Griya Journal of Mathematics Education and Application
Volume 6 Nomor 1, Maret 2026
e-ISSN 2776-124X||p-ISSN 2776-1258
https://mathjournal.unram.ac.id/index.php/Griya/index

# Time Series Modelling Using ARIMA-GARCH: Forecasting the Jakarta Stock Exchange Index Price

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**Accepted: 26-03-2026 ; Revised: 20-03-2026 ; Published: 25-03-2026**

**Abstract**
The high volatility of the Indonesian capital market (JKSE) poses significant challenges for investors in decision-making. Classical linear forecasting methods are often inadequate due to their inability to capture heteroskedasticity and asymmetric responses in financial data. This study aims to systematically compare and select the best hybrid model combining ARIMA with various GARCH specifications (Standard GARCH, EGARCH, GJR-GARCH, and TGARCH) under different error distributions, and to forecast JKSE price movements for the next three months. Using weekly closing price data from November 2022 to November 2025, the evaluation based on the lowest Akaike Information Criterion (AIC) identifies the ARIMA (0,0,4)-GJR-GARCH model with a Normal distribution as the most robust specification. This finding confirms the presence of a leverage effect in the Indonesian stock market, where volatility responds more intensely to negative shocks than to positive ones. The model demonstrates high accuracy with an RMSE of 2.090. The forecast projects a short-term correction followed by a gradual upward trend reaching the 8,603.62 level by March 2026, accompanied by widening confidence intervals that indicate increasing uncertainty risks in the future. Overall, while the projected market direction suggests growth, the inherent volatility risks necessitate a strategy of cautious optimism and disciplined risk management for investors.

**Keywords:** ARIMA; GARCH; JKSE; Forecasting; Asymmetric Volatility.

**Abstrak**
Volatilitas pasar modal Indonesia (IHSG) yang tinggi menghadirkan tantangan signifikan bagi investor dalam pengambilan keputusan. Metode peramalan linier klasik sering kali tidak memadai karena ketidakmampuannya menangkap karakteristik heteroskedasticity dan respons asimetris pada data keuangan. Penelitian ini bertujuan untuk membandingkan dan memilih model hybrid terbaik antara ARIMA dengan berbagai spesifikasi GARCH (Standard GARCH, EGARCH, GJR-GARCH, dan TGARCH) di bawah berbagai distribusi error, serta memprediksi pergerakan harga IHSG untuk tiga bulan ke depan. Menggunakan data harga penutupan mingguan dari November 2022 hingga November 2025, hasil evaluasi berdasarkan nilai Akaike Information Criterion (AIC) terendah menunjukkan bahwa model ARIMA (0,0,4)-GJR-GARCH dengan distribusi Normal adalah spesifikasi yang paling robust. Temuan ini mengonfirmasi keberadaan leverage effect di pasar saham Indonesia, di mana volatilitas merespons guncangan negatif lebih kuat daripada guncangan positif. Model ini menghasilkan akurasi tinggi dengan RMSE sebesar 2,090. Hasil peramalan memproyeksikan koreksi jangka pendek yang diikuti oleh tren kenaikan bertahap menuju level 8.603,62 pada Maret 2026, namun disertai dengan pelebaran interval kepercayaan yang mengindikasikan peningkatan risiko ketidakpastian di masa depan. Secara keseluruhan, meskipun tren pasar mengindikasikan pertumbuhan, risiko volatilitas yang membayangi menuntut investor untuk menerapkan sikap optimis namun berhati-hati serta manajemen risiko yang ketat.

**Kata Kunci:** ARIMA; GARCH; IHSG; *Forecasting*, Volatilitas Asimetris.

## 1. INTRODUCTION

The Indonesian capital market constitutes a critical component of the national financial system, providing a platform for resource allocation and serving as a reflection of macroeconomic conditions (Akbariaza, 2024). The Jakarta Stock Exchange Index (JKSE), as the principal indicator of market performance, captures a broad spectrum of economic signals and is therefore widely used by investors, analysts, and policymakers in evaluating market outlooks (Fauziyah et al., 2021; Permana et al., 2023). In recent years, the JKSE has been characterized by pronounced volatility triggered by shifts in global monetary policies, geopolitical uncertainty, and domestic structural developments (Dwi Yudiono et al., 2024; Zul Ihsan Mu'arrif, 2024). These conditions highlight the importance of accurate forecasting models capable of supporting evidence-based investment decisions and enhancing market stability.

