Mathematical Journal of Modelling and Forecasting
Vol. 2, No. 2, December 2024, pp. 9-19

Application of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model in Forecasting the Volatility of Optimal Portfolio Stock Returns of the MNC36 Index

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Abstract. Investment is a capital investment made by investors through the purchase of several stocks that are usually long-term with the hope that investors will benefit from increased stock prices. The most commonly used risk indicator in investing is volatility. Therefore, it is necessary to carry out modeling that can overcome the effects of heteroscedasticity to predict future volatility. Efforts are made to overcome the effects of heteroscedasticity by applying the Generalized Autoregressive Conditional Heterossexicity (GARCH) Model in Forecasting the Volatility of Optimal Portfolio Stock Returns on the MNC36 Index. This type of research is applied research that begins with reviewing the problem, analyzing relevant theories, and reviewing the problem and its application. Based on the results of data analysis using the residual normality test through the Jarque-Bera test, it was obtained that the GARCH model has a normal residual and is not heteroscedasticity so that it can be used as a forecasting model. BNGA shares obtained the most stable forecast results with almost constant volatility, indicating that this stock has the lowest risk compared to BBCA and BMRI stocks.

Keywords: Volatility Return, Generalized Autoregressive Conditional Heteroskedasticity, Stocks, Fluctuations.

1 Introduction

Investment involves the purchase of stocks by investors with a long-term perspective, aiming to gain profits from potential future increases in stock prices. Investors must consider the expected returns and associated risks [1]. The most commonly used risk indicator in investing is volatility. Volatility is the fluctuation of a stock's return-return in a given period [1]. In reality, stock price fluctuations tend to be high, leading to varying volatility over time. The MNC36 Index reflects the stock performance of a portfolio of 36 companies listed in the MNC Group. In this context, forecasting the volatility of stock returns in optimal portfolios has a significant role for investors, portfolio managers, and capital market stakeholders. Based on data obtained from www.yahoofinance.com, BBCA, BBRI, and BNGA, weekly stock prices are volatile, which means that the stock prices are unstable and tend to change due to the high volatility in financial data and volatility that fluctuates occasionally. Therefore, it is necessary to carry out modeling that can overcome the effects of heteroscedasticity to predict future volatility.

In 1982, Robert F. Engle introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, which was used to overcome variance heterogeneity [2]. Then, in 2012, Chand et al. compared the ARCH and GARCH models in modeling volatility; based on several tests they conducted, the results of the study were obtained, which stated that the GARCH model (1,1) was better than the ARCH model (1) in modeling volatility [3]. Therefore, this study will use the GARCH model to forecast the volatility of stock returns that will be carried out on stocks contained in the MNC36 index. Stock price data is a series of time data; according to Eliyawati (2014), data in the financial sector, such as stock price indices, are usually random and have high volatility or heteroscedasticity. To handle data that is heteroscedastic, the GARCH method can be used to handle the effects of heteroscedasticity [4].

In 2022, research was conducted by Ganesh using financial data from Dapentel to conduct analysis related to forecasting stock return volatility. The previous researcher used the Single Index Model (SIM) method for optimal portfolio formation and the GARCH method to forecast optimal portfolio stock return volatility. However, this research differs in several important aspects. First, this study uses stock closing price data from the MNC36 index, and in this study, the Mean-Variance Efficient Optimal Portfolio (MVEP) method is used to form an optimal portfolio. In 2022, Zhang compared the Markowitz and single-index models on the S&P 500. The study showed that the Single Index model requires fewer estimators than the Markowitz model and simplifies the actual operation. However, for some people with assets with correlated residual returns, the Markowitz model performs better than the Single Index Model. Portfolios with the Single Index Model have higher returns and risks than optimal portfolios formed with the Markowitz model. Portfolios based on the Markowitz Model perform better in minimizing risk[5]. Therefore, it is necessary to carry out modeling that can overcome the effects of heteroscedasticity to predict future volatility. Heteroskedasticity in volatility data can have several negative impacts, including distorting statistical inference, reducing the efficiency of estimators, and leading to biased or inconsistent results in modeling. This can make it more challenging to accurately predict volatility and assess risk, ultimately affecting decision-making processes in financial analysis and investment strategies.

