

**VALUE AT RISK IN STOCK PORTFOLIO USING T-COPULA:  
Case Study of PT. Indofood Sukses Makmur, Tbk.  
and Bank Mandiri (Persero), Tbk.**

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**Abstract:** Value at Risk (VaR) is a measuring tool that can calculate the amount of the worst losses that occur in the stock portfolio with a certain level of confidence and in certain period of time. In general, financial data has a high volatility value, which is caused the variance of residual model is not constant and nonnormally distributed. In this case, Copula-GARCH can be used to calculate the VaR. The Generalized Autoregressive Conditional Heterocedasticity (GARCH) model can resolve the time series models that have non-constant residual variance. This research use the t-Copula to model the dependency structure in the combined distribution of stock returns. The t-copula function is good in terms of reaching the extreme value state that often occurs in the financial data of stock returns and has *heavytails*. The empirical data uses the stock return data of PT. Indofood Sukses Makmur, Tbk (INDF) and Bank Mandiri (Persero) Tbk (BMRI) in the period of October 8, 2012 - October 8, 2017. In this research, Value at Risk is calculated using the period 1 day ahead at 90% confidence level that is 0.042, at 95% confidence level that is 0.025 and at 99% confidence level that is 0.017 with weight of each stock is 50%.

**1. INTRODUCTION**

Company-owned property is known as an asset, for one or more of which investment normally is targeted. Using a long period, the investors expect to earn a profit (Sunariyah, 2006). Currently, stocks are one type of investment that promises benefits but also inflicts risks for investors. Shares are obtained through purchases or other means that give rights to shareholders to obtain profits or profit sharing in accordance with their investments in a company. Risk investments lead to uncertainty about what will happen in the future. Investors or potential investors are required to master knowledge about risk (Jorion, 2006).

A portfolio is based on a basic concept of the way to allocate a number of funds to several types of investments to gain optimal profits. One way to measure risk is to calculate Value at Risk (VaR), one of the predictions of the maximum loss that occurs in a portfolio of stocks with a certain level of confidence and within a certain time period. The accuracy of the VaR is very important in determining the amount of capital to be provided by the company to overcome the possible losses (Darmawan, 2014).

Stock data is time series data resulted from observations from time to time. Stock data tend to fluctuate rapidly leading to constantly changing residual variance. Time series modeling for data with non-constant residual variance is Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (Makridakis, et al. 1999).

The methods to determine the VaR of a stock portfolio include the Exponentially Weighted Moving Average (EWMA) approach, with historical data simulations, and with Monte-Carlo simulations. Some researchers known to use the Exponentially Weighted Moving Average (EWMA) approach are Buchdadi (2008), who applied it to shares of sharia-based companies, and Fadilah et al. (2018), who also applied to shares of sharia-based companies. Determination of VaR by historical data simulation methods and Monte-Carlo simulations was carried out by Artini et al. (2012). Historical data simulation methods assume multivariate normal data distribution. Stock data (stock returns) usually do not meet multivariate normal assumptions. One way to overcome this is to use copula. Copula theory is a very powerful tool for modeling joint distributions because it does not require multivariate normal assumptions from the data making it flexible enough for various data especially for stock return data as it can capture tail dependence between each variable (Gilli and Killezi, 2006).

One type of copula is t-copula which originates from Elliptical copula. Financial data generally have fat tails. Hence, it is suitable to use student-t copula because in probability theory, the student-t distribution has fatter tails than the normal distribution. Some researchers using copula in determining VaR are Dharmawan (2014), Iriani et al. (2013) and Ningrum et al. (2017).

This study used a Monte-Carlo simulation method with t-copula. The use of Monte-Carlo simulation methods to measure risk was introduced by Boyle in 1977. The estimation of the Value at Risk (VaR) at a single exchange rate or portfolio with Monte Carlo simulations has several types of algorithms. However, the point is to do a simulation by generating random numbers based on the characteristics of the data to generate and using them to estimate the VaR.

This study determined the Value at Risk portfolio of stock returns using the Copula-GARCH method of the t-Copula type of two Indonesian shares, namely PT. Indofood Sukses Makmur Tbk. (INDF) and Bank Mandiri (Persero Tbk (BMRI) for the period of 8 October 2012 - 8 October 2017. The study resulted in an optimal portfolio (determining the weight of each stock return) of the two stock return data making the investments have minimal risk of loss (the smallest absolute VaR value).

