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Forecasting the Share Price of Islamic Banks in Indonesia Using the Arima and Garch Methods

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Abstract. This study aims to analyze and forecast the stock price movements of PT Bank Syariah Indonesia Tbk (BRIS) using a time series approach. The Autoregressive Integrated Moving Average (ARIMA) model is employed to capture the mean pattern of stock prices, while the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are applied to analyze volatility dynamics characterized by heteroskedasticity. Daily stock price data of BRIS are tested for stationarity using the Augmented Dickey-Fuller (ADF) test and become stationary after differencing. The results indicate significant volatility, suggesting that the GARCH model is more appropriate for further analysis. Based on the evaluation using Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ), the ARIMA dan GARCH model is selected as the best model, achieving an average accuracy of 80%. These findings demonstrate that the combination of ARIMA and GARCH provides a more comprehensive understanding of the movement and volatility patterns of Islamic stock prices, serving as a useful reference for investors and policymakers in formulating investment strategies.

Keywords: ARIMA; Bank Syariah Indonesia; Forecasting; GARCH; Stock Price

1. INTRODUCTION

The capital market plays an important role in the modern economy as a means of intermediation between parties with excess funds and those in need of funds. One of its main instruments is shares, which offer the potential for profits in the form of dividends and capital gains, but carry a high risk due to price fluctuations (Pratama et al., 2025). Every investment instrument carries a certain level of risk, with the potential for loss being the most common risk faced. In general, investment activities take place in the capital market, where issuers offer and trade securities to investors (Susilawati et al. 2025). Stock price movements are influenced by fundamental and technical factors, as well as macroeconomic variables, making them difficult to predict simply and requiring a quantitative approach.

In quantitative analysis, the ARIMA model is widely used to predict stationary time series data and focuses on modelling average values. However, stock price data generally exhibits high volatility and non-constant variance (heteroscedasticity), so the use of ARIMA alone is often insufficient to capture the characteristics of the data comprehensively (Safitry & Kristin 2017). On the other hand, the ARCH-GARCH model is designed to model volatility dynamics, but does not specifically address the mean pattern of the data. Therefore, a research problem arises regarding how to combine the ARIMA and ARCH-GARCH models in order to model the mean and volatility of stock prices more accurately, thereby improving the accuracy of the forecasting results (Pratama et al., 2025).

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This study focuses on forecasting the share price of PT Bank Syariah Indonesia Tbk (BRIS) using the ARIMA and ARCH-GARCH methods on time series data of share prices during a specific research period. The selection of BRIS shares is based on its position as the largest Islamic bank in Indonesia, resulting from the merger of three state-owned Islamic banks, so that it can represent the performance of the national Islamic banking industry. The ARIMA method is used to model the average stock price pattern, while the ARCH-GARCH method is used to capture the volatility dynamics that often appear in stock price data (Nusrang & Haryadi, 2025). The combination of these two methods is expected to produce more accurate and comprehensive forecasts of BRIS stock prices, both academically in the development of literature.

2. LITERATURE REVIEW

Stock

A stock represents a certificate of ownership in a limited liability company that grants its holder the right to receive a portion of the company's profits in the form of dividends, as well as the potential for capital gains derived from the difference between buying and selling prices (Yuliarti 2024). Stocks are traded on capital markets and have become one of the most popular investment instruments due to the attractive profit opportunities they offer. However, they also carry inherent risks stemming from price fluctuations driven by internal company factors, macroeconomic conditions, and market sentiment. According to Darmadji (2006), a stock is evidence of a person's ownership in a company, typically represented in the form of a paper certificate or securities document. The proportion of ownership is determined by the amount of capital or investment contributed to the company (Bbri et al., 2024).

Forecasting

Forecasting is the process of estimating future conditions or values by utilizing historical data as the basis of analysis. In the field of finance, forecasting is widely applied to predict stock price movements, market indices, and various economic indicators. Forecasting approaches can be conducted either qualitatively or quantitatively, one of which is through time series analysis (Nasirudin & Dzikrullah 2023). Taylor (2004) classifies forecasting into three categories based on its time horizon: long-term forecasting, which covers a period of approximately two to ten years and is generally used in strategic planning and long-term resource needs (Adelia et al. 2024); medium-term forecasting, which spans one to twenty-four months and is typically applied to production planning, cash flow management, and budget preparation; and short-term forecasting, which focuses on a period of one to five weeks and serves as the basis for daily to weekly operational decision-making.