2 Theoretical Basic

2.1 ARCH Models

The ARCH model was first introduced by Engle (1982). According to Engle (1982), the variable residual variance occurs because the residual variance not only depends on the free variable but also depends on how large the square of the residual is in the previous period. In general, the ARCH(p) model can be expressed in the form of the following equation [6]:

$$Y_t = \beta_0 + \beta_t X_t + e_t$$
$${\sigma_t}^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_p e_{t-p}^2$$

${\sigma_t}^2$	= Residual variants
α_0	= Constant
$\alpha_1, \alpha_2, \dots, \alpha_p$	= Estimation coefficients at lag 1 to lag p
$e_{t-1}^2, e_{t-2}^2, \dots, e_{t-p}^2$	= Residual square of the previous period
p	= Elements of ARCH

2.2 GARCH Models

The Generalized Autoregressive Conditional Heteroscedastic (GARCH) model was developed by Bollerslev in 1986, a generalization of the ARCH model [7]. In general, the GARCH model, namely GARCH*(p,q)*, can be expressed through the following equation:

$${\sigma_t}^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$$

${\sigma_t}^2$	= Residual variants
α_0	= Constant
$\alpha_1, \alpha_2, \dots, \alpha_p$	= Estimation coefficients at lag 1 to lag p
$e_{t-1}^2 + e_{t-2}^2 + \cdots + e_{t-p}^2$	= Residual square of the previous period
$\sigma_{t-1}^2 + \sigma_{t-2}^2 + \cdots + \sigma_{t-q}^2$	= Residual variance of the previous period
$\lambda_1, \lambda_2, \dots, \lambda_q$	= GARCH Parameters
p	= Elements of ARCH
q	= Elements of GARCH

3 Method

This type of research is applied research that begins by reviewing the problem, analyzing relevant theories, and continuing with reviewing the problem, analyzing relevant theories, and continuing with its application.

The data used is secondary data, namely closing stock price data on stocks that are listed and consistently have never exited the MNC36 index from April 1, 2019, to February 26, 2024, and are listed on the Indonesia Stock Exchange.

In this study, a data collection technique is used by recording or copying closing stock price data through Yahoo. finance and verified by the Indonesia Stock Exchange Gallery FEB UNP (GIBEI FEB UNP). A model that pays attention to stock indices in determining which stocks are included in the optimal portfolio is the Mean-Variance Efficient Portfolio (MVEP). Table 1 shows the procedure steps of the research method.

Table 1. Research Method Procedure

Procedure Method Mean Variance Efficient Portfolio (MVEP)	**GARCH Modeling Procedure**
1. Calculate the value of the i share return in the tth period ($\boldsymbol{R}_{it}$) 2. Calculate the estimated value of the expected return of the ith share $\boldsymbol{E}(\boldsymbol{R_i})$ 3. Sort stock data by value $\boldsymbol{E}(\boldsymbol{R_i})$ largest to smallest; 4. Calculate the risk value of the ith stock ($\boldsymbol{\sigma_i}^2$) 5. Elimination of data based on value $\boldsymbol{E}(\boldsymbol{R_i})$ negative values, as well as $\boldsymbol{E}(\boldsymbol{R_i}) < \boldsymbol{\sigma_i}^2$; 6. Calculating the variance-covariance matrix of stocks Calculate the weight value (W) of each stock in the optimal portfolio.	1. Identify the ARIMA Model 2. Create a Data Plot a. Conducting stationery tests and checking data stationery through data plots b. Differencing the data if the data is not stationary c. Determining the interim model through ACF and PACF d. Overfitting the temporary model 3. Diagnostic Assessment a. Estimating parameters b. Choosing a model that matches the test parameters 4. Heteroscedasticity test using the ARCH-LM Test of the ARIMA model 5. Forming the GARCH model 6. Estimating GARCH's conjecture model 7. Selection of the best model 8. Forecast volatility and stock returns for the next 13 periods.

