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Pertamina Geothermal Energy Stock Price Prediction and Risk Analysis: ARIMA-GARCH and VaR with Cornish-Fisher Expansion

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ABSTRACT

The geothermal energy sector makes a strategic contribution to supporting long-term domestic energy sustainability and attracts investor attention due to high market volatility. Therefore, analysis that can accurately describe stock price dynamics and risks is needed. This study aims to model and predict the share price of PT Pertamina Geothermal Energy (PGEO) and estimate the associated investment risk. This study uses a quantitative time series approach with ARIMA–GARCH modeling and the Value at Risk method using Cornish–Fisher Expansion. This study uses weekly closing price data for PGEO stocks from February 2023 to September 2025. The methods used include ARIMA-GARCH modeling for stock price prediction and Cornish–Fisher Expansion based Value at Risk to estimate investment risk. The results indicate that the ARIMA(2,2,0)–GARCH(2,0) model provides the most adequate representation of PGEO stock price dynamics and volatility, achieving an RMSE value of 258.33 and a MAPE of 16.21% as measures of forecasting performance. Meanwhile, risk measurement using the Cornish–Fisher Expansion Value at Risk method produced a VaR value that increased along with the holding period and confidence level, with a risk range of 8.21% to 19.95%. The novelty of this research lies in the integration of ARIMA–GARCH volatility modeling and the Value at Risk method using Cornish–Fisher Expansion, thereby providing a more comprehensive analytical framework for price prediction and investment risk estimation in renewable energy stocks. The findings of this study are expected to serve as an empirical reference for investors and policymakers in assessing potential risks and supporting more informed investment decisions within the renewable energy sector.

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A. INTRODUCTION

The energy sector plays a vital role in supporting Indonesia's economic development and is among the key sectors for achieving sustainable development goals (Hardi et al., 2025). In the context of the Sustainable Development Goals (SDGs), particularly SDG 7, which emphasizes clean and affordable energy, the transition to a sustainable energy system has become a global priority. The availability of reliable and sustainable energy not only supports public welfare but also contributes significantly to economic productivity and financial market stability (Wang et al., 2025; Supartoyo, 2025). The energy sector is also closely related to investment attractiveness because energy availability and policy stability influence investor confidence in the capital market (Li et al., 2025). However, the energy market often faces high uncertainty due to global oil price fluctuations, policy changes, and geopolitical tensions that can affect market stability (Ma'arif et al., 2022). These conditions highlight the importance of comprehensive analysis to understand the dynamics and risks associated with investment in the energy sector.

The government's efforts to strengthen the energy sector are reflected in the establishment of the Anagata Nusantara Energy Investment Management Agency (Danantara) on February 24, 2024. The purpose of establishing Danantara is to optimize the management of state-owned enterprise (BUMN) assets and support national strategic projects (Sekretariat Kabinet RI, 2025). PT Pertamina Geothermal Energy Tbk (PGEO), a subsidiary of PT Pertamina, is one of the geothermal energy companies that has benefited from this policy through access to large-scale funding, including an investment cooperation agreement worth USD 5.4 billion in August 2025 (Pertamina, 2025). The impact is evident in increased market confidence, with PGEO shares rising more than 56% since the beginning of 2025 (MNC Sekuritas, 2025).

Since its initial listing on the Indonesia Stock Exchange (IDX) on February 24, 2023, with an IPO price of IDR 875 per share, PGEO has successfully entered the LQ45 index a year later due to a significant surge in revenue (Bakarbessy & Manjaruni, 2024). In 2025, its market capitalization reached Rp 50.09 trillion, making it one of the 40 companies with the largest capitalization in Indonesia (IDX, 2025). PGEO shares also experienced considerable price volatility, with a range of Rp 650 to Rp 1,685, and a cumulative increase of 65% compared to the IPO price (Investing.com, 2025). This high volatility created challenges for investors, as price instability increased the risk of investment losses.