Modelling stock market behaviour, however, poses substantial empirical challenges. Financial time series typically exhibit nonlinearity, heteroskedasticity, and asymmetric responses to shocks, all of which reduce the effectiveness of classical linear forecasting techniques (Hamdani et al., 2024; Oprasianti et al., 2024). Against this backdrop, hybrid modelling approaches that combine autoregressive dynamics with conditional volatility frameworks have gained increasing attention in empirical finance. Numerous studies have shown the advantages of these hybrid models; Xiang (2022) demonstrates the improved forecasting performance of ARIMA–GARCH in predicting forward prices, while Raju & Kumar (2025) show that EGARCH yields more accurate volatility estimates in the presence of asymmetry. Further evidence from Hafizhah et al. (2024) indicates that GJR-GARCH can outperform other specifications in markets experiencing leverage effects. In addition, recent work by Ariyoga & Aeli (2025) highlights that asymmetric models such as TGARCH may offer superior forecasting accuracy, reinforcing the importance of incorporating asymmetry in volatility modelling.

However, gaps remain in the existing literature. First, there is a lack of recent empirical studies focusing on the post-2022 volatility shock period, during which market dynamics have undergone substantial structural changes. Most prior research relies on pre-2022 data, potentially limiting the relevance and robustness of their findings under current market conditions. Second, existing studies generally adopt a single-model approach or limited comparisons, without conducting a systematic evaluation across multiple GARCH-family models combined with different error distributions. In particular, the absence of a comprehensive comparison involving symmetric and asymmetric GARCH models under normal, Student-t, and skewed distributions constrains the ability to identify the most appropriate model for capturing complex return and volatility dynamics in the JKSE.

To address this issue, the present study pursues two main objectives. First, it conducts a systematic comparison to select the best-fitting ARIMA model and the volatility model (comparing GARCH, EGARCH, GJR-GARCH, and TGARCH under normal, Student-t, and skew-t distributions) to capture the return dynamics and volatility patterns, respectively. Second, the study provides three-month-ahead forecasts of the JKSE to offer empirical insights for investment decision-making, risk management, and broader economic analysis.

## 2. METHOD

This study utilizes secondary data in the form of time-series observations derived from the historical weekly closing prices of the Jakarta Stock Exchange Composite (JKSE). The observation period spans from November 27, 2022 to November 23, 2025, with all data obtained from the financial portal investing.com, consisting of the variables Date and Closing Price. Prior to model construction, the price series is transformed into logarithmic returns to ensure stationarity, a requirement for ARIMA modeling, as it stabilizes both trend and variance in financial time series.

After the transformation, the dataset is divided sequentially using a time-series split, ensuring that the test set remains a strictly out-of-sample segment that is never exposed during the model-building phase, thereby preventing information leakage. All data processing steps, modeling procedures, and visualizations were carried out using the Python programming language. The complete methodological workflow of the research is illustrated in the flowchart presented in Figure 1.

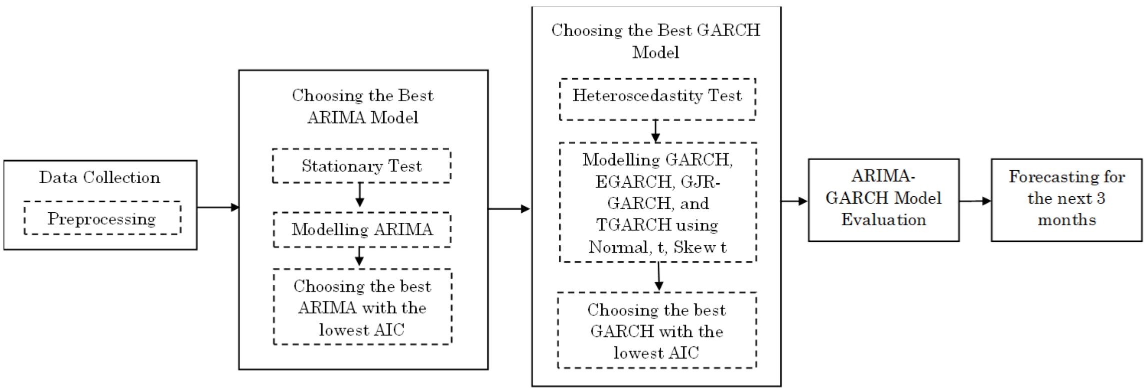



**Figure 1.** Flowchart of the research

The modeling process begins with determining the optimal ARIMA model through stationarity testing, estimation of several candidate models, and identification of the specification with the lowest AIC value. Once the mean equation is determined, the next step involves selecting the best volatility model by conducting heteroskedasticity tests and estimating various GARCH variants, including GARCH, EGARCH, GJR-GARCH, and TGARCH, under several error distribution assumptions, with the final model chosen based on the lowest AIC.