## **2. LITERATURE REVIEW**

### **2.1 Stock Returns**

Stock Return is the rate of return or the results obtained from investments (Ruppert, 2004). The return value is calculated using the following formula (Tsay, 2002):

$$R_{it} = \ln \frac{P_t}{P_{t-1}}$$

where  $R_{it}$  is the  $i$  stock return,  $P_t$  is the closing price of the current period and  $P_{t-1}$  is the closing price of the previous period. Conversely, the stock portfolio return formula can be calculated as follows:

$$R_{pt} = \sum_{i=1}^N w_i R_{ti}$$

The weight of  $w_i$  is determined by trial and error with the condition  $\sum_{i=1}^n w_i = \mathbf{1}_N^T \mathbf{w} = 1$ . The weights resulted from trial and error are used to form a portfolio and the maximum VaR is calculated, formed, and selected from each portfolio.

## 2.2. Time Series Analysis

Time series data analysis is used to analyze data that considers the influence of time. Time series analysis is based on the principle that the current events ( $y_t$ ) are influenced by several previous events ( $y_{t-k}$ ),  $k = 1, 2, \dots, q$ . In simple terms, time series data analysis is used because statistically there is a correlation (dependent) between the series of observations (Makridakis et.al 1999).

### 2.2.1. Box-Jenkins Model

The Box-Jenkins model is an analysis model generally used for modeling time series data. This model assumes stationarity of the AR, MA, and ARMA models and the non-stationary time series model of the ARIMA model, with the following models:

a. *Autoregressive Model (AR)*

$$y_t = \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + a_t$$

b. *Moving Average Model (MA)*

$$y_t = a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}$$

c. *Autoregressive Moving Average (ARMA) Model*

$$y_t = \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}$$

d. *Autoregressive Integrated Moving Average (ARIMA) Model*

$$\phi(B)(1-B)^d Z_t = \theta(B)a_t$$

The stages for modeling ARIMA, according to Wei (1989), are (1) The models are identified with ACF plot and PACF, (2) Parameter estimation was done using Ordinary Least Square or Maximum Likelihood Estimation method, (3) Parameter Significance Test, (4) Verification of the residual model consists of the residual independence test using the Ljung-Box test, the residual normality test using the Jarque-Bera, and residual homogeneity test using Lagrange Multiplier.

#### *Ljung-Box Test*

Hypothesis:

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_K = 0$$

(no residual correlation between lags)

$$H_1 : \text{There is at least one } \rho_i \neq 0 \text{ with } i = 1, 2, \dots, K$$

there is a residual correlation between lags)

Test Statistics:

$$Q = n(n+2) \sum_{k=1}^K (n-k)^{-1} \hat{\rho}_k^2$$

where  $n$  is the amount of data,  $m$  is the number of parameters tested, and  $\hat{\rho}_k$  is the residual autocorrelation in the  $k$ -th lag.  $Q$  has a chi-square distribution with free degrees  $m$ . Each lag of this test statistic value is calculated, so there are several  $Q$  values in one model.

Test Criteria:

$$H_0 \text{ is rejected if } Q_{(m)} > \chi_{(K-m)}^2 \text{ or } p\text{-value} < \alpha$$

### Jarque-Bera Test

Hypothesis:

$H_0$  : Residuals are normally distributed

$H_1$  : Residuals are not normally distributed

Test Statistics:

$$JB = \frac{n}{6} \left( S^2 + \frac{(K-3)^2}{4} \right)$$

$$K = \frac{\frac{1}{n} \sum_{t=1}^n (y_t - \bar{y})^4}{\left( \frac{1}{n} \sum_{t=1}^n (y_t - \bar{y})^2 \right)^2}$$

$$S = \frac{\frac{1}{n} \sum_{t=1}^n (y_t - \bar{y})^3}{\left( \frac{1}{n} \sum_{t=1}^n (y_t - \bar{y})^2 \right)^{3/2}}$$

where  $n$ : the amount of data,  $k$ : the number of parameter,  $S$ : skewness, and  $K$ : kurtosis.

