



Determination of Risk Value Using the ARMA-GJR-GARCH Model on BCA Stocks and BNI Stocks

Rizki Apriva Hidayana^{1*}, Herlina Napitupulu², Jumadil Saputra³

¹ Master's Program of Mathematics, Faculty of Mathematics and Natural Sciences, Padjadjaran University, Jatinangor, West Java, Indonesia

² Department of Mathematics, Faculty of Mathematics and Natural Sciences, Padjadjaran University, Jatinangor, West Java, Indonesia

³ Faculty of Business, Economics and Social Development, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia

*Corresponding author email: rizki20011@mail.unpad.ac.id

Abstract

Stocks are common investments that are in great demand by investors. Stocks are also an investment instrument that provides returns but tends to be riskier. The return time series is easier to handle than the price time series. In investment activities, there are the most important components, namely volatility and risk. All financial evaluations require accurate volatility predictions. Volatility is identical to the conditional standard deviation of stock price returns. The most frequently used risk calculation is *Value-at-Risk* (VaR). Mathematical models can be used to predict future stock prices, the model that will be used is the *Glosten Jagannathan Runkle-generalized autoregressive conditional heteroscedastic* (GJR-GARCH) model. The purpose of this study was to determine the value of the risk obtained by using the time series model. GJR-GARCH is a development of GARCH by including the leverage effect. The effect of leverage is related to the concept of asymmetry. Asymmetry generally arises because of the difference between price changes and value volatility. The method used in this study is a literature and experimental study through secondary data simulations in the form of daily data from BCA shares and BNI shares. Data processing by looking at the heteroscedasticity of the data, then continued by using the GARCH model and seeing whether there is an asymmetry in the data. If there is an asymmetric effect on the processed data, then it is continued by using the GJR-GARCH model. The results obtained on the two stocks can be explained that the analyzed stock has a stock return volatility value for the leverage effect because the GJR-GARCH coefficient value is > 0 . So, the risk value obtained by using VaR measurements on BCA stocks is 0.047247 and on BNI stocks is 0.037355. Therefore, the ARMA-GJR-GARCH model is good for determining the value of stock risk using VaR.

Keywords: Risk, ARMA, GJR-GARCH, VaR

1. Introduction

Investment is an amount of money or other resources that are carried out at this time in the hope of obtaining benefits in the future (Tandelilin, 2010). One investment that can be an option is a stock investment. Shares are securities as proof of participation or ownership of a person or legal entity in a company, especially a company that trades its shares. Investors choose to invest in shares of a company based on the desire to earn profits in the future which can be seen from the number of stock returns. In investing in stocks, there are several important things, namely, return and risk.

The return on an asset is the amount obtained from the investment opportunity. According to Campbell, Lo, and MacKinley (1998), the use of returns has two main reasons. First, for the average investor, return is a complete investment summary and is scale-free. Both return series are easier to handle than the price series because they have more interesting statistical properties (Tsay, 2005). The return time series is also easier to handle than the price time series. In investment activities, there is the most important component, namely volatility. In this case, volatility is the variance of stock returns. High volatility values indicate stock prices will fluctuate (up and down). Meanwhile, volatility is said to be low if the stock price is constant or does not change.

Investment risk is the loss experienced by investors in investing. There are several types of investment risk, namely business risk, financial risk, inflation risk, liquidity risk, country risk, currency risk, market risk, and interest

risk (Sulistianingsih, et al., 2021). In financial markets, the measure of risk that determines the potential for loss can be *Value-at-Risk*. *VaR* is defined as the maximum potential loss in a certain period with a certain level of confidence under normal (market) conditions (Dwipa, 2016). *VaR* risk determination can be done using a time series model with historical data.

There are previous studies that discuss the calculation of risk using the time series model. Sukono et al. (2019) examine the *Autoregressive Integrated Moving Average-Generalized Autoregressive Conditional Heteroscedasticity* (ARIMA-GARCH) model which is carried out to estimate the shortfall of several stocks in the Indonesian capital market. Based on the analysis in this study, the closing data of each selected stock has an average value and standard deviation that varies from one another. Tamiselman and Vali (2016) use the GARCH model in predicting the volatility of the Muscat security market stock market by concluding that the GARCH (1,1) model is the best estimate for symmetric data and there is no leverage effect on the data used. The GARCH model cannot be used on data that has a leverage effect.

