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IMPLEMENTATION OF THE GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY METHOD FOR FORECASTING THE STOCK RETURN OF PT LIPPO GENERAL INSURANCE TBK

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Abstract: *The Indonesian capital market is one of the investment destinations for investors from developed countries. The development of Indonesia's economic conditions is considered good for investors to invest their funds. Financial sector shares are one of the sectors that have experienced development throughout this year. One of the seven stocks showing good growth is PT Lippo General Insurance Tbk (LPGI). The important thing that is the main concern of investors is the level of yield or return from a stock. Based on this, stock return forecasting analysis can be an important source of information for investors. This research uses the GARCH method to forecast LPGI stock returns. The analysis results indicate that the best model for LPGI stock returns is ARIMA (2,0,0) GARCH (1,1), characterized by a very small return value and a negative sign. Thus, these results suggest that the forecasting period is not the optimal time for investors to buy LPGI shares. However, investors who have bought LPGI shares and made a profit are advised to sell LPGI shares before the forecast period. The empirical evidence from this study demonstrates that the GARCH model can effectively capture the volatility pattern of LPGI stock returns in a financial market. This finding supports the application of GARCH in modeling return fluctuations in emerging markets.*

Keywords: *GARCH, heteroscedasticity, LPGI, forecasting, stock returns*

1. INTRODUCTION

Economic conditions have a significant impact on the welfare of a country's people. Economic conditions are an essential factor in ensuring the continuity of people's lives. The development of globalization in the economic sector has made the capital market play a crucial role for a country [1]. One form of financial instrument traded on the capital market is shares. The condition of the capital market has a direct influence on share price movements. Stable and positive capital markets tend to support increased share prices, while unstable and negative capital market conditions can cause share prices to decline. Factors such as interest rates, economic growth, and investor sentiment collectively influence capital market conditions, which in turn impact a company's share price.

The stock market is an investment means for investors and a means of funding for companies or other institutions. Stock market indices are often used to see the economic condition of a country [2]. Movements in the stock price index in a country can be used as an indicator to see the State of the country's economy. Increased stock market performance indicates good economic conditions. When a country's economic conditions are good, the company will experience increased profits and produce a higher share value. The decline in stock market performance is often attributed to a decline in investor confidence resulting from economic conditions that lead to reduced company profits [3].

The financial sector in Indonesia is one sector that has experienced significant growth, with a growth rate of 7.76%. Among the stocks in the financial sector, several insurance companies have performed exceptionally well. The majority of insurance company shares listed on the Indonesia Stock Exchange (BEI) experienced positive growth. There are at least seven insurance companies whose shares are growing well, and one of the seven stocks with the fastest growth is PT Lippo General Insurance Tbk (LPGI) [4].

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In time series data analysis, volatility plays a vital role in observing stock return movements. Volatility is an important measure of risk in empirical finance because it can be used to measure uncertainty in stock markets, futures contracts, derivative instruments, and inflation rates [5]. Time series data, particularly financial data such as stock price indices, often exhibit high volatility. Stock data movements are relatively high and decline at certain times, resulting in volatility [6]. Volatility can cause data variance to be non-constant, resulting in heteroscedasticity problems. Therefore, investors should be able to predict share price movements to know the right time to carry out selling or buying activities.

Forecasting is an analytical technique that can be used as a tool to help capital market players make decisions. Foreign and domestic conditions can impact the State of the stock market in each country and influence volatility. A stable economy tends to lead to stable fluctuations in the stock market. This is different when an economic shock occurs; volatility will tend to increase. The selection of the best model for forecasting aims to obtain predicted volatility values precisely and accurately. Investors can control and minimize market risk for all traded assets by estimating volatility through modeling [4].

Volatility is a situation that is difficult to avoid and often occurs in financial markets. One approach to overcoming the volatility problem is to utilize a model developed by Robert Engle, known as the Autoregressive Conditional Heteroscedasticity (ARCH) model. Engle explained that the residual variance often changes because it not only involves the residual variance itself but also depends on residual variables from the past. Then, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is a development of the ARCH method carried out by Tim Bollerslev (1986). The ARCH model, previously developed, explains that the residual variance, which frequently changes, is influenced by past residual variables. Meanwhile, the GARCH model explains that the residual variance of the time series model is also influenced by the residual variance in the previous period [6].

In this research, the author employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method to forecast the stock returns of PT Lippo General Insurance Tbk (LPGI). LPGI's share price remained relatively stagnant from the fourth quarter of 2019 to the fourth quarter of 2021. This happened as a result of the COVID-19 pandemic. However, at the beginning of 2022, share prices began to increase significantly because the COVID-19 pandemic began to decline. This shows that LPGI stock return data are volatile [7]. So, the appropriate method to use is GARCH modeling for forecasting LPGI stock returns. The results of this research can help investors make more informed decisions about buying or selling LPGI shares.

