ARIMA-GARCH Model for Estimation of Value-at-Risk and Expected shortfall of Some Stocks in Indonesian Capital Market

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Abstract

In stock investments, keep in mind the movements and risk of losses that may occur from investments made. One way to calculate risk is to use Value-at-Risk and Expected Shortfall. The purpose of this research is to determine the amount Value-at-Risk and Expected Shortfall of selected stocks using the time series model approach. The data used in this study is the daily closing price of some stocks for three years. In the time series modeling process, the models used for predicting stock movements are Autoregressive Integrated Moving Average (ARIMA) for the mean model, and Generalized Autoregressive Conditional Heteroscedasticty (GARCH) for the volatility model. The values of mean and variance obtained from the model are then used to calculate the Value-at-Risk and Expected Shortfall of each preferred stock. Based on the analysis, it was found that from the selected stocks, Bank Mandiri stocks had the lowest risk level and Mustika Ratu stocks had the highest risk level with the Value-at-Risk value of stocks generally smaller than the Expected Shortfall value.

Keywords:
Time Series Model, ARIMA, GARCH, Value-at-Risk, Expected Shortfall.

1. Introduction

In general, investment is the saving of assets or funds carried out by a party for a certain period to obtain profits or benefits in the future. One of the most well-known forms of investment that is still carried out to date is stock investment or rather share ownership rights. Shares are proof of ownership of a portion of capital of a limited liability company that gives rights to dividends and others according to the size of paid-up capital or the right owned by people (shareholders) to the company thanks to the transfer of part of capital so that it is considered to be shared in ownership and supervision. Each investment has its advantages and risks, including shares (Sukono et al., 2017.a; 2017.c; 2018.c). To make a profit, you must consider the benefits derived from the price of the return with the existing risk. Own shares have price movements that tend to be difficult to ascertain, making shares have their risks compared to other forms of stock. The risks posed by stock investments make investors need to be aware of seasonal variances and price movements. There are several kinds of ways to estimate risk in investing, such as volatility, Value at Risk, and Expected Shortfall. This research will use the last two methods in analyzing stock risk with time series models (Sukono et al., 2017.b; 2018.a; 2018.b; 2019).

These models are widely used for time series analysis of data type sharing. The following are some previous studies regarding the use of the ARIMA-GARCH model. Uw surroundyimana et al. (2015) researched forecasting inflation in Kenya using ARIMA-GARCH models. This research was motivated by the inflation rate in Kenya which at that time became out of control. The purpose of this study is to develop a model that can explain Kenya's inflation rate from 2000 to 2014 using time series analysis. Data analysis using the least-squares method and Autoregressive Conditional Heteroscedastic (ARCH). After being analyzed separately through the ARIMA model and the GARCH model, the ARIMA(1,1,12) model was obtained from forecasting based on stationarity test and data patterns that are more accurate than the GARCH(1,2) model. It was concluded that the ARIMA(1,1,12)-GARCH (1,2) model yields the most accurate estimate when compared to other models. Besides, Iriani et al. (2013) examined the estimated Value-at-Risk (VaR) on a stock portfolio with Copula. This research is motivated by the risk of investment in the form of shares which tend to be high. One method of determining investment risk is Value-at-Risk (VaR). The purpose of this study was to determine the VaR return of several stocks from 2005 to 2010 using the Copula method. The study uses the ARMA-GARCH model to obtain residual GARCH(1,1) which is then used for copula modeling and VaR estimation. Copula used is several Archimedean Copula, namely Clayton, Frank, and Gumbel. Research shows that modeling Copula Clayton as the best copula model can capture heavy tail better based on the VaR produced. Similar research has also been carried out by Ariany (2012), Yamai & Yoshiba (2002),.

