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Stock Price Forecasting Using the ARMA-GARCH Model

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Abstract. The capital market plays a crucial role as a global economic indicator. This study aims to analyze the volatility and forecast the stock prices of PT Asuransi Tugu Pratama Indonesia using the ARMA-GARCH method with STATA application on stock price data from 2019 to 2023. The analysis process involves transforming the data into a time series, stationarity testing, ARCH-LM testing, and model evaluation using AIC criteria. The results indicate that the ARMA-GARCH method is effective with a low error rate of 9.61% (MAPE), providing accurate stock price forecasts to support investment decision-making. These findings offer insights into volatility dynamics and better investment strategies in the stock market.

Introduction

Capital market development plays a pivotal role in the global economy (Istiqomah & Novika, 2025) by facilitating efficient capital allocation and serving as an important indicator of a country's economic performance and financial stability (Saada, 2025). Within the capital market framework, stock indices and individual stock prices function as key barometers that reflect overall market conditions, investor expectations, and market sentiment (M. A. Khan et al., 2024). Consequently, the ability to accurately forecast stock price movements has become increasingly essential for investors, portfolio managers, policymakers, and researchers in supporting investment decision-making and risk management processes (Liu et al., 2022).

In recent years, global financial markets have experienced heightened volatility due to various external shocks, including the COVID-19 pandemic (M. Khan et al., 2023), geopolitical conflicts (M. N. Khan, 2025), inflationary pressures, and shifts in monetary policy across major economies (Schnabel, 2022). These developments have increased the uncertainty and complexity of financial markets (Maharani et al., 2026), thereby creating significant challenges in predicting stock price movements and motivating the development of more robust and sophisticated forecasting approaches (Phan et al., 2021).

Time-series forecasting models have been widely employed to analyze stock market behavior and volatility dynamics (Masbratha et al., 2026). Among these approaches, the Autoregressive Moving Average (ARMA) model has long been recognized as an effective method for capturing

linear dependencies and temporal structures in financial time-series data (Box et al., 2015). Nevertheless, financial market data frequently exhibit characteristics such as volatility clustering, leptokurtosis, and heteroscedasticity, where the variance of errors changes over time. To address these limitations, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was developed to specifically model time-varying volatility in financial series (Bollerslev, 1986). The integration of ARMA and GARCH models has therefore become a widely accepted framework for simultaneously modeling the conditional mean and conditional variance of financial asset returns (Huang et al., 2024).

In addition to model development, the evaluation and validation of forecasting performance constitute critical aspects of financial time-series analysis. Conventional evaluation measures, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), remain widely utilized to assess predictive accuracy (Hodson, 2022). However, recent studies emphasize the importance of more comprehensive evaluation frameworks capable of capturing directional accuracy, turning points, and volatility persistence in financial markets (Lim & Loh, 2021). Such evaluation methods are particularly relevant in highly volatile and uncertain market environments.

In the Indonesian capital market context, the application of ARMA-GARCH models has gained considerable attention due to the relatively high volatility of domestic financial assets (Toong et al., 2023), especially during periods of economic disruption such as the COVID-19 pandemic. The Indonesian stock market is characterized by sensitivity to both domestic and global economic conditions (Rusydiana et al., 2022), including political uncertainty, commodity price fluctuations, exchange rate movements, and external market spillover effects. These conditions highlight the necessity of employing volatility models capable of capturing dynamic market behavior and improving forecasting accuracy (Nugroho & Suwono, 2024).

One of the publicly listed companies that has attracted investor attention in the Indonesian capital market is PT Asuransi Tugu Pratama Indonesia Tbk., commonly known as TUGU. Established on November 25, 1981, the company operates in the general insurance, reinsurance, and sharia insurance sectors, with its headquarters located in Jakarta. PT Asuransi Tugu Pratama Indonesia Tbk. was officially listed on the Indonesia Stock Exchange (IDX) on May 28, 2018, under the ticker code TUGU. The proceeds obtained from the Initial Public Offering (IPO) were allocated to strengthen business development and enhance capital participation in the reinsurance sector. As of recent ownership records, the majority of the company's shares are held by PT Pertamina (Persero), indicating strong institutional backing and strategic significance within the Indonesian insurance industry.