2. METHODOLOGY

2.1. Stock Return

Essentially, volatility or market turmoil affects investment returns. Return is the profits obtained by the company, individuals, or other institutions based on the results of their investments. Mark Stock returns can be calculated using the formula [8]. This section provides detailed information on data sources, research variables, sampling techniques, data collection methods, and data analysis methods.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

where R_t is the return value at time t, P_t is the stock price at time t and $P_{t-1}$is the stock price at time $t-1$. Risk is the difference between the actual return received and the expected return.

2.2. Unit Root Test

One method to test stationarity is the unit root test. Unit test root is a term that indicates the eigenvalue of the data is one. For obtaining an overview of the unit root test, the following AR (1) process will be shown: [9]:

$$Z_t = \omega Z_{t-1} + \varepsilon_t \tag{2}$$

The following is a stationary test hypothesis using the unit root test (Dickey-Fuller Test):

H_0 : $\omega = 1$ (data has a unit root or data is non-stationary)

H_1 : $\omega < 1$ (data has no unit root or data is stationary)

Test Statistics:

$$DF = \frac{\widehat{\omega}}{SE(\widehat{\omega})} \tag{3}$$

$$SE = \sqrt{\frac{S_d^2}{n}}\ ;\ S_d^2 = \frac{1}{n-1}\sum_{i=1}^{n}(z_t - \bar{z})^2$$

The unit root test results are obtained by comparing the ADF value with the critical value of McKinnon. If the ADF value < critical value McKinnon then reject H_0 meaning no, there is a unit root or stationary data, and if ADF value > Mc-Kinnon critical value, then accept H_0 means there is a unit or data root that is not stationary [10].

2.3. ARCH-Lagrange Multiplier (ARCH-LM) Test

Testing to find out the problem of heteroscedasticity in time series was developed by Engle, known as the ARCH-LM test. The main idea of this test is that residual variance is not just a function of the independent variable but depends on the squared residual of the previous period [11]. For example, $\varepsilon_t = X_t - \mu_t$ is residual from the average equation. Line up ε_t^2 it is used to check conditional heteroscedasticity or the ARCH effect. This test is the same as the F statistic in general to test $\alpha_i = 0$, $i = 1,2,\ldots,p$ in linear regression.

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \omega_t\ ; t = m+1,\ldots,T \tag{4}$$

where ω_t is the error, m is an integer, and T is the sample size or number of observations [12].

The ARCH-LM testing hypothesis is as follows:

H_0 : $\alpha_1 = \alpha_2 = \cdots = 0$ (there is no ARCH effect)

H_1 : $\exists\alpha_i \neq 0$, $i = 1,2,\ldots,p$ (there is ARCH effect)

with a significance level $\alpha = 0.05$, reject H_0 if $F > \chi_p^2(\alpha)$ or $p - value < \alpha$ [12].

2.4. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The GARCH model was developed by Bollerslev (1986), which is a development of the ARCH model. This model is built to avoid order too high in the ARCH model based on the principle of parsimony or choosing a simpler model, so it will guarantee that the variance is always positive [11]. According to Tsay (2005), $\varepsilon_t = X_t - \mu_t$ is said to follow the GARCH model (p, q) if [12];

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_p\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\gamma_i\sigma_{t-i}^2 \tag{5}$$

2.5. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is one of the most widely used measures for model comparison and selection in statistical modeling. The concept was first introduced by Hirotugu Akaike (1974) as an information-theoretic criterion based on the concept of Kullback–Leibler divergence**,** which quantifies the distance between the actual model and the approximating model [13]. The AIC is mathematically defined as:

$$AIC = -2\ln(L) + 2k \tag{6}$$

3. RESULTS AND DISCUSSION

3.1. Data Exploration

The data used in this research are the stock return data of PT Lippo General Insurance Tbk (LPGI) for the period from October 11, 2019, to October 10, 2023, totaling 973 data points. The LPGI stock return data were obtained from the closing prices of LPGI shares, as shown in Figure 2.

