinese stock index, though they also noted that frequent volatility limited the model's performance[8].

This limitation has prompted researchers to combine ARIMA with GARCH (Generalized Autoregressive Conditional Heteroskedasticity), which extends the ARCH model by incorporating past residuals and variances. The hybrid ARIMA-GARCH model combines ARIMA's ability to capture trends and GARCH's capacity to handle volatility[9].

One researcher has used the hybrid ARIMA-GARCH model as a better approach because the time series data under study exhibit high volatility[10]. Their study evaluated forecasting performance using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), and compared the results with those obtained from the standard ARIMA model. The findings indicate that the hybrid ARIMA-GARCH model produced lower forecasting errors than the ARIMA model alone. Thus, it can be concluded that the hybrid model performs better under conditions of high volatility.

The Walk-Forward method is a technique applied in a financial context, where it is used to set optimal parameters in a trading strategy to improve forecasting accuracy[11]. The approach in this method allows the model to be updated each time new data is generated. A study that used this method was conducted by Sidra Mehtab and Jaydip Sen, where it was applied to multivariate time series data using the Walk-Forward method. The results of the study showed that the use of the Walk-Forward method can improve forecasting quality compared to not applying the method[12].

To overcome the limitations of ARIMA in modeling volatile financial data, researchers have developed the hybrid ARIMA-GARCH model, which combines the strengths of ARIMA in capturing linear patterns and GARCH in modeling time-varying volatility. In this study, we used the hybrid ARIMA-GARCH model with the Walk-Forward method to forecast the movement of LQ45 stock prices. The forecasting results were then compared with the actual stock price data. However, the stock price data was not directly used to build the model. Instead, the stock price data were first processed into return data. Stock return refers to the income or profit obtained from stock investments, which depends on the amount of money invested and the investment period[13]. Few studies have applied the hybrid ARIMA-GARCH model to LQ45 stock forecasting using walk-forward validation on high-frequency daily data, leaving a methodological gap in capturing both volatility and real-time predictability. Thus, this study aims to develop and evaluate a hybrid ARIMA-GARCH model with the Walk-Forward method on LQ45 stock price forecasting, thereby providing a more accurate and adaptive forecasting framework.

2. RESEARCH METHODS

2.1. Type of Research

This study is classified as applied research, employing the hybrid ARIMA-GARCH model with the Walk-Forward method. The data used are secondary data in the form of daily closing stock prices of the LQ45 index, obtained from the website https://finance.yahoo.com.

2.2. Location and Time of Research

The research was conducted at the Public Library of State University of Makassar (UNM), starting in June 2024 and continuing until completion.

2.3. Data and Data Sources

The study utilizes secondary data consisting of daily closing prices of stocks listed in the LQ45 index for the period from January 2022 to May 2024. The data were obtained from the website https://finance.yahoo.com and were used to assess the forecasting accuracy of the hybrid ARIMA-GARCH model with the Walk-Forward method.

2.4. Research Procedure

This research used R Studio software for data processing. The analytical procedures in this study were carried out in the following stages:

2.4.1 Preprocessing

1. Preparing the LQ45 daily closing stock price data from January 2022 to May 2024.
2. Converting the daily closing price data into return data.
3. Performing exploratory data analysis by plotting the initial time series and computing descriptive statistics.
4. Splitting the data using the Walk-Forward method: 80% as in-sample data for model building and 20% as out-of-sample data for validation and forecasting.
5. Conducting stationarity tests on the return data using time series plots, the ADF test, and ACF/PACF plots.

2.4.2 Modeling

1. Identifying tentative ARIMA models based on ACF and PACF plots or model estimation.

2. Estimating ARIMA model parameters using the Maximum Likelihood Estimation (MLE) method and testing their significance.
3. Conducting diagnostic checks of the ARIMA model, including the Ljung-Box test for white noise and the Kolmogorov-Smirnov test for residual normality.
4. Selecting the best ARIMA model based on the lowest AIC value and model assumptions.
5. Testing for ARCH effects in the ARIMA model residuals using the ARCH-LM test to determine the presence of heteroscedasticity.
6. If residuals are found to be heteroscedastic, estimating the conditional variance using the GARCH model on the stationary residuals.
7. Estimating the parameters of the ARIMA-GARCH model using MLE and testing their significance.
8. Conducting diagnostic checks of the ARIMA-GARCH model, including the ARCH-LM test and white noise test.
9. Combining the results of the linear ARIMA model and the nonlinear GARCH model to form a hybrid ARIMA-GARCH model.

