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Analysis of Stock Return Volatility of PT Asuransi Multi Artha Guna Tbk Using the GARCH-M Model

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Abstract

This study aims to analyze the volatility of stock returns of PT Asuransi Multi Artha Guna Tbk using the Generalized Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) model during the 2019–2024 period. The data used in this study are secondary data in the form of daily closing stock prices of AMAG.JK obtained from Yahoo Finance, with a total of 1,466 observations. The analytical stages include the calculation of log returns, stationarity testing using the Augmented Dickey-Fuller (ADF) test, Ljung-Box autocorrelation test, ARCH-LM test, selection of the best GARCH model based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), estimation of the GARCH-M model, conditional volatility analysis, and volatility forecasting. The results indicate that the stock return data of AMAG.JK are stationary and contain ARCH effects, making them appropriate for analysis using the GARCH model. Based on the AIC and BIC criteria, the best model selected is GARCH(1,2). The estimation results of the GARCH(1,2)-M model show that the ARCH and GARCH parameters are statistically significant, indicating the presence of volatility clustering and volatility persistence phenomena in the stock returns of AMAG.JK. However, the risk premium parameter in the GARCH-M model is not statistically significant, implying that conditional volatility does not significantly affect expected stock returns. The volatility forecasting results show that the volatility level of AMAG.JK stock tends to increase gradually in future periods. Overall, the GARCH(1,2)-M model is capable of describing the dynamics of volatility in AMAG.JK stock returns during the research period effectively.

Keywords: volatility, stock returns, GARCH-M, volatility clustering, AMAG.JK.

1. Introduction

The capital market is one of the important components of a country's financial system, including in Indonesia (Aulia et al., 2022). The development of the Indonesia Stock Exchange has been marked by an increasing number of companies listed on the exchange from various business sectors (Saputra et al., 2023). This condition provides opportunities for investors to gain profits, but it also involves risks due to fluctuating stock prices. In modern financial theory, the relationship between risk and return is known as the risk-return tradeoff concept, which states that the greater the investment risk, the greater the expected return. This concept serves as the foundation for various asset pricing models, one of which is the Capital Asset Pricing Model (CAPM), whose relevance continues to be examined in contemporary financial literature (Mutinda & Langat, 2024).

Unstable stock price movements cause stock returns to experience volatility. This condition gives rise to the phenomenon of volatility clustering, in which periods of high volatility tend to be followed by other periods of high volatility, while periods of low volatility are followed by low volatility periods (Nusrang et al., 2025). This phenomenon indicates the presence of conditional heteroskedasticity that cannot be explained by conventional statistical models assuming constant variance. Therefore, the Autoregressive Conditional Heteroskedasticity (ARCH) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model are widely used in volatility analysis in financial markets (Cahyani et al., 2023).

This study focuses on the stock of PT Asuransi Multi Artha Guna Tbk, an insurance sector company listed on the Indonesia Stock Exchange. The selection of this stock is based on the characteristics of the insurance sector, which is relatively sensitive to changes in economic conditions and market risk. In addition, the research period from 2019 to 2024 includes the COVID-19 pandemic period and the economic recovery period, both of which are expected to affect the volatility of stock returns in insurance companies (Fordian et al., 2023).

In analyzing the relationship between risk and stock returns, this study employs the Generalized Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) model. The GARCH-M model allows for the direct examination of the effect of volatility on expected returns, making it consistent with the concept of the risk-return tradeoff (Gupta, 2024). In addition, the GARCH-M model is considered capable of describing the volatility dynamics of financial data more effectively because it can accommodate changes in variance over time, as demonstrated in various recent empirical studies (Trifonov & Potanin, 2024).

Based on the foregoing explanation, this study aims to analyze the volatility of stock returns of PT Asuransi Multi Artha Guna Tbk, identify the presence of ARCH effects, and examine the effect of conditional volatility on expected stock returns using the GARCH-M model during the 2019–2024 period.