ARIMA

The ARIMA (Autoregressive Integrated Moving Average) model is one of the methods used to model and forecast time series data based on its historical patterns (Alfaki 2015). This model consists of three main components: Autoregressive (AR), which represents the dependence of a current value on its previous values; Integrated (I), which refers to the differencing process applied to render the data stationary; and Moving Average (MA), which captures the influence of errors from previous periods on the current value. According to Arsyad (1995), ARIMA is a forecasting method that works by analyzing and combining historical data patterns to produce estimates of future values. Mathematically, the AR component is expressed as the relationship between the current variable and a number of its past values plus an error component, while the MA component is expressed as a function of errors in previous periods (Studi et al. 2025). The ARIMA model as a whole integrates mean values, the influence of certain parameters, and disturbance components to produce more accurate forecasts for time series data. The general equation for ARIMA(p, d, q) is as follows:

$$Z_t = c + \varphi 1 Z_t - 1 + \varphi 2 Z_t - 2 + \ldots + \varphi p Z_t$$

Based on the formula above, where Zt represents the error, c is an unknown constant, and φi, i = 1, 2, …, p, are the parameters of the AR model. One key advantage of ARIMA is its ability to model non-stationary data by first applying differencing. However, accurate forecasting requires correct identification of the model's order (p, d, q).

Heteroscedasticity Testing

Heteroscedasticity refers to the condition in which the variance of errors or residuals is not constant over time. In the context of financial data, this phenomenon is often referred to as volatility clustering, where periods of high volatility tend to be followed by similarly high-volatility periods, and vice versa. If the results of the ARCH effect test indicate significance in a time series, then the ARCH model is considered appropriate for estimation. Through this estimation, conditional volatility (σ_t) can be calculated using historical information from previous periods (Talumewo et al., 2023). The presence of heteroscedasticity indicates that the data exhibits dynamic, changing variance, making it unsuitable for models that assume constant variance. Therefore, heteroscedasticity testing is a critical step in determining whether a time series is better modeled using ARCH or GARCH models, which are specifically designed to capture non-constant volatility patterns. This suggests that when financial data exhibits signs of volatility clustering, ARCH/GARCH-based models are more appropriate and are expected to yield superior forecasting performance compared to standard models that assume homoscedasticity.

Previous Research

This section discusses the limitations and shortcomings of relevant prior studies. The discussion aims to clarify the position of the current research and highlight how it differs from previous work. To facilitate understanding, a summary table of previous studies along with their methods, strengths, and limitations is presented below:

Table 1. Previous Research

No	Researcher (Year)	Research Title	Method	Strengths	Limitations
1	Antika, Mugayat, and Sukartini (2025)	Analisis Volatilitas Saham dengan Metode ARCH-GARCH pada Bank Rakyat Indonesia Tahun 2019–2022	ARCH-GARCH using Eviews	The ARCH-GARCH method effectively captures heteroscedasticity characteristics (volatility clustering) in stock data, yielding more accurate analysis results.	Stock price data are highly volatile, making the model highly sensitive to market conditions and external factors, such as the COVID-19 pandemic which caused 2020 to exhibit the highest level of risk.
2	Rafulta et al. (2025)	Pemodelan dan Peramalan Volatilitas Memori Panjang pada Return Saham ANTM: Studi Komparatif Model GARCH dan FIGARCH	GARCH(1,1) and FIGARCH(1,d,1)	GARCH(1,1) effectively captures short-term volatility clustering with better predictive accuracy (lower RMSE and MAPE). FIGARCH(1,d,1) captures the long memory effect (d = 0.461007), providing a more realistic representation of long-term volatility. Both models are valid and yield reasonably consistent forecasts.	Further development is needed, such as the use of weekly/monthly data or hybrid models (machine learning + GARCH/FIGARCH) to improve prediction accuracy.
3	Kakombohi, Prang, and Salaki (2024)	Prediksi Harga Saham PT AKR Corporindo Tbk (AKRA.JK) Menggunakan Model ARIMA-GARCH	Quantitative time series analysis using ARIMA-GARCH	The ARIMA-GARCH combination offers greater accuracy by capturing volatility patterns in stock prices.	The ARIMA-GARCH model requires strict assumptions of stationarity and normality; if data conditions change drastically (e.g., due to a financial crisis), predictions may become less valid.
4	Nurfajriyah, Harjadi, and Adzimatinur (2023)	Analisis Perbandingan Metode ARCH dan GARCH dalam	Documentation and literature study, processed using Eviews 10	Compares two popular models (ARCH and GARCH) to determine which	Only compares ARCH and GARCH models; does not incorporate other methods such as ARIMA-GARCH,