In time series analysis, high volatility often causes heteroscedasticity, a condition in which the residual variance changes over time. This phenomenon is commonly found in financial time series data, where market shocks and investor reactions cause fluctuations in price variance (Wang et al., 2025). This condition causes conventional ARIMA models to be less than optimal when volatility effects are not taken into account (Rubio et al., 2023). To overcome this problem, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is widely used to capture conditional variance and better describe the phenomenon of volatility clustering in financial markets (Singh et al., 2023; Wang et al., 2022). In addition to volatility modeling, investment risk is often measured using the Value at Risk (VaR) approach, which estimates the maximum potential loss of an asset at a given confidence level and time period (Souffargi & Boubaker, 2025). However, financial return distributions often exhibit excessive skewness and kurtosis, making the assumption of a normal distribution less appropriate (Kim & Kim, 2025). Therefore, the Cornish–Fisher Expansion approach is often used to adjust the quantiles of the normal distribution by incorporating the effects of skewness and kurtosis, thereby making VaR estimates more accurate (Chai & Zhou, 2018).

Previous studies show that the ARIMA–GARCH model and the Cornish-Fisher VaR method have been widely used in stock volatility and risk analysis. Ramayanti et al. (2023) found that the GARCH(1,1) model was able to model the volatility of PT Gudang Garam Tbk shares well and showed that increased volatility had a direct impact on increased investment risk. Cahyasari et al. (2023) identified GARCH (2,1) as the best model for mining sector stocks with a MAPE value of 15.52%, while Putri et al. (2021) showed that ARIMA (1,1,1)–GARCH(2,2) effectively addressed heteroscedasticity in PT Jasa Marga stocks with a MAPE of only 1.56%. In the context of risk measurement, Rosyidah et al. (2024) prove that Cornish-Fisher Expansion

VaR is valid for estimating the risk of PT SAMF stocks, and Maruddani & Astuti (2021) find that the same method produces a risk estimate of 3.6% at a 95% confidence level. However, most of these studies still focus on conventional sectors such as banking, mining, and infrastructure, while research on renewable energy stocks, particularly geothermal energy companies such as PGEO, remains limited. In addition, previous studies generally analyze stock price volatility and investment risk separately, resulting in a limited understanding of the relationship between price dynamics and risk estimates for renewable energy stocks.

Therefore, this study was conducted to model and predict PGEO stock prices using the ARIMA–GARCH approach, as well as to estimate investment risk through the Cornish-Fisher Expansion VaR method. The novelty of this study lies in its integrated framework, which not only focuses on volatility modeling using GARCH but also simultaneously integrates Value at Risk (VaR) estimates based on the Cornish-Fisher Expansion. This combined approach provides a more comprehensive assessment of price dynamics and investment risk. The findings are expected to support investors and policymakers in assessing uncertainty in the energy market and making more informed investment decisions.

B. METHODS

1. Data Sources and Variables

This study uses a quantitative research design with a time series modeling approach to analyze stock price dynamics and investment risk. The data used in this study consists of weekly closing prices of PT Pertamina Geothermal Energy Tbk (PGEO) shares obtained from the website id.investing.com. The observation period runs from February 26, 2023, to September 7, 2025, with a total of 133 observations. The data was then divided into two parts, namely 90% training data and 10% testing data. The training data covers the period from February 26, 2023, to June 8, 2025, with 120 observations, while the testing data covers the period from June 15, 2025, to September 7, 2025, with 13 observations. The research variable used consisted of one main variable, namely the weekly closing price of PGEO shares. The use of weekly closing stock prices as the main variable aims to capture medium-term market movements while reducing short-term fluctuations that often appear in daily stock price data. This variable was used as the basis in the prediction process using the ARIMA–GARCH model and in risk analysis using the Cornish-Fisher Expansion-based Value at Risk (VaR) method.

2. ARIMA-GARCH Method

Time series analysis is a statistical method for studying data recorded sequentially based on time with the aim of recognizing patterns and predicting future values (Mills, 2019). Financial data is generally stochastic and has random fluctuations that cannot be fully explained by deterministic models, so a probabilistic approach is more relevant. One important characteristic in financial data is heteroscedasticity, which is a condition where the residual variance changes over time or is conditional heteroscedasticity (Cahyasari et al., 2023). This condition causes ordinary time series models such as Autoregressive Integrated Moving Average (ARIMA) to be insufficient to capture volatility dynamics, thus requiring additional variance modelling (Safitri et al., 2025). Modeling begins with ARIMA to model the mean component. The general form of the ARIMA(p,d,q) model is expressed as (Wei, 2006):