Despite its strategic position, the stock price of PT Asuransi Tugu Pratama Indonesia Tbk. has experienced fluctuations influenced by both firm-specific and macroeconomic factors. The period from 2019 to 2023 is particularly important for analysis, as it encompasses significant economic disruptions caused by the COVID-19 pandemic and subsequent market recovery phases. These conditions provide an appropriate context for examining stock price volatility and evaluating the effectiveness of econometric volatility models.

Based on the foregoing discussion, this study aims to analyze the stock price volatility of PT Asuransi Tugu Pratama Indonesia Tbk. during the 2019–2023 period using the ARMA-GARCH approach. Specifically, the study seeks to identify the characteristics of stock return volatility, estimate the most appropriate ARMA-GARCH model, and evaluate its forecasting performance in predicting stock price movements. Furthermore, the findings of this study are expected to provide strategic insights for investors and market participants regarding volatility-based investment decision-making and risk management in the Indonesian capital market.

Method

This study was conducted between August 2024 and January 2025 using secondary data obtained from the Indonesia Stock Exchange (IDX) and Yahoo Finance. The analysis was performed using Stata as the primary statistical tool. The dataset consisted of monthly stock price data of PT Asuransi Tugu Pratama Indonesia Tbk. (TUGU) covering the period from 2019 to 2023. Specifically, this study employed adjusted closing prices (Adj. Close), collected at the beginning of each month to capture early market movement tendencies and investor sentiment during the opening trading period.

This research adopted a quantitative descriptive approach. Data collection techniques included documentation and literature review, involving the compilation of historical stock price data and supporting theoretical references related to time-series analysis and financial volatility modeling.

The analytical procedures in this study were conducted systematically through several stages based on the methodology proposed in Stata documentation (StataCorp, 2023), as described below:

1. Data Preparation

   The initial stage involved importing stock price data into Stata and transforming the data into stock returns. Stock returns were calculated using the continuously compounded return formula based on the natural logarithm of the ratio between the current stock price and the previous period's stock price, multiplied by 100 to obtain percentage values.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \quad (1)$$

   where R_t represents stock return at time t, P_t denotes the stock price in the current period, and P_{t-1} represents the stock price in the previous period. Subsequently, the dataset was structured as time-series data using the tsset command to ensure proper temporal recognition within Stata.

2. Descriptive Statistical Analysis

   Descriptive statistical analysis was conducted to examine the fundamental characteristics of the stock return data. This stage included the calculation of measures of central tendency, such as mean and median, as well as measures of dispersion, including variance and standard deviation. In addition, normality tests were performed using the Skewness–Kurtosis test and the Shapiro–Wilk test. Time-series plots were also generated to visualize data patterns, trends, and potential outliers.

3. Stationarity Testing

   Stationarity testing constitutes a critical prerequisite in time-series modeling. In this study, stationarity was examined using the Augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test. A time series is considered stationary when its statistical properties, including mean and variance, remain constant over time. The null hypothesis of the ADF and PP tests indicates the presence of a unit root (non-stationarity). Therefore, the null hypothesis is rejected when the probability value is below the selected significance level, indicating that the data are stationary. If non-stationarity was detected, differencing procedures were applied to achieve stationarity.

4. ARMA Model Identification

The identification of the appropriate ARMA model was performed through analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These correlograms were used to determine the optimal autoregressive (AR) and moving average (MA) orders by observing temporal dependence patterns in the return series. Several ARMA specifications were subsequently compared using information criteria, particularly the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), where the model with the lowest criterion value was considered preferable.

5. ARCH Effect Testing

   After estimating the ARMA model, the presence of heteroscedasticity was examined using the ARCH-Lagrange Multiplier (ARCH-LM) test. This test aimed to determine whether the residual variance remained constant over time or exhibited volatility clustering, which is commonly observed in financial time-series data. Residual and squared residual plots were also analyzed to visually identify volatility persistence and justify the application of GARCH modeling.

6. ARMA-GARCH Model Estimation

   At this stage, several ARMA-GARCH model specifications with varying AR, MA, ARCH, and GARCH orders were estimated. The optimal model was selected based on statistical significance and information criteria, including AIC and BIC values. The model with the smallest information criterion value and statistically significant parameters was identified as the best-fitting model for the data. The ARMA-GARCH framework enabled simultaneous estimation of the conditional mean and conditional variance of stock returns.