During the evaluation stage, backtesting is performed on both the ARIMA and GARCH components, individually and in their integrated form. The forecasting performance is assessed using several error metrics—Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE)—to comprehensively evaluate predictive accuracy. Once a valid and optimal model is obtained, the workflow concludes with the forecasting stage, which produces three-month-ahead JKSE predictions using the selected hybrid model.

### 2.1 AutoRegressive Integrated Moving Average (ARIMA) Model

The ARIMA (Autoregressive Integrated Moving Average) model is a Box–Jenkins time-series framework designed to capture linear dependence between current observations and their past values. According to Gujarati & Porter (2009), ARIMA provides reliable short-term forecasts by combining autoregressive terms, moving-average terms, and differencing to achieve stationarity. The general ARIMA (p, d, q) form is:

$$\Phi_p(B)(1-B)^d X_t = \Theta_q(B)\varepsilon_t \#(1)$$

where $\Phi_p$and $\Theta_q$denote the AR and MA polynomials, and $d$represents the order of differencing. This method emphasizes data-driven modeling of stochastic processes without requiring exogenous regressors (Gujarati & Porter, 2009).

### 2.2 Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) Family Model

In financial time series modeling, the assumption of homoscedasticity is frequently violated due to time-varying volatility. To address this, Bollerslev (1986) developed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH model allows conditional variance to depend on both past shocks and past variances. The GARCH $(p,q)$ model is defined as:

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

with non-negativity constraints ensuring $\sigma_t^2 > 0$. This structure is effective in capturing volatility clustering and persistence, where periods of high variance tend to follow large shocks (Bollerslev, 1986).

While the standard GARCH model captures volatility clustering, it assumes a symmetric response to positive and negative shocks. However, financial data often exhibit asymmetry or the "leverage effect," where negative shocks (bad news) increase volatility more significantly than positive shocks (good news). To overcome this limitation, several asymmetric variants were developed, specifically EGARCH, GJR-GARCH, and TGARCH.

Nelson (1991) introduced the Exponential GARCH (EGARCH) model to handle asymmetric volatility responses. This model specifies the log-variance as:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(\varepsilon_{t-i}) + \sum_{j=1}^{p} \beta_j \ln\left(\sigma_{t-j}^2\right) \#(3)$$

where the function $g(\varepsilon_t)$ accommodates both the magnitude and sign of the shock. This logarithmic formulation naturally ensures that $\sigma_t^2$ remains positive without requiring additional parameter constraints and explicitly captures the leverage effect (Nelson, 1991; Tsay, 2014).

Furthermore, Glosten, Jagannathan, and Runkle (1993) proposed the GJR-GARCH model to capture asymmetry through an indicator variable for negative shocks. Its general form is:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i + \gamma_i I_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \#(4)$$

where $I_{t-i}$ equals 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. The presence of the parameter $\gamma$ allows the model to assign greater weight to volatility following negative returns, thereby capturing leverage patterns while retaining a direct variance specification (Glosten et al., 1993; Hayashi, 2011).

Another variant is the Threshold GARCH (TGARCH) introduced by Zakoian (1994). Unlike GJR-GARCH, which models conditional variance, TGARCH models the conditional standard deviation ($\sigma_t$) using a threshold mechanism:

$$\sigma_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i D_{t-i})|\varepsilon_{t-i}| + \sum_{j=1}^{p} \beta_j \sigma_{t-j} \#(5)$$

The indicator variable $D_{t-i}$ allows the model to differentiate the impact of negative and positive innovations on volatility increases. This enables the TGARCH model to effectively capture leverage effects and asymmetric volatility patterns found in financial time series (Rabemananjara & Zakoian, 1993; Zakoian, 1994).

## 3. RESULTS AND DISCUSSION

### 3.1 Data Collection and Preprocessing

The dataset employed in this study comprises the weekly closing prices of the Jakarta Stock Exchange Index (JKSE). Prior to analysis, the raw price series was transformed into log-returns using the formula $r_t = 100 \times \log(P_t/P_{t-1})$ to stabilize the mean and variance. As depicted in Figure 2, the return series fluctuates consistently around zero, providing a preliminary indication of stationarity in the mean. Furthermore, the plot visually confirms the presence of volatility clustering, where periods of significant market turbulence are typically followed by high volatility, and stable periods by low volatility. This distinct characteristic of heteroskedasticity underscores the necessity of employing GARCH-family models to effectively capture the time-varying variance.