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)a_t \tag{1}$$

where d is the order of differencing, $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$, $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$, and a_t is the residual at time t. To address heteroscedasticity in ARIMA residuals, the Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle, (1982) is used. The ARCH(p) model models the residual variance as a quadratic function of the previous period's residual:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 \tag{2}$$

with $\alpha_0 > 0$ and $\alpha_i > 0$. The ARCH model effectively addresses short-term variance changes, but has limitations when the required order is high. To overcome this weakness, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) developed by Bollerslev, (1986) is used. The GARCH(p,q) model incorporates an autoregressive component in the variance, making it more flexible in capturing volatility persistence:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{3}$$

with $\beta_j \geq 0$ and the condition $\sum_{i=1}^{p,q}(\alpha_i + \beta_i) < 1$. The combination of ARIMA for the mean and ARCH/GARCH for the variance produces a model that is able to capture price movement patterns and volatility more comprehensively (Y. Wang et al., 2022). The selection of the best ARIMA–GARCH model was based on several criteria, namely parameter significance, residual diagnostic tests, and information criteria values such as the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), dan Mean Squared Error (MSE) criteria.

3. Cornish-Fisher Expansion VaR method

Value at Risk (VaR) is a method commonly used in risk management to estimate the maximum potential loss of an asset or portfolio within a certain period with a certain confidence level (Maruddani & Trimono, 2020). Although VaR is often calculated based on the assumption of a normal distribution, financial data in reality often shows high skewness and kurtosis, so that VaR estimates based on a normal distribution can be inaccurate. To address this issue, this study uses the Cornish–Fisher expansion VaR approach, which is a method that improves the quantiles of the normal distribution by accommodating skewness and kurtosis through a Taylor series expansion. Standard normal quantile $q_{1-\alpha}$ is then expanded through the Cornish–Fisher Expansion (ECF) formula as follows (Maruddani & Trimono, 2020):

$$ECF = q_{1-\alpha} + \frac{((q_{1-\alpha})^2 - 1)S(X)}{6} + \frac{((q_{1-\alpha})^3 - 3q_{1-\alpha})\psi(X)}{24} - \frac{(2(q_{1-\alpha})^3 - 5q_{1-\alpha})S^2(X)}{36} \tag{4}$$

with
$S(X)$: Stock return skewness value
$\psi(X)$: Excess kurtosis difference

If the kurtosis value is less than 3, then the value of $\psi(X)$ is replaced with the value of $K(X)$ as the stock return kurtosis value. After the quantiles are expanded, the VaR value using the Cornish–Fisher approach is calculated using the equation 5:

$$VAR_{\alpha}^{ECF} = -V_0 \times (\mu_x - ECF\sigma_x) \times \sqrt{T} \tag{5}$$

with the following explanation:
V_0: initial investment value
μ_x: average stock return
σ_x: standard deviation of return
T: length of holding period.

To evaluate the reliability of the VaR estimates obtained, a backtesting procedure was performed using the likelihood ratio approach to compare the risk estimates with the actual losses incurred.

4. Stage of Data Analysis

The data analysis in this study was carried out through several structured stages as follows:

a. Preliminary Exploration and Descriptive Analysis of PGEO Stock Price Data.
   1) Visualize PGEO stock price data using time series plots to observe price movements.
   2) Summarize the characteristics of the data using descriptive statistics to capture overall price behavior.
   3) Divide the dataset into training and testing sets for model development and evaluation.

b. Identification and Estimation of the ARIMA Model.
   1) Examine stationarity in variance and apply Box–Cox transformation when necessary.
   2) Test stationarity in mean using the Augmented Dickey–Fuller (ADF) test.
   3) Apply differencing until the series satisfies stationarity assumptions.
   4) Identify ARIMA model orders based on ACF and PACF plots.
   5) Estimate model parameters and evaluate their statistical significance.
   6) Conduct diagnostic checks on residuals using white noise and normality tests.
   7) Select the best ARIMA model based on the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Mean Squared Error (MSE) criteria.

c. Detection and Modeling of Volatility Using the ARCH–GARCH Framework.
   1) Detect conditional heteroscedasticity using squared residuals from the selected ARIMA model.
   2) Confirm the presence of ARCH effects through the ARCH–LM test.
   3) Determine the appropriate ARCH–GARCH specification and estimate volatility model parameters and perform diagnostic tests.
   4) Select the optimal volatility model using information AIC, SBC, and MSE criteria.