7. Model Diagnostic Testing

   Diagnostic testing was subsequently performed to evaluate the adequacy and robustness of the selected model. This stage included residual normality testing, residual autocorrelation testing using the Ljung–Box Q statistic, and re-examination of remaining ARCH effects using the ARCH-LM test. These procedures were intended to ensure that the model successfully captured the autocorrelation structure and volatility dynamics present in the stock return series.

8. Forecasting and Model Evaluation

   The final ARMA-GARCH model was then employed to forecast future stock return volatility. Forecasting results included both point forecasts and confidence intervals to estimate potential future return ranges. Forecast accuracy was evaluated using Mean Absolute Percentage Error (MAPE) and backtesting procedures. According to Lewis (2023), MAPE values below 10% indicate very good forecasting performance, values between 11%–20% indicate good performance, values between 21%–30% indicate fair performance, values between 31%–50% indicate poor performance, and values above 50% indicate very poor forecasting performance.

9. Interpretation of Results

   Finally, the estimated model parameters and forecasting outcomes were interpreted by considering their statistical significance and economic implications. The interpretation focused on explaining stock return behavior, volatility persistence, and the implications of the findings for investment decision-making and risk management strategies.

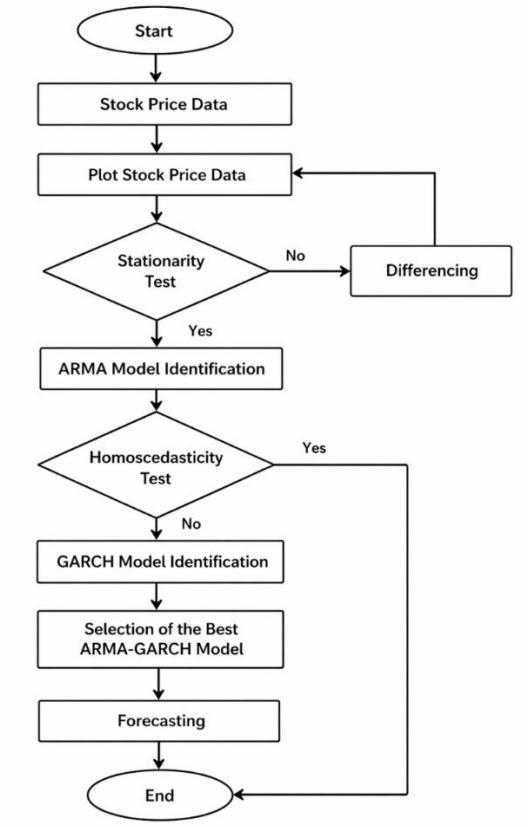


Image 1. ARMA GARCH Forecasting Flowchart

Results and Discussion

Stock Price Volatility

The volatility analysis of PT Asuransi Tugu Pratama Indonesia Tbk.'s stock prices for the 2019–2023 period was conducted by calculating the variance of monthly stock prices for each year using Microsoft Excel. Variance was employed as a measure of stock price volatility to identify the degree of price fluctuations over time. The calculation was performed using the following formula:

$$\text{VAR. P}(X_1 : X_{12})$$

where X_1 to X_{12} represent monthly stock prices from January to December within a given year. The resulting variance values, which represent stock price volatility, are summarized in Table 1.

Table 1. Stock Price Volatility of PT Asuransi Tugu Pratama Indonesia Tbk.

Year	Volatility
2019	12,718.93
2020	70,913.28
2021	4,392.89
2022	50,517.85
2023	23,932.97

Based on the variance results presented in Table 1, the stock prices of PT Asuransi Tugu Pratama Indonesia Tbk. exhibited substantial fluctuations throughout the 2019–2023 period. The highest volatility occurred in 2020, which may be associated with heightened market uncertainty during the COVID-19 pandemic period, while the lowest volatility was observed in 2021. These findings indicate that the stock experienced varying levels of price dispersion across different years.