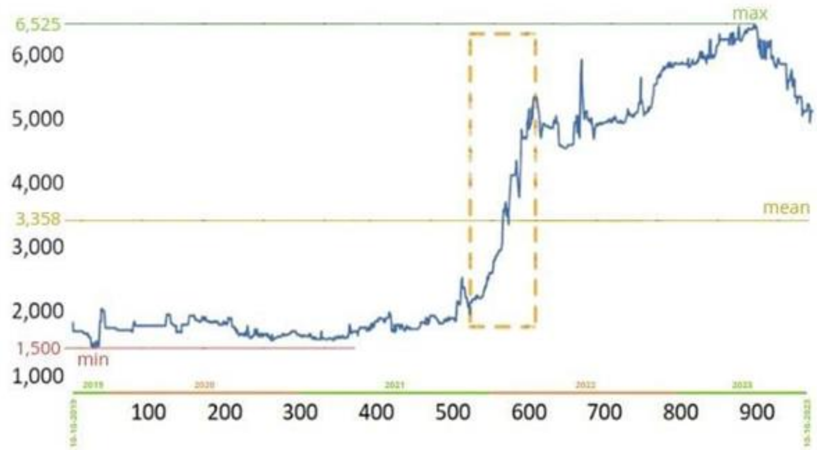

Figure 1. LPGI Stock Closing Price Chart

The graph above shows that the average share price data for PT Lippo General Insurance Tbk during the period from October 10, 2019, to October 10, 2023, is IDR 3,358.00. The graph also explains that the highest share price during the observation period was IDR 6,525.00. Meanwhile, the lowest share price received by investors was IDR 1,500.00. The graph above also shows volatility in the share price of PT Lippo General Insurance Tbk during the observation period.

3.2. Stationarity Test

Stationarity is a test carried out in research using time series data and functions as a first step before proceeding to the ARIMA method. The stationarity test for this research was conducted using the Augmented Dickey-Fuller (ADF) unit root test. The following results were obtained based on the ADF unit root test.

Table 1. ADF Test Results Level level

Return	T	Lag Order	P-value
LPGI	-10.064	9	0.01

Based on Table 1, the results show that the p-value (0.01) < α (0.05). The decision from the output is that H_0 is rejected, so it can be concluded that the LPGI return data is stationary. The next step is to identify the ARIMA model sequence

3.3. ARIMA Model Identification

Initial identification of the ARIMA model was carried out using ACF and PACF plots obtained from LPGI stock return data. This plot is used to determine the initial estimate of the ARIMA model, which is suitable for modeling LPGI stock return data.

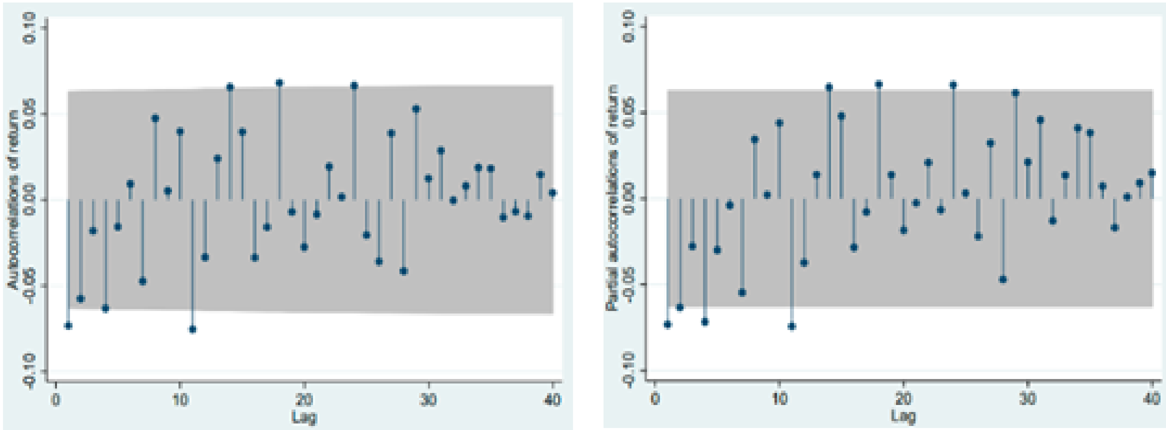

Figure 2. Plot ACF and PACF Returns of LPGI Shares

The ACF and PACF plots for LPGI stock returns are shown in Figure 2. The autocorrelation function (ACF) is significant for lag 1, indicating that the proposed LPGI stock return model is ARMA (0,[1]). On the other hand, the partial autocorrelation function (PACF) shows that the ARMA estimation model is ARMA ([1,2],0). This indicates that today, LPGI stock returns are influenced by the stock returns of the previous day and the day before. Identification of the two ARIMA models was carried out using the auto ARIMA function in RStudio with the following results:

Table 2. Auto ARIMA Command Results

Model	Variable	Coeff
	AR (1)	0.6203
ARIMA (2,0,1)	AR (2)	-0.0148
	MA (1)	-0.7042

The results above show that the model obtained is ARIMA (2,0,1). This also confirms that the data used is stationary. Then, the ARIMA (2,0,1) model also fits the ACF and PACF plots. However, these results must be further analyzed to obtain the best ARIMA model. The ARIMA model obtained is used as the maximum order for both the AR and MA orders. Therefore, it is necessary to compare the ARIMA model obtained with the ARIMA model of a smaller order to determine which model is the most suitable. Thus, the results of the ARIMA model identification are obtained as follows:

1) ARIMA (2,0,1)
2) ARIMA (2,0,0)
3) ARIMA (1,0,1)
4) ARIMA (1,0,0)
5) ARIMA (0,0,1)

3.4 ARIMA Model Estimation

The following is the parameter estimation hypothesis and significance test of the ARIMA model parameters:

H_0: $\phi = 0$ (parameters in the ARIMA model are not significant)

H_1: $\phi \neq 0$ (parameters in the ARIMA model are significant)

Decision: p-value < α (Reject H_0).