2. Materials and Methods

2.1. Types and Sources of Data

The data used in this study are secondary data in the form of daily closing prices of the stock of PT Asuransi Multi Artha Guna Tbk. The data were obtained from Yahoo Finance, which is one of the most comprehensive and publicly accessible financial data sources. This study uses daily stock price data of AMAG.JK from January 2, 2019, to December 31, 2024. After the data cleaning process by excluding stock exchange holidays and weekends, a total of 1,466 observations were obtained and used in the analysis.

2.2. Stock Returns (Log Return)

Stock returns are a measure of changes in investment value over a certain period. In modern financial research, log returns or logarithmic returns are more commonly used than arithmetic returns because of several advantages, including producing a distribution that is closer to normal, being additive over time, and avoiding the possibility of returns below -100%.

Daily log returns are calculated using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where:

Rt is the log return on day *t,*

Pt is the stock closing price on day *t,*

Pt-1 is the stock closing price on the previous day.

Volatility is a measure of the degree of variation in stock returns over time that reflects the level of investment risk. In financial data, volatility is generally not constant, but instead exhibits the phenomenon of volatility clustering, a condition in which periods of high volatility tend to be followed by other periods of high volatility, while periods of low volatility are followed by periods of low volatility. This phenomenon indicates the presence of conditional heteroskedasticity, which forms the basis for the use of ARCH and GARCH models in volatility analysis.

2.3. Research Model

The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Robert F. Engle in 1982 is used to model conditional variance that changes over time. Furthermore, the model was developed into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by Tim Bollerslev in 1986 by incorporating past conditional variance into the variance equation.

The model used in this study is the Generalized Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) model. This model was introduced by Robert F. Engle, David M. Lilien, and Russell P. Robins in 1987 as an extension of the GARCH model by incorporating conditional variance into the mean return equation, thereby allowing the examination of the relationship between risk and return.

The specification of the GARCH-M model used in this study was determined based on the best model selected using the Akaike Information Criterion (AIC) (Agatha et al., 2026; Melantika et al., 2024) and the Bayesian Information Criterion (BIC). Based on the model selection results, the best model obtained was GARCH(1,2).

Mean Equation:

$$R_t = \mu + \lambda\sigma_t^2 + \varepsilon_t \tag{2}$$

Variance Equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{(t-1)}^2 + \beta_1\sigma_{(t-1)}^2 + \beta_2\sigma_{(t-2)}^2 \tag{3}$$

where:

Rt = stock log return at period t
μ = constant in the mean equation
λ = risk premium coefficient
σ_t^2 =conditional variance at period t
ε_t =residual at period t
α_0 =constant in the variance equation
α_1 =ARCH coefficient
β_1 dan β_2 =GARCH coefficients indicating the effect of previous period volatility on current volatility

If the value of $\lambda > 0$ and is statistically significant, then there is a positive relationship between risk and expected return, which is consistent with the concept of the risk-return tradeoff.

2.4. Conceptual Framework and Hypothesis

This study is based on the relationship between volatility, risk, and stock returns in modern financial theory. Changes in stock prices generate daily returns that contain conditional volatility as a proxy for investment risk. The effect of this risk on expected stock returns is then examined using the GARCH-M model.

Alur kerangka pemikiran penelitian adalah sebagai berikut:

AMAG.JK Stock Price Data → Daily Log Return → Conditional Volatility (σ_t^2) → Risk → Expected Return

Based on the conceptual framework, the research hypothesis is formulated as follows:

H1: There is an ARCH effect (conditional heteroskedasticity) in the daily returns of AMAG.JK stock during the research period.

H2: Risk, proxied by conditional volatility, has a positive and significant effect on the expected return of AMAG.JK stock based on the GARCH-M model.