In this paper, a study of the ARIMA-GARCH model is conducted to estimate the Value-at-Risk (VaR) and Expected Shortfall of some shares in the Indonesian Capital Market. The aim is to determine the characteristics of selected stock data analyzed, estimate the ARIMA-GARCH model from historical data of several stocks, and determine the value of Value-at-Risk (VaR) and Expected Shortfall stock data based on the ARIMA-GARCH model. The results are expected to be used as a consideration in making investment decisions, especially in some of the stocks analyzed in this paper.

2. Methodology

2.1 Stock

Stocks are one of the most promising forms of investment because they have the opportunity to provide relatively large profits. However, these benefits also need to be compared with the risks involved. To analyze the stock data itself, returns are usually used which are formulated as follows (Dowd, 2002):

$$r_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right), \tag{1}$$

where r_t is the return value of data at the t-time, P_t is the data value at the t-time, and P_{t-1} is the data value at time $t-1$ (one time before).

For the analysis of the value of stock returns, usually to make stationary data, the data is derived or differentiated with the analyzed data calculated using the formula (Sukono et al., 2017.b):

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right). \tag{2}$$

2.2 Normality Test

The normality test aims to find out whether the data tested is normally distributed. The data for normality test in this study is the residual data return model in which the normality test uses the Jarque-Berra test. The test uses the following hypothesis H_0: the data tested are normally distributed, and H_1: the data tested are not normally distributed.

The test statistic used has the following equation (Jarque et al., 1980; Situngkir, 2006):

$$JB = n\left(\frac{\varsigma^2}{6} + \frac{(k-3)^2}{24}\right), \tag{3}$$

where n is the sample size, ς is skewness, and k is kurtosis. The test criteria is H_0 rejected if $JB \geq \chi^2$.

2.3 Mean Model

In this section, the ARMA and ARIMA models for research will be discussed. The ARMA model in time series is used to briefly describe stationary stochastic processes, namely autoregression and moving averages. This model was popularized in 1970 by Box and Jenkins. As the name implies, this model combines the AR model and the MA model to predict time series data for a certain period. This model is denoted by ARMA(p,q) where p is the AR order and q is the MA order. The ARMA model equation (p,q) is as follows (Adhikari and Agrawal, 2013; Alli et al., 2013):

$$W_t = \beta_0 + \varepsilon_t + \sum_{i=1}^{p} \beta_i W_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \tag{4}$$

where W_t is t-time data, β_0 is a constant, β_i is the parameter coefficients of the AR model that depend on the lag limit, θ_i is the parameter coefficient of the MA model which depends on the lag limit, and ε_t is the data error at time t. To choose good p and q, PACF is used in determining p and ACF in determining q. Apart from that, AIC can also be used.

The ARIMA model is a generalization of the ARMA model. This model is used as a tool to explain the time series analyzed and forecast the value of data in the future (forecasting). This model is denoted by ARIMA(p,d,q) where p is the order for the AR process, d is the degree of data integration so that the data is stationary (the number of times the data value is disputed with the previous data), and q is the order for the MA process with p, d, and q are non-negative integers (Box, 1994; Sukono et al., 2017.b). Process $\{W_t\}$ is ARIMA(p,d,q) if $\Delta^d W_t = (1-L)^d W_t$ is ARMA (p,q). In general, the model is written as follows:

$$\beta(L)(1-L)^d W_t = \theta\varepsilon_t; \{\varepsilon_t\} \sim WN(0, \sigma^2), \tag{5}$$

with ε_t follow white noise (WN). L is the lag operator where $L^k W_t = W_{t-k}$ where the autoregressive operator and moving average are defined as follows:

$$\beta(L) = 1 - \beta_1(L) - \beta_1(L^2) - \cdots - \beta_p(L^p) \tag{6}$$

$$\theta(L) = 1 - \theta_1(L) - \theta_1(L^2) - \cdots - \theta_p(L^q).$$

The functions β and θ are autoregressive and moving average polynomials with the order p and q in the L variable, $\theta(L) \neq 0$ jika $|\theta| < 1$, $\{W_t\}$ stationary if and only if $d = 0$, which makes the model become ARMA(p,q). To estimate this model, the steps that need to be done are estimating the shape of the model using correlograms, selecting the best form, then verifying and validating the model, as well as diagnostic tests (Box, 1994; Sukono et al., 2017.b).