Based on the parameter estimates of several ARIMA models for all orders used, the following results were obtained:

Table 3. Estimation Test Results and Significance of the ARIMA Model

Model	Variable	Coeff	p-value	Desicion	AIC
ARIMA (2,0,1)	AR (1)	0.638	2.971×10^{-7}	Reject H0	-4469.10
	AR (2)	-0.0131	0.731	Do not Reject H0	
	MA (1)	-0.7241	1.989×10^{-9}	Reject H0	
ARIMA (2,0,0)	AR (1)	-0.0787	0.014	Reject H0	-4464.09
	AR (2)	-0.0634	0.047	Reject H0	
ARIMA (1,0,1)	AR (1)	0.465	0.001	Reject H0	-4467.07
	MA (1)	-0.5698	$5.988 \times 10-5$	Reject H0	
ARIMA (1,0,0)	AR (1)	-0.0733	0.021	Reject H0	-4460.15
ARIMA (0,0,1)	MA (1)	-0.084	0.014	Reject H0	-4460.92

Based on Table 3, the results show that only the ARIMA (2,0,1) model has one parameter that is not significant. The model taken for further analysis is the ARIMA model with all significant parameters and a small AIC value. So, the two best models that meet these requirements and will be analyzed further are ARIMA (2,0,0) and ARIMA (1,0,1).

3.5 ARCH–Lagrange Multiplier 9ARCH-LM)

The ARCH-Lagrange Multiplier test is used to test whether there is heteroscedasticity in the residuals of the ARIMA (2,0,0) and ARIMA (1,0,1) models, with the following hypothesis:

H_0: $\phi = 0$ (There is no heteroscedasticity in the ARIMA model residuals)

H_1: $\phi \neq 0$ (There is heteroscedasticity in the residuals of the ARIMA model)

Decision: *p-value* < α (Reject H_0).

Table 4. Heteroscedasticity Test Results on ARIMA Model Residuals

Model	p-value	Decision
ARIMA (2,0,0)	9.969×10^{-8}	Reject H0
ARIMA (1,0,1)	$1.728e \times 10^{-7}$	Reject H0

Based on Table 4, the results indicate heteroscedasticity in the residuals of the ARIMA (2,0,1) and ARIMA (1,0,1) models. The ARIMA model, which has heteroscedasticity in its residuals, can be continued with ARCH/GARCH modeling. So, the ARIMA (2,0,0) and ARIMA (1,0,1) models can be continued at the ARCH/GARCH model identification stage.

3.6 Identify ARCH/GARCH Models

Identification of the GARCH model can be observed from the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the squared residuals obtained from the ARIMA model. One of the ARIMA models that will be identified with the ARCH/GARCH model is the ARIMA (2,0,0) model. Below are the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the squared residuals from the ARIMA (2,0,0) model.

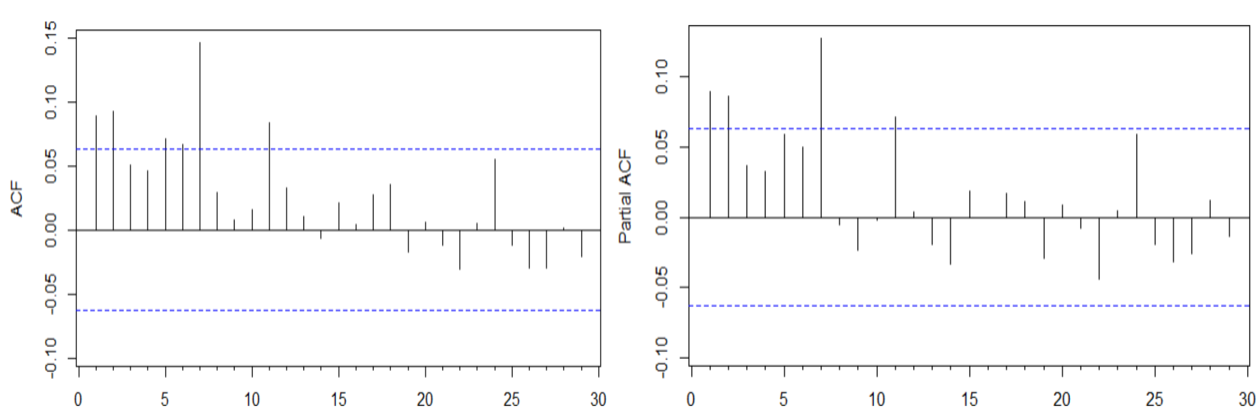

Figure 3. ARIMA Squared Residual ACF and PACF Plot (2,0,0)

Based on Figure 3, it is known that the ACF and PACF plots of the squared residuals from the ARIMA (2,0,0) model cut off at lags 1 and 2. These results confirm that the model has an ARCH effect. The temporary model estimates are as follows:

1) ARIMA (2,0,0) with ARCH (1)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, ARCH (1) indicates that today's residual variance is dependent on the residual variance from the previous day.