3. Results and Discussion

3.1. AMAG.JK Stock Price Movement

The following is a graph of the AMAG.JK stock price movement:

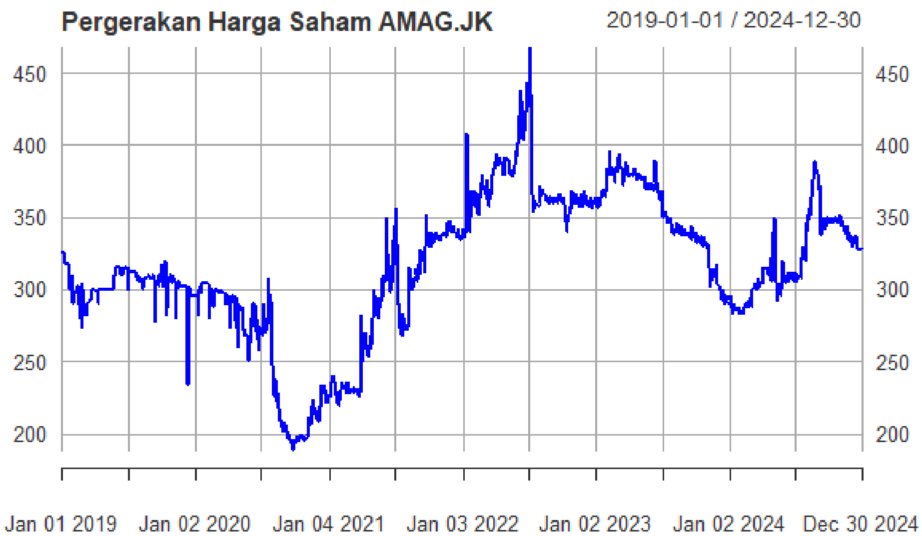

Figure 1: Stock Price Movement of PT Asuransi Multi Artha Guna Tbk (AMAG.JK) for the 2019–2024 Period

Based on Figure 1, the stock price of AMAG.JK during the 2019–2024 period experienced relatively high fluctuations. From 2020 to early 2021, the stock price showed a significant decline, which was presumably influenced by the COVID-19 pandemic conditions. Furthermore, during the 2021–2022 period, the stock price increased and reached its highest point above 450 rupiah before experiencing further fluctuations in 2023–2024.

The fluctuating stock price movements indicate volatility in AMAG.JK shares, so analysis using the GARCH-M model is considered appropriate to study the relationship between risk and stock returns.

3.2. Daily Log Return of AMAG.JK Stock

The following is a graph of the daily log return of AMAG.JK:

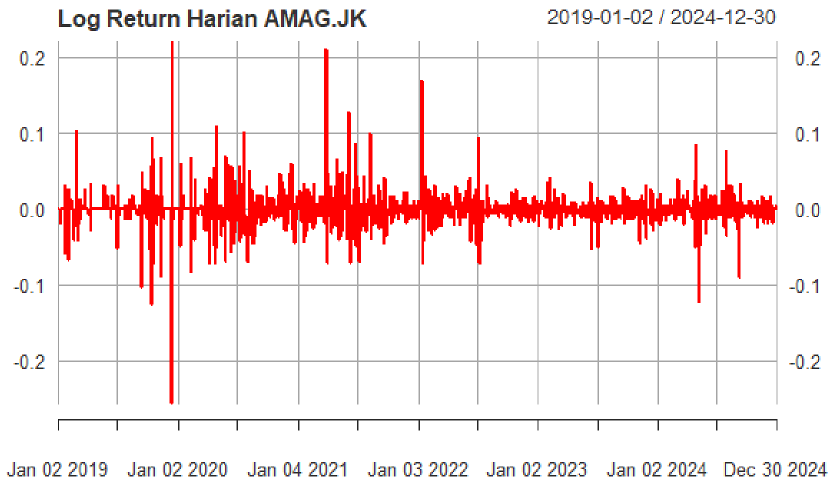

Figure 2: Daily Log Return of AMAG.JK Stock for the 2019–2024 Period

Based on Figure 2, the daily log return of AMAG.JK stock exhibited fluctuating movements throughout the research period. Several relatively extreme positive and negative return spikes can be observed, particularly during the 2020–2022 period. This condition indicates the presence of high volatility in AMAG.JK stock.