Test criteria:

$$H_0 \text{ is rejected if } JB > \chi_{(2)}^2 \text{ or } p\text{-value} < \alpha$$

### Lagrange Multiplier Test

Residual homoscedasticity test is used to test the homogeneity of the variance of residuals. In this case, the Lagrange Multiplier (LM) test can also be used to detect the ARCH/GARCH process by regressing the square of the ARIMA residual model as follows (Tsay 2002).

$$a_t^2 = \psi_0 + \psi_1 a_{t-1}^2 + \psi_2 a_{t-2}^2 + \dots + \psi_k a_{t-k}^2 + e_t, \quad t = k+1, \dots, n$$

Hypothesis:

$$H_0 : \psi_1 = \psi_2 = \dots = \psi_k = 0$$

(no ARCH/GARCH effect in the residuals until the  $k$ -th lag)

$$H_1 : \text{there is at least one value } \psi_i \neq 0, \quad i = 1, 2, \dots, k$$

(there is an ARCH/GARCH in residuals until the  $k$ -th lag)

Test Statistics:

$$LM = \frac{(SSR_0 - SSR_1)/m}{SSR_1/(n-2m-1)}$$

$$SSR_0 = \sum_{t=m+1}^n (a_t^2 - \bar{\omega})^2$$

$$\bar{\omega} = \frac{\sum_{t=1}^n e_t^2}{n}$$

$$SSR_1 = \sum_{t=m+1}^n e_t^2$$

where  $m$  is the maximum lag

Test Criteria:

$H_0$  is rejected if the value of  $LM > \chi^2_{(\alpha, m)}$  or  $p\text{-value} < \alpha$

### 2.2.2. GARCH Model

The GARCH model is used to model residual volatility that often occurs in financial data. The general form of the GARCH model ( $m, s$ ) is as follows (Tsay, 2002):

$$\sigma_t^2 = a_0 + \sum_{i=1}^m \alpha_i a_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2$$

where  $a_0$ : positive constant,  $\alpha_i$ : parameter of ARCH,  $a_{t-i}^2$ : squared residuals at time  $t-i$ ,  $\beta_j$ : parameter of GARCH, and  $\sigma_{t-j}^2$ : variance of residuals at  $t-j$ . The coefficients of the GARCH model ( $m, s$ ) are:

1.  $\alpha_0 > 0$
2.  $\alpha_i \geq 0$  for  $i=1, 2, \dots, m$
3.  $\beta_j \geq 0$  for  $j=1, 2, \dots, s$
4.  $\sum_{i=1}^{\max(m, s)} (\alpha_i + \beta_j) < 1$

To estimate GARCH model parameter we can use the Maximum Likelihood method. As an illustration, if we have the following GARCH(1,1) model (Cryer, 2008)

$$\sigma_t^2 = a_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

with the density probability function of :  $f(a_t | a_{t-1}, \dots, a_1) = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp[-\frac{a_t^2}{2\sigma_t^2}]$

and the combined function of the density opportunities of:

$$f(a_m, \dots, a_1) = f(a_{m-1}, \dots, a_1) f(a_m | a_{m-1}, \dots, a_1)$$

Then the likelihood function is as follows:

$$L(a_0, \alpha_1, \beta_1) = -\frac{n}{2} \log(2\pi) - \frac{1}{2} \sum_{i=1}^n \left\{ \log(\sigma_{t-1}^2) + \frac{a_t^2}{\sigma_t^2} \right\}$$

These estimates are completed numerically (Newton-Rapshon's method), because the likelihood function is not closed form for parameters  $a_0, \alpha_1$  and  $\beta_1$  and the residual homogeneity test uses the Lagrange Multiplier test.

### 2.2.3. Selecting The Best Model

If the diagnostic test indicates several models that are worthy of use, it is necessary to choose the best model. The best model selection is done by the AIC (Akaike Information Criterion) method with the following formula (Wei, 1989):

$$AIC = N \ln(\hat{\sigma}_a^2) + 2M$$

where:  $N$  : number of observations in the parameter estimation process

$\hat{\sigma}_a^2$  : maximum likelihood estimator of  $\sigma_a^2$

M : number of parameters expected in the model

The best model is that with the smallest AIC value.