d. Forecasting Performance Evaluation Using the ARIMA–GARCH Model.
   1) Generate stock price forecasts using the selected ARIMA–GARCH model on the testing dataset.
   2) Evaluate forecasting accuracy using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics.

e. Investment Risk Estimation Based on Cornish–Fisher Expansion Value at Risk.
   1) Analyze PGEO stock returns and assess their distribution characteristics.
   2) Estimate investment risk using the Cornish–Fisher Expansion Value at Risk method for various confidence levels and holding periods.
   3) Validate the VaR estimates through backtesting procedures.

C. RESULT AND DISCUSSION

1. Descriptive Statistics

In this study, descriptive statistics were used to summarize the basic characteristics of PGEO stock price data, including the mean, minimum, maximum, and standard deviation. In addition, a time series plot was presented to identify patterns in stock price movements during the observation period. A summary of the statistics for the research variables is shown in Table 1.

Table 1. Descriptive Statistics

Variable	N	Mean	St. Dev	Min	Date (Min)	Max	Date (Max)
PGEO Stock Price	133	1118.1	237.9	650.0	02/04/2023	1685.0	27/07/2025

Based on Table 1, PGEO's stock price has an average value of 1118.1, with a standard deviation of 237.9, indicating significant fluctuations in price. The minimum value recorded was 650, while the maximum value reached 1685, indicating a wide range of price movements throughout the research period. The median value of 1170 shows that most prices were around that middle value. Overall, the data shows high volatility, which is relevant for further modeling using the ARCH/GARCH approach, as shown in Figure 1.

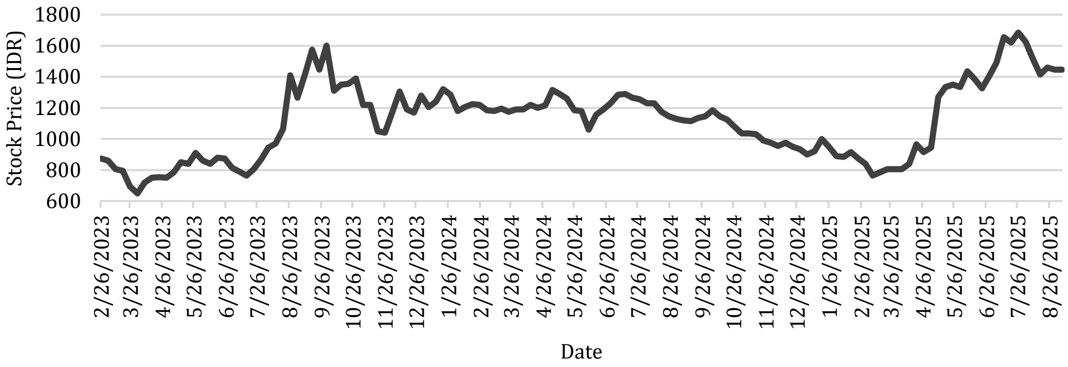


Figure 1. Time Series Plot

Based on Figure 1, PGEO's stock price movement shows significant fluctuations with several phases of sharp increases and decreases. This pattern reflects market dynamics that are unstable and influenced by various external and internal factors. In addition, changes in volatility as seen from the large variations in price movements support the use of the ARIMA-GARCH method, as this model is able to capture changes in mean patterns as well as variance dynamics over time.

2. ARIMA-GARCH Forecasting

Stationarity is a key requirement in time series modeling using ARIMA. Based on the Box–Cox transformation results in Figure 2, λ value of –0.5 was obtained, indicating that PGEO stock price data is not stationary in variance because the lambda value is different from one. Therefore, a transformation is needed to stabilize the variance before the modeling process can continue.

