Available online at http://iorajournal.org/indx.php/orics/index

Operations Research: International Conference Series

e-ISSN: 2722-0974
p-ISSN: 2723-1739

Vol. 2, No. 3, pp. 71-74, 2021

Determination of VaR on BBRI Stocks and BMRI Stocks Using the ARIMA-GARCH Model

Herlina Napitupulu[1], Rizki Apriva Hidayana[2*], Jumadil Saputra [3]

[1]*Department of Mathematics, Faculty of Mathematics and Natural Sciences, Padjadjaran University, Jatinangor, West Java, Indonesia*
[2] *Master's Program 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 investment instruments that are much in demand by investors as a basis in financial storage. Return and risk are the most important things in investing. Return is a complete summary of investment and the return series is easier to handle than the price series. The movement of risk of loss is obtained from stock investments with profits. One way to calculate risk is value-at-risk. The movement of stocks is used to form a time series so that the calculation of risk can use time series. The purpose of this study was to find out the Value-at-Risk value of BBRI and BMRI stock using the ARIMA-GARCH model. The data used in this study was the daily closing price for 3 years. The time series method used is the Autoregressive Integrated Moving Average (ARIMA)-Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. The stage of analysis is to determine the prediction of stock price movements using the ARIMA model used for the mean model and the GARCH model is used for volatility models. The average value and variants obtained from the model are used to calculate value-at-risk in BBRI and BMRI stock. The results obtained are the ARIMA(3,0,3)-GARCH(1,1) and ARIMA(2,0,2)-GARCH(1,1) model so with a significance level of 5% obtained Value-at-Risk of 0.04058 to BBRI stock and 0.10167 to BMRI stock.

Keywords: Risk, ARIMA, GARCH, *VaR*

1. Introduction

Investment is a delay in consumption now to be put into productive assets during a certain period to get profits in the future and increase the asset value owned (Tandelilin, 2010). An investment that can be an option is a stock investment. Shares are securities as evidence of the inclusion or ownership of a person or legal entity over a company, especially the company that trades its shares.

Investing in stocks is faced with high risk because stock returns are volatile. Stock returns change in a very fast period so the value of stock indices also changes, this movement is known as stock return volatility. High volatility will result in high risk as well if low volatility results in low risk. How to estimate risk in investments can use *Value-at-Risk*. This research will use the *Value-at-Risk* method in conducting stock risk analysis with a time series model.

Some researchers have used various time series models in financial problems, one of which is the ARCH model introduced by (Engle, 1982). Sukono *et al.* (2019) researched the Model Autoregressive Integrated Moving Average-Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH) conducted to estimate the shortfall of several stocks in the Indonesian capital market. Based on the analysis of the study, the closing data of each selected stock has an average value and standard deviation that varies from each other. Chand *et al.* (2012) examines "Modeling and Volatility Analysis of Share Prices Using ARCH and GARCH Models" so that the model handles the problem of autocorrelation in the model.

In this study, the model that will be used is the ARIMA-GARCH model to estimate the *Value-at-Risk* of Bank Republik Indonesia Tbk (BBRI) stock and Bank Mandiri (Persero) Tbk (BMRI) stock. The purpose of this study was to apply the ARIMA-GARCH model to BBRI and BMRI stock data. The purpose of this study was to estimate the

ARIMA-GARCH model in determining the amount of *Value-at-Risk* obtained in BBRI and BMRI stock. The study used the Eviews 10 and Microsoft Excel applications.

2. Literature Review

2.1. Return

The observed observations are based on the return value of each stock, because there are differences in each volatility response. Ruppert (2011) explains that return is the rate of return on the results obtained as a result of investing. The return formula is as follows:

$$R_t = \ln\left(\frac{S(t_i)}{S(t_{i-1})}\right) \quad (1)$$

by R_t declaring a stock return, $S(t_i)$ declares the stock price in the t_i period and $S(t_{i-1})$ declares the stock price in the t_{i-1} period, assuming $S(0) = 1$.

2.2. Mean Model

Box and Jenkins introduced the ARIMA model in 1970. This model is also referred to as the Box-Jenkins methodology, consisting of estimation, estimation, and diagnosis models with time series data. The ARIMA model is also a leading model in financial data estimation. The ARIMA model is expressed as follows (Ariyo *et al.*, 2014):

$$Y_t = \phi_0 + \varepsilon_t + \sum_{i=1}^{p} \phi_i Y_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (2)$$

with Y Data at the t, ϕ_0 Constant, ϕ_i coefficients of AR model parameters that depend on limits *lag*, θ_i coefficient of MA model parameters that depend on the limit *lag*, and ε_t This is a data error at time t.