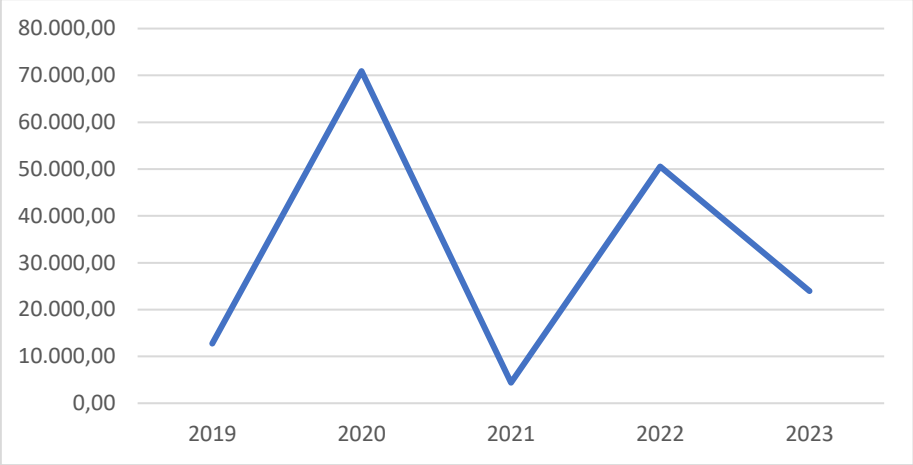


Image 2. Volatility Stock Price of PT Asuransi Tugu Pratama Indonesia Tbk.

Furthermore, the volatility pattern was visualized using a volatility graph, as presented in Image 2. The graph illustrates clear upward and downward movements in stock price volatility over the observation period. Although the volatility trend appears relatively linear, this pattern is primarily attributable to the transformation of monthly stock price data into annual variance data, which simplifies short-term fluctuations into yearly observations. The presence of considerable volatility fluctuations suggests that the stock price series contains dynamic variance behavior and potential heteroscedasticity. Therefore, forecasting using the ARMA–GARCH approach is considered appropriate, as this method is capable of modeling both the mean process and time-varying volatility characteristics of financial time-series data.

ARMA – GARCH Model for Stock Price Forecasting of PT Asuransi Tugu Pratama Indonesia

In this study, forecasting analysis was conducted to examine the volatility and future movement of PT Asuransi Tugu Pratama Indonesia Tbk.'s stock prices. The analysis began with collecting historical stock price data from the Indonesia Stock Exchange. Subsequently, stock price forecasting was performed using the ARMA–GARCH method (Alaminos et al., 2024) implemented in Stata.

1. Descriptive Analysis

   The forecasting process using the ARMA–GARCH approach began with descriptive analysis and data preparation. Historical stock price data were imported into Stata, and the variable representing stock prices was labeled as *harga* (price). The data were then transformed into time-series format by assigning monthly time units, such as 2019m2 to 2024m2. Furthermore, the time format was converted from daily observations into monthly observations to facilitate time-series analysis. At this stage, graphical visualization of stock prices was also conducted prior to forecasting to observe preliminary movement patterns and identify fluctuations within the dataset.

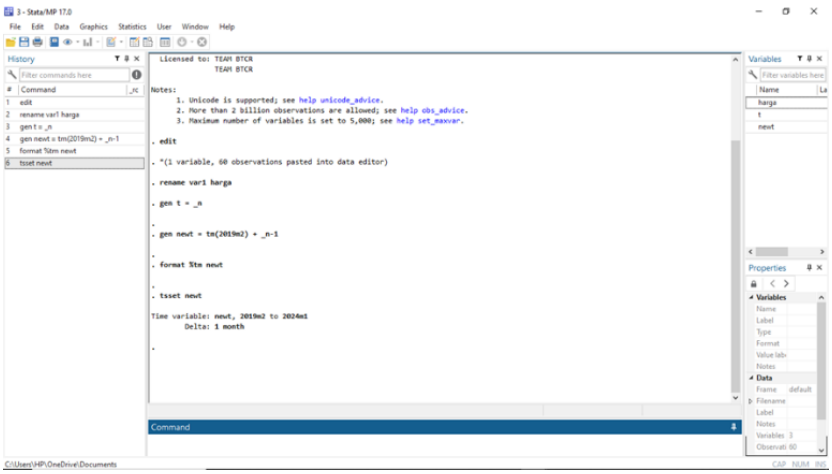


Image 3. Descriptive Analysis in STATA

The Stata syntax used in this stage included the following:

a. edit : importing and entering data from Excel into Stata

b. gen t : generating time variables

c. gen newt : generating monthly period variables

d. format %tm : converting daily data format into monthly format

e. tsset newt : defining the dataset as time-series data

f. twoway line : generating line graphs

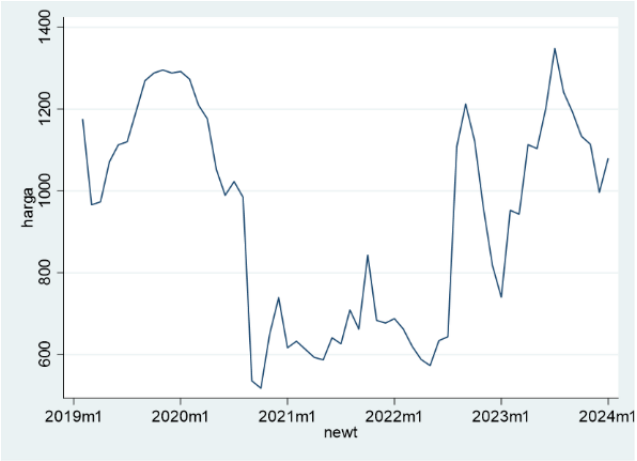


Image 4. Stock Price

Based on the Image 4, PT Asuransi Tugu Pratama Indonesia Tbk.'s stock prices experienced substantial fluctuations during the 2019–2023 period. The lowest stock prices were observed during the 2020–2021 period, while the highest stock prices occurred during the 2023–2024 period. These fluctuations indicate dynamic market behavior and justify the application of volatility modeling techniques.

2. Stationarity Test

The next stage involved stationarity testing using the Augmented Dickey–Fuller (ADF) test. Stationarity testing is an essential prerequisite in ARMA modeling because non-stationary data may produce biased and spurious estimations. In Stata, the ADF test was conducted using command in Image 5.

```
. dfuller harga

Dickey-Fuller test for unit root                  Number of obs   =        59
Variable: harga                                   Number of lags  =         0

H0: Random walk without drift, d = 0

                     Test                 Dickey-Fuller critical value
                statistic           1%            5%            10%
------------------------------------------------------------------------------
 Z(t)             -1.888          -3.567        -2.923        -2.596
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.3376.
```