No	Researcher (Year)	Research Title	Method	Strengths	Limitations
		Peramalan Indeks Harga Saham (Studi pada Indeks Harga Saham Sub Sektor Teknologi Periode 2021-2023)	and Microsoft Excel	yields greater accuracy.	EGARCH, or TGARCH.
5	Fadhilah, Kankan Parmikanti, and Budi Nurani Ruchjana (2024)	Peramalan Return Saham Subsektor Perbankan Menggunakan Model ARIMA-GARCH	ARIMA-GARCH	Combines ARIMA and GARCH, enabling simultaneous capture of both trend and volatility.	The forecasting period tested is relatively short (only 6 periods ahead).

Based on the review of previous studies presented above, it is evident that ARCH-GARCH-based models have been widely applied and have demonstrated considerable capability in capturing volatility dynamics in financial time series data. The integration of ARIMA and GARCH models, in particular, has shown promising results in simultaneously modeling trend and volatility. These findings provide a strong theoretical and empirical foundation for the current study, which builds upon the ARIMA-GARCH framework while seeking to address the limitations identified in prior research, including the relatively narrow scope of data, short forecasting horizons, and the absence of comparative analysis with alternative volatility models.

3. RESEARCH METHOD

Data collection in this study used secondary data in the form of daily closing prices of Bank Syariah Indonesia (BRIS) shares obtained from the website www.investing.com for the period 1 January 2020 to 30 July 2025. The time series data was then tested for stationarity using the Augmented Dickey-Fuller (ADF) Test, and if the data was not stationary, a differencing process was carried out until it met the stationarity assumption. Furthermore, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses were used to determine the initial order of the ARIMA model, which was then estimated with several candidate models and the best model was selected based on the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ) values. The selected ARIMA-GARCH combined model is then used to forecast BRIS stock prices, while the accuracy of the forecast results is evaluated by comparing the actual data and the predicted results using the

RMSE, MAE, and MAPE error measures, where smaller error values indicate better model performance.

4. HASIL DAN PEMBAHASAN

Data Collection

The case study was conducted on the closing price of shares to predict the shares of Bank Syariah Indonesia (BRIS). The data used was daily data from 1 January 2020 to 30 July 2025. The data was obtained from https://www.investing.com/.

Stationarity Testing

The analysis began with a stationarity test to determine whether the data was stationary. This test was important because the ARIMA model can only be applied to stationary data. In addition, this stage aimed to ensure that the stock price data had a constant mean and variance over time.

Null Hypothesis: SAHAM has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.'
Augmented Dickey-Fuller test statistic		-1.347002	0.609
Test critical values:	1% level	-3.435841	
	5% level	-2.863853	
	10% level	-2.568052	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM)
Method: Least Squares
Date: 08/05/25 Time: 13:54
Sample (adjusted): 1/02/2020 6/30/2025
Included observations: 1146 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prol
SAHAM(-1)	-0.003490	0.002591	-1.347002	0.17
C	8.138731	4.632588	1.756843	0.07

R-squared	0.001584	Mean dependent var	2.4153
Adjusted R-squared	0.000711	S.D. dependent var	62.508
S.E. of regression	62.48632	Akaike info criterion	11.109
Sum squared resid	4466794.	Schwarz criterion	11.118
Log likelihood	-6363.753	Hannan-Quinn criter.	11.112
F-statistic	1.814413	Durbin-Watson stat	1.8853
Prob(F-statistic)	0.178246		

Figure 1. Level data

Null Hypothesis: D(SAHAM) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.98043	0.0000
Test critical values:	1% level	-3.435846	
	5% level	-2.863855	
	10% level	-2.568053	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM,2)
Method: Least Squares
Date: 08/05/25 Time: 13:55
Sample (adjusted): 1/06/2020 6/30/2025
Included observations: 1145 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SAHAM(-1))	-0.944556	0.029535	-31.98043	0.0000
C	2.288379	1.847410	1.238696	0.2157