2) ARIMA (2,0,0) with ARCH (2)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, ARCH (2) shows that today's residual variance depends on the residual variables of the previous two days.

3) ARIMA (2,0,0) with GARCH (1,1)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, the GARCH (1,1) model shows that today's residual variance depends on both the previous day's residual variable and the previous day's residual variance.

4) ARIMA (2,0,0) with GARCH (1,2)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, the GARCH (1,2) model suggests that today's residual variance is dependent on the residual variable from one day prior and the residual variance from two days prior.

5) ARIMA (2,0,0) with GARCH (2,1)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, GARCH (2,1) shows that today's residual variance depends on the residual variables of the previous two days and the residual variance of the previous day.

6) ARIMA (2,0,0) with GARCH (2,2)

   The ARIMA (2,0,0) model indicates that the LPGI stock return for today is partially dependent on the LPGI stock return two days earlier. Then, GARCH (2,2) shows that today's residual variance depends on the residual variables of the previous two days and the residual variance of the previous two days.

Next, the ARIMA model that will be identified as the ARCH/GARCH model is the ARIMA (1,0,1) model. The identification of the GARCH model can also be observed from the ACF and PACF plots of the squared residuals from the ARIMA model. The following is a plot of the ACF and PACF of the squared residuals from the ARIMA model (2,0,0).

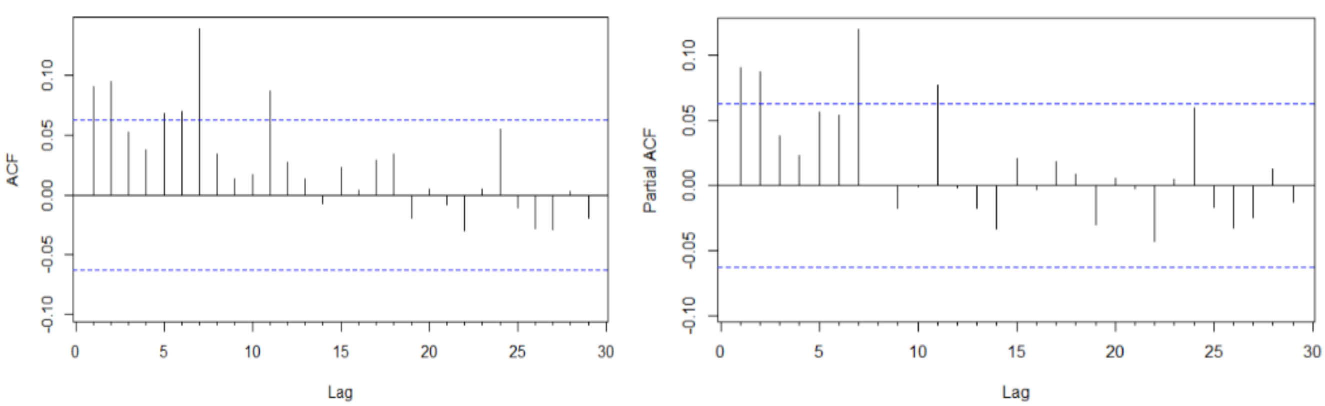

Figure 4. ARIMA Squared Residual ACF and PACF Plot (1,0,1)

Based on Figure 4, it is known that the ACF and PACF plots of the squared residuals from the ARIMA model (1,0,1) cut off at lags 1 and 2. These results confirm that the model has an ARCH effect. The temporary model estimates are as follows:

1) ARIMA (1,0,1) with ARCH (1)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, ARCH (1) indicates that today's residual variance is dependent on the residual variance from the previous day.

2) ARIMA (1,0,1) with ARCH (2)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, ARCH (2) shows that today's residual variance depends on the residual variables of the previous two days.

3) ARIMA (1,0,1) with GARCH (1,1)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, the GARCH (1,1) model shows that today's residual variance depends on both the previous day's residual variable and the previous day's residual variance.

4) ARIMA (1,0,1) with GARCH (1,2)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, the GARCH (1,2) model indicates that today's residual variance is dependent on the residual variable from one day prior and the residual variance from two days prior.