In addition, the graph also shows the phenomenon of volatility clustering, namely periods of high volatility followed by other periods of high volatility, as well as periods of low volatility followed by low volatility. This phenomenon indicates the presence of conditional heteroskedasticity in the stock return data, suggesting that the ARCH-GARCH and GARCH-M models are appropriate for use in this study.

3.3. Descriptive Statistics

Table 1: Descriptive Statistics

Descriptive Statistics	Value
Number of Observations	1466
Mean	0.00001265
Median	0.00000000
Minimum	-0.2551
Maximum	0.2214
Standard Deviation	0.02334
Skewness	0.4378
Kurtosis	28.3752
Jarque-Bera	39378
Jarque-Bera p-value	< 0.0001

The standard deviation value of 0.02334 indicates that AMAG.JK stock returns had a relatively high level of volatility during the research period. The kurtosis value, which is far above 3, indicates the presence of a fat-tail phenomenon, while the positive skewness value suggests that the return distribution is skewed to the right. Based on the Jarque-Bera test, the AMAG.JK stock return data are not normally distributed because the p-value is smaller than 0.05.

3.4 Data Stationarity Test

Before estimating the GARCH-M model, a stationarity test was first conducted on the log return data of AMAG.JK stock using the Augmented Dickey-Fuller (ADF) test. This test aims to determine whether the data contain a unit root or are already stationary. Stationary data are an important requirement in time series analysis to ensure that the model estimation does not produce spurious regression results.

Based on the ADF test results, the Dickey-Fuller test statistic obtained was -12.644 with a p-value of 0.01. Since the p-value is smaller than the 5 percent significance level (0.05), the null hypothesis stating that the data contain a unit root is rejected. Therefore, the log return data of AMAG.JK stock are stationary at the level form and do not require further differencing.

These results indicate that the mean and variance of the return data tend to remain constant throughout the observation period, suggesting that the data are suitable for volatility analysis using the ARCH-GARCH and GARCH-M models.

Table 2: Results of the Augmented Dickey-Fuller (ADF) Test

Variable	Dickey-Fuller	Lag	p-value	Description
AMAG.JK Stock Return	-12.644	11	0.01	Stationary

3.5. Autocorrelation Identification

The following is Figure X, which presents the ACF and PACF plots of the stock return data:

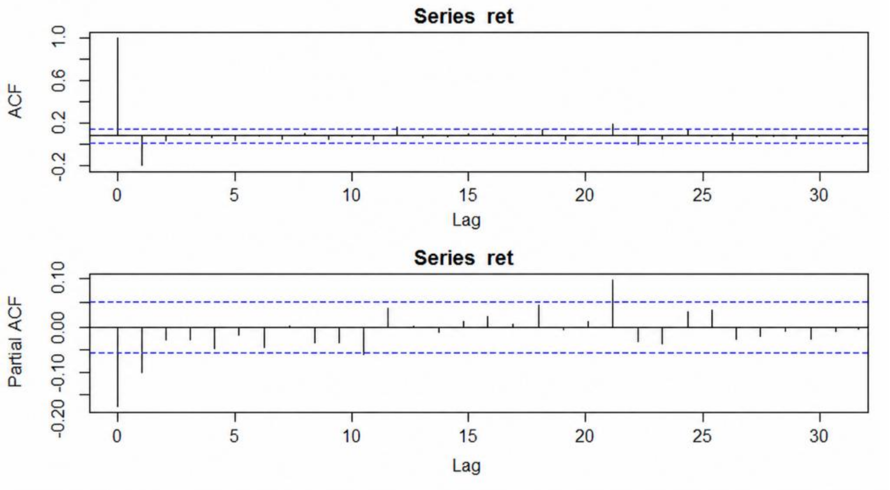

Figure 3: ACF and PACF Plots of the Stock Return Data

Based on the Ljung-Box test results for the AMAG.JK stock return data, the test statistic obtained was 91.117 with a p-value of 4.725×10^{-11}. Since the p-value is smaller than the 5 percent significance level (0.05), the null hypothesis stating that there is no autocorrelation is rejected.