### 2.3. Tau-Kendall

The most commonly known invariant scale size of the combined distribution is Tau-Kendall which measures the shape of the dependencies referred to as concordants. Suppose that P states a concordant size and Q states a discordant size, the Tau-Kendall correlation value can be defined as follows (Nelson, 2006):

$$\tau = \frac{P-Q}{P+Q} = \frac{P-Q}{\binom{n}{2}}$$

where n is the sample size.

Tau Kendall Correlation Hypothesis testing is:

H<sub>0</sub> :  $\tau = 0$  (no correlation between variables)

H<sub>1</sub> :  $\tau \neq 0$  (there is a correlation between variables)

Test Statistics:

$$Z_{hit} = \sqrt{\frac{9n(n-1)}{2(2n+5)}} |\tau|$$

Test Criteria: H<sub>0</sub> is rejected if  $Z_{hit} > Z_{\alpha/2}$  or  $p\text{-value} < \alpha$

### 2.4. Copula

Copula is a tool to model shared distributions because it does not require multivariate normal assumptions (Paralo and Hotta, 2006). Copula is described as a function that encompasses various forms of marginal distribution into a combined form of distribution (Sklar, 1959).

#### 2.4.1. Sklar's theorem

Sklar's theorem (1959) explains that the combined distribution of H can be separated into its marginal distribution function  $F_i$ ,  $i = 1, 2, \dots, d$  which is commonly called margins and its dependency structure, namely the Copula C function which satisfies :

$$H(x_1, \dots, x_d) = C(F_1(x_1), \dots, F_d(x_d))$$

The Sklar Theorem points out that the combined distribution function, marginal distribution function and its dependent structure (copula) can be separated. Suppose H is a d-dimensional distribution function, then:

$$C(u_1, \dots, u_d) = H(F_1^{-1}(u_1), \dots, F_d^{-1}(u_d))$$

where  $u_i \in [0,1]$ ,  $u_i = F_d^{-1}(u_d)$ ,  $i = 1, 2, \dots, d$  and  $F^{-1}(t) = \inf\{x \in \mathbb{R} \mid F(x) \geq t\}$  is an inverse function of the marginal distribution of  $F_i$ .

#### 2.4.2. Student-t Copula

$C_{v,\rho}^t$  is the copula of the standard t-student distribution of the d-dimension formed from free degrees  $v > 0$  and the correlation matrix  $\rho$ . It is the distribution of random vectors  $(t_v(X_1), \dots, t_v(X_d))$ . Suppose X is a random vector that has a distribution of  $X \sim t_d(v, 0, \rho)$  the t-copula function is a single function of the random vector X which is defined as follows (Bob, 2013):

$$C_{v,\rho}^t = P(t_v(X_1) \leq u_1, \dots, t_v(X_d) \leq u_d) = t_{v,\rho}^d(t_v^{-1}(u_1), \dots, t_v^{-1}(u_d))$$

where  $t_v$  is the t-student univariate distribution function and  $t_{v,\rho}$  is the combined distribution function of the random vector  $\mathbf{X} \sim t_d(v, 0, \rho)$ .

*Student-t* Copula is one type of copula that uses the t-student distribution. The t-student copula form using the bivariate student distribution is written as follows:

$$C_{v,\rho}^t = t_{v,\rho}^2(t_v^{-1}(u_1), t_v^{-1}(u_2))$$

#### 2.4.3. Estimation of Copula Parameters with Maximum Likelihood Estimation (MLE)

This study used two variables, so the form of the L likelihood function in the bivariate case is written as follows (Nelson, 2006):

$$L = c_{u_1, u_2} \{F_1(x_1), F_2(x_2)\} f_1(x_1) f_2(x_2)$$

It can be explained as follows:

$$\ln h(x_1, x_2; v, \rho) = \ln c(F_1(x_1; v), F_2(x_2; v), ; \rho) + \ln f_1(x_1; v) + \ln f_2(x_2; v) \quad (a)$$

where the  $\rho$  parameter indicates the overall dependency between two random variables and  $v$  is the degree of freedom from the marginal parameters of the copula. Estimated parameters  $v$  and  $\rho$  are inseparable. The equation (a) is not the closed form so it is completed numerically.