2.4 Volatility Model

This section discusses the ARCH and GARCH models for research. The ARCH model is a statistical model that illustrates the variance of the time series residuals analyzed. This model is used when the error variance in the model follows the autoregressive (AR) form. To model the time series using the ARCH(p) process, ε_t is used which denotes the residual return of the mean model, as follows:

$$\varepsilon_t = \sigma_t Z_t, \{Z_t\} \sim iid\ N(0,1), \tag{7}$$

where σ_t is a time-dependent standard deviation and z_t random variable that is white noise. Series ${\sigma_t}^2$ modeled as follows (Box, 1994; Sukono et al., 2017.b):

$${\sigma_t}^2 = \alpha_0 + \alpha_1 {\varepsilon_{t-1}}^2 + \alpha_2 {\varepsilon_{t-2}}^2 + \cdots + \alpha_p {\varepsilon_{t-p}}^2 \tag{8}$$

where $\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1,2,\ldots,p$, and Z_t with $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_t$ independent for each t. The GARCH model is a generalization of the ARCH model developed by Bollerslev in 1986, where if ARCH is used when an AR model residual is used, GARCH is used when the ARMA model residual model. The GARCH(p,q) model has a shape like the ARMA model as follows:

$$\varepsilon_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N(0,1)$$

where

$${\sigma_t}^2 = \alpha_0 + \alpha_1 {r_{t-1}}^2 + \cdots + \alpha_p {\varepsilon_{t-p}}^2 + \beta_1 {\sigma_{t-1}}^2 + \cdots + \beta_q {\sigma_{t-q}}^2 \tag{9}$$

with $\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1,2,\dots,p$, $\beta_j \geq 0$, $j = 1,2,\dots,q$.

If $\{r_t\}$ is the return of the mean, $\boldsymbol{\varepsilon_t}$ is a Gaussian white noise with mean 0 and unit variance, $\{W_t\} = \{r_1, r_2, \dots, r_{t-1}\}$, then $\{r_t\}$ is GARCH(1,1) if (Box, 1994; Sukono et al., 2017.b):

$$\varepsilon_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N(0,1)$$

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 r_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2.$$

To estimate this model from the previous ARIMA model, it must first be seen whether the residual model is heteroscedastic (containing the ARCH element), and if there is the next step it is more or less the same as the estimated mean model. If a diagnostic test has been carried out and the model is obtained, it must be re-checked for the heteroscedasticity of the estimated model. If the estimated model contains ARCH elements, then the model can already be used.

The variances and averages of these models will then be used at a later stage, namely the Value-at-Risk and Expected Shortfall estimates.

2.5 Value-at-Risk and Expected Shortfall

Value-at-Risk (VaR) is an investment risk measurement that shows the maximum value of losses that might be obtained. Therefore, Value at Risk is the value of large losses that may be obtained from a certain amount with a level of confidence α in the period T. The VaR value is calculated in certain market conditions with a certain level of risk within a certain period. VaR estimates usually use the standard method which assumes that the data return has one variable and is normally distributed with an average μ and a standard deviation σ.