5) ARIMA (1,0,1) with GARCH (2,1)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, GARCH (2,1) shows that today's residual variance depends on the residual variables of the previous two days and the residual variance of the previous day.

6) ARIMA (1,0,1) with GARCH (2,2)

   The ARIMA (1,0,1) model indicates that the LPGI stock return for today depends on the LPGI stock return from the previous day, and also partially depends on the LPGI stock return from the day before. Then, GARCH (2,2) shows that today's residual variance depends on the residual variables of the previous two days and the residual variance of the previous two days.

The identification results show that the ARCH/GARCH order is the same for both ARIMA models. This can happen because the ACF and PACF plots of the two cut-off models are at the same lag. After identifying the ARCH-GARCH model, the next step is to estimate the obtained ARCH/GARCH model.

3.7 ARCH/GARCH Model Estimation

The results of the model identification obtained will be used for parameter estimation and significance testing. A good model is one where all parameters are significant. If all models have significant parameters, then the best model will be selected based on the smallest AIC value. The results of the parameter estimation and significance tests are presented below.

H_0: $\phi = 0$ (parameters in the ARCH/GARCH model are not significant)

H_1: $\phi \neq 0$ (parameters in the ARCH/GARCH model are significant)

Decision: p-value < α (Reject H_0).

Table 5. ARCH/GARCH Estimation from ARIMA Model (2,0,0)

ARIMA	ARCH/ GARCH	Parameter	Coefficient	p-value	Decision	AIC
(2,0,0)	ARCH (1)	α_1	0.999000	0.000000	Reject H0	-5.5629
	ARCH (2)	α	0.7432	0.00000	Reject H0	-5.5812
		α_2	0.255768	0.007577		

ARIMA	ARCH/ GARCH	Parameter	Coefficient	p-value	Decision	AIC
	GARCH (1,1)	α_1	0.494266	0.000000	Reject H0	**-5.8598**
		β_1	0.497792	0.000000		
	GARCH (1,2)	α_1	0.518732	0.000000	Reject H0	-5.7917
		β_1	0.349997	0.000000		
		β_2	0.118601	0.000000		
	GARCH (2,1)	α_1	0.446252	0.000371	Do not Reject H0	-5.8327
		α_2	0.026282	0.495524		
		β_1	0.519723	0.000000		
	GARCH (2,2)	α_1	0.501223	0.000000	Do not Reject H0	-5.8058
		α_2	0.056492	0.662155		
		β_1	0.311586	0.000311		
		β_2	0.126445	0.000476		

Based on Table 5, it can be concluded that:

1) The models that have passed the significance test are the ARCH (1), ARCH (2), GARCH (1.1), and GARCH (1.2) models. This is based on the p-value parameter for all parameters < α (0.05).
2) For models that do not pass the significance test, namely the GARCH (2,1) and GARCH (2,2) models.
3) There are GARCH (1,1) and GARCH (1,2) models, which can be seen in the Resid2(α) value, and the GARCH(β) value has a significant p-value. These results indicate that the model has GARCH properties.
4) The model that has the smallest absolute AIC value is GARCH (1.1).

The interpretation above indicates that the best ARCH/GARCH model from the ARIMA (2,0,0) model is the GARCH (1,1) model. This is based on the AIC value of this model being the smallest compared to other models, namely (-5.8598). The next stage is estimating the ARCH/GARCH model from the ARIMA model (1,0,1).

H_0: $\phi = 0$ (ARCH/GARCH parameters are not significant)

H_1: $\phi \neq 0$ (ARCH/GARCH parameters are significant)

Decision: p-value < α (Reject H_0).

Table 6. ARCH/GARCH Estimation from ARIMA Model (1,0,1)

ARIMA	ARCH/ GARCH	Parameter	Coefficient	p-value	Decision	AIC
	ARCH (1)	α_1	0.999000	0.000000	Reject H0	-5.5616
	ARCH (2)	α_1	0.746541	0.000001	Reject H0	-5.5810
		α_2	0.252459	0.008605		
	GARCH (1,1)	α_1	0.29217	0.00000	Reject H0	-5.6787
		β_1	0.62141	0.00000		
		α_1	0.52160	0.000000		
	GARCH (1,2)	β_1	0.32884	0.000000	Reject H0	**-5.7792**
(1,0,1)		β_2	0.14331	0.000000		
		α_1	0.423673	0.000044		
	GARCH (2,1)	α_2	0.032797	0.338998	Do Not Reject H0	-5.8189
		β_1	0.532257	0.000000		
		α_1	0.501223	0.000000		
	GARCH (2,2)	α_2	0.056492	0.662155	Do Not Reject H0	-5.8058
		β_1	0.311586	0.000311		
		β_2	0.126445	0.000476		

Based on Table 6, it can be interpreted as follows:

1) The models that have passed the significance test are the ARCH (1), ARCH (2), GARCH (1.1), and GARCH (1.2) models. This is based on the p-value parameter for all parameters < α (0.05).