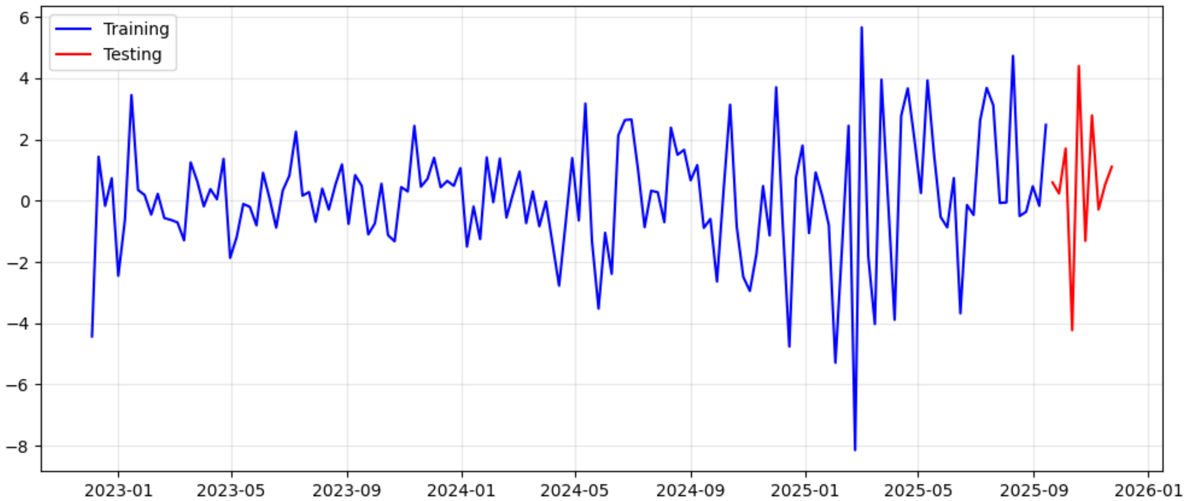



**Figure 2.** The Splitting data of the JKSE Weekly Log Return

Although GARCH-family models are frequently applied to large, high-frequency datasets, the sample size of 154 weekly observations in this study is analytically adequate and intentionally selected for several reasons. From a theoretical perspective, the standard Box & Jenkins (1976) methodology recommends a minimum of 50 observations to build a reliable ARIMA model, a threshold this study comfortably exceeds. Furthermore, utilizing weekly data rather than daily data helps filter out short-term market microstructure noise and day-of-the-week effects, allowing the model to capture more persistent macroeconomic volatility cycles (Tsay, 2014).

Practically, the specific three-year observation window (late 2022 to late 2025) was chosen to ensure parameter stability. Extending the dataset further back would incorporate the extreme structural breaks and abnormal volatility shocks induced by the COVID-19 pandemic (2020–2021). By restricting the sample to the post-pandemic recovery phase, the estimated ARIMA-GARCH parameters more accurately reflect the current, stable market regime, thereby producing more reliable short-term forecasts.

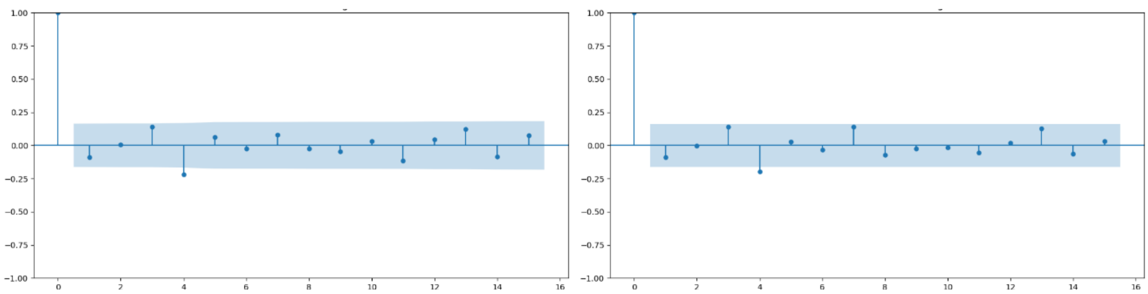
For model development and evaluation, the total dataset of 154 observations was partitioned into two distinct subsets, as illustrated in Figure 2. The first 144 observations were allocated to the training set for parameter estimation, while the subsequent 10 observations were reserved as the testing set to assess out-of-sample forecasting accuracy. This division was executed strictly chronologically rather than randomly to maintain the temporal order and integrity of the time series data, ensuring that the model is tested on future unseen data

### 3.2 Choosing The Best ARIMA Model

The construction of the mean equation begins by verifying the stationarity of the JKSE log-return series. As presented in Table 1, the Augmented Dickey-Fuller (ADF) test yields a test statistic of -6.474 with a p-value of 0.000. Since the p-value is significantly less than the 0.05 threshold, the null hypothesis of a unit root is rejected, confirming that the data is stationary at level ($d = 0$) without the need for further differencing. To identify potential model orders, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the training data are analyzed in Figure 3.