4 Results and Discussion

The results and discussions described in this chapter are based on the methodology described earlier. Furthermore, the data collection steps are as follows:

4.1 Optimal portfolio formation procedure using MVEP

Of the 14 stocks that are consistently included in the MNC36 index from April 1, 2019 to February 26, 2024, the returns from each stock are obtained using the following formula [8] :

$$R_{it} = ln\left(\frac{P_{it}}{P_{i(t-1)}}\right)$$

This means that to find the value of the i-th share return, the current stock price is compared with the stock price from the previous period. Then, the price change is converted into a logarithmic return. The following is the calculation of BBCA's April 8, 2019 share return.

$$R_{BBCA} = ln\left(\frac{5500}{5530}\right) = -0.0054$$

Furthermore, Microsoft Excel software assists in calculating the value of the expected return of the stock and the variance of the stock. It is done by calculating the total return of each stock in all periods analyzed, then dividing the total return by the total number of periods n to get the expected stock return. By the equation [9]

$$E(R_i) = \frac{1}{n} \cdot \sum_{t=1}^{n} R_{it}$$

For example, the following is a calculation of BBCA stock return expectations for 257 periods.

$$E(R_{BBCA}) = \frac{1}{257} \cdot \sum_{t=1}^{257} R_{BBCA}$$

$$E(R_{BBCA}) = \frac{1}{257} \cdot 0.572195 = 0.00223$$

Stock variance is obtained by adding the result of the stock return value minus the expected value of stock return and then squared. This number is then divided by the number of periods minus 1. With the equation [10]

$${\sigma_i}^2 = \frac{1}{n-1} \cdot \sum_{t=1}^{n} (R_{it} - E(R_{it}))^2$$

As an example of the variance calculation, use the following BBCA shares:

$${\sigma_i}^2 = \frac{1}{257-1} \cdot ((-0.00515 - 0.00223) + (0.022473 - 0.00223) + \ldots + (-0.00255 - 0.00223) = 0.000973$$

The results of the analysis can be seen in Table 2.

Table 2. Calculation of Expected Return and Stock Variation

No.	Stock	*Expected Return*	Variance
1	BMRI	0.00244	0.001905
2	BNGA	0.002396	0.001822
3	BBCA	0.002235	0.000973
4	AKRA	0.002101	0.003069
5	ANTM	0.002013	0.005324
6	BBRI	0.001813	0.00186
7	ICBP	0.000942	0.0011
8	BBNI	0.000755	0.002432
9	CTRA	0.000468	0.003995
10	INDF	8.95E-05	0.001158
11	KLBF	-0.0001	0.001611
12	UNTR	-0.00053	0.002279
13	ASII	-0.00156	0.001788
14	MNCN	-0.00339	0.00365

Next, the selection of stocks to be selected to be optimal portfolio candidates is carried out, which is obtained in Table 3.

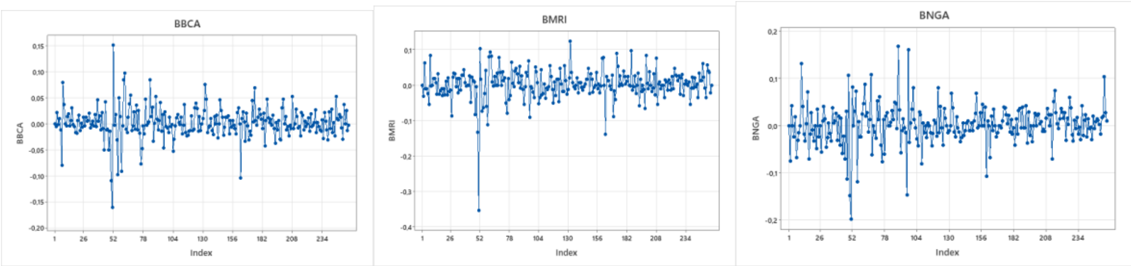
Table 3. Calculation of Expected Return and Stock Variation

No.	Stock	*Expected Return*	Variance
1	BMRI	0.00244	0.001905
2	BNGA	0.002396	0.001822
3	BBCA	0.002235	0.000973

From table 3, it can be seen that if a stock has a high expected return value, it will have a high risk or variance value as well, and vice versa.

4.2 GARCH modeling procedure

The data used is MNC36 index stock return data for April 1, 2019 – February 26, 2024, which has been eliminated in the MVEP method procedure. These stocks are BBCA, BMRI, and BNGA stocks with 257 data. The data plot of BBCA, BMRI, and BNGA stock returns can be seen from the graph Figure 1.