2.4.3 Validation

Forecasting and validating the daily closing stock prices using the hybrid model, then comparing the forecast results with out-of-sample data using the MAPE metric.

3. RESULTS AND DISCUSSIONS

3.1. Descriptive Analysis

The data used in this study consisted of LQ45 stock price time series data from January 2022 to May 2024. The data was divided into two parts: in-sample data, covered the period from January 2022 to November 2023 with a total of 448 observations, and out-of-sample data, covered the period from November 2023 to May 2024 with a total of 109 observations. The in-sample data was utilized for the process of model identification, estimation, and selection. Once the best model was obtained, then it was applied to the out-of-sample data for forecasting purposes. The out-of-sample data was used to evaluate the model's forecasting performance and to compare the actual values with the predicted values to assess accuracy. A description of the LQ45 stock return time series data was presented in **Table 1** and **Figure 2**.

Table 1. Descriptive Statistics of The Data

Statistic	LQ45
Mean	0.065
Maximum	0.091
Minimum	0.010
Standard Deviation	0.009
Skewness	-0.579
Kurtosis	6.430

Table 1 showed that the LQ45 stock return had an average (mean) daily return of 0.065, or 6.5% when expressed as a percentage. The standard deviation was 0.009, or 0.9%, indicating the level of daily return volatility. The maximum and minimum returns observed were 0.091 (9.1%) and 0.01 (1%) respectively. The skewness value was negative

at -0.579, suggested that the return distribution was left-skewed, with more extreme negative returns. The kurtosis value was 6.43, which indicated a leptokurtic distribution—meaning that the returns exhibited a sharper peak and heavier tails compared to a normal distribution. The time series plot of the LQ45 stock returns was shown in Figure 2.

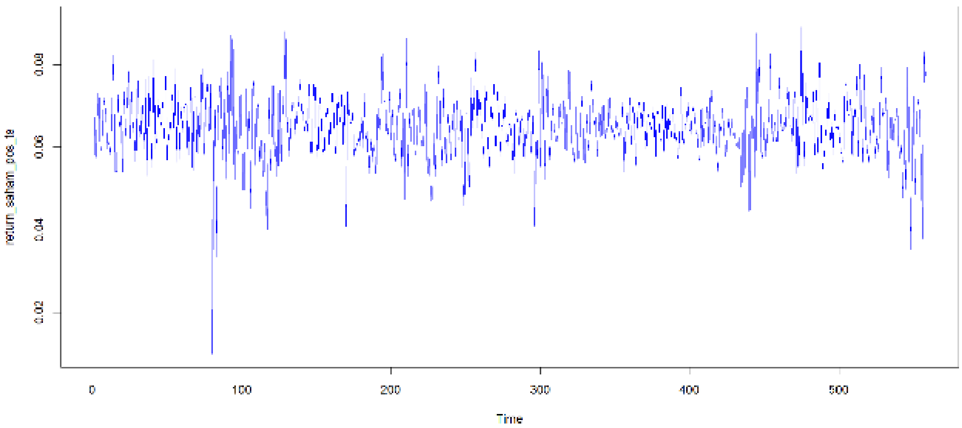

Figure 2. **Preliminary Time Series Plot of LQ45 Stock Returns**

3.2. Stationarity Testing

Stationarity refers to the condition in which fluctuations in time series data occur around a constant mean, and the variance remains stable over time. The Augmented Dickey-Fuller (ADF) test on the stock return data yielded a p-value of 0.01, which was below the significance level ($\alpha = 0.05$), indicated that the stock return data was stationary.

3.3. ARIMA Model Identification

Figure 3 presented the ACF and PACF plots of the in-sample (training) data. Based on the ACF plot, the first lag clearly exceeded significance boundary, which indicated the potential suitability of an MA(1) component. Similarly, the PACF plot showed that the first lag also exceeded significance boundary, suggested the relevance of an AR(1) component.