#### 2.5. Value at Risk

VaR is a measuring tool that can calculate the magnitude of the worst losses that may occur by knowing the position of assets, the level of confidence in the occurrence of risk, and the period of asset placement (time horizon) (Jorion, 2006). VaR at the level of confidence  $(1-\alpha)$  in the time period  $t$  days on a single return or portfolio can be calculated with (Ruppert, 2004):

$$VaR_{(1-\alpha)}(t) = W_0 R^* \sqrt{t}$$

where:  $W_0$  : initial investment of portfolio fund

$R^*$  :  $\alpha$ -quantile value of the portfolio return distribution

$T$  : time periode

### 3. RESEARCH METHODS

#### 3.1. Data Sources and Research Variables

This study used secondary data obtained from finance.yahoo.com, in the form of the daily share price of Bank Mandiri (Persero), Tbk (BMRI) and PT. Indofood Sukses Makmur, Tbk (INDF) on 8 October 8 2012 to 8 October 2017.

#### 3.2. Data Analysis Steps

The analysis covers the following steps:

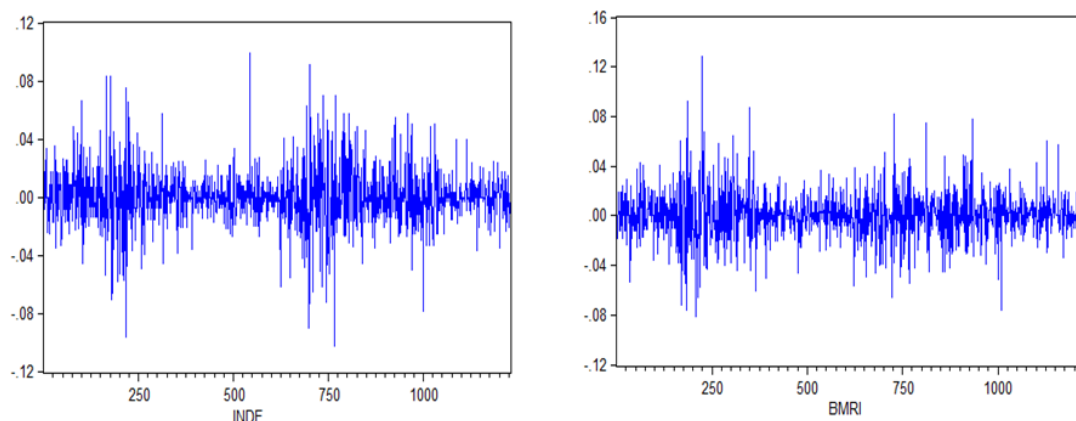
1. Calculating the return of each stock and its characteristics.
2. Conducting the stationarity test of each stock return. If the data is not stationary in the variant, a Box-Cox transformation is performed. Whereas if the data is not stationary in the mean, differentiation is performed.
3. Making ACF and PACF plots of each stock return.

4. Identifying the ARIMA model of each stock return.
5. Estimating the model parameters of each stock return.
6. Testing the significance of the model parameters of each stock return.
7. Verifying the model that is residual independence test, residual homoscedasticity test and residual normality test. If the test is not fulfilled, the ARIMA model cannot be used.
8. Choosing the best model based on the smallest AIC value.
9. Forming the ARIMA-GARCH model if needed.
10. Testing the residual normality model of the ARIMA-GARCH model. If the normality assumption is fulfilled, the ARIMA-GARCH model can be used and the analysis is complete, but if the normality assumption is not met, the t-copula model is used. The process continues in the next step and so on.
11. Testing the Tau Kendall correlation between BMRI shares and INDF shares.
12. Estimating t-copula parameters and forming t-copula.
13. Calculating the Value at Risk (VaR) value using data generation from t-copula with a Monte Carlo simulation.

## 4. RESULTS AND DISCUSSION

### 4.1. Data Characteristics

Data on INDF and BMRI shares for the period of 8 October 2012 - 8 October 2017 was obtained from finance.yahoo.com. The data of each stock return was added with a time series plot as shown in Figure (1).



**Figure 1** Stock Return Plot for INDF dan BMRI

Figure 1 shows that the data is around the average line. This means that the data has been stationary in the average. Augmented Dickey Fuller test for both stock returns obtained the  $P_{\text{value}} = 0,0000$ , indicating that both data are stationary.