R-squared	0.472238	Mean dependent var	0.029694
Adjusted R-squared	0.471776	S.D. dependent var	85.94873
S.E. of regression	62.46670	Akaike info criterion	11.10889
Sum squared resid	4460087.	Schwarz criterion	11.11770
Log likelihood	-6357.839	Hannan-Quinn criter.	11.11222
F-statistic	1022.748	Durbin-Watson stat	2.000173
Prob(F-statistic)	0.000000		

Figure 2. 1st Difference

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM,3)
Method: Least Squares
Date: 08/05/25 Time: 13:56
Sample (adjusted): 2/05/2020 6/30/2025
Included observations: 1127 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SAHAM(-1),2)	-10.57167	0.693617	-15.24137	0.0000
D(SAHAM(-1),3)	8.663578	0.681549	12.71161	0.0000
D(SAHAM(-2),3)	7.794256	0.660309	11.80395	0.0000
D(SAHAM(-3),3)	7.003217	0.631557	11.08881	0.0000
D(SAHAM(-4),3)	6.248218	0.597297	10.46082	0.0000
D(SAHAM(-5),3)	5.540001	0.558400	9.921213	0.0000
D(SAHAM(-6),3)	4.908579	0.516541	9.502781	0.0000
D(SAHAM(-7),3)	4.294223	0.473205	9.074762	0.0000
D(SAHAM(-8),3)	3.747814	0.429291	8.730244	0.0000
D(SAHAM(-9),3)	3.221895	0.384316	8.383445	0.0000
D(SAHAM(-10),3)	2.703556	0.338331	7.990871	0.0000
D(SAHAM(-11),3)	2.128161	0.291336	7.304821	0.0000
D(SAHAM(-12),3)	1.612544	0.243823	6.613590	0.0000
D(SAHAM(-13),3)	1.156955	0.195977	5.903510	0.0000
D(SAHAM(-14),3)	0.797600	0.149414	5.338200	0.0000
D(SAHAM(-15),3)	0.480684	0.105584	4.552638	0.0000
D(SAHAM(-16),3)	0.247880	0.065027	3.811981	0.0001
D(SAHAM(-17),3)	0.084793	0.030387	2.790412	0.0054
C	0.232637	1.907098	0.121985	0.9029

R-squared	0.817661	Mean dependent var	0.060337
Adjusted R-squared	0.814699	S.D. dependent var	148.7173
S.E. of regression	64.01774	Akaike info criterion	11.17291
Sum squared resid	4540884.	Schwarz criterion	11.25767
Log likelihood	-6276.936	Hannan-Quinn criter.	11.20494
F-statistic	276.0333	Durbin-Watson stat	2.002870
Prob(F-statistic)	0.000000		

Figure 3. 2nd Difference

Stationarity testing on Bank Syariah Indonesia (BRIS) stock price data was conducted using the Augmented Dickey-Fuller (ADF) Test. The test results showed that at the original data level, the ADF probability value was greater than 0.05, indicating that the data was not yet stationary. After the first differencing process, the ADF probability value decreased to less than 0.05, which means that the data is stationary at the first differentiation (d=1). Thus, BRIS stock price data meets the stationarity requirement after first differencing. This is in line with the characteristics of stock data, which is generally non-stationary at the level but can be made stationary through the differencing process. These results form the basis for proceeding to the ARIMA model identification stage through ACF and PACF analysis.

Correlogram Testing

After the data is declared stationary, the next step is to perform Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis. Based on the patterns formed from these two analyses, several ARIMA model candidates were obtained that were suitable for further testing, namely ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1).