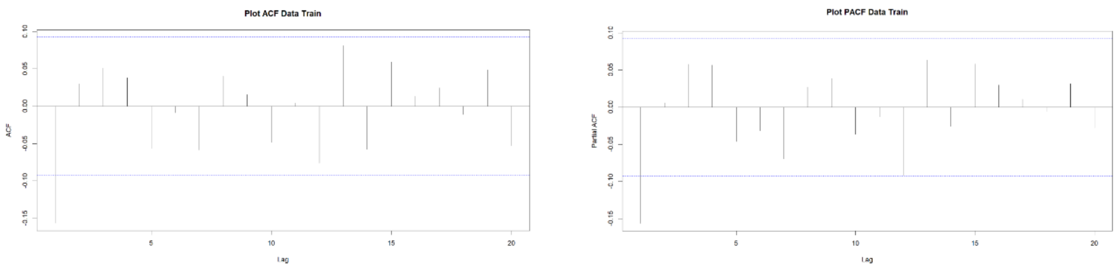

Figure 3. **ACF and PACF Plots of The In-Sample (Training) Data**

As a result, three tentative ARIMA models were considered: ARIMA(0,0,1), ARIMA(1,0,0), and ARIMA(1,0,1). Among these, the ARIMA(1,0,0) model was selected as the best-fitting model based on the lowest AIC value. Additionally, the residual diagnostics showed no significant autocorrelation, and the residuals were approximately normally distributed, indicated that the ARIMA(1,0,0) model provided good balance between simplicity and predictive accuracy.

3.4. Parameter Estimation of The Tentative ARIMA Models

The results of the parameter estimation for the tentative ARIMA models applied to the LQ45 stock return data were presented in **Table 2**.

Table 2. **Estimation Results of Tentative ARIMA Models**

Tentative Model	Parameters	S.E.	Z	Pr(> $\|z\|$)	Description
ARIMA$(\mathbf{0},\mathbf{0},\mathbf{1})$	$ma(1) = -0.15$	0.04	-3.34	0.0009	Significant
ARIMA$(\mathbf{1},\mathbf{0},\mathbf{0})$	$ar(1) = -0.16$	0.05	-3.36	0.0008	Significant
ARIMA$(\mathbf{1},\mathbf{0},\mathbf{1})$	$ar(1) = -0.17$	0.23	-0.76	0.45	Not Significant
	$ma(1) = 0.02$	0.23	0.08	0.94	Not Significant

The p-value indicates statistical significance of each parameter. A parameter is considered statistically significant if its p-value is less than 0.05, implying that the corresponding lag component contributes meaningfully to the model. Based on **Table 2**, only ARIMA(0,0,1) and ARIMA(1,0,0) yielded statistically significant parameters, while ARIMA(1,0,1) contained insignificant parameters and therefore wasn't further to be considered. To select the best-fitting model among the candidates, model selection criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used. Both AIC and BIC balance model fit and complexity—lower values indicate a better model. In this study, the ARIMA(1,0,0) model achieved the lowest AIC, made it most optimal among the tentative models. Thus, ARIMA(1,0,0) was selected as the best-fitting model based on the combination of parameter significance (p-values) and model evaluation criteria (AIC and BIC), ensured both statistical reliability and predictive efficiency.

3.5. Diagnostic Test of ARIMA Model

The diagnostic test results for the ARIMA(p, d, q) models based on the previous estimation are presented in **Table 3**.

Table 3. **Diagnostic Test of ARIMA Model**

ARIMA Models	White Noise Test		Normality Test	
	Chi-Square	p-value	KS	p-value
ARIMA$(\mathbf{0},\mathbf{0},\mathbf{1})$	0.02	0.88	0.04	0.04
ARIMA$(\mathbf{1},\mathbf{0},\mathbf{0})$	0.0004	0.98	0.04	0.05

Based on **Table 3**, the result of white noise test with Ljung-Box Statistic indicated that the ARIMA(1,0,0) model yielded a p-value of 0.98, suggested that residuals met the white noise assumption. However, the result of normality test with Kolmogorov–Smirnov Statistic showed a p-value of 0.05, indicated that the residuals were not normally distributed. This non-normality might reflect the presence of heteroscedasticity, which could cause the residual variance to vary over time.

To address this issue, further testing was conducted to detect ARCH effects in the residuals. The presence of heteroscedasticity justifies the application of the GARCH model, which is designed specifically to model time-varying volatility. Among various alternatives for handling volatility (such as exponential smoothing, rolling variance models, or ARCH family variants), the ARIMA-GARCH hybrid model was selected due to its proven effectiveness in modeling time series data of finance that exhibited both autocorrelation and conditional heteroscedasticity. Moreover, previous studies have shown that combining ARIMA for capturing linear patterns and GARCH for modeling volatility provides superior forecasting performance compared to using ARIMA alone. Therefore, the choice of the ARIMA-GARCH model in this study is based on both statistical diagnosis and empirical evidence from literature.