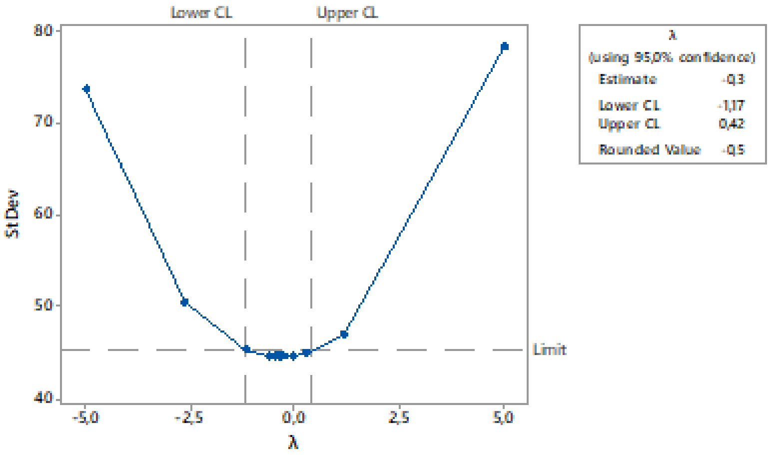
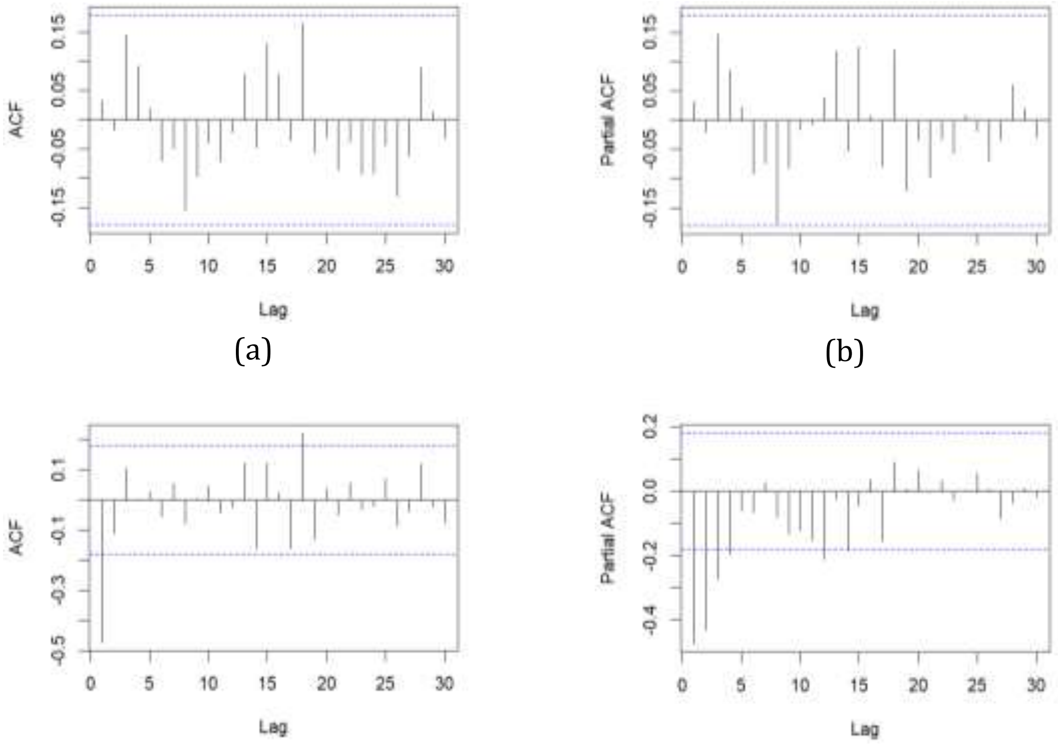


Figure 2. Results of the Box–Cox Transformation

Furthermore, testing for stationarity in the mean of the data using Augmented Dickey–Fuller (ADF) shows that PGEO stock price data is not stationary, as indicated by a p-value of 0.207, which is greater than the 5% significance level. This condition indicates that differencing is necessary to achieve stationarity in the mean. In the first differencing stage, although the data showed improvement in stationarity, the ACF and PACF plots did not show any significant lags.

This indicates that the autocorrelation structure of the data has not been adequately formed for the purposes of identifying the ARIMA model order. Therefore, the process was continued with a second differencing to obtain a more stationary and informative data structure, as shown in Figure 3.