Based on previous research, there are several shortcomings in the research of Sukono et al. (2019), Tamiselman and Vali (2016), namely the study only used the GARCH model without checking the asymmetric effect on the model, then calculating the risk value. Therefore, this study uses the ARMA-GJR-GARCH time series model for asymmetric data. The purpose of this study was to determine the value of the risk obtained by using the time series model. Then calculate the risk value using *Value-at-Risk*. This research uses Excel and Eviews 10 software.

2. Literature Review

2.1. Return

Return is the amount of profit made by investors in investing. According to Tsay (2005), there are several definitions of return, including assuming that the selected stock does not pay dividends. The return formula used is:

$$s_t = \frac{l_t - l_{(t-1)}}{l_{(t-1)}} \quad (1)$$

where s_t represents the value of the time return to- t , l_t represents the stock price time to- t , and $l_{(t-1)}$ represents the time stock price—($t - 1$) or the share price one period before the time- t .

2.2. Mean Model

This model is denoted by ARMA (p, q) where p is AR order and q is an MA order. In general, the form of the ARMA model is as follows (Tsay, 2005):

$$z_t = \phi_0 + \sum_{i=1}^p \phi_i z_{t-i} - \sum_{i=1}^q \theta_i e_{t-i} + e_t \quad (2)$$

where ϕ_0 is a constant, ϕ_i coefficient of AR model parameters that depend on *lag*, θ_i is the MA model parameter coefficient that depends on *lag*, z_t is the stock return at the time of t , and e_t is the data error at time t .

ARMA modeling process:

1. In general, the ARMA modeling process is:
2. 1. Identify the model by determining the values of p and q with the autocorrelation function (ACF) and partial autocorrelation function (PACF) from the correlogram plot.
3. 2. Parameter estimation can use the method of least squares or maximum likelihood
4. 3. Diagnostic test with white noise and non-correlation test on residuals using Box-Pierce or Ljung-Box
5. 4. Forecasting, if the model is suitable, it can be used for recursive predictions.

2.3. Volatility Model

The GARCH model is a generalization of the ARCH model developed by Bollerslev in 1986. Based on its development, the GARCH model is a supporter of time series analysis on the capital market by providing a volatility estimator. The GARCH model (p, q) is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \theta_i a_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + u_t \quad (3)$$

The GARCH equation above shows that the conditional variance is the volatility (ARCH) and the previous variance (GARCH) as seen from the squared residual (p) and previous residual variance (q) (Olowe, 2010). The things that characterize the GARCH model are the GARCH model in forecasting volatility with low accuracy and in many stock data, stock returns have an asymmetric effect that is not detected by the GARCH model (Dwipa, 2016).

The GJR model (Glosten, Jagannathan, and Runkle) is another asymmetric GARCH model which is a general form of the GJR-GARCH model (p, q) . Model GJR-GARCH (p, q) defined as follows (Hidayana et al., 2022):

$$\sigma_t^2 = \omega + \sum_{i=1}^p \theta_i a_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} a_{t-i}^2 \quad (4)$$

$$I_{t-i} = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0, & \varepsilon_{t-i} \geq 0 \end{cases}$$

where I_{t-i} is a dummy variable which means I_{t-i} is a functional index whose value is 0 when ε_{t-i} positive and worth 1 when ε_{t-i} negative. If parameter $\gamma_i > 0$ then the negative error does not work, which means that the effect of bad news is greater than the effect of good news (Dritsaki, 2017).

GJR-GARCH model process:

1. Estimation of the GARCH model with time series model
2. Use the residuals from the GARCH model to test the ARCH effect
3. Conduct diagnostic tests to observe the suitability of the model
4. Asymmetric effect test
5. If there is an asymmetric effect, it can be used to predict based on recursive prediction

2.4. Value-at-Risk

One of the instruments of risk measurement is *Value-at-Risk* (*VaR*). *VaR* can be defined as the maximum loss in a particular period with a certain level of trust. *VaR* estimates usually use the standard method assuming that the return has one variable and is a normal distribution with μ being the average and σ being the standard deviation (Dwipa, 2016).