(a) (b) (c)

Fig 1. Graph of BBCA stock return (a), BMRI stock return (b), and BNGA share return (c).

The stock's return data visually appears stationary because there is no clear trend, and the variance is relatively stable except for a few extreme spikes. ADF tests can be carried out to ensure the data is stationary using Eviews software. The results of the ADF Test of BBCA shares can be seen in Figure 2

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		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.77150	0.0000
Test critical values:	1% level	-3.994453	
	5% level	-3.427546	
	10% level	-3.137100	

*MacKinnon (1996) one-sided p-values.

Fig 2. Test of ADF Return of BBCA Shares

The t-statistic value in the ADF test is -15.77150, smaller than MacKinnon's t-statistic in the 99% confidence interval is -3.994453, and the p-value is 0.00 < alpha=0.05, then the H(0) is subtracted, which means that in the 99% confidence interval, the data is stationary. If we use the t-statistical values of ADF at the 95% and 90% confidence intervals, the t-statistical values are -3.427546 and -3.137100, respectively. The results of the ADF test of BMRI shares can be seen in Figure 3.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.50751	0.0000
Test critical values:	1% level	-3.994453	
	5% level	-3.427546	
	10% level	-3.137100	

*MacKinnon (1996) one-sided p-values.

Fig 3. ADF Return Test of BMRI Shares

The t-statistical value in the ADF test is -15.50751, smaller than MacKinnon's t-statistic in the 99% confidence interval is -3.994453, and the p-value is 0.00 < alpha=0.05, then the H(0) is subtracted, which means that in the 99% confidence interval, the data is stationary. If we use the t-statistical values of ADF at the 95% and 90% confidence intervals, the t-statistical values are -3.427546 and -3.137100, respectively. The results of the ADF Test of BNGA shares can be seen in Figure 4.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.07832	0.0000
Test critical values:	1% level	-3.994453	
	5% level	-3.427546	
	10% level	-3.137100	

*MacKinnon (1996) one-sided p-values.

Fig 4. ADF Return Test of BNGA Shares

The t-statistical value on the ADF test is -18.07832, smaller than MacKinnon's t-statistic on the 99% confidence interval, which is -3.994453 as, well as the value of *p-value* 0.00 < $\alpha = 0.05$ then reject H_0 This means that 99% of the data is stationary in the confidence interval. If we use the t-statistical values of ADF at the 95% and 90% confidence intervals, the t-statistical values are -3.427546 and -3.137100, respectively. The three data are stationary at intervals, so there is no need for a differencing process. Next, use Minitab software to create and analyze the ACF and PACF plots and their estimated values. The estimated value of ACF is obtained using the equation [11]

$$r_k = \frac{\sum_t^{n-k}(Y_t - \overline{Y})(Y_{t+k} - \overline{Y})}{\sum_t^{n-k}(Y_t - \overline{Y})^2}$$

Also, the ACF plot can be seen in Figure 5.

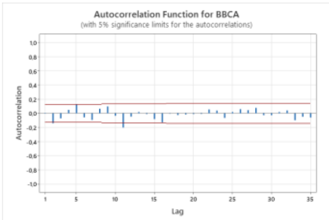


Fig. 5 ACF plot of BBCA shares

The autocorrelation line is already within the boundary of the significance line, which indicates that the data is stationary. Three ACF values are out of line or truncated at lag 2, lag 5, and lag 11. So that the Supreme Court process is determined with the 3rd order. Then, the PACF estimate value is used as an equation [10]

$$\phi_{kk} = \frac{r_k - \sum_{j=1}^{k-1} \phi_{k-1,} r_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,} r_j} \quad (k = 2,3,4,\dots) \text{ with}$$

$$\phi_{kj} = \phi_{k-1,j} - \phi_{kk}\phi_{k-1,k-j} \quad (k = 3,4,\dots)\ (j = 1,2)$$

The PACF plot from BBCA stock return data was obtained to determine the order of the Autoregressive (AR) process based on Figure 6.