ARIMA model process:
(i) Performing data stationarity test using Augmented Dickey-Fuller (ADF) by differencing method,
(ii) Model identification by determining p and q values with autocorrelation function (ACF) and partial autocorrelation function (PACF) from the correlogram plot,
(iii) Parameter estimation can be used. using the least squares or maximum likelihood method,
(iv) a Diagnostic test with white noise and non-correlation test on residuals using Box-Pierce or Ljung-Box.
(v) Forecasting if the model fits, then it can be used for recursive prediction.

2.3. Volatility Model

Financial data analysis has received considerable attention in the literature over the years. Several models have been suggested to capture specific features of financial data, and most of the GARCH models have conditional variance properties that depend on the past. One of the most frequently used models is the ARCH model introduced by Engle (1982). Theoretical results on ARCH and related properties have played a special role in empirical work in the analysis of data on exchange rates, stock prices, and so on. The GARCH model was introduced by Bollerslev (1986). The GARCH process (p, q) is defined as follows (Horv *et al.*, 2003):

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

GARCH model process:
(i) Estimated GARCH model with time series model,
(ii) Use residuals from the GARCH model to test the effects of ARCH,
(iii) Perform diagnostic tests to observe the suitability of the model,
(iv) If model telah sesuai, it can be used to predict based on recursive predictions.

2.4. Value-at-Risk

Value-at-Risk (VaR) is an instrument for measuring risk. Tsay (2005) defines VaR under a probability framework. This distribution function is measured in terms of currency and is a random variable at time index t. Cumulative distribution function (CDF) from $\Delta V(l)$ stated by $F_l(x)$.

VaR losses are usually considered negative when α is small. A negative sign indicates a loss. The VaR definition for short-position shareholders is as follows:

$$\alpha = P[\Delta V(l) \geq VaR] = 1 - \Pr[\Delta V(l) \leq VaR] = 1 - F_l(VaR)$$

For small α, the short-term shareholder VaR is usually assumed to be positive. A positive sign indicates a loss. For each CDF $F_l(x)$ *univariate* and α probability, such that $0 < \alpha < 1$, quantity

$$x_\alpha = \inf\{x | F_l(x) \geq \alpha\} \quad (4)$$

is called the quantile to-α from $F_l(x)$, where inf is the smallest real number that satisfies $F_l(x) \geq \alpha$. The equation becomes (Dokov *et al.*, 2008):

$$VaR = \inf\{x | F_l(x) \geq \alpha\} \quad (5)$$

The standard method assumes that the return on assets has a normal univariate distribution, has two parameters, namely the average (*mean*) μ and standard deviation σ. VaR estimation is done using the following equation:

$$VaR = -1 \cdot \left(\mu + \sigma_t F^{-1}(\alpha)\right) \quad (6)$$

where μ is the mean, σ^2 is the variance, and σ is the standard deviation.

3. Result and Discussion

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

3.1. Data

The data used in this study is the closing price of shares of BBRI and BMRI. The data was obtained from the website https://finance.yahoo.com/ with a data period of 3 years from December 17 2018 to December 14 2021. Data analysis was assisted by Eviews 10 and Excel software.

3.2. Statistic Descriptive

Before descriptive statistics, the first thing to do is calculate stock returns using equation (1). Descriptive statistics are in Table 1.

Table 1. Descriptive statistics of data

Code	Samples	Mean	Median	Maximum	Minimum	Standard Deviation
BBRI	746	0.00046	0	0.20492	-0.09092	0.02361
BMRI	746	0.00024	0	0.15803	-0.12992	0.02362

Then check the stationary of the data with the help of Eviews 10 software. Based on the stationarity test, the data used was stationary at the beginning for BBRI shares and BMRI shares. Therefore, the estimation of the average model that can be done is the ARMA model (p, d) or ARIMA (p, d, q) model with parameter $d = 0$.