The equation for determining the var value is as follows:

$$VaR(r_t) = -\inf(r_t | F(r_t) \geq \alpha) \quad (5)$$

$$VaR(r_t) = -\hat{\mu}_t - \hat{\sigma}_t F^{-1}(\alpha) \quad (6)$$

VaR performance can be measured using backtesting. In 1998 Lopez introduced the size-adjusted frequency approach model as follows:

$$C_t = \begin{cases} 1 + (r_t - VaR_t)^2, & r_t > VaR_t \\ 0, & r_t \leq VaR_t \end{cases} \quad (7)$$

To test risk performance *VaR* can use a quadratic probability score (QPS). The equation is as follows:

$$QPS = \left(\frac{2}{n}\right) \sum_{i=1}^n (C_t - p)^2 \quad (8)$$

where n That's a lot of data, p It's a probability value, C_t It's an indicator of loss. If the QPS value is in the range of values $[0,2]$ Then var performance is said to be good. The value of 0 is the minimum value that occurs when $r_t \leq VaR_t$ and 2 is the maximum value that occurs when the value $r_t > VaR_t$ (Sukono et al., 2019).

3. Result and Discussion

This section discusses data analysis using a time series model. Then calculate the value of risk with *Value-at-Risk*.

3.1. Data

In this study, the data used is the daily historical data of stock closing prices for the period 17 December to 14 December 2021. The analyzed data is obtained from the website <https://finance.yahoo.com/>. The software used in this research is Eviews and Excel.

3.2. Statistic Descriptive

The descriptive statistics of the data are in Table 1.

Table 1. Descriptive statistics of data

Kode	Samples	Mean	Median	Maximum	Minimum	Standard Deviation
BBCA	746	0.00061	0	0.17333	-0.0791	0.0171

BBNI	746	2.1041×10^{-6}	0	0.13647	-0.1171	0.0245
------	-----	-------------------------	---	---------	---------	--------

Furthermore, a stationary test of the data was carried out based on the returns obtained using the Eviews 10 software, so that it was obtained that the original data was stationary. Therefore, the model used is the ARMA model (p, q). Then the model identification is carried out to determine the selected ARMA (p, q) model.

3.3. Mean Model Estimation

Based on the model identification using Eviews 10 software, the best average model is ARMA (1, 3) for BBKA shares and ARMA (1, 1) for BBNI shares. The selected model has been tested for diagnostic models so the model is said to be significant. The estimation of BBKA's stock model and BBNI's stock model by following equation (2) is as follows

$$\text{BBKA stock: } z_t = -0.514166z_{t-1} + 0.117129a_{t-3} + a_t$$

$$\text{BBNI stock: } z_t = -0.064438z_{t-1} - 0.999472a_{t-2} + a_t.$$

3.4. Volatility Model Estimation

The selected ARMA model was checked for the ARCH effect. Checking ARCH-LM using Eviews 10 software, it is found that the selected average model has an ARCH effect. Furthermore, an estimation of the volatility model is carried out to overcome the ARCH effect. After estimating the volatility model, the chosen model is GARCH (1, 1) for BBKA shares and BBNI shares. The model is said to be significant because it has performed a white noise diagnostic test and the residuals are normally distributed. The estimation of the GARCH model on BBKA and BBNI stocks is

$$\text{BBKA stock: } \sigma_t^2 = 3.55 \times 10^{-5} + 0.297815a_{t-1}^2 + 0.643384\sigma_{t-1}^2 + u_t$$

$$\text{BBNI stock: } \sigma_t^2 = 1.08 \times 10^{-5} + 0.101445a_{t-1}^2 + 0.883664\sigma_{t-1}^2 + u_t$$