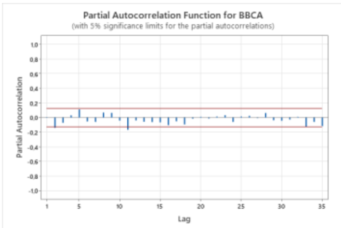


Fig. 6 Plot of BBCA stock PACF

The PACF value that goes out of the significant line boundary or is truncated at lag 2, lag 5, and after lag 30, then the order of AR is determined to be 3. Based on the ACF and PACF plots from Figures 4 and 5, the model to be used is the ARIMA model with AR in order 3 and MA in order 3. The analysis of the data plot of time series, ACF and PACF BBCA stock return data, it can be concluded that the data is stationary and a temporary model is obtained, namely the ARIMA model (3,0,3).

Furthermore, the ACF plot of BMRI shares the results which can be seen in Figure 7.

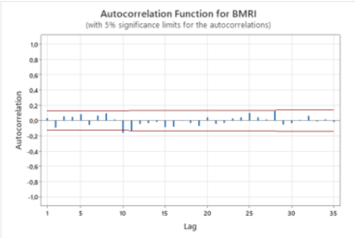


Fig 7. ACF plot of BMRI shares

It can be seen that there are three ACF values of BMRI shares that go out of the line or are cut off at lag 10, lag 11, and after lag 25 so that the Supreme Court process is determined with the 3rd order. Then, the PACF plot from BMRI's stock return data. Furthermore, the ACF plot of BMRI shares whose results can be seen in Figure 8.

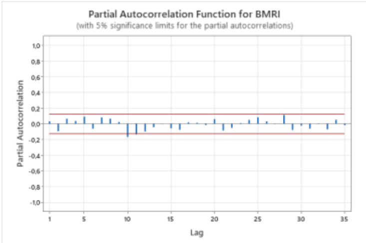


Fig 8. PACF plot of BMRI shares

Two PACF values go out of the significant line boundary or are truncated at lag 10 and lag 11, so the order of AR is set to be 2. Based on the ACF and PACF plots from Figures 6 and 7, the model to be used is the ARIMA model with AR order 2 and MA order 3. The analysis of the time series data plot, ACF and PACF BMRI stock return data can be concluded that the data is stationary and a temporary model is obtained, namely the ARIMA model (2,0,3). Finally, the plot of ACF and PACF shares of BNGA. The results of the ACF plot of BNGA shares can be seen in Figure 9.

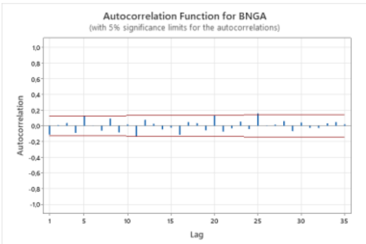


Fig 9. ACF plot of BNGA shares

It can be seen that there are three ACF values of BNGA shares that are out of line or truncated in lag 5, lag 11, and lag 25. Thus, the Supreme Court process is determined with the 3rd order. Then, the PACF plot from BNGA stock return data is created. Furthermore, the PACF plot of BNGA shares the results which can be seen in Figure 10.

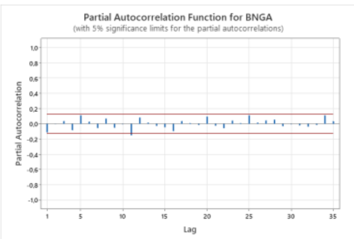


Fig 10. Plot of PACF BNGA shares

If one PACF value goes out of the significant line boundary or is truncated at lag 11, then the order of AR is set at 1. Based on the ACF and PACF plots from Figures 8 and 9, the ARIMA model with AR order 1 and MA order 3 is the model to be used. The analysis of the time series data plot, ACF, and PACF BNGA stock return data shows that the data is stationary, and a temporary model is obtained, namely the ARIMA model (1,0,3).

After obtaining the provisional ARIMA model, the next step is to overfit the temporary model by changing the AR and MA orders. From the results of Overfitting, provisional models were obtained for BBCA shares, namely 15 alternative models, BMRI shares 11 alternative models, and BNGA shares 7 alternative models. Then, a parameter assessment was carried out to obtain parameters from each model [12]. The parameter is said to be significant if the obtained *p-value* $< \alpha$. The best model of each stock is obtained based on Table 4.