(a) (b)

(c) (d)

Figure 3. Plot (a) ACF and (b) PACF after first differencing;
Plot (c) ACF and (d) PACF after second differencing

After the second differencing, the data was retested using Augmented Dickey–Fuller (ADF) and obtained a p-value of 0.010, which is smaller than the 5% significance level. This result indicates that the data has reached a stationary condition. In addition, at this stage, the ACF and PACF plots began to show significant lags, as seen in Figures 3c and 3d, indicating that the data had a fairly clear autocorrelation structure. Thus, the ARIMA model order identification process could be performed on the data with second differencing, and the ARIMA model with order (p,2,q) was then tested as the best model candidate. From the results of the ACF and PACF after second differencing plots in Figures 3c and 3d, the ARIMA order was estimated by conducting diagnostic tests with the moving average order ranging from 0 to 1 and the autoregressive order ranging from 0 to 4. The diagnostic tests consisted of parameter significance tests, white noise residuals, and normal distribution residual tests. The results of the diagnostic tests for several ARIMA model estimates are presented in Table 2.

Table 2. Model Diagnostic Test

Model	Significance Parameters	*White Noise*	Residual Normality
ARIMA (0,2,1)	Yes	Yes	No
ARIMA (1,2,0)	Yes	No	No
ARIMA (1,2,1)	No	Yes	No
ARIMA (2,2,0)	Yes	Yes	Yes
ARIMA (2,2,1)	Yes	No	No
ARIMA (3,2,0)	Yes	Yes	No
ARIMA (3,2,1)	Yes	Yes	Yes
ARIMA (4,2,0)	Yes	Yes	No
ARIMA (4,2,1)	No	Yes	No

Based on Table 2, there are two models that pass the significance test, namely the ARIMA(2,2,0) and ARIMA(3,2,1) models. Furthermore, the selection of the best model is carried out by considering the information criteria and forecasting error measures shown in Table 3.

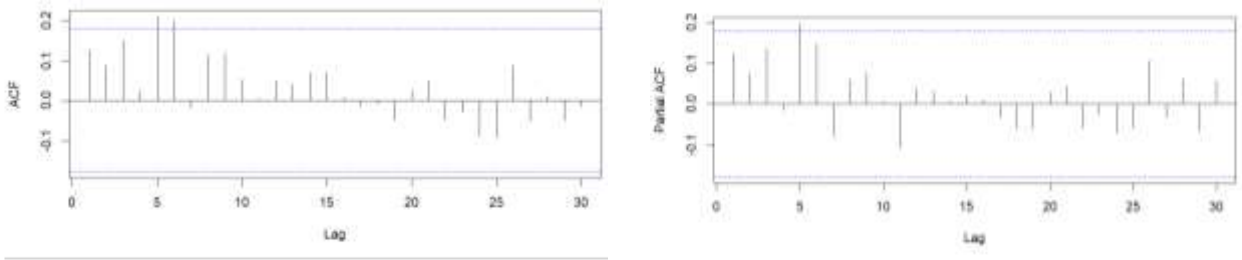
Table 3. Best Model Selection

Model	AIC	SBC	MSE
ARIMA (2,2,0)	-1590.2746	-1584.7332	0.0000013562
ARIMA (3,2,1)	-1584.1724	-1573.0896	0.0000013806

As shown in Table 3, the ARIMA(2,2,0) model outperforms alternative specifications by producing the minimum AIC, SBC, and MSE values. These results indicate that the model provides the most efficient balance between forecasting performance and parameter complexity. The mathematical representation of the estimated ARIMA(2,2,0) model is presented below.

$$Z_t = Z_{t-1} - 0.4308Z_{t-1} + 0.4308Z_{t-2} - 0.3118Z_{t-2} + 0.3118Z_{t-3} + a_t \tag{6}$$

The residuals from the ARIMA(2,2,0) model are then analyzed further to detect heteroscedasticity, which forms the basis for modeling volatility by employing the ARCH–GARCH approach in the next stage, as shown in Figure 4.



(a) (b)

Figure 4. Residual Quadratic Model ARIMA (2,2,0) (a) Plot ACF, (b) Plot PACF

Based on Figure 4, several significant lags are visible, indicating the presence of ARCH or GARCH effects on the residuals. This is reinforced by the Lagrange Multiplier (LM) test in Table 4, where the p-value is significant at several lags, indicating that the residuals contain conditional heteroscedasticity, thus requiring ARCH/GARCH modeling.