2) The models that did not pass the significance test were the GARCH (2.1) and GARCH (2.2) models.
3) In the GARCH (1,1) and GARCH (1,2) models, it can be seen that Resid2(α) and the value of Garch(β) have a significant p-value. These results indicate that the model has GARCH properties.
4) The model that has the smallest absolute AIC value of the models that pass the significance test is GARCH (1.2).

The interpretation above indicates that the best ARCH/GARCH model among the ARIMA (1,0,1) models is the GARCH (1,2) model. This is based on a model that passed the significance test with the smallest AIC value, namely (-5.7792). Meanwhile, the previous ARCH/GARCH model estimation result from the ARIMA (2,0,0) model was GARCH (1,1) with an AIC value of (-5.8598). Based on the smallest AIC value, the best model is ARIMA (2,0,0) GARCH (1,1). So, the model can be continued at the ARCH/GARCH model suitability testing stage.

Test the suitability of the ARIMA (2,0,0) GARCH (1,1) model to analyze whether there is still heteroscedasticity in the residuals of the model. The hypothesis for the heteroscedasticity test for the residuals of the ARIMA (2,0,0) GARCH (1,1) model is as follows:

H_0: $\phi = 0$ (does not have heteroscedasticity)

H_1: $\phi \neq 0$ (has heteroscedasticity)

Decision: p-value < α (Reject H_0).

The results of the model suitability test obtained a p-value of 1. Where this value is greater than α (0.05), which means that H0 is not rejected, this shows that the ARIMA (2,0,0) GARCH (1,1) model no longer has heteroscedasticity. Therefore, this model can be utilized for forecasting the analysis of PT Lippo General Insurance Tbk stock returns.

3.8 Forecasting

When analyzing time series data, forecasting is crucial for identifying the best model. Apart from using the AIC value to prove that the ARIMA (2,0,0) GARCH (1,1) model is the best method, a forecasting estimate will be carried out using the ARIMA (2,0,0) GARCH (1,1) model given in the following image:

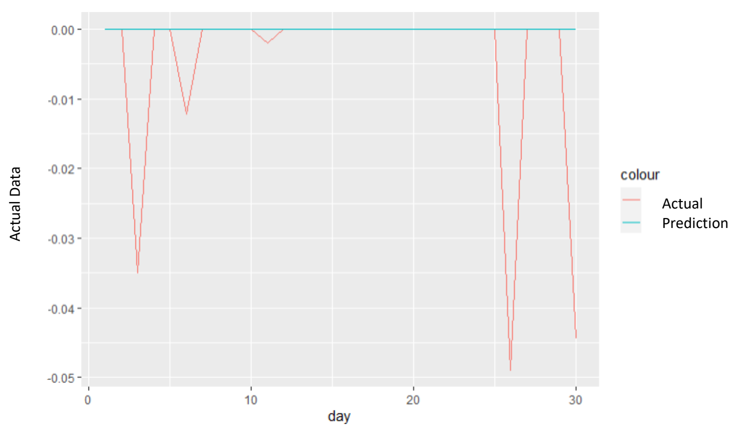

Figure 6. ARIMA (2,0,0) GARCH (1,1) Forecasting Results

The number of periods from the forecast results above is 30 periods, as long as the stock exchange is open from 11 October 2023 to 21 November 2023. From the 30 periods, the forecast results show that the LPGI stock return value is very small and even close to zero. Meanwhile, for the actual return value, there are 25 periods with a value of zero, and the other 5 periods have a return value, namely -0.035000, -0.012145, -0.002028, -0.04893, and -0.04445. The return value of the 5 periods has a negative sign, indicating that LPGI shares experienced a decline from the previous period. However, the value is not so great that it does not show a drastic price reduction. Based on this data, it can be inferred that over the following 30 periods, LPGI share prices will remain relatively stagnant or change only slightly. The actual and forecasted values of LPGI share returns are presented in the table below.

Table 7. Forecasting and Actual Estimation Results ARIMA (2,0,0) GARCH (1,1)