Table 4 Results of ARIMA's Best Model

Stock	**Model**	**Coefficient**	**T- *Count***	***P-value***	**MSE**
BBCA	ARIMA (2,0,2)	$\phi_1 = 0.3141$	6.09	0.00	0.0009328
		$\phi_2 = -0.9368$	-16.37	0.00	
		$\mu = 0.00226$	1.24	0.216	
		$\theta_1 = 0.2975$	3.84	0.00	
		θ_2 =-0.8498	-10.02	0.00	
BMRI	ARIMA (2,0,3)	$\phi_1 = 1.424$	13.02	0.00	0.0018617
		$\phi_2 = -0.7289$	-8.95	0.00	
		$\mu = 0.00238$	0.75	0.454	
		$\theta_1 = 1.3998$	15.89	0.00	
		$\theta_2 = -0.5971$	-9.09	0.00	
		$\theta_3 = -0.1631$	-3.96	0.00	
BNGA	ARIMA (1,0,0)	$\phi_1 = -0.1131$	-1.81	0.071	0.0018055
		μ =0.00242	1.02	0.311	

The next step is to examine the residual mean model's heteroscedasticity. In this example, inhomogeneity in BBCA, BMRI, and BNGA stock return data is examined by plotting residual data using Eviews software based on Figure 11.

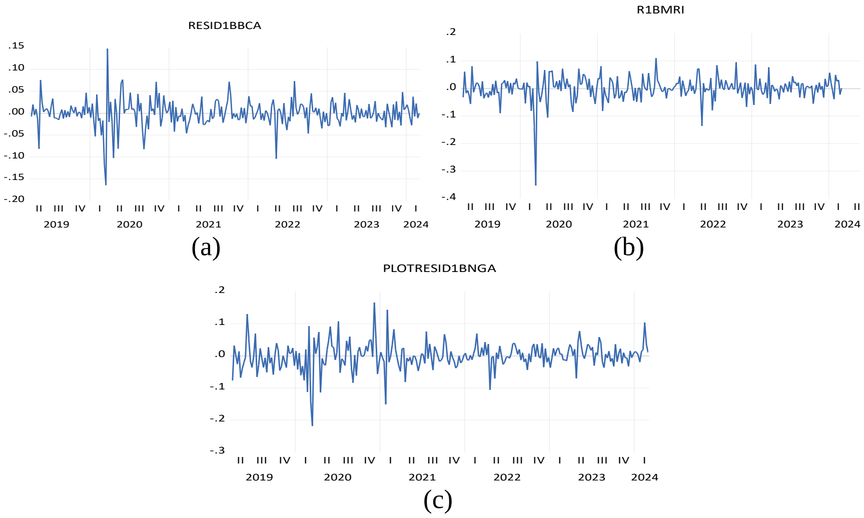
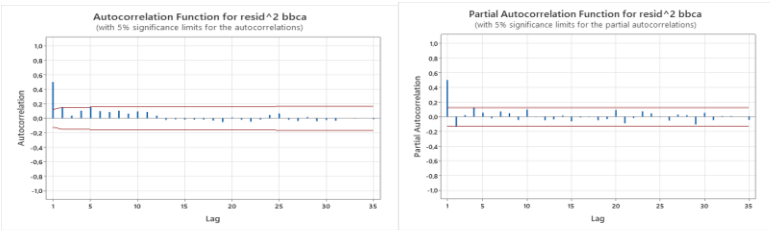


Fig 11. Residual Plot Graph of Stocks (a) BBCA Model ARIMA (2,0,2), (b) BMRI Model ARIMA (2,0,3), (c) BNGA Model ARIMA (1,0,0).

The residual plot in the figure above exists, so it is assumed that the residual variance contains elements of heteroscedasticity. However, it must be examined whether the ARIMA (2,0,2) BBCA shares, ARIMA (2,0,3) BMRI shares, and ARIMA (1,0,0) BNGA shares have an ARCH effect on the model. This can be done using the ARCH-LM test using the equation [13].

$$e_t{}^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2\right) + v_t$$

It can be seen that each stock has a P-value of <alpha=0.05. This states that the null hypothesis is rejected. This means there is a heteroscedastic effect on the quadratic residual data, which will then be formed in GARCH modeling to deal with the heteroscedastic effect. The next step is to form a GARCH model to solve the volatility problem in heteroscedasticity by looking at the quadratic residual correlogram. The higher the order of ARCH and GARCH models that are tried, the less significant the parameters. The results of the ACF and PACF plots can be seen in Figure 12.