VaR estimation is done by determining percentiles $(1-\alpha)\%$ from a standard normal distribution $z_{1-\alpha}$ (Artzner et al., 1999; Sukono et al., 2019):

$$1 - \alpha = \int_{-\infty}^{q} f(r)dr = \int_{-\infty}^{z_{1-\alpha}} \phi(z)dz = N(z_{1-\alpha}), \quad (10)$$

by quantile $q = z_{1-\alpha}\sigma + \mu$,

where $\phi(z)$ is a standard distribution opportunity density function, $N(z)$ is cumulative normal distribution function, r is the value of the random variable of stock returns denoted by *R,* and $f(r)$ is a density function of the normal log return distribution with an average μ and variance σ^2. So the equation used to determine VaR is as follows (Artzner et al., 1999; Sukono et al., 2019):

$$\begin{aligned} r_t &= \mu_t + \sigma_t z_t, \\ \widehat{VaR}_{\alpha}^{t}(r_t) &= -\inf(r_t \mid F(r_t) \geq \alpha) \\ &= -\hat{\mu}_t - \hat{\sigma}_t F^{-1}(\alpha). \end{aligned} \quad (11)$$

Expected Shortfall is another method of measuring the maximum possible loss that exceeds VaR. This method was proposed by (Artzner et al., 1999; Sukono et al., 2019.a) when they pointed out some weaknesses of Value-at-Risk, including the neglect of losses greater than the value of the Value at Risk level and unable to meet the axioms coherence because Value-at-Risk is not subadditive. Yamai and Yoshiba (2002) define ES, where X is a random gain or loss variable and VaR (X) with a level of confidence $100(1-\alpha)\%$, as follows:

$$\begin{aligned} ES_{\alpha}^{t}(x) &= -E[X \mid X \leq VaR_{\alpha}(X)] \\ &= -\frac{1}{\alpha}\int_{-\infty}^{-VaR_{\alpha}} x f(x)dx, \\ &= -\mu_t + \sigma_t \frac{\phi(z_{1-\alpha})}{\alpha}, \end{aligned} \quad (12)$$

where ϕ is a standard normal density function.

There are cases where the distribution of data is not normal due to excess skewness and kurtosis resulting in deviations. Therefore, to estimate VaR and ES, Cornish-Fisher expansion will be used to obtain the following formula (Dowd, 2002; Sukono et al., 2019.b):

$$F_{CF}^{-1}(\alpha) = \phi^{-1}(\alpha) + \frac{\varsigma}{6}([|\phi^{-1}(\alpha)|]^2 - 1) + \frac{k-3}{24}([|\phi^{-1}(\alpha)|]^3 - 3\phi^{-1}(\alpha))$$

$$-\frac{\varsigma^2}{36}(2[|\phi^{-1}(\alpha)|]^3 - 5\phi^{-1}(\alpha)) \tag{13}$$

$$ES_\alpha^2(x) = -\widehat{\mu_t} + \frac{\widehat{\sigma_t}}{\alpha\sqrt{2\pi}} e^{\frac{(F_{CF}^{-1}(\alpha))^2}{2}} \tag{14}$$

where $\widehat{\mu_t}$ is the estimated average of the data at time t, $\widehat{\sigma_t}$ is variance of data at time t, $F_{CF}^{-1}(\alpha)$ is quantile-α from the distribution z_t, $\phi^{-1}(\alpha)$ isquantile-α from the normal distribution, and ς, k are the skewness and kurtosis of $\widehat{z_t}$, where $\widehat{z_t} = \frac{x_t - \widehat{\mu_t}}{\widehat{\sigma_t}}$.

3. Results and Discussion

This section discusses the data used for analysis and analysis results in the form of mean models, volatility models, and estimated Value-at-Risk and Expected Shortfalls for each preferred stock.

3.1 Stationary Data and Tests

The data used in this study are historical daily closing price data from several stocks, namely Gudang Garam Tbk (GGRM), Telekomunikasi Indonesia Persero Tbk (TLKM), Mustika Ratu Tbk (MRAT), Mayora Indah Tbk (MYOR), and Bank Mandiri Persero (BMRI) from 1 September 2015 to 31 August 2018. Data obtained at www.financeyahoo.id. The data used has descriptive statistics given in Table 1.