Table 4. Lagrange Multiplier Test Results

Lag Order	Significance LM-Test
6	0.005
8	0.010
10	0.014
12	0.032

Due to heteroscedasticity in the ARIMA(2,2,0) model, a model is needed to address this issue, namely the GARCH model. Table 5 below shows several GARCH model estimates that were tested for parameter significance.

Table 5. GARCH Models Specification

Model	Parameters	Coefficient	P-value	Significance
GARCH (1,0)	α_0	4.4648×10^{-9}	0.9850	No
	α_1	0.0519	0.0000	Yes
GARCH (2,0)	α_0	3.3172×10^{-7}	0.0000	Yes
	α_1	0.5583	0.0249	Yes
	α_2	0.4407	0.0467	Yes
GARCH (1,1)	α_0	4.047×10^{-8}	0.9683	No
	α_1	0.3208	0.0041	Yes
	β_1	0.6782	0.0000	Yes
GARCH (1,2)	α_0	4.0473×10^{-8}	0.9831	No
	α_1	0.3208	0.2823	No
	β_1	0.6782	0.5513	No
	β_2	2.9474×10^{-7}	1.0000	No

An evaluation of the results in Table 5 confirms that the GARCH(2,0) model provides the best fit, with all parameters exhibiting statistical significance at the 5% significance level. The estimated form of the model is given in Equation 7.

$$h_t = 3.3172 \times 10^{-7} + 0.5583 {a_{t-1}}^2 + 0.4407 {a_{t-2}}^2 \tag{7}$$

Furthermore, we evaluate the forecasting ability of the model on the testing data between the ARIMA model alone and the ARIMA-GARCH model. This comparison is done to assess the extent to which the addition of the GARCH component can improve prediction accuracy compared to the pure ARIMA model. The prediction results are shown in Figure 5 and the prediction accuracy is shown in Table 6 below.

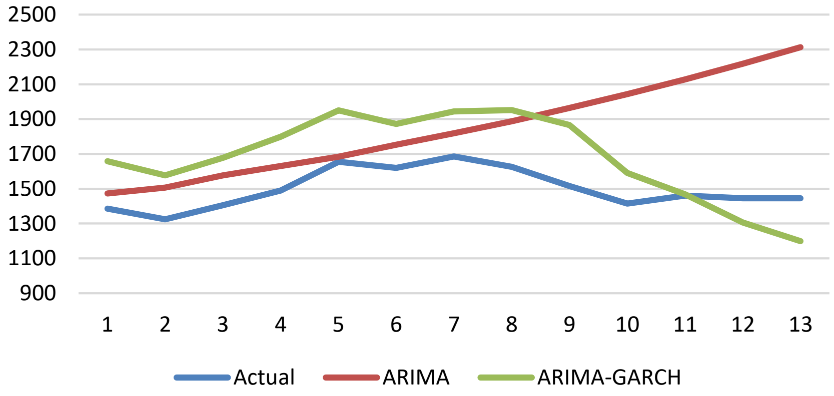


Figure 5. Plot Comparison of Actual PGEO Stock Price and Prediction Results

Table 6. Model Prediction Evaluation

Model	RMSE	MAPE
ARIMA(2,2,0)	445.98	23.76%
ARIMA(2,2,0)-GARCH(2,0)	258.33	16.21%

Based on Table 6, the ARIMA(2,2,0)–GARCH(2,0) model shows better forecasting performance than the ARIMA(2,2,0) model without volatility components. This is indicated by a decrease in the RMSE value from 445.98 in the ARIMA(2,2,0) model to 258.33 in the ARIMA(2,2,0)–GARCH(2,0) model, as well as a decrease in the MAPE value from 23.76% to 16.21%. The decrease in RMSE and MAPE values indicates that the ARIMA(2,2,0)–GARCH(2,0) model has a lower prediction error rate and better accuracy in following PGEO stock price movements.

The visualization of the prediction results in Figure 5 reinforces these findings. The pure ARIMA(2,2,0) model tends to produce smoother and relatively constant predictions, making it less responsive to sharp price changes. In contrast, the ARIMA(2,2,0)–GARCH(2,0) model shows greater flexibility in adjusting to stock price fluctuations, because the GARCH component explicitly models volatility based on shocks in the previous period. This causes the ARIMA(2,2,0)–GARCH(2,0) prediction line to be closer to the actual data. The results are consistent with volatility modeling theory and previous studies such as Ramayanti et al. (2023) and Cahyasari et al. (2023), which demonstrate that GARCH-type models provide a better representation of stock market volatility than models that only capture the mean process.