These results indicate that the AMAG.JK stock return data contain autocorrelation, or a relationship between observation periods. Therefore, the return data exhibit time dependence patterns, suggesting that time series models such as ARCH-GARCH and GARCH-M are appropriate for use in this study.

Table 3: Ljung-Box Test Results

Statistic	Value
Ljung-Box (Q)	91.117
Degrees of Freedom (df)	20
p-value	4.725×10^{-11}
Description	Autocorrelation is present

3.6. ARCH-LM Test

Based on the ARCH-LM test results for the AMAG.JK stock return data, the Chi-squared value obtained was 176.12 with 20 degrees of freedom (df) and a p-value $< 2.2 \times 10^{-16}$. Since the p-value is smaller than the 5% significance level (0.05), the null hypothesis stating that there is no ARCH effect is rejected.

These results indicate that the AMAG.JK stock return data contain ARCH effects or conditional heteroskedasticity, suggesting that the ARCH/GARCH model is appropriate for volatility analysis.

Table 4: ARCH-LM Test Results

Statistic	Value
Chi-squared	176.12
Degrees of Freedom (df)	20
p-value	$< 2.2 \times 10^{-16}$
Description	ARCH effect is present

3.7. GARCH Model Selection

The GARCH model selection was conducted by comparing several model specifications, namely GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2). The best model was selected based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The model with the lowest AIC and BIC values is considered the most appropriate model for explaining the volatility of stock return data.

Based on the estimation results, the GARCH(1,2) model has the lowest AIC value of -5.609732 and a BIC value of -5.588080. These values are lower than those of the other GARCH models, so the GARCH(1,2) model is selected as the best model in this study. This result indicates that the GARCH(1,2) model is more capable of capturing the volatility patterns in AMAG.JK stock returns compared to other model specifications.

Table 5: Comparison of GARCH Models

Model	Akaike (AIC)	Bayesian (BIC)
GARCH(1,1)	-5.604461	-5.586418
GARCH(1,2)	-5.609732	-5.588080
GARCH(2,1)	-5.602416	-5.580764
GARCH(2,2)	-5.608523	-5.583262

Therefore, subsequent analysis uses the GARCH(1,2) model because it yields the lowest information criteria values and is considered the most appropriate for modeling the volatility of AMAG.JK stock returns during the research period.

3.8. Estimation of the Best GARCH-M Model

Based on the model selection results using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), the best model obtained is the GARCH(1,2)-M model. The model estimation was conducted using the Maximum Likelihood Estimation (MLE) method under the assumption of a normal distribution.

The estimated parameters of the GARCH(1,2)-M model are presented in Table 3.6 below.

Table 6 : Estimation Results of the GARCH(1,2)-M Model

Parameter	Estimate	p-value	Description
μ	0.001265	0.630092	Not significant
λ (archm)	-0.063894	0.620149	Not significant
ω	0.000015	0.076162	Not significant
$\alpha1$	0.048807	0.000000	Significant
$\beta1$	0.448799	0.000000	Significant
$\beta2$	0.474895	0.000000	Significant

Based on the estimation results of the GARCH(1,2)-M model, the ARCH parameter $\alpha1$ and the GARCH parameters ($\beta1$ and $\beta2$) are statistically significant at the 5% significance level. This indicates that the volatility of AMAG.JK stock returns is influenced by shocks and past-period volatility, meaning that the model is able to capture the volatility clustering phenomenon.

The relatively large GARCH coefficients indicate the presence of volatility persistence, meaning that volatility shocks tend to persist over several periods.

Meanwhile, the risk premium parameter (λ), represented by the archm variable, has a p-value of 0.620149 (> 0.05), indicating that conditional volatility does not have a significant effect on the expected return of AMAG.JK stock. Therefore, the risk-return tradeoff relationship in AMAG.JK stock is not empirically supported during the research period.