Image 5. ADF test

The initial ADF test results indicated a probability value (p-value) of 0.33, suggesting that the stock price series was non-stationary. Since the null hypothesis of the ADF test indicates the presence of a unit root, the data were differenced to achieve stationarity. The differenced series was tested using syntax in Image 6.

```
. dfuller D.harga

Dickey-Fuller test for unit root                  Number of obs   =        58
Variable: D.harga                                 Number of lags  =         0

H0: Random walk without drift, d = 0

                     Test                 Dickey-Fuller critical value
                statistic           1%            5%            10%
------------------------------------------------------------------------------
 Z(t)             -7.000          -3.569        -2.924        -2.597
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Image 6. Differencing test

After differencing, the p-value became statistically significant and approached 0.00, indicating that the data had become stationary and were therefore suitable for ARMA modeling.

3. ACF and PACF Test

Prior to ARMA estimation, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) tests were performed to determine the appropriate autoregressive (AR) and moving average (MA) orders.

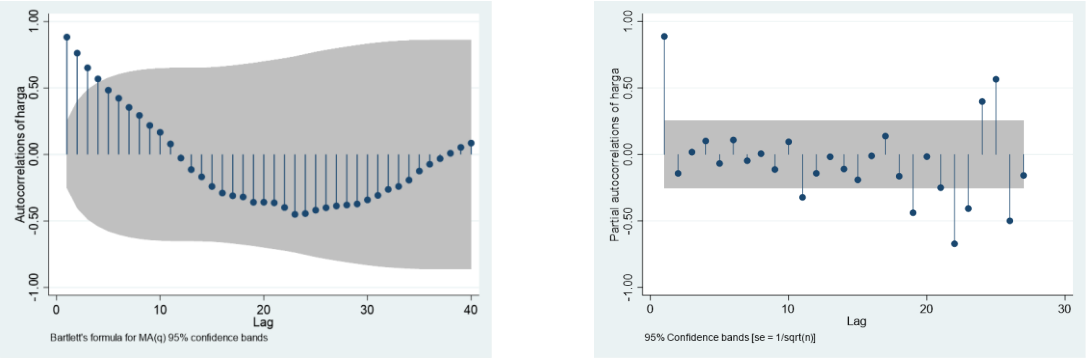


Image 7. ACF and PACF Graph

The ACF Graph in Image 7 illustrated the autocorrelation structure of the stock price data and indicated that the maximum MA order was 2, based on the significant spikes outside the confidence interval bands. Meanwhile, the PACF plot suggested that the AR order was 5, determined from the first significant positive spike beyond the confidence interval. The results of the ACF and PACF analyses provided preliminary guidance for identifying candidate ARMA models to be evaluated in the subsequent stage.

4. ARMA model estimation

The ARMA model estimation stage was conducted to identify the most appropriate forecasting model based on the results of the ACF and PACF analyses. Several ARMA specifications were estimated and compared using the Akaike Information Criterion (AIC). The model with the lowest AIC value was considered the most suitable model because lower AIC values indicate better model fit and predictive performance. The comparison of AIC values for alternative ARMA models is presented in Table 2.

Table 2. Comparison of ARMA Model AIC Values

Model	AIC
(1,1,1)	739.5915
(1,1,2)	739.5966
(1,1,3)	741.3876
(1,1,4)	743.3079
(1,1,5)	743.1101
(2,1,0)	739.3021
(2,1,1)	739.9734
(2,1,2)	740.6799
(2,1,3)	739.9684
(2,1,4)	743.2055
(2,1,5)	744.0002

Based on the AIC comparison, the ARMA(2,1,0) model was selected as the optimal model because it produced the lowest AIC value among all candidate models. In addition, the estimated parameters were statistically significant, indicating that the model adequately captured the autocorrelation structure of the stock price series based on Image 8.

ARCH family regression -- ARMA disturbances

Sample: 2019m2 thru 2024m1 — Number of obs = 60
Wald chi2(2) = 79.69
Log likelihood = -361.4548 — Prob > chi2 = 0.0000

harga	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
harga						
_cons	1028.802	67.0663	15.34	0.000	897.3541	1160.249
ARMA						
ar L2.	.8531644	.1294954	6.59	0.000	.599358	1.106971
ma L1.	.8993499	.1013126	8.88	0.000	.7007808	1.097919
ARCH						
arch L1.	-.1728655	.0827602	-2.09	0.037	-.3350724	-.0106585
garch L1.	1.193985	.092545	12.90	0.000	1.012601	1.37537
_cons	-491.4835	.	.	.	.	.

Image 8. ARMA results

5. Homogenity Test

A homogenity test was subsequently conducted as a prerequisite for GARCH modeling. This test aimed to determine whether the variance structure of the data was homogeneous. The study employed the F-Test Two-Sample for Variances by comparing the adjusted closing stock prices with their residual values.

Table 3. Homogenity Test

	Variable 1	*Variable 2*
Mean	931.5144399	0.056829
Variance	66983.20526	14150.43
Observations	60	60
Df	59	59
F	4.73365171	
P(F<=f) one-tail	6.64287E-09	
F Critical one-tail	1.539956607	

The test results indicated that the calculated F-statistic was 4.73, while the critical F-value was 1.53. Since the calculated F-statistic exceeded the critical value, the data were considered homogeneous and suitable for further GARCH analysis.

6. GARCH Model Identification and ARMA–GARCH Model Selection

Following the homogeneity test, GARCH model identification was performed using Stata to determine the most appropriate volatility model. The estimation results showed that the GARCH parameters were statistically significant, indicating the presence of volatility clustering and conditional heteroscedasticity in the stock price data. Consequently, the ARMA–GARCH model was selected for forecasting stock price volatility.

ARCH family regression -- ARMA disturbances

Sample: 2019m2 thru 2024m1 — Number of obs = 60
Wald chi2(2) = 79.69
Log likelihood = -361.4548 — Prob > chi2 = 0.0000

harga	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
harga						
_cons	1028.802	67.0663	15.34	0.000	897.3541	1160.249
ARMA						
ar L2.	.8531644	.1294954	6.59	0.000	.599358	1.106971
ma L1.	.8993499	.1013126	8.88	0.000	.7007808	1.097919
ARCH						
arch L1.	-.1728655	.0827602	-2.09	0.037	-.3350724	-.0106585
garch L1.	1.193985	.092545	12.90	0.000	1.012601	1.37537
_cons	-491.4835	.	.	.	.	.

Image 9. ARMA-GARCH

The ARMA–GARCH framework was considered appropriate because it simultaneously models the conditional mean and conditional variance of stock returns, thereby improving forecasting performance in highly volatile financial time-series data.

7. Forecasting results

The final stage involved forecasting stock prices using the selected ARMA–GARCH model. Forecasting was conducted for the period from January 2024 to June 2024. The following Stata syntax was used to generate forecasts and confidence intervals:

```
gen forecast_lower = yhat - 1.96sqrt(variance_f)

gen forecast_upper = yhat + 1.96sqrt(variance_f)

predict yhat, dynamic(m(2024m7))

twoway (tsline harga) (tsline yhat), title("Stock Price Forecast")
```

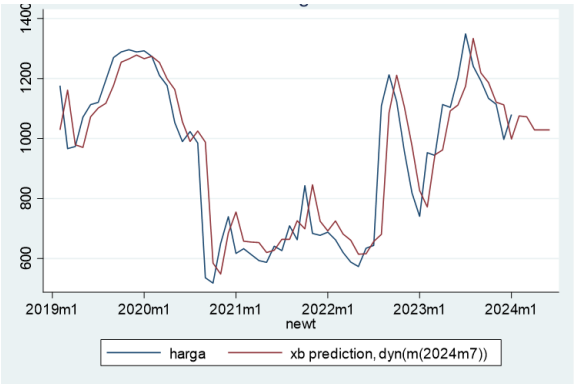


Image 10 Forecasting Graph

The forecasting results generated both lower and upper confidence interval bounds for monthly stock prices. The highest forecasted upper bound reached 1,508.33 in February 2020, while the lowest forecasted lower bound reached 290.59 in August 2022. The forecasting results for January–June 2024 are summarized in Table 5.

Table 4. Forecasting Results

Date	Forecast
2024m1	998.089
2024m2	1,075.311
2024m3	1,072.482
2024m4	1,028.802
2024m5	1,028.802
2024m6	1,028.802

The forecasted adjusted closing stock prices indicate a declining trend during the forecasting period. In addition, graphical forecasting results illustrated the fluctuation patterns of future stock prices. However, the forecasting capability of Stata in this study was limited beyond four future periods, causing the forecast values for May and June 2024 to remain identical to the April 2024 forecast.

8. Mean Absolute Percentage Error (MAPE)

To evaluate forecasting accuracy, the Mean Absolute Percentage Error (MAPE) was calculated to measure the prediction error of the ARMA–GARCH model. The following Stata syntax was employed:

```
gen abs_pe = abs((harga - yhat)/harga)*100
egen mape = mean(abs_pe)
display "MAPE = " mape
display "MAPE = " mape "%"
```

The estimation results produced a MAPE value of 9.61%. According to the established forecasting accuracy criteria, a MAPE value below 10% indicates very good forecasting performance. Therefore, the ARMA–GARCH model can be considered highly effective in forecasting the monthly stock prices of PT Asuransi Tugu Pratama Indonesia Tbk.

Conclusion

Based on the results of this study, it can be concluded that the volatility of PT Asuransi Tugu Pratama Indonesia Tbk.'s stock prices fluctuated throughout the 2019–2023 observation period due to various internal and external factors affecting market conditions. The lowest volatility level was observed during the 2021–2022 period, which was closely associated with the economic

disruptions caused by the COVID-19 pandemic. During this period, uncertainty in global and domestic financial markets significantly affected investor behavior and stock market performance. Following the pandemic period, stock price volatility gradually increased as global economic conditions began to recover, reflecting improved market sentiment and economic revitalization in the post-pandemic era. Subsequently, volatility entered a recovery phase characterized by relatively more stable fluctuations and the absence of severe declines compared to the earlier crisis period.

The empirical findings further demonstrate that the ARMA–GARCH method is effective in forecasting the stock prices of PT Asuransi Tugu Pratama Indonesia Tbk. The forecasting model produced a Mean Absolute Percentage Error (MAPE) value of 9.61%, indicating a very good level of forecasting accuracy. These results suggest that the ARMA–GARCH approach is capable of capturing both the mean dynamics and volatility behavior of stock price movements, making it suitable for financial time-series forecasting.

The forecasting results for the 2019–2024 period indicate that the company's stock prices experienced a declining trend during the early forecasting horizon. Nevertheless, this decline may provide potential investment opportunities for investors to purchase shares at relatively lower prices, particularly during January 2024, with the expectation of future price appreciation in subsequent periods. However, this study also identified several technical limitations associated with the use of Stata, particularly its limited capability in generating long-horizon forecasts beyond four future periods within the applied modeling framework.

Overall, this study confirms that the ARMA–GARCH model provides a reliable and robust approach for analyzing and forecasting stock price volatility, thereby offering useful insights for investors, financial analysts, and researchers in supporting investment decision-making and risk management strategies in the Indonesian capital market.

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