**Table 1**. ADF stationarity test results for the log-return series

| Variable | Test Statistic | p-value | Result |
|---|---|---|---|
| Log-Return | -6.474 | 0.000 | Stationary |



(a) (b)

**Figure 3.** (a) ACF plot of the training data; (b) PACF plot of the training data

The plots reveal significant spikes at lag 4 in both the ACF and PACF, while other lags remain largely within the confidence bounds. This dual pattern suggests potential AR, MA, or ARMA structures, necessitating a comparative evaluation of multiple candidate models specifically around the fourth-order lag.

Based on these identification patterns, several candidate models were estimated using autoARIMA and compared in Table 2. Although broader specifications were considered, the ARIMA(4,0,4) model was discarded due to its excessive complexity, which resulted in overfitting—where the model captures noise rather than the underlying data pattern. Consequently, the selection criteria prioritized the principle of parsimony, focusing on models with significant coefficients and the lowest Akaike Information Criterion (AIC). Among the tested specifications, the ARIMA(0,0,4) model emerged as the optimal fit, achieving the lowest AIC value of 598.838. To ensure the model's reliability, diagnostic tests were conducted on the residuals as shown in Table 3. The Ljung-Box test produces a p-value of 0.86 ($> 0.05$), confirming that the residuals are white noise and free from autocorrelation. Additionally, the normality test indicates that the residuals deviate from a normal distribution (Jarque-Bera p-value $< 0.05$), which is a common characteristic of financial time series and further justifies the subsequent use of GARCH-type models to address the remaining heteroskedasticity.

**Table 2**. AIC of ARIMA Models

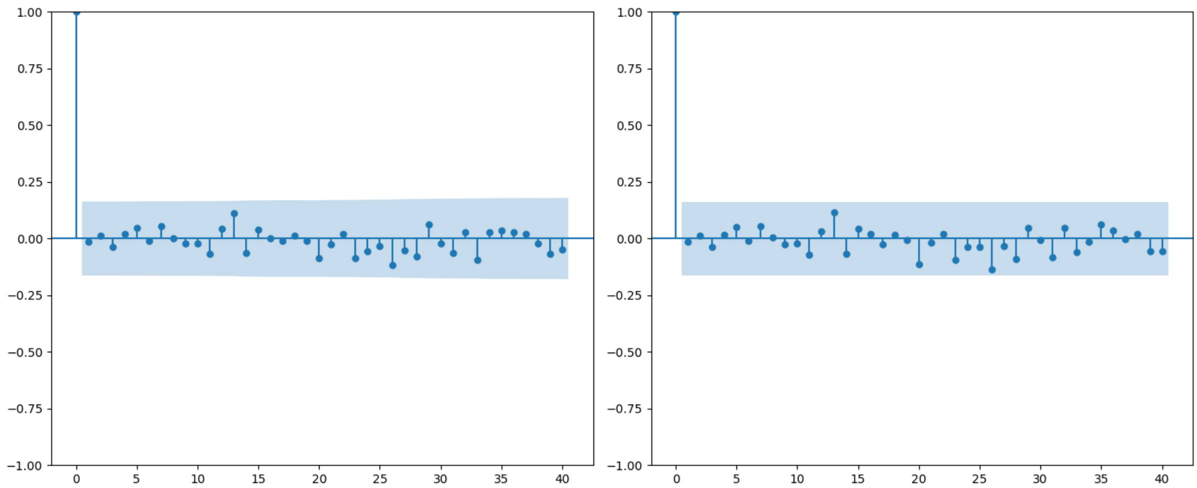
| ARIMA Model (p,d,q) | AIC | p-value | Significance |
|---|---|---|---|
| ARIMA(0,0,0) | 603.980 | - | - |
| ARIMA(0,0,1) | 604.897 | 0.192 | Not Significant |
| ARIMA(1,0,0) | 604.859 | 0.155 | Not Significant |
| **ARIMA(0,0,4)** | **598.838** | **0.000** | **Significant** |
| ARIMA(4,0,0) | 601.977 | 0.005 | Significant |