Based on the Log-Likelihood value of 3547.731 and the AIC value of -4.8318, the GARCH(1,2)-M model is considered to be adequate in modeling the volatility of AMAG.JK stock returns.

3.9. Model Diagnostics

The model diagnostic stage is conducted to evaluate whether the estimated GARCH(1,2)-M model is able to eliminate autocorrelation and ARCH effects in the model residuals.

3.9.1. Residual Autocorrelation Test

Based on the Ljung-Box test results for the model residuals, the test statistic obtained was 91.274 with 20 degrees of freedom and a p-value of 4.436×10^{-11}. Since the p-value is smaller than the 5 percent significance level, the null hypothesis stating that there is no autocorrelation in the residuals is rejected.

These results indicate that the model residuals still contain autocorrelation, suggesting that the GARCH(1,2)-M model has not fully eliminated serial dependence in the AMAG.JK stock return data.

Table 7: Ljung-Box Test Results of Residuals

Statistic	Value
Ljung-Box (Q)	91.274
Degrees of Freedom (df)	20
p-value	4.436×10^{-11}
Description	Residual autocorrelation is present

3.9.2. ARCH Test on Residuals

Based on the ARCH-LM test results on the model residuals, the Chi-squared value obtained was 178.89 with 20 degrees of freedom and a p-value $< 2.2 \times 10^{-16}$. Since the p-value is smaller than 0.05, the null hypothesis stating that there is no ARCH effect is rejected.

These results indicate that the model residuals still exhibit conditional heteroskedasticity or ARCH effects. Therefore, the GARCH(1,2)-M model has not fully captured the volatility of AMAG.JK stock returns optimally.

Table 8: ARCH-LM Test Results of Residuals

Statistic	Value
Chi-squared	178.89
Degrees of Freedom (df)	20
p-value	$< 2.2 \times 10^{-16}$
Description	ARCH effect is still present

3.9.3. Residual Normality Test

Based on the Jarque-Bera test results for the model residuals, the test statistic obtained was 39,969 with a p-value $< 2.2 \times 10^{-16}$. Since the p-value is smaller than 0.05, it indicates that the model residuals are not normally distributed. This condition is commonly observed in financial data due to leptokurtic characteristics and fat tails.

This condition indicates that the residuals still exhibit fat-tail characteristics or extreme outliers, which are commonly found in stock return data.

Table 9: Jarque-Bera Test Results of Residuals

Statistic	Value
Jarque-Bera	39,969
Degrees of Freedom (df)	2
p-value	$< 2.2 \times 10^{-16}$
Description	Residuals are not normally distributed

3.9.4. Interpretation of Model Diagnostics

Overall, the GARCH(1,2)-M model is able to capture the volatility dynamics of AMAG.JK stock returns; however, it is not yet fully optimal because the model residuals still exhibit autocorrelation, ARCH effects, and non-normality.

These results indicate that the model used has not fully captured all characteristics of AMAG.JK stock return data. Therefore, future research may consider alternative model specifications or different error distributions, such as the Student-t distribution or EGARCH/GJR-GARCH models, to obtain a better-fitting model.

3.10. Conditional Volatility Analysis

The conditional volatility analysis is conducted using the conditional standard deviation generated from the estimation of the GARCH(1,2)-M model. Conditional volatility reflects the level of risk in stock returns, which varies over time in accordance with market conditions.

Based on the model estimation results, the initial conditional volatility value was 0.023366 on January 2, 2019. This value then changed over subsequent periods, indicating that the volatility of AMAG.JK stock returns is dynamic and not constant.

Table 3.10 below presents several initial values of conditional volatility obtained from the estimation of the GARCH(1,2)-M model.