3.6. Selection of the Best ARIMA Model

Based on the evaluations conducted in the previous steps, the ARIMA(1,0,0) model was selected as the best-fitting model, as it produced the smallest AIC value of $-\mathbf{3004.88}$. Therefore, the ARIMA(1,0,0) model can be expressed as follows[14]:

$$\begin{aligned}&\boldsymbol{\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t}\\&\Leftrightarrow \boldsymbol{(1-(-0.16)B)(1-B)^0 Z_t = a_t}\\&\Leftrightarrow \boldsymbol{(1+0.16B)Z_t = a_t}\\&\Leftrightarrow \boldsymbol{Z_t = \frac{a_t}{1+0.16B}}\end{aligned} \tag{1}$$

After simplification, the ARIMA(1,0,0) model equation was expressed as follows:

$Z_t = -0.16Z_{t-1} + a_t$

The AIC value was used to select the best model, as presented in Table 4.

Table 4. AIC Values of ARIMA Model Candidates

ARIMA Models	AIC Values
ARIMA($\mathbf{0,0,1}$)	-3004.31
ARIMA($\mathbf{1,0,0}$)	-3004.88

Based on Table 4, the selected model is ARIMA(1,0,0), which has the smallest AIC value of -3004.88. Additionally, based on the results of the normality test, only the ARIMA(1,0,0) model meets the criteria.

3.7. Identification of Heteroscedastic Effects

The results of heteroscedasticity testing with the ARCH-LM (Lagrange Multiplier) test indicated that the ARIMA(1,0,0) model produced a p-value of 0.00088, which was less than the significance level ($\alpha = 0.05$). Therefore, the null hypothesis (H_0) was rejected, and the alternative hypothesis (H_1) was accepted, indicated the presence of an ARCH effect in the estimated model.

3.8. Selection of the Best ARCH-GARCH Model

The estimation results and parameter significance of the ARCH-GARCH models are presented in Table 5.

Table 5. AIC and BIC Values of ARCH-GARCH Models

Model Estimation	AIC Values	BIC Values
ARCH($\mathbf{1}$)	-6.79	-6.74
GARCH($\mathbf{1,1}$)	-6.83	-6.78

Based on Table 5, the estimation results indicate*d* that the ARCH-GARCH(1,1) model had the lowest AIC and BIC values, at -6.83 and -6.78 respectively. Therefore, the

ARCH-GARCH(1,1) model was selected as the *best fitting* model. The equation of the GARCH(1,1) model was as follows:

$$\begin{aligned}
&\boldsymbol{\sigma_1^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2} \\
&\Leftrightarrow \boldsymbol{\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2} \\
&\Leftrightarrow \boldsymbol{\sigma_1^2 = 0.000002 + 0.07\varepsilon_{t-1}^2 + 0.91\sigma_{t-1}^2}
\end{aligned} \tag{2}$$

Where $\varepsilon_t = \alpha_t$ the GARCH(1,1) equation became as follows:
$\sigma_1^2 = 0.000002 + 0.07(\alpha_{t-1})^2 + 0.91\sigma_{t-1}^2$

3.9. Diagnostic Test of the ARCH-GARCH Model

The results of the white noise test using Ljung-Box Statistic showed that the ARCH-GARCH(1,1) model produced a p-value greater than significance level ($\alpha = 0.05$), specifically 0.94. This led to acceptance of H_0, indicated that the residuals of the model exhibited white noise characteristics.

Furthermore, ARCH-LM test results indicated that the ARCH-GARCH(1,1) model yielded a $p - value$ of 0.77, which was also greater than significance level ($\alpha = 0.05$). This suggested model no longer contained ARCH effects (heteroscedasticity). Based on the results of both tests, the model was considered valid for forecasting purposes.