Descriptive analysis results for each INDF and BMRI stock returns can be seen in Table 1. Based on Table 1, the two stock returns have a positive average value, meaning that the two stocks will provide benefits for investors. The standard deviation of BMRI is slightly lower than INDF, meaning that INDF has more potential for loss. The highest return value is shown by BMRI with a profit of 0,128121 and the lowest return value is indicated by INDF with a loss of 0,102279. The skewness value of the two shares is not equal to zero and both stock returns have a kurtosis value of more than 3. This insinuates that the data are not normally distributed and it is often found that the value of stock returns is not normally distributed.



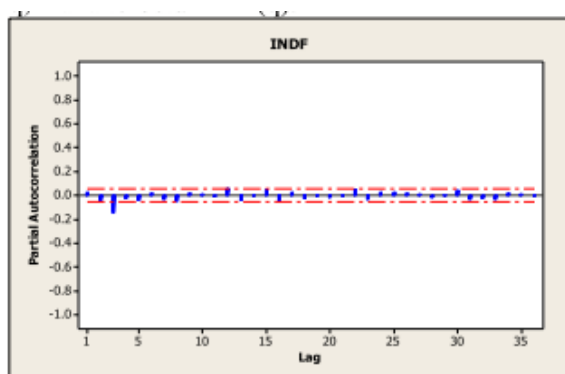
**Table 1** Descriptive Statistics of Stock *Return* of INDF and BMRI

| Variabel              | INDF      | BMRI      |
|-----------------------|-----------|-----------|
| Mean                  | 0.000316  | 0.000398  |
| Standard of Deviation | 0.019795  | 0.019706  |
| Minimum               | -0.102279 | -0.081550 |
| Maximum               | 0.098672  | 0.128121  |
| Skewness              | 0.065573  | 0.297623  |
| Kurtosis              | 6.778511  | 6.614423  |

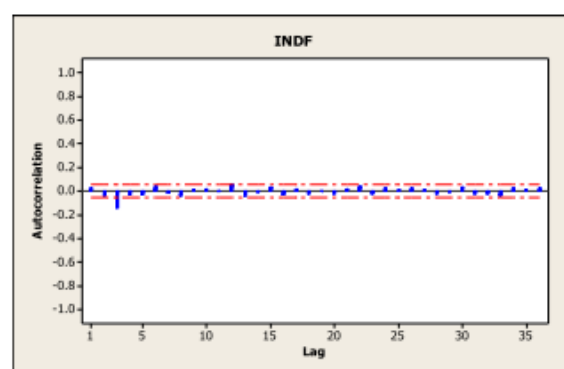
#### 4.2. Model Identification

Data stationarity test is the first step to identify the time series model. In Figure 1, we can see that the two stock returns are stationary in a visual average. The Box-Cox Transformation produces a rounded value for both stock return data of 1, so that the data has been stationary in variants. Based on the Augmented Dickey Fuller test, both of these stock returns have a p value of 0.000 so stationary data is on average. Next, the ARMA model is determined by looking at the ACF and PACF plots of both stock returns (Figure 2 and Figure 3). The AR order is determined by looking at the PACF plot. If it is interrupted in the p-lag, AR (p) is formed. The MA order is determined by looking at the ACF plot. If interrupted in the q-lag, MA (q) is formed.

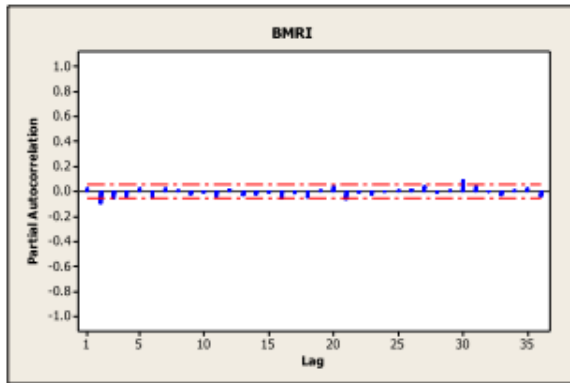
Figure 2 highlights that the INDF stock return for the ACF plot is truncated at lag 3 and the PACF plot is truncated at lag 3. Meanwhile, the ACF of BMRI stock returns based on Figure 3 is truncated in lags 2 and 30 and the PACF plot is truncated at lags 2 and 30. However, in ACF plot lag 3, 20, 21 and in PACF plot lag 3 and 21 are located around the ACF and PACF boundary lines. Thus, these lags need to be incorporated into possible models.