Tabel 10: Initial Value of Conditional Volatility

Date	Conditional Volatility
2019-01-02	0.023366
2019-01-03	0.023366
2019-01-04	0.022798
2019-01-07	0.022539
2019-01-08	0.022142
2019-01-09	0.022210

Based on these results, the volatility of AMAG.JK stock returns shows relatively fluctuating changes over time. This condition indicates the presence of conditional heteroskedasticity, which is a common characteristic of financial data.

Selain itu, hasil estimasi juga menunjukkan adanya fenomena volatility clustering yang menunjukkan adanya persistence volatility pada return saham, yaitu periode volatilitas tinggi yang cenderung diikuti oleh volatilitas tinggi lainnya serta periode volatilitas rendah yang diikuti oleh volatilitas rendah. Hal tersebut menunjukkan bahwa shock volatilitas pada saham AMAG.JK memiliki efek yang bertahan dalam beberapa periode.

Dengan demikian, model GARCH(1,2)-M dinilai mampu menggambarkan dinamika volatilitas return saham AMAG.JK selama periode penelitian.

3.11. Volatility Forecasting

Volatility forecasting is carried out using the best GARCH(1,2)-M model with a 10-period forecast horizon. The forecasting results produce predicted return values (series) and predicted volatility (sigma), which represent the level of risk of AMAG.JK stock in future periods.

Based on the forecasting results, the predicted volatility values (sigma) show a gradual increasing trend from 0.01628 at period T+1 to 0.01769 at period T+10. This condition indicates that the volatility of AMAG.JK stock returns is expected to remain relatively high in the future periods.

Table 11: Forecast Results of GARCH(1,2)-M Volatility

Period	Forecast Return	Forecast Volatility (Sigma)
T+1	0.0002251	0.01628
T+2	0.0002073	0.01655
T+3	0.0002004	0.01666
T+4	0.0001887	0.01684
T+5	0.0001798	0.01698
T+6	0.0001699	0.01714
T+7	0.0001609	0.01728
T+8	0.0001518	0.01742
T+9	0.0001431	0.01756
T+10	0.0001346	0.01769

These results show that the predicted returns tend to decline gradually, while the predicted volatility increases slowly. This indicates that the market risk of AMAG.JK stock is expected to remain relatively high in the short term.

The increase in sigma values across forecast periods also indicates volatility persistence, meaning that volatility effects continue to persist into subsequent periods. This condition is consistent with financial data characteristics that exhibit volatility clustering.

Thus, the GARCH(1,2)-M model is not only able to model historical volatility but can also be used to forecast the volatility of AMAG.JK stock in future periods.

4. Conclussion

Based on the results of the study on volatility analysis of PT Asuransi Multi Artha Guna Tbk (AMAG.JK) stock returns using the GARCH-M model for the 2019–2024 period, several conclusions can be drawn. The ARCH-LM test results show that AMAG.JK stock return data exhibit ARCH effects or conditional heteroskedasticity. This condition indicates that return variance is not constant, so ARCH/GARCH models are appropriate for analyzing stock return volatility. Based on the model selection process using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), the best model obtained is the GARCH(1,2) model because it has the lowest AIC and BIC values compared to other models. The estimation results of the GARCH(1,2)-M model show that the ARCH parameter α_1 and the GARCH parameters (β_1 and β_2) are statistically significant. These results indicate that AMAG.JK stock return volatility is influenced by shocks and past volatility, showing the presence of volatility clustering and volatility persistence.

In addition, the risk premium parameter (λ) in the GARCH-M model is not statistically significant. This indicates that conditional volatility does not have a significant effect on the expected return of AMAG.JK stock, so the relationship between risk and return (risk-return tradeoff) for AMAG.JK during the study period cannot be empirically confirmed. The volatility forecasting results show that predicted volatility tends to increase gradually over several future periods. This condition indicates that the risk level of AMAG.JK stock is still relatively high in the short term. Overall, the GARCH(1,2)-M model is able to explain the volatility dynamics of AMAG.JK stock returns, although the diagnostic results indicate that the model is not yet fully optimal.

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