Furthermore, the asymmetric effect was tested to determine whether there was an asymmetric effect in the model. After testing the asymmetric effect using Eviews 10 software, it was found that both models have an asymmetric effect. Then estimate the GJR-GARCH model for the volatility model. So that the GJR-GARCH (1, 1) model is obtained for BBKA and BBNI stocks. Then based on section 2.3 the estimation of the volatility model is as follows

$$\text{BBKA stock: } \sigma_t^2 = 8.53 \times 10^{-6} + 0.038909a_{t-1}^2 + 0.159906a_{t-1}^2 I_{t-1} + 0.861201\sigma_{t-1}^2 + \varepsilon_t$$

$$\text{BBNI stock: } \sigma_t^2 = 7.73 \times 10^{-6} + 0.041698a_{t-1}^2 + 0.064183a_{t-1}^2 I_{t-1} + 0.916975\sigma_{t-1}^2 + \varepsilon_t$$

3.5. VaR Estimation

The *Value-at-Risk* calculation is based on the results of the average and variance estimates that have been carried out using the time series model. The parameter used to calculate VaR is the average $\hat{\mu}$ and standard deviation $\hat{\sigma}$ about section 2.4. Furthermore, backtesting calculations are carried out to determine the VaR performance where the value obtained is not more than the range [0, 2]. VaR calculation results can be seen in Table 2.

Table 2. Calculation Results of *Value-at-Risk* and QPS

Stocks	$\hat{\mu}_t$	$\hat{\sigma}_t^2$	$\hat{\sigma}_t$	VaR_t	QPS
BBKA	0.006608	0.001072	0.032741	0.047247	0.026745
BBNI	0.000261	0.000523	0.022869	0.037355	0.104060

4. Conclusions

The conclusion obtained is that the average model for BBKA shares is ARMA (1, 3) and for BBNI ARMA shares (1, 1). The volatility model chosen for BBKA and BBNI stocks is GJR-GARCH (1,1). The average and variance models used to calculate the risk value are ARMA (1, 3)-GJR-GARCH (1, 1) for BBKA shares and ARMA

(1, 1)-GJR-GARCH (1, 1) models for BBNI shares. VaR calculation results for BBNI shares are 0.047247 and for BBNI shares are 0.037355. This means that if an investment is made in BBNI and BBNI shares of IDR 100,000,000.00, then the estimated maximum loss that has the potential to cause losses is estimated at IDR 4,724,000 and IDR 3,735,000.

References

- Campbell, J. Y., Lo, A. W., MacKinlay, A. C., & Whitelaw, R. F. 1998. The econometrics of financial markets. *Macroeconomic Dynamics*, 2(4), 559-562.
- Dritsaki, C. 2017. An empirical evaluation in GARCH volatility modeling: Evidence from the Stockholm stock exchange. *Journal of Mathematical Finance*, 7(2), 366-390.
- Dwipa, N. M. S. 2016. Identifikasi Model I-Garch (Integrated Generalized Autoregressive Conditionally Heterocedastic) Untuk Peramalan Value At Risk. *Jurnal Derivat: Jurnal Matematika dan Pendidikan Matematika*, 3(1), 25-38.
- Hidayana, R., Napitupulu, H., & Sukono, S. (2022). An investment decision-making model to predict the risk and return in stock market: An Application of ARIMA-GJR-GARCH. *Decision Science Letters*, 11(3), 235-246.
- Olowe, R. A. 2010. Oil price volatility, global financial crisis and the month-of-the-year effect. *International Journal of Business and Management*, 5(11), 156.
- Sukono, S. E., Simanjuntak, A., Santoso, A., Ghazali, P. L., & Bon, A. T. 2019. ARIMA-GARCH Model for Estimation of Value-at-Risk and Expected shortfall of Some Stocks in Indonesian Capital Market. In *Proceedings of the International Conference on Industrial Engineering and Operations Management Riyadh, Saudi Arabia* (pp. 327-334).
- Sulistianingsih, E., & Rosadi, D. (2021, June). Risk analysis of five stocks indexed by LQ45 using credible value at risk and credible expected tail loss. In *Journal of Physics: Conference Series* (Vol. 1918, No. 4, p. 042023). IOP Publishing.
- Tamilselvan, M., & Vali, S. M. 2016. Forecasting stock market volatility-evidence from muscat security market using garch models. *International Journal of Commerce and Finance*, 2(1), 37-53.
- Tandelilin, E. 2010. Portofolio and investment. *Edisi Pertama*. Yogyakarta: BPFE.
- Tsay, R. S. 2005. *Analysis of financial time series* (Vol. 543). Chicago: John Wiley & Sons.