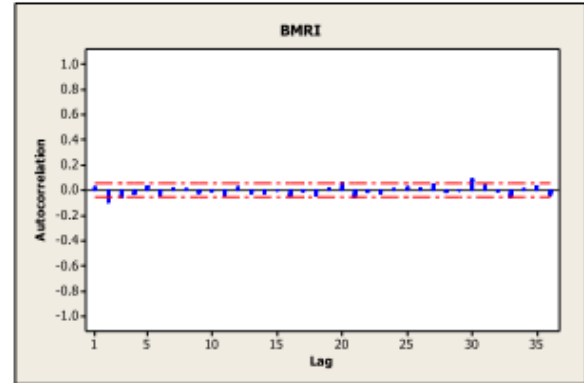
**Figure 2a** PACF Plot of INDF Stock Return



**Figure 2b** ACF Plot of INDF Stock Return



**Figure 3a** PACF Plot of BMRI Stock Return



**Figure 3b** ACF Plot of BMRI Stock Return

After determining the possible models, a model verification test was performed and the best model was selected with the smallest AIC value. Then, it led to the best ARIMA model for the two stock returns:

1. INDF : ARMA([3],0)

$$y_t = -0.144316y_{t-3} + a_t$$

2. BMRI : ARMA([2,3],[30]);

$$y_t = -0.092048y_{t-2} - 0.054822y_{t-3} + a_t - 0.090136a_{t-30}$$

#### 4.3. Lagrange Multiplier Test

Lagrange Multiplier (LM) test aims to see whether the ARIMA model has the GARCH effect or not. The LM Test results for both INDF and BMRI stock returns have p-value = 0.0000 so it can be concluded that all ARIMA models have heterogeneous residuals or have an ARCH / GARCH effect.

#### 4.4. ARIMA-GARCH Modeling

The initial GARCH models formed for INDF stock returns are ARIMA ([3], 0.0) GARCH (1.1) and ARIMA ([3], 0.0) GARCH (1.2). While the BMRI stock returns are ARIMA ([2,3], 0, [30]) GARCH (1,1) and ARIMA ([2,3], 0, [30]) GARCH (1,2). Then the parameter significance test was conducted to choose the best model for each stock, namely:

1. INDF : ARIMA ([3],0,0) GARCH(1,2).

$$y_t = -0.159576y_{t-3} + a_t$$

$$\sigma_t^2 = 0.000012 + 0.123838a_{t-1}^2 + 0.442775\sigma_{t-1}^2 + 0.403667\sigma_{t-2}^2$$

2. BMRI : ARIMA([2,3],0,[30]) GARCH(1,1)

$$y_t = -0.098132y_{t-2} - 0.061610y_{t-3} + a_t - 0.088134a_{t-30}$$

$$\sigma_t^2 = 0.000006 + 0.055129a_{t-1}^2 + 0.928182\sigma_{t-1}^2$$

Then the residual normality test was obtained using the Jarque-Bera test, which produced residuals in the two models that were not normally distributed.

#### 4.5. Student-t Copula

The residuals resulted from the ARIMA-GARCH model of INDF and BMRI shares are determined by the dependency structure using the Tau Kendall correlation. The results of INDF and BMRI stock returns have a correlation of 0.216. Based on the correlation test,

the value of  $Z_{hitung} = 24.40814 > Z_{5\%} = 1.96$ . It can be concluded that the INDF and BMRI stock returns are correlated. Thus, the analysis continued with t-copula. The process began by transforming the ARIMA-GARCH residual data into the form  $U \sim (0,1)$ . The transformation data was used to find the t-copula parameter using maximum likelihood estimation (MLE). The estimated results of the t-copula parameter are:  $\rho = 0.3387$  and  $v = 5.5947$ . The t-copula model for INDF and BMRI shares is:

$$C_{v,\rho}^t = P(t_v(X_1) \leq u_1, \dots, t_v(X_d) \leq u_d) = t_{v,\rho}^d(t_v^{-1}(u_1), \dots, t_v^{-1}(u_d))$$

$$C_{5.5947,0.3387}^t = P(t_{5.5947}(X_1) \leq u_1, t_{5.5947}(X_2) \leq u_2)$$

$$C_{5.5947,0.3387}^t = t_{5.5947,0.3387}^2(t_{5.5947}^{-1}(u_1), t_{5.5947}^{-1}(u_2))$$