3.10. Hybrid ARIMA-GARCH Model

The best hybrid ARIMA-GARCH model is the ARIMA(1,0,0)-GARCH(1,1), expressed by the following equation[15]:

$$\hat{y}_t^{\,hybrid} = \alpha\hat{y}_t^{\,ARIMA} + (1-\alpha)\hat{y}_t^{\,GARCH}$$

The hybrid ARIMA-GARCH model equation was derived as follows:

1. The ARIMA(1,0,0) model equation was given by:
   $Z_t = -0.16Z_{t-1} + a_t$
2. The GARCH(1,1) model equation for the residual a_t was given by:
   $a_t = Z_t + 0.16Z_{t-1}$
   $\Leftrightarrow \sigma_1^2 = 0.000002 + 0.07(\alpha_{t-1})^2 + 0.91\sigma_{t-1}^2$

With substitute α_{t-1} into the GARCH(1,1) model, the ARIMA(1,0,0)-GARCH(1,1) model equation became as follows:
$\sigma_1^2 = 0.000002 + 0.07(Z_t + 0.16Z_{t-1})^2 + 0.91\sigma_{t-1}^2$
$\Leftrightarrow \sigma_1^2 = 0.000002 + 0.07(Z_{t-1}^2 + 0.32Z_{t-1}Z_{t-2} + 0.0256Z_{t-2}^2) + 0.91\sigma_{t-1}^2$
$\Leftrightarrow \sigma_1^2 = 0.000002 + 0.07Z_{t-1}^2 + 0.0224Z_{t-1}Z_{t-2} + 0.001792Z_{t-2}^2 + 0.91\sigma_{t-1}^2$

3.11. Hybridizing ARIMA-GARCH Forecasting

The selected ARIMA-GARCH model was used for forecasting and model validation on out-of-sample data, where the model chosen based on the smallest AIC value. The results of the forecasting and model validation were shown in **Table 6**.

Table 6. Forecasting Results and Validation of ARIMA-GARCH Model

No.	Actual	Forecast
1.	0.06622	0.07625
2.	0.05786	0.07490
3.	0.06425	0.07507
4.	0.06780	0.07500
5.	0.08274	0.07497

Based on **Table 6**, forecast results for the closing prices of stock returns using the ARIMA-GARCH model were closely approximate the actual values. Furthermore, the residual diagnostic tests revealed that the normality test using the Kolmogorov-Smirnov statistic produced a low p-value, indicated that residuals were not normally distributed. This violation suggested the presence of heteroscedasticity in the residuals, which justified the application of the GARCH model to model the conditional variance. The non-normality implied that the residuals exhibit volatility clustering—a common trait in financial time series—hence reinforced the suitability of the ARIMA-GARCH hybrid approach in this study.

3.12. Forecasting Evaluation of the ARIMA-GARCH Model

The Mean Absolute Percentage Error (MAPE) is used to measure forecast accuracy. A smaller MAPE value indicates higher accuracy of the forecasting model. The selected model, ARCH-GARCH(1,1), yields a MAPE value of 17.8%, suggesting that the model is sufficiently accurate for further use. These results indicate that the ARIMA-GARCH model provides more effective forecasting for LQ45 stock returns compared to using the ARIMA model alone.

In its development, several related studies**[16]**, **[17]**, **[18]**, **[19]**, **[20]** have examined stock prices and forecasting using various data samples and methods. However, none of these studies have conducted forecasting using a full population of daily closing stock prices from the LQ45 index with a hybrid ARIMA-GARCH model employing the walk-forward method.

This study uses daily closing price data of LQ45 stocks from January 2022 to May 2024, comprising 558 data points. Prior to model building, the stock price data is transformed into stock returns. The walk-forward method is applied to divide the data into two parts: 80% (448 data points) as in-sample data for model building, and 20% (109 data points) as out-of-sample data for model validation and forecasting. Descriptive statistics of the LQ45 stock return data in **Table 1** show a mean of 0.065, a standard deviation of 0.009, a maximum value of 0.091, a minimum of 0.01, a skewness of −0.579, and a kurtosis of 6.43.

The tentative ARIMA models formed are ARIMA(0,0,1), ARIMA(1,0,0), and ARIMA(1,0,1). Following model identification, parameter estimation is conducted to select models with statistically significant parameters. From the estimation of tentative ARIMA(p,d,q) models, only ARIMA(0,0,1) and ARIMA(1,0,0) produce significant parameters (as shown in **Table 3**. A diagnostic check is then conducted. The ARIMA(1,0,0) model satisfies the white noise assumption **Table 4** but fails the normality assumption, indicating the potential presence of heteroscedasticity. Therefore, an ARCH-LM test is conducted. Prior to that, the best ARIMA model is selected based on the lowest AIC value. **Table 5** shows that ARIMA(1,0,0) has the smallest AIC of −3004.88, making it the best-fitting ARIMA model in this study.