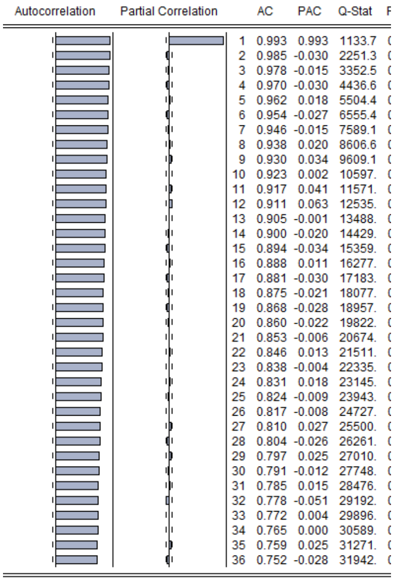

Figure 4. Level data

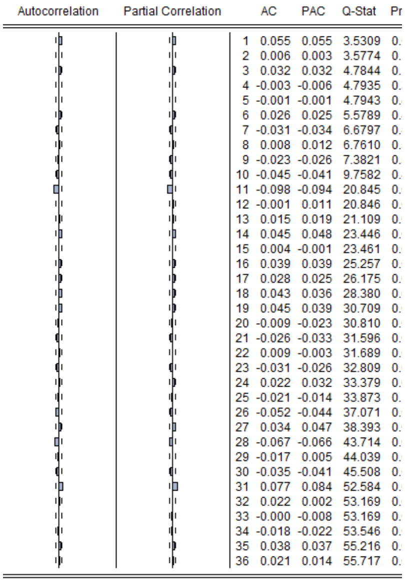

Figure 5. 1st Difference

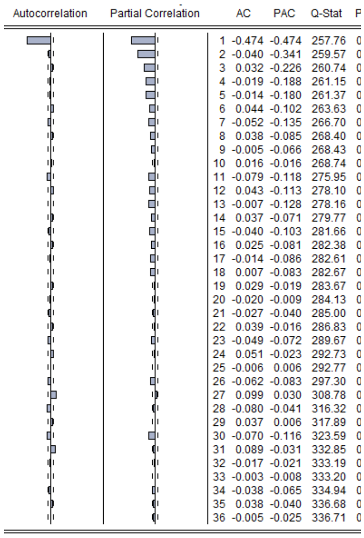

Figure 6. 2nd Difference

After the BRIS stock price data was stationised at the first difference, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyses were performed to identify the initial order of the ARIMA model. The ACF plot results showed significant autocorrelation at the first lag, while the PACF also displayed a significant pattern at the first lag. This pattern indicates that the appropriate ARIMA model candidates are ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1). The three model candidates were then tested further to determine the most appropriate model based on information criteria (AIC, SC, and HQ).

Testing and Determining the Best ARIMA

Based on the ARIMA testing that has been carried out previously, the best of the three candidates was selected based on the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ). Below is a table of the ARIMA test results:

Table 2. Results of the Best ARIMA Test

Variable	Model	ARIMA	AIC	SC	HQ
Saham		110	11.10977	11.12297	11.11476
Saham		011	11.10979	11.12299	11.11477
Saham		111	11.11140	11.12901	11.11805

As can be seen in the table above, it shows that of the three values, the result is ARIMA (1,1,0), which is the best ARIMA because it has the lowest AIC value compared to the other two models, namely 11.10977.

Heteroscedasticity Testing

After obtaining the best ARIMA model, the next step is to conduct a heteroscedasticity test to determine whether the residual variance is constant. This test is performed on the ARIMA model residuals to see if there are indications of heteroscedasticity or variance instability over time.

Heteroskedasticity Test: ARCH

F-statistic	38.92602	Prob. F(1,1143)	0.0000
Obs*R-squared	37.70988	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/05/25 Time: 14:34
Sample (adjusted): 1/06/2020 6/30/2025
Included observations: 1145 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3188.137	536.1955	5.945848	0.0000
RESID^2(-1)	0.181477	0.029087	6.239072	0.0000

R-squared	0.032934	Mean dependent var	3894.820
Adjusted R-squared	0.032088	S.D. dependent var	18025.83
S.E. of regression	17734.27	Akaike info criterion	22.40613
Sum squared resid	3.59E+11	Schwarz criterion	22.41494
Log likelihood	-12825.51	Hannan-Quinn criter.	22.40946
F-statistic	38.92602	Durbin-Watson stat	2.036601
Prob(F-statistic)	0.000000		

Figure 7. Results of Heteroscedasticity Testing

The heteroscedasticity test aims to determine whether the variance of the regression model residuals is constant (homoscedastic) or not constant (heteroscedastic) over time. In the context of financial data such as stock prices, heteroscedasticity often arises due to unstable volatility fluctuations or the phenomenon of volatility clustering. The results of the heteroscedasticity test in this study using the ARCH-LM Test show that the test probability value is less than 0.05, indicating heteroscedasticity in the ARIMA model residuals. In other words, the error variance is not constant, so the data is more accurately modelled using the GARCH approach to capture the volatility dynamics that occur.

Testing and Determining the Best GARCH

Several GARCH models were then tested, starting from GARCH (1,0), (1,1), (1,2), (2,1) to GARCH (2,2). The following table shows the results of the GARCH tests that were conducted previously.