(a) (b)

Fig 12. (a) ACF plot and (b) PACF residual squared of BBCA shares

The best GARCH model for each stock can be seen in Table 5.

Table 5 GARCH model of each stock

Stock	Models
BBCA	GARCH(1,1)
BMRI	GARCH(1,1)
BNGA	GARCH(1,1)

Considering that the estimation used is the maximum likelihood and evaluation of whether there is still heteroscedasticity in the residual. Examination of residual normality through the Jarque-Bera test. With the value of *p-value* as $0.00000 < \alpha = 0{,}05$ which is produced in the figure below, at an error rate of 5% normal residual [14]. The histogram of BBCA shares can be seen in Figure 13.

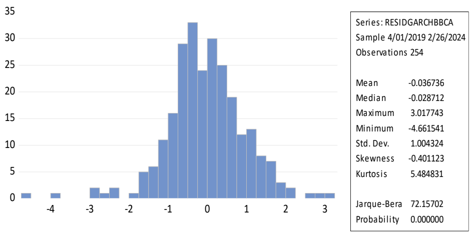


Fig 13. Residual Histogram Chart of GARCH (1.1) BBCA stock

Furthermore, the value of the Prob Chi-squared of BBCA shares was obtained $0.3447 > \alpha = 0.05$. It can be concluded that in the GARCH model (1,1), there is no heteroscedasticity problem in the residual with a significance level of 5%. So, each stock is significant for forecasting the volatility of stock returns. Based on the equation [15]

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$$

then the GARCH model for each of the formed stocks is as follows:

a) PT Bank Central Asia Tbk (BBCA) – GARCH(1,1)
$\sigma_t^2 = 0.0000764 + 0.181466 e_{t-1}^2 + 0.7301462 \sigma_{t-1}^2$

b) PT Bank Mandiri Tbk (BMRI) – GARCH(1,1)
$\sigma_t^2 = 0.000709 + 0.385774 e_{t-1}^2 + 0.226589 \sigma_{t-1}^2$

c) PT Bank CIMB Niaga Tbk (BNGA) – GARCH(1,1)
$\sigma_t^2 = 0.000146 + 0.133170 e_{t-1}^2 + 0.786084 \sigma_{t-1}^2$

The model above provides information that the volatility of BBCA, BMRI, and BNGA stocks is influenced by the amount of the residual value of the return one week before and the amount of the standard deviation from the average return for the previous week. Results of forecasting volatility in stock price returns using Eviews software for the following 13 periods (3 months) based on Table 6.

Table 6 Results of Stock Return Volatility Forecasting

Period	Date	BBCA	BMRI	BNGA
1	March 4, 2024	0.005958	0.005955	0.002267
2	March 11, 2024	0.008401	0.002840	0.002938
3	March 18, 2024	0.000955	0.003456	0.002878
4	March 25, 2024	-0.002549	0.003595	0.002884
5	April 1, 2024	0.003492	0.003525	0.002883
6	April 8, 2024	0.007695	0.003531	0.002883
7	April 15, 2024	0.003036	0.003534	0.002883
8	April 22, 2024	-0.001549	0.003533	0.002883
9	April 29, 2024	0.009599	0.003533	0.002883
10	May 6, 2024	0.001807	0.003533	0.002883
11	May 13, 2024	0.004332	0.003533	0.002883
12	May 20, 2024	-0.000253	0.003533	0.002883
13	May 27, 2024	0.000877	0.003533	0.002883

1) PT Bank Central Asia Tbk (BBCA)
The results of the BBCA stock return volatility forecast show that BBCA will have a maximum return value of 0.009599 for the next 13 weeks, an average monthly return of 0.003215, and a standard deviation of 0.003841.