#### 4.6. Value at Risk

The estimated VaR will be carried out for the next 1 day at a confidence level of 99%, 95% and 90% by performing a Monte-Carlo simulation with a repetition of 2500 times. The programming using R led to the VaR as presented in Table 2.

**Tabel 2** Value at Risk in the Confidence Level of 99%, 95%, and 90%

| Weight |      | Value at Risk |             |             |
|--------|------|---------------|-------------|-------------|
| BMRI   | INDF | 99%           | 95%         | 90%         |
| 0.9    | 0.1  | -0.04735481   | -0.03016964 | -0.01984257 |
| 0.8    | 0.2  | -0.04493325   | -0.02798011 | -0.01892359 |
| 0.7    | 0.3  | -0.04302594   | -0.02628314 | -0.01817486 |
| 0.6    | 0.4  | -0.04203865   | -0.02509852 | -0.01766649 |
| 0.5    | 0.5  | -0.04184399   | -0.02448757 | -0.01731187 |
| 0.4    | 0.6  | -0.04283844   | -0.02434828 | -0.01723275 |
| 0.3    | 0.7  | -0.04507268   | -0.02466021 | -0.01758310 |
| 0.2    | 0.8  | -0.04812428   | -0.02539512 | -0.01831818 |
| 0.1    | 0.9  | -0.05155981   | -0.02657656 | -0.01936621 |

Table 2 highlights that the best weight for stock investment in BMRI and INDF is of 50% for each because it has the smallest VaR value. In a simple interpretation, if an investor makes an initial investment of IDR 100,000,000, at a significance level of 99%, it will lead to the VaR value of -0.042. Then, within the next 1 day, it is likely to experience a maximum loss of IDR 4,200,000. The 95% confidence level leads to a VaR value of -0.025, and within the next 1 day, it is likely to experience a maximum loss of IDR 2,500,000. Meanwhile, the 90% confidence level results in a VaR value of -0.017, and within the next 1 day, it is likely to experience a maximum loss of IDR 1,700,000.

A research by Dharmawan (2014) on portfolios of the Jakarta Stock Exchange index and Kuala Lumpur Stock Exchange index revealed the VaR t-copula that was better than VaR Gaussian copula. Its free t-copula degree was  $v = 4.3$  with  $\rho = 0.5002$ , but the VaR results were not very good. Ningrum et al. (2017) examining portfolio of shares of PT Vale Indonesia Tbk, PT Bank Central Asia Tbk (BBCA) and PT Indocement Tunggal Perkasa Tbk (INTP), using the Frank copula, Gumbel copula and Clayton copula revealed the VaR portfolio that was best with Gumbel copula, VaR at a 99% with a confidence level of 3.922%, VaR at a 95% with a confidence level of 2.397%, and VaR at a 90% with a confidence level of 1,745%. Whereas Iriani et al. (2013), analyzed a VaR of the Indonesian Telecommunications stock portfolio (TLKM), Gudang Garam (GGRM), Bank Rakyat Indonesia (BBRI) and Astra International (ASII) using Clayton copula and obtained VaR of 0.1472872.

## 5. CONCLUSION

Characteristics of INDF and BMRI stock returns based on the value of the standard deviation indicates that BMRI is slightly lower than INDF, meaning that INDF has the potential to experience greater losses than BMRI. The t-Copula model parameters obtained free degrees of  $\nu = 5.5947$  and  $\rho = 0.3387$ . Value at Risk in the period of 1 day in the future is 0.042 at a confidence level of 90%, 0.025 at a confidence level of 95% and 0.017 at a confidence level of 99% with a weighting of each INDF and BMRI shares at 50%.

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