Table 3. GARCH Test Results

Variable	D(BNSI)-ARI MA (1,1,1)				
	GARCH (1,0)	**GARCH (1,1)**	**GARCH (1,2)**	**GARCH (2,1)**	**GARCH (2,2)**
AIC	10.74806	10.50932	10.50543	10.49013	10.46012
SC	10.76568	10.53134	10.53186	10.51655	10.49095

The selection of the best model again refers to the smallest AIC, SC, and HQ values. Based on the results in the table above, GARCH (2,2) is the best model because it provides the lowest information criterion value.

Forecasting

After obtaining the best ARIMA and GARCH models, the next step is to forecast stock prices using a combination of the ARIMA (1,1,1) and GARCH (2,2) models. In this study, the forecasting process was carried out to predict the share price of PT Bank Syariah Indonesia Tbk (BRIS). Forecasting was carried out for seven days, namely from 1 July to 10 July 2025, on certain trading days by applying the ARIMA-GARCH model. The following presents the results of the share price prediction for PT Bank Syariah Indonesia Tbk (BRIS).

7/01/2025	3156.719	3156.714	47.49053	2254.185
7/02/2025	3156.137	3156.133	44.69557	1996.529
7/03/2025	3155.555	3155.551	42.78944	1829.771
7/07/2025	3154.969	3154.969	41.47055	1718.642
7/08/2025	3154.384	3154.384	40.53138	1641.628
7/09/2025	3153.798	3153.798	39.83429	1585.605
7/10/2025	3153.213	3153.213	39.29037	1542.568

Figure 8. Results of the Stock Price Prediction of PT Bank Syariah Indonesia

The accuracy of the forecasting results was measured. In this study, the accuracy level was calculated using the ARIMA method, with the following calculation results:

Table 4. Stock Price Accuracy Data

No	Date	Stock Price Prediction	Current Stock Price	Accuracy
1.	07/01/2025	3,156.719	2,510	79,5%
2.	07/02/2025	3,156.137	2,460	77,9%
3.	07/03/2025	3,155.555	2,480	78,5%
4.	07/07/2025	3,154.969	2,570	81,4%
5.	07/08/2025	3,154.384	2,600	82,%
6.	07/09/2025	3,153.798	2,610	82,%
7.	07/10/2025	3,153.213	2,710	85%

5. CONCLUSION AND SUGGESTIONS

This study successfully addressed its core research objective of developing an accurate and comprehensive forecasting model for the stock price of PT Bank Syariah Indonesia Tbk (BRIS) by integrating the ARIMA and GARCH methodologies. The ADF stationarity test confirmed that the BRIS daily closing price series achieves stationarity after first differencing (d=1), providing a sound basis for ARIMA identification. Among the three candidate models evaluated, ARIMA(1,1,0) was selected as the optimal mean model based on the lowest AIC value of 11.10977. Subsequent ARCH-LM testing of the ARIMA residuals confirmed the presence of significant heteroskedasticity, validating the necessity of a GARCH extension. Of the five GARCH variants tested, GARCH (2,2) yielded the lowest information criterion values across AIC, SC, and HQ measures and was thus identified as the best volatility model. The combined ARIMA (1,1,1)–GARCH (2,2) model generated seven-day out-of-sample forecasts for the July 1–10, 2025 trading period with an average accuracy of 80.5%, demonstrating that the hybrid specification captures both the directional trend and volatility clustering inherent in BRIS stock data more effectively than either model used in isolation. These results offer practical value for investors, portfolio managers, and policymakers seeking evidence-based tools for navigating the Islamic capital market.

Notwithstanding these contributions, several limitations of the present study merit acknowledgment. First, the model relies exclusively on historical price data and does not incorporate exogenous macroeconomic variables such as inflation rates, exchange rates, or Bank Indonesia benchmark rates that may exert material influence on Islamic bank stock prices. Second, the GARCH (2,2) specification adopted here is symmetric and therefore does not distinguish between the differential impact of positive and negative shocks on volatility, a phenomenon widely documented in equity markets as the leverage effect. Third, the seven-day forecast horizon, while useful for short-term trading decisions, may not generalize to medium- or long-term investment horizons. Future research is recommended to address these limitations by incorporating relevant macroeconomic covariates through ARIMAX or GARCH-X extensions, exploring asymmetric volatility models such as EGARCH or GJR-GARCH, and extending the evaluation to multiple Islamic banking stocks to assess the generalizability of the ARIMA GARCH framework across the broader Islamic financial sector in Indonesia.

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