2) PT Bank Mandiri Tbk (BMRI)
The results of forecasting the volatility of BMRI stock returns show that BMRI will have a maximum return value of 0.005955 for the next 13 weeks, an average monthly return of 0.003664, and a standard deviation of 0.000715.

3) PT Bank CIMB Niaga Tbk (BNGA)
The BNGA stock return volatility forecast results show that BNGA has a maximum return value of 0.002938 over the next 13 weeks, with an average monthly return of 0.002840 and a standard deviation of 0.000173.

5 Conclusion

Forming an optimal portfolio uses the mean-variance efficient portfolio (MVEP) method by calculating the value of stock returns, expected returns, and stock variance. The analysis showed that BBCA shares showed the most unstable volatility with significant fluctuations, including periods of negative volatility. This indicates higher risk and the potential for sharp price swings, while BMRI shares show pretty good stability with consistent volatility around 0.0035 after the initial decline, indicating moderate risk potential. For BNGA shares, the most stable forecast results were obtained with almost constant volatility, indicating that this stock has the lowest risk compared to BBCA and BMRI shares.

References

[1] Ervina, Dadan Kusnandar, N. I. (2020). Peramalan Volatilitas Saham Menggunakan Model Threshold Generalized Autoregressive Conditional Heteroscedasticity. Buletin Ilmiah Mat. Stat. Dan Terapannya (Bimaster), Volume 09(1), 79–86.
[2] Ningsih, S. R., Sumarjaya, I. W., & Sari, K. (2019). Peramalan Volatilitas Saham Menggunakan Model Exponential Garch Dan Threshold Garch. E-Jurnal Matematika, 8(4), 309. https://doi.org/10.24843/mtk.2019.v08.i04.p270
[3] Ganesh, N. M. (2022). Peramalan Volatilitas Return Saham Portofolio Optimal Menggunakan Metode Generalized Autoregressive Conditional Heteroscedasticity (GARCH).
[4] Eliyawati, W. Y., R. R. Hidayat, & D. F. Azizah. 2014. Penerapan Model GARCH (Generalized Autoregressive Conditional Heteroscedasticity) Untuk Menguji Pasar Modal Efisien Di Indonesia. Jurnal Administrasi Bisnis (JAB). Vol. 7 No. 2.
[5] Zhang, Z. (2022). Study of Portfolio Performance Under Certain Restraint Comparison: Markowitz Model and Single Index Model on S&P 500. Proceedings of the 2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022), 652(Icssed), 1930–1938. https://doi.org/10.2991/aebmr.k.220405.323
[6] Bollerslev, T. (2023). Reprint of: Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 234, 25–37. https://doi.org/10.1016/j.jeconom.2023.02.001
[7] Tandelilin, Eduardus. 2010. Portofolio dan Investasi: Teori dan Aplikasi. Yogyakarta: Kanisius.
[8] Nurani, L., & Qudratullah, M. F. (2016). Analisis Portofolio Syariah Optimal Menggunakan Model Mean Variance Efficient Portofolio (MVEP) Dengan Pendekatan Data Envelopment Analysis (DEA). Jurnal Fourier, 5(1), 41.
[9] Makridakis, S., Megee, E., & Wheel, W.S. 1999. Metode dan Aplikasi Peramalan Jilid I.(H. Suminto, Trans). Jakarta: Erlangga
[10] Suhartini. 2007. Peramalan dengan model ARCH. Yogyakarta: Universitas Sanata Dharma
[11] Widarjono, Agus. 2009. Ekonometrika Pengantar dan Aplikasinya. Edisi Ketiga. Yogyakarta : Ekonisia
[12] Arsyad, Lincolin. 1999. Peramalan Bisnis Edisi Pertama. Yogyakarta: BPFE-Yogyakarta
[13] Widarjono, Agus. 2005. Ekonometrika: Teori dan Aplikasi untuk Ekonomi dan Bisnis. Yogyakarta : Ekonisia
[14] Rosadi, Dedi. 2011. Analisa Data Runtun Waktu. Yogyakarta: Fakultas MIPA Universitas Gajah Mada
[15] Prasetyo, H. (2006). Analisis Pengaruh Hari Perdagangan Terhadap Return , Abnormal Return , Dan Volatilitas Return Saham. Tesis, Semarang: Universitas Diponegoro.