**Table 3. Diagnostic Test of the ARIMA(0,0,4) Model**

| Test | p-value |
|---|---|
| Ljung-Box | 0.860 |
| Normality (Jarque-Bera) | 0.000 |

### 3.3 Choosing The Best GARCH Model

To address the residual dynamics, the analysis first examines the squared residuals of the ARIMA model. As illustrated in Figure 4, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the squared residuals exhibit significant spikes, visually suggesting the presence of volatility clustering. This observation is statistically corroborated by the ARCH-LM test, which yielded a p-value of 0.0015 ($< 0.05$). This significant result leads to the rejection of the null hypothesis of homoskedasticity, confirming that the variance of the series is not constant but time-dependent (ARCH effect). Consequently, the linear ARIMA framework is proven insufficient, necessitating the application of GARCH-family models to effectively capture these heteroskedastic patterns.




(a) (b)

**Figure 4.** Residual diagnostics of the selected ARIMA model: (a) ACF plot; (b) PACF plot.

Table 4 presents a systematic comparison of symmetric (Standard GARCH) and asymmetric (EGARCH, GJR-GARCH, TGARCH) volatility specifications coupled with Normal, Student-t, and Skew-t error distributions. Based on the selection criteria, the

GJR-GARCH(1,1) model with a Normal distribution emerged as the most robust specification, achieving the lowest Akaike Information Criterion (AIC) value of 569.707. The superiority of the GJR-GARCH specification carries an important theoretical implication: it confirms the presence of a significant "leverage effect" in the Indonesian capital market. This indicates that the JKSE volatility reacts asymmetrically to market shocks, where "bad news" (negative shocks) generates higher volatility than "good news" (positive shocks) of the same magnitude.

**Table 4.** AIC of GARCH models under different error distributions

| GARCH Models | Distributions | | |
|---|---|---|---|
| | **normal** | t-student | skew t |
| GARCH | 570.002 | 571.025 | 570.319 |
| EGARCH | 572.497 | 572.936 | 571.960 |
| **GJR-GARCH** | **569.707** | 571.191 | 570.307 |
| TGARCH | 574.854 | 574.760 | 572.699 |

The estimation results and diagnostic checks for the selected model are detailed in Table 5. The statistical significance of the ARCH (α), GARCH (β), and the asymmetry coefficient (γ) validates the model structure. Most critically, the ARCH-LM test on the standardized residuals yields a p-value of 0.891 ($>$ 0.05). This result indicates that the null hypothesis of no ARCH effect cannot be rejected, proving that the GJR-GARCH model has successfully absorbed the volatility patterns. Thus, the model is statistically adequate for forecasting purposes.

**Table 5. Diagnostic Test of the GJR-GARCH Normal Model**

| Model | Statistical Significance | | | |
|---|---|---|---|---|
| | ARCH($\alpha$) | GARCH($\beta$) | Asymmetry coeff.($\gamma$) | ARCH-LM test |
| GJR-GARCH normal | 0.168 | 0.000 | 0.189 | 0.891 |

### 3.4 The Best ARIMA-GARCH Model Evaluation

Based on the comprehensive selection process detailed in the previous sections, the hybrid ARIMA(0,0,4)-GJR-GARCH with a Normal distribution was identified as the most robust framework for modeling the JKSE return dynamics. This model captures the linear dependency through the moving average terms and addresses the asymmetric volatility response to market shocks. The mathematical formulation of the estimated model is expressed as follows:

Mean Equation: $$r_t = \varepsilon_t - 0.2718\varepsilon_{t-4} \#(6)$$

Variance Equation: $$\sigma_t^2 = 0.0757 + 0.0321\varepsilon_{t-1}^2 + 0.1468\varepsilon_{t-1}^2 I_{t-1} + 0.8770\sigma_{t-1}^2 \#(7)$$

Where $r_t$ represents the log-return, $\sigma_t^2$ is the conditional variance, and $I_{t-1}$ is the indicator function for negative shocks (leverage effect).

The forecasting performance of this model is visually assessed in Figure 5, which plots the predicted values against the actual testing data (out-of-sample). The point forecast line (red), generated by the ARIMA mean equation, closely tracks the trajectory of the actual JKSE returns (blue), demonstrating the model's capability to replicate the direction of market fluctuations. Furthermore, the plot illustrates the 95% confidence intervals (shaded area). These uncertainty bounds are constructed based on the conditional volatility forecasted by the GJR-GARCH variance equation with normal distribution. Notably, the majority of the actual observations fall well within this confidence band, indicating that the volatility component successfully quantifies the inherent market risk and provides reliable interval forecasts.