Date	Forecast			Actual
	Return	St.Dev GARCH (1,1)	Variance GARCH (1,1)	Return
11-10-2023	-0.05522×10^{-7}	0.024484	0.000599	0
12-10-2023	-0.05192×10^{-7}	0.024472	0.000599	0
13-10-2023	-0.05038×10^{-7}	0.024459	0.000598	-0.035000
16-10-2023	-0.05058×10^{-7}	0.024447	0.000598	0
17-10-2023	-0.05061×10^{-7}	0.024434	0.000597	0
18-10-2023	-0.05061×10^{-7}	0.024422	0.000596	-0.012146
19-10-2023	-0.05061×10^{-7}	0.024409	0.000596	0
20-10-2023	-0.05061×10^{-7}	0.024397	0.000595	0
23-10-2023	-0.05061×10^{-7}	0.024384	0.000595	0
24-10-2023	-0.05061×10^{-7}	0.024372	0.000594	0
25-10-2023	-0.05061×10^{-7}	0.024360	0.000593	-0.002028
26-10-2023	-0.05061×10^{-7}	0.024347	0.000593	0
27-10-2023	-0.05061×10^{-7}	0.024335	0.000592	0
30-10-2023	-0.05061×10^{-7}	0.024323	0.000592	0
31-10-2023	-0.05061×10^{-7}	0.024310	0.000591	0
1-10-2023	-0.05061×10^{-7}	0.024298	0.000590	0
2-10-2023	-0.05061×10^{-7}	0.024286	0.000590	0
3-10-2023	-0.05061×10^{-7}	0.024273	0.000589	0
6-10-2023	-0.05061×10^{-7}	0.024261	0.000589	0
7-10-2023	-0.05061×10^{-7}	0.024249	0.000588	0
8-10-2023	-0.05061×10^{-7}	0.024237	0.000587	0
9-10-2023	-0.05061×10^{-7}	0.024225	0.000587	0
10-10-2023	-0.05061×10^{-7}	0.024213	0.000586	0
13-10-2023	-0.05061×10^{-7}	0.024200	0.000586	0
14-10-2023	-0.05061×10^{-7}	0.024188	0.000585	0
15-10-2023	-0.05061×10^{-7}	0.024176	0.000584	-0.048900
16-10-2023	-0.05061×10^{-7}	0.024164	0.000584	0
17-10-2023	-0.05061×10^{-7}	0.024152	0.000583	0
20-10-2023	-0.05061×10^{-7}	0.024140	0.000583	0
21-10-2023	-0.05061×10^{-7}	0.024128	0.000582	-0.044440

Based on Table 7, it can be seen that the forecasting results show that the LPGI stock return value is very small and close to zero. However, the return value has a negative sign, indicating that LPGI shares are more likely to experience a decline over the subsequent 30 periods. Meanwhile, the actual value of LPGI stock returns for the next 30 periods is dominated by zero. This shows that the LPGI share price is relatively stagnant or fixed. Of the 30 periods, there are only 5 periods that have a value less than zero, namely, the 3rd period, which amounts to -0.035000, the 6th period, which amounts to -0.012146, the 11th period, which amounts to -0.002028, the 26th period, which amounts to -0.048900, and the 30th period, which amounts to -0.044440. The five periods have a negative sign, indicating that the LPGI share price declined in each period from the previous one.

The forecasting results show a return value that is very small and close to zero, and has a negative sign. A negative value indicates that the LPGI share price is expected to decline over the following 30 periods. However, the very small value indicates that there will be no significant price decline. In general, these results suggest that LPGI share prices remain relatively stagnant or exhibit minimal changes over the subsequent 30 periods. Meanwhile, the actual return value is dominated by zero, and there are only five periods with negative values, slightly below zero. This shows that there is no significant difference between the forecasted return value and the actual return value. The results differ somewhat from prior findings, which generally indicated higher volatility in developed markets. This difference suggests that LPGI stock movements are relatively stable, reflecting the low-risk characteristics of the Indonesian insurance sector. Hence, this study contributes to the literature by providing empirical evidence that the ARIMA–GARCH model can effectively capture the relatively low volatility of stock returns in emerging markets, particularly in the financial and insurance sectors. Therefore, it can be concluded that the ARIMA (2,0,0) GARCH (1,1) model is quite effective in modeling the stock returns of PT Lippo General Insurance Tbk.

4. CONCLUSION

The results of PT Lippo General Insurance Tbk's stock return data processing for the period from October 11, 2019, to October 10, 2023, indicate that LPGI stock returns are volatile, which can be modeled using a GARCH (1,1) model. The coefficient on GARCH (1,1) is statistically significant, and there is no longer an ARCH element in the ARCH LM test. The GARCH (1,1) model has an AIC value of -5.8598. The results of the forecasting analysis indicate that LPGI stock returns are minimal, close to zero, and have a negative sign. A negative value indicates that the LPGI share price is expected to decline over the next 30 periods. However, the very small value indicates that there will not be a significant decline. In general, these results show that LPGI share prices are relatively stagnant or do not experience substantial changes for the next 30 periods. Therefore, investors who do not currently own LPGI shares are advised not to purchase LPGI shares during the forecast period. However, investors who have bought LPGI shares and made a profit are advised to sell LPGI shares before the forecast period. The empirical evidence from this study demonstrates that the GARCH model can effectively capture the volatility pattern of LPGI stock returns in a financial market. This finding supports the application of GARCH in modeling return fluctuations in emerging markets.

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