3. Cornish Fisher Expansion VaR Risk Estimation

Investment is an important aspect of stock market analysis, especially for assets with high volatility such as PT Pertamina Geothermal Energy (PGEO) shares. One of the methods commonly used to measure risk is Value at Risk (VaR), which provides an estimate of the maximum potential loss that may occur at a certain confidence level and holding period. VaR helps investors understand the magnitude of losses they may face under normal market conditions, thereby serving as a basis for investment decisions.

In this study, risk measurement was not performed using normal distribution-based VaR, but rather using Cornish–Fisher Expansion VaR. This method was chosen based on the characteristics of PGEO stock returns, which are not normally distributed. The analysis results show that the skewness value is 0.8615 and the kurtosis is 4.0176, which deviates from the characteristics of a normal distribution with skewness approaching 0 and kurtosis of 3 (Maruddani & Trimono, 2020). These conditions indicate an asymmetric distribution with fat tails, so the use of normal VaR has the potential to produce inaccurate risk estimates. Therefore, the Cornish–Fisher Expansion VaR is used because it can accommodate the effects of skewness and kurtosis in risk quantile calculations. The Value at Risk estimation results are shown in Table 7 below.

Table 7. VaR Estimation

Holding Period	**Confidence Level**		
	90%	**95%**	**99%**
1 week	8.21%	9.59%	11.52%
2 weeks	11.61%	13.56%	16.29%
3 weeks	14.22%	16.61%	19.95%

Based on Table 7, the results of the Cornish–Fisher Expansion VaR calculation show that the risk value varies depending on the holding period and confidence level. The results show that the longer the holding period and the higher the confidence level, the greater the risk value faced by investors. Overall, the lowest VaR value obtained was 8.21%, while the highest VaR value reached 19.95%. The VaR value obtained in this study represents the maximum potential loss that investors may experience in normal market conditions at a certain confidence level and holding period. A VaR value of 8.21% at a 90% confidence level with a holding period of 1 week can be interpreted as meaning that there is a 90% confidence level that the maximum loss that investors may experience in one week will not exceed 8.21% of their investment value, while there is a 10% possibility that the loss will exceed this value.

To test the accuracy of the VaR estimates obtained, a backtesting test was conducted using the likelihood ratio approach. The test results show that the VaR estimates with a holding period of 1 week are valid at confidence levels of 90%, 95%, and 99%. Conversely, for holding periods of 2 weeks and 3 weeks, most of the backtesting results were invalid, indicating that the VaR estimates for these periods were not fully able to represent the actual risk. These findings show that the Cornish–Fisher Expansion VaR approach is the most reliable for estimating short-term risk in PGEO stocks. These results are also in line with previous studies such as Rosyidah et al. (2024) and Maruddani & Astuti (2021), which reported that the VaR method is capable of providing reliable estimates of potential investment losses in short-term market conditions. From a practical perspective, these findings indicate that VaR is more suitable for short-term investment horizons, while its accuracy may decline over longer holding periods due to increased market uncertainty and changes in volatility patterns.

D. CONCLUSION AND SUGGESTIONS

Based on the analysis results, the ARIMA(2,2,0) –GARCH(2,0) model is the best model for modeling the stock price movements of PT Pertamina Geothermal Energy (PGEO) because it is able to capture the mean and heteroscedastic volatility patterns, with a fairly good forecasting accuracy as indicated by an RMSE value of 258.33 and a MAPE of 16.21%. In addition, the Cornish–Fisher Expansion Value at Risk approach produces investment risk estimates ranging from 8.21% to 19.95%, with backtesting results showing that VaR estimates are primarily valid for a one-week holding period. Overall, this study concludes that the ARIMA–GARCH and Cornish–Fisher VaR approaches are capable of providing an important picture of the integration of volatility modeling and risk estimation in understanding stock price behavior and investment risk in the renewable energy market. While further research is recommended to consider the use of alternative volatility models such as EGARCH and VaR–GARCH risk estimation under the assumption of normally distributed stock returns, as well longer observation periods to improve the accuracy of risk estimation and forecasting.

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