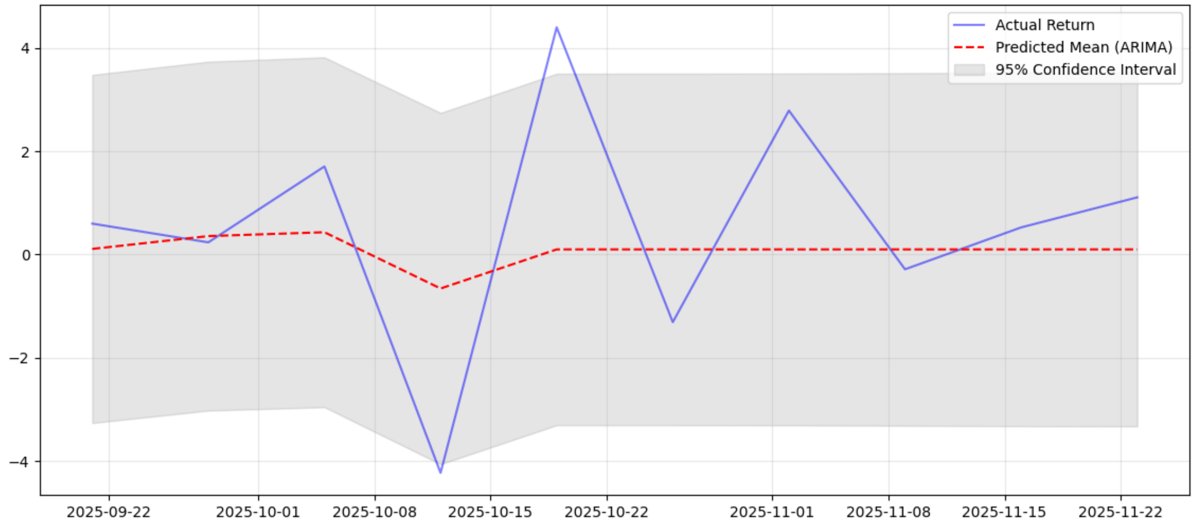



**Figure 5.** Backtesting plot of actual returns and ARIMA-GARCH forecast with 95% confidence interval

To provide a quantitative assessment, Table 6 summarizes the forecasting accuracy metrics. The model yielded a Mean Squared Error (MSE) of 4.372, a Root Mean Squared Error (RMSE) of 2.090, and a Mean Absolute Error (MAE) of 1.568. These low error values confirm the model's precision in predicting short-term market movements. Consequently, the combination of visual alignment and minimal error metrics validates the ARIMA(0,0,4)-GJR-GARCH as a dependable tool for projecting future JKSE return trends.

**Table 6.** Forecast error metrics of the ARIMA(0,0,4) model

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| ARIMA-GJR-GARCH normal | 4.372 | 2.090 | 1.568 |

### 3.5 Forecasting

To provide actionable insights, the forecasted log-returns generated by the ARIMA-GJR-GARCH model were back-transformed to the original price scale to project the Jakarta Stock Exchange Index (JKSE) trajectory for the next three months. Figure 6 visualizes this projection, where the blue line represents historical closing prices and the red dashed line depicts the future forecast. The forecast indicates an immediate short-term correction, with the price dipping to 8,437.10 on November 30, 2025, accompanied by a significant volatility range (95% CI: 8,131.47 – 8,754.21). Following this, the market shows a steady, gradual upward trend, expected to reach a level of 8,603.62 by March 8, 2026. However, the 95% confidence interval exhibits a widening pattern over time, ending with a broad range between 8,285.64 (lower bound) and 8,933.81 (upper bound).

This expansion signifies accumulating uncertainty, implying that while the expected direction is positive, the range of potential price outcomes becomes increasingly broad further into the future.