Table 1. Descriptive Statistics of Preferred Shares

Stock	**GGRM**	**MRAT**	**MYOR**	**TLKM**	**BMRI**
Samples (*N*)	747	751	751	751	751
Average	66984.640	205.676	1899.535	3866.398	6014.397
Median	67325.0	204.0	1905.0	3950.0	5812.5
Minimum	40500.0	168.0	3140.0	2600.0	3762.5
Maximum	85275	250	1014	4800	9050
Standard Deviation	9635.243	11.653	604.060	532.370	1173.498
Skewness	-0.746314	0.123755	0.381379	-0.552827	0.283579
Kurtosis	3.536839	4.727354	2.232361	2.731526	2.108689

Based on Table 1, it can be seen that each stock has a different average value and standard deviation and indicates that the data is quite varied from one another.

Then by using the help of Eviews 7, it is found that the original data is not stationary. Therefore, the data must be transformed using equation (2) until the data is stationary. After one transformation, the data on the transformation of each share is stationary. So, it can be concluded that the order *d* for the ARIMA(*p*,*d*,*q*) model for each selected stock is 1.

3.2 Estimation of the Mean Model

After knowing that the data is stationary, it can be estimated the shape of the model. For the form of the mean model, the model used is the ARIMA model. After the estimation stage as described in Section 2.3, it was found that the estimation of the mean stock model is shaped as follows: ARIMA(2,1,2) for GGRM, ARIMA(3,1,3) for MRAT, ARIMA(0,1,2) for MYOR, ARIMA(5,1,5) for TLKM, and ARIMA(3,1,3) for BMRI. Each form of this model does not have residuals that are normally distributed. The estimated models for each preferred stock are as follows:

- Mean model for stock return data of GGRM:
  $\hat{r}_t = 2.349489 r_{t-1} - 0.502268 r_{t-1} + 1.394100 a_{t-1} - 0.630449 a_{t-2}$;
- Mean model for stock return data of MRAT:
  $\hat{r}_t = r_{t-1} + 0.502268 r_{t-2} - 0.502259 r_{t-3} + 0.695850 a_{t-2}$;
- Mean model for stock return data of MYOR:
  $\hat{r}_t = 0.001329 - 0.190445 a_{t-1}$;
- Mean model for stock return data of TLKM:
  $\hat{r}_t = r_{t-1} + 0.45964 r_{t-2} + 0.149631 r_{t-3} - 0.852521 r_{t-4} - 1.36241 r_{t-5}$

$+0.537760a_{t-2} + 0.632567a_{t-3} - 0.256857r_{t-4} - 0.879839r_{t-5}$;

- Mean model for stock return data of BMRI:
  $\hat{r}_t = -0.648861r_{t-1} + 1.289558r_{t-2} - 0.640497r_{t-3} - 0.698482a_{t-1} + 0.777545a_{t-2} + 0.479510a_{t-3}$;

3.3 Estimation of the Volatility Model

Before estimating the volatility model, first determine whether the mean model from the previous section has the ARCH element. After having done the ARCH-LM Test on each model using the help of Eviews 7, it was found that each model has an ARCH element. Because the model has an ARCH element, the volatility model estimation can be done. After the estimation phase is carried out, the volatility model of each preferred stock is obtained with the following form: GARCH(1,1) for GGRM, MRAT, and MYOR and GARCH(2.2) for TLKM and BMRI. These models are significant after the validation test and the residuals are white noise and not normally distributed after the diagnostic test. Then after being examined, the models have ARCH elements so they can be used for modeling. Here are the models:

- Model for stock of GGRM:
  $\hat{\sigma}_t^2$=$0.0000367 + 0.075830a_{t-2}^2 + 0.604916\sigma_{t-1}^2$;
- Model for stock of MRAT:
  $\hat{\sigma}_t^2$=$0.0000508 + 0.202302a_{t-1}^2 + 0.604916\sigma_{t-1}^2$;
- Model for stock of MYOR:
  $\hat{\sigma}_t^2$=$0.000175 + 0.389903a_{t-1}^2 + 0.246131\sigma_{t-1}^2$;
- Model for stock of TLKM:
  $\hat{\sigma}_t^2$=$0.000059 + 0.151247a_{t-1}^2 + 0.105779a_{t-2}^2 - 0.250815\sigma_{t-1}^2 + 0.773375\sigma_{t-2}^2$;
- Model for stock of BMRI:
  $\hat{\sigma}_t^2$=$0.235788a_{t-1}^2 - 0.178785a_{t-2}^2 + 0.632555\sigma_{t-1}^2 + 0.283944\sigma_{t-2}^2$;

The variance and mean obtained from the estimation of these models are then used to estimate Value-at-Risk and Expeted Shortfall in the next section.

3.4 Estimation of the Value-at-Risk and Expected Shortfall

The models of each preferred stock do not have a normal distribution because the residuals on the model are also not normally distributed. Therefore, for the estimated Value-at-Risk and Expected Shortfall of each preferred stock, equations (12), (13), and (14) are used. The estimated results of each preferred stock are shown in Table 2.

Table 2. Value at Risk and Expected Shortfall Value for Each Preferred Stock

Stock	**GGRM**	**MRAT**	**MYOR**	**TLKM**	**BMRI**
Average	0.00273	0.00748	0.001321	0.00321	0.000832
Variance	0.0021	0.00453	0.000470	0.000269	0.000015
Standard Deviation	0.045826	0.0673053	0.021677	0.016410	0.003858
Skewness *z*	0.168729	-0.41130	0.381379	-0.011567	0.050116
Kurtosis *z*	3.893378	8.711026	2.232361	5.857518	5.902366
$\phi^{-1}(5\%)$	-1.644854	-1.644854	-1.644854	-1.644854	-1.644854
$F_{CF}^{-1}(5\%)$	-1.578328	-1.643336	-1.54920	-1.590472	-1.571975
$VaR_{5\%}$	0.069598	0.103125	0.032261	0.022876	0.005233
$ES_{5\%}$	0.102493	0.131698	0.050772	0.033732	0.008116

Based on Table 2, it can be seen that the shares of Gudang Garam have a VaR of 0.069598. In other words, if an investment is made for GGRM shares amounting to IDR 1,000,000.00 in 37 days (5% of 747 days) the investment period with a 95% confidence level the maximum loss that may be borne by investors is IDR 69,598.00. While the ES value of GGRM shares is 0.102493. Means, if an investment is made for GGRM shares for IDR 1,000,000.00 in 37 days (5% of 747 days) the investment period with a 95% confidence level the possibility of the expected loss to be borne by investors is IDR102,493.00. Then the results of the calculation of other stocks can also be read in this way.

4. Conclusions

This paper has discussed the ARIMA-GARCH model for estimating Value-at-Risk (VaR) and Expected Shortfall of some shares in the Indonesian Capital Market. Based on the results of the analysis it can be concluded that the closing data of each selected stock has a mean value and varying standard deviations, and indicates that the data are quite varied between one another. Then, the mean stock model is quite varied with the ARIMA(2,1,2) for GGRM, ARIMA(3,1,3) for MRAT, ARIMA(0,1,2) for MYOR, ARIMA(5,1,5) for TLKM, and ARIMA(3,1,3) for BMRI. While there are 2 volatility models obtained from preferred shares, namely GARCH(1.1) for GGRM, MRAT, and MYOR shares and GARCH(2.2) for TLKM and BMRI shares. The estimated risk of preferred shares varies, where BMRI shares have the lowest risk level with a Value-at-Risk value of 0.005233 and Expected Shortfall 0.008116 while MRAT shares have the greatest risk with a value of Value-at-Risk of 0.103125 and Expected Shortfall of 0.131698. Besides, for each stock, the value of Value at Risk is smaller than the Expected Shortfall.

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