3.3. Mean Model Estimation

The estimated average model chosen is ARIMA (3, 0, 3) for BBRI shares and ARIMA (2, 0, 2) for BMRI shares. The selected model has been carried out diagnostic tests using Eviews 10 software so that the model has white noise and residuals are normally distributed. The ARIMA model equation chosen by following equation (2) is as follows

BBRI stock: $z_t = -0.957706 z_{t-1} - 0.952060 z_{t-2} + 0.042409 z_{t-3} - 0.987832 a_{t-3} + a_t$

BMRI stock: $z_t = 0.338607 z_{t-2} - 0.474612 a_{t-2} + a_t$

3.4. Volatility Model Estimation

Before estimating the volatility model, the first thing to do is to check the effect of heteroscedasticity on the average model. The ARCH-LM test on the average model is assisted by Eviews 10 software, so the results show that all models have a heteroscedasticity effect. Then proceed with the estimation of the volatility model to overcome the effect of heteroscedasticity. After estimating the model using Eviews 10 software, the model selected for the two stocks analyzed is GARCH (1, 1). The model has been significant because the white noise diagnostic test has been carried out and the residuals are normally distributed. So, the GARCH (1, 1) model for BBRI and BMRI shares is

BBRI stock: $\sigma_k^2 = 1.31 \times 10^{-5} + 0.113634 a_{k-1}^2 + 0.862452 \sigma_{k-1}^2 + u_k$

BMRI stock: $\sigma_k^2 = 4.01 \times 10^{-5} + 0.148979 a_{k-1}^2 + 0.821305 \sigma_{k-1}^2 + u_k$

3.5. Value-at-Risk Estimation

Value-at-Risk calculation is based on the estimation results of the average and variance model which is carried out using the time series model. The parameters used for the VaR calculation are the mean and standard deviation which refer to equation (6). The results of the VaR calculation are shown in Table 2.

Tabel 2. Value-at-Risk calculation results

Code	$\hat{\mu}_t$	$\hat{\sigma}_t^2$	$\hat{\sigma}_t$	VaR_t
BBRI	0.000302	0.000382	0.019545	0.04058
BMRI	0.002055	0.004064	0.063750	0.10167

Based on Table 2, the VaR value obtained is 0.04058 on BBRI shares, so it can be explained that the risk accepted by investors is 4.058%. The risk obtained in BMRI shares is 10.167%.

4. Conclusions

The conclusion from the analysis that has been carried out is that the average model acquisition for BBRI shares is ARIMA (3, 0, 3) and BMRI ARIMA shares (2, 0, 2). The volatility model generated for BBRI and BMRI stocks is GARCH (1, 1). Then the risk calculation for the three shares is 0.04058 shares of BBRI and 0.10167 shares of BMRI. This means that if an investor invests IDR100,000,000 in BBRI shares and BMRI shares, then the maximum estimated loss obtained by the investor is estimated at IDR4,058,000 and IDR10,167,000, respectively.

References

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In *2014 UKSim-AMSS 16th international conference on computer modelling and simulation* (pp. 106-112). IEEE.)

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), 307-327.

Chand, S., Kamal, S., & Ali, I. (2012). Modeling and volatility analysis of share prices using ARCH and GARCH models. *World Applied Sciences Journal*, *19*(1), 77-82.

Dokov, S., Stoyanov, S. V., & Rachev, S. 2008. Computing VaR and AvaR of skewed-t distribution. *Journal of Applied Functional Analysis*, *3*, 189-209.

Dowd, K. 2007. *Measuring market risk*. England: John Wiley & Sons.

Engle, R. F., "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation", *Econometrica: Journal of the econometric society*, 1982. pp. 987-1007.

Horv, L., & Kokoszka, P. (2003). GARCH processes: structure and estimation. *Bernoulli*, *9*(2), 201-227.

Ruppert, D. 2011. Statistics and Data Analysis For Financial Engineering. Second Edition. Spinger text in statistics. New York.

Sukono., Soeryana, E., and Simanjuntak, A., "ARIMA-GARCH Model for Estimation of Value-at-Risk and Expected shortfall of Some Stocks in Indonesia Capital Market", *Proceedings of the International Conference on Industrial Engineering and Operations Management Riyadh*, Saudi Arabia, 2019.

Tandelilin, E., Portofolio and investment. Theory and Application. *First Edition*. Yogyakarta: Kanisius, 2010.

Tsay, R. S. 2005. *Analysis of financial time series* (Vol. 543). Chicago: John Wiley & Sons.