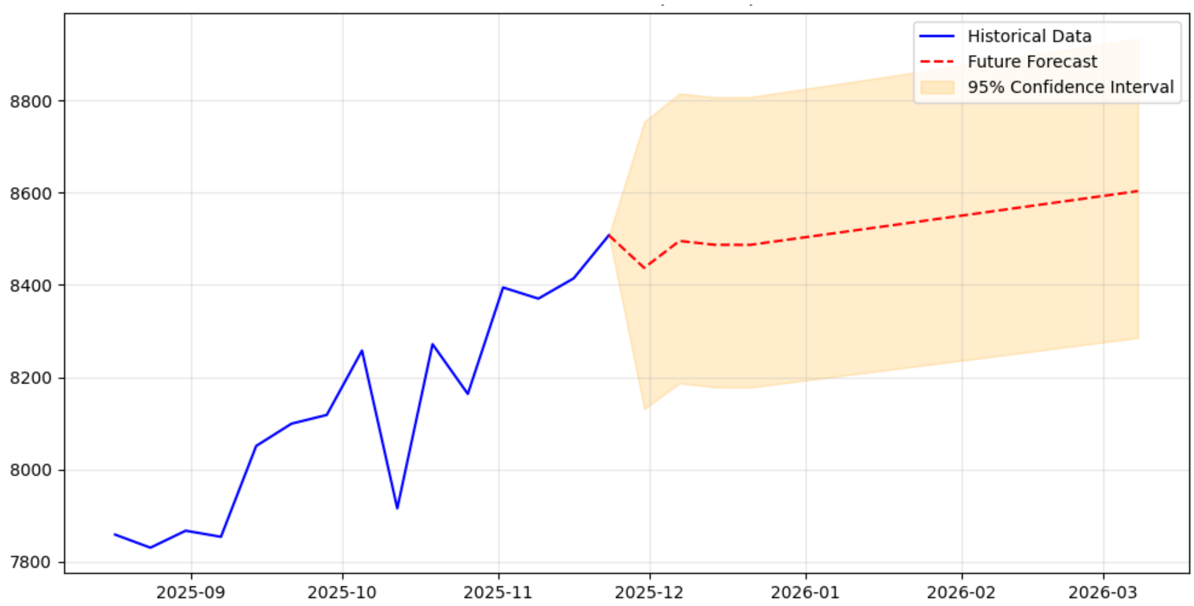



**Figure 6.** Forecasting plot of JKSE's Price using proposed ARIMA-GJR-GARCH model with 95% confidence interval

These empirical findings offer critical inputs for investment strategies and risk management. The projected moderate upward trend signals potential opportunities for long positions, yet the expanding confidence interval warns of significant volatility risk. Therefore, investors are advised to adopt a "cautious optimism" approach. While the market shows growth potential, the high probability of fluctuation necessitates the implementation of strict risk mitigation strategies, such as setting dynamic stop-loss limits near the lower bound of 8,200 or diversifying portfolios. For institutional policymakers, the anticipated volatility underscores the need for close monitoring of market stability mechanisms during this period.

This necessity for vigilant monitoring is structurally supported by the asymmetric volatility captured in the model results. The presence of the leverage effect indicates that the market is far more sensitive to downward corrections than to upward recoveries. Consequently, the projected initial dip serves not just as a temporary setback, but as a potential catalyst for prolonged market anxiety. This inherent fragility explains the widening uncertainty observed in the forecast, suggesting that while the long-term trajectory is positive, the market remains psychologically vulnerable to negative shocks, reinforcing the urgency for the defensive investment strategies outlined above.

## 4. CONCLUSION

Based on the comprehensive analysis and discussion, this study derives two primary conclusions. First, the systematic comparison confirms that the hybrid ARIMA(0,0,4)-GJR-GARCH framework with a Normal distribution is the most robust model for capturing the dynamics of JKSE returns. The superiority of the GJR-GARCH specification statistically validates the existence of a significant asymmetric "leverage effect" in the Indonesian capital market, indicating that the market reacts more intensely to negative shocks than to positive ones of the same magnitude.

Second, the out-of-sample forecasting results project a positive trajectory for the next three months, with the index expected to gradually recover to the 8,603.62 level by early March 2026. However, the widening pattern of the 95% confidence intervals highlights accumulating uncertainty over the forecast horizon. Consequently, while the projected market direction suggests growth, the inherent volatility risks necessitate a strategy of "cautious optimism" and the implementation of disciplined risk management measures for market participants.

## 5. RECOMMENDATION

Given that this study was limited to a univariate analysis relying solely on historical closing prices, future research should aim to expand the scope by incorporating exogenous variables and utilizing high-frequency data. Specifically, researchers are recommended to integrate macroeconomic indicators such as inflation rates, the IDR/USD exchange rate, and global indices like the S&P 500 into the variance equation to observe how external structural factors influence JKSE volatility. Furthermore, shifting from weekly observations to daily or intraday data would provide more granular insights, allowing for a deeper analysis of intraday volatility patterns and the immediate impact of market news.

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