To formally test for heteroscedasticity, the Lagrange Multiplier (LM) test is used. The hypothesis tested is whether the residuals exhibit an ARCH effect, indicating a need for ARCH-GARCH modeling. The estimation results of both ARCH(1) and ARCH-GARCH(1,1) models are compared. The ARCH-GARCH(1,1) model is selected based on the smallest AIC and BIC values of -6.83 and -6.78, respectively, as shown in **Table 7**. Residual diagnostic testing is then performed to confirm that the model satisfies the white noise assumption and no longer contains heteroscedasticity (ARCH effect), as indicated in **Table 8**.

The best hybrid model identified is ARIMA(1,0,0)-GARCH(1,1), which is subsequently used for forecasting. The Mean Absolute Percentage Error (MAPE) of the hybrid model is 17.8%, indicating that the ARIMA-GARCH model provides more accurate forecasts than the ARIMA model alone. The small difference between the actual and forecast values in the out-of-sample data further confirms the model's forecasting effectiveness. This finding aligns with previous studies such as **[17]** and **[18]**, which also highlighted the superiority of GARCH-based models in handling volatility in stock return forecasting. However, those studies used either weekly or monthly data and did not apply the walk-forward validation technique.

Compared to their reported MAPE values, which generally ranged between 20% and 25%, the current study achieved a lower MAPE of 17.8%. This suggests an improvement in forecasting accuracy, likely due to the use of high-frequency daily data and a more dynamic validation method. These findings are consistent with previous studies such as **[17]** and **[18]**, which also demonstrated that GARCH-based models could reduce forecast errors in volatile financial time series. Furthermore, this study complements and extends the work of Zili et al. **[20]**, who applied the ARIMA-GARCH model with walk-forward validation but used a narrower data scope. By incorporating a full population of daily closing prices from the LQ45 index and applying walk-forward validation, this research provides stronger evidence that hybrid models are effective for accurate and adaptive stock forecasting.

4. CONCLUSIONS

The hybrid ARIMA-GARCH model significantly improves forecasting accuracy compared to the ARIMA model alone, as evidenced by its lower MAPE and its superior ability to capture volatility in LQ45 stock returns. This confirms the model's effectiveness in handling the non-linear and heteroskedastic characteristics typical of financial time series data.

Specifically, the best ARIMA model identified is ARIMA(1,0,0), with the smallest AIC value, and is represented by the equation: $Z_t = -0{,}16Z_{t-1} + a_t$. The best ARCH-GARCH model is GARCH(1,1), which has the smallest AIC and BIC values and passes residual diagnostic tests, indicating the absence of heteroscedasticity. Its equation is: $\sigma_1^2 = 0{,}000002 + 0{,}07(\alpha_{t-1})^2 + 0{,}91\sigma_{t-1}^2$. Combining these results, the final hybrid model ARIMA(1,0,0)-GARCH(1,1) is used for forecasting and is expressed as: $\sigma_1^2 = 0{,}000002 + 0{,}07Z_{t-1}^2 + 0{,}0224Z_{t-1}\, Z_{t-2} + 0{,}001792Z_{t-2}^2 + 0{,}91\sigma_{t-1}^2$.

In addition to the improved forecasting performance, this study offers a novel contribution by applying the hybrid ARIMA-GARCH model to high-frequency daily data from the LQ45 index, using a walk-forward validation approach. This methodological combination—rarely employed in previous research—enhances the model's out-of-sample reliability and practical relevance. It provides a more dynamic and realistic framework for predicting stock prices, especially in emerging markets such as Indonesia.

ACKNOWLEDGMENTS

The author first expresses heartfelt appreciation to her beloved parents for their endless prayers, unwavering support, and encouragement throughout the completion of this study. The author also extends sincere gratitude to her academic advisors and colleagues at the State University of Makassar for their valuable insights and encouragement during the preparation of this research.

FUNDING INFORMATION

Authors state there is no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable.

ETHICAL APPROVAL

Not applicable.

DATA AVAILABILITY

The data that support the findings of this study are available from a public source (https://finance.yahoo.com) and were processed by the author using R software.

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