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RISK ASSESSMENT OF STOCKS PORTFOLIO THROUGH ENSEMBLE ARMA-GARCH AND VALUE AT RISK (CASE STUDY: INDF.JK AND ICBP.JK STOCK PRICE)

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Abstract: Stocks portfolio is a form of investment that can be used to minimize the risk of loss. In a stock portfolio, the Value at Risk (VaR) can be predicted through the portfolio return. If portfolio return variance is heteroskedastic risk prediction can be done by using VaR with ARIMA-GARCH or Ensemble ARIMA-GARCH model approach. Furthermore, the accuracy of VaR is tested through Backtesting test. In this study, the portfolio is formed from PT Indofood CBP Sukses Makmur (ICBP.JK) and PT Indofood Sukses Makmur Tbk (INDF.JK) stocks from 01/01/2018 to 07/30/2021. The results showed that the best model is Ensemble ARMA-GARCH with MSE 1.3231×10-6. At confidence level of 95% and 1 day holding period, the VaR of the Ensemble ARMA-GARCH was -0.0213. Based on the Backtesting test, it is proven to be very accurate to predict the value of loss risk because the value of the Violation Ratio (VR) is equal to 0.

1. INTRODUCTION

Stock investment in the capital market is one form of investment which is greatly sought after by investors because stocks are considered providing greater profits, have high liquidity, and are easy to transact. Basically, besides offering large and relatively fast profits, stock investment also has a risk factor for losses that can occur at any time. This is because in stock trading activities, stock prices often experience fluctuations caused by various factors. Therefore, investors must choose the right stocks that can produce maximum profits with the smallest possible risk value.

One way to minimize the risk is to do diversification. Through the diversion concept, investors are expected to be able to maximize profits and minimize the risk of loss that must be accepted. Diversification is carried out by forming a portfolio consisting of several stocks, in this case the portfolio formed is a portfolio that has a minimum risk. According to Lai (2016), the portfolio chosen by investors from several efficient portfolio choices is called the optimal portfolio. Meanwhile, efficient portfolios are defined by Radovic, Radukic, &

Njegomir (2018) as portfolios that produce a certain level of profit with the lowest risk, or a certain level of risk with the highest level of profit.

The value of the profits and losses of stocks portfolio investments can be seen from the value of the portfolio returns. Therefore, it is important to know the prediction of portfolio return values for future periods. Based on variance values, portfolio returns have two characteristics, namely homoskedastic (portfolio returns have constant variance values), and heteroskedastic (portfolio returns have non constant variance values). For returns with homoskedastic variance, return predictions can be modeled using the ARIMA model (Wabomba, Mutwiri, & Fredrick, 2016). As for returns with heteroskedastic variance, ARIMA-GARCH model or ARIMA-GARCH Ensemble can be utilized to predict the returns (Faulina & Suhartono, 2014).

Prediction of the value of loss risk in the future period for stocks portfolio can be done using a risk measure. The risk measure used in this study is Value-at-Risk (VaR). VaR was chosen because it has several advantages. For instance, it can be used for most of the financial data (including stock price data), and has a good ability to analyze the risks critically through systematic analysis (Zhang, Zhang & Zhao, 2019). VaR is defined as the maximum loss value of an asset in normal market conditions for a certain level of confidence and period of time.

Previous studies related to VaR and ARIMA-GARCH models among others, Siaw, Hene and Evans (2017) constructed predictions of return value on stocks portfolios using the GARCH model, which is considered to be very suitable for predicting return values in future periods because it provides excellent modeling predictions value. Faulina & Suhartono (2014), used the Ensemble ARIMA-ANFIS model to predict rainfall in East Java Province, Indonesia. Kaya and Guloglu (2017) predicted the risk prediction of investment in gold, crude oil and silver commodities using the VaR GARCH model.

In this study, portfolio return predictions and VaR predictions will be performed using ARMA-GARCH and Ensemble ARMA-GARCH. Afterwards, the two models will be compared based on the MSE value to determine the optimum model. The data used in this study is the daily stock price of PT Indofood CBP Sukses Makmur (ICBP.JK) and PT Indofood Sukses Makmur Tbk (INDF.JK) in the period of 01/01/2018 to 30/07/2021.

2. THEORITICAL FRAMEWORK

2.1. Portfolio Investment

Stocks portfolio is defined as a series of combinations of several single stocks that are invested and held by investors, both individuals and institutions. An efficient stocks portfolio is a portfolio that produces a certain level of profit with the lowest risk, or a certain level of risk with the highest level of profit (Husnan, 1998). Most investors tend to avoid risk (risk averse), for example, when investors are faced with two investments with the same expected return and different risks, then they will choose investments with lower risk levels. Suppose that, $P_{1,t}$ and $P_{2,t}$ are stochastic processes which state the price of the first and second stocks in period *t*, the stocks portfolio formed is formulated as:

$$S_t = P_{1,t} + P_{2,t} \tag{1}$$

Then, the portfolio return is obtained as follows:

$$X_t = R_{1,t} + R_{2,t} \tag{2}$$

where X_t is portfolio return of S_t in period *t*. $R_{1,t}$ and $R_{2,t}$ are the returns of P_1 and P_2 in period *t*.

2.2. Minimum Variance Efficient Portfolio (MVEP)

According to Maruddani (2019), MVEP is defined as a portfolio that has a minimum variance among all possible portfolios that can be formed. If the investor's preference for risk is assumed to be risk averse, then a portfolio that has a mean variance efficient (mean variance efficient portfolio) is a portfolio that has a minimum variance of its mean return. This is the same as optimizing weights based on the maximum mean return of the given variance.

More formally, the MVEP method helps to find the weighting vector **w** so that the portfolio formed has a minimum variance based on two constraints, namely:

1. Initial specification of mean return μ_p has to be achieved which is $\mathbf{w}^T\boldsymbol{\mu}$.
2. Proportion number of the formed portfolios is equal to 1 that is $\mathbf{w}^T\mathbf{1}_N = 1$, where $\mathbf{1}_N$ is a vector with dimension of $N \times 1$.

The optimization problem can be solved by the Lagrange function

$$L = \mathbf{w}^T\boldsymbol{\Sigma}\mathbf{w} + \lambda_1\left(\mu_p - \mathbf{w}^T\boldsymbol{\mu}\right) + \lambda_2\left(1 - \mathbf{w}^T\mathbf{1}_N\right) \tag{3}$$

where, L is Lagrange function, and λ = Lagrange multiplier factor.

For the case of portfolios with efficient variance, there is no limitation on the portfolio mean $(\lambda_1 = 0)$, so the weighting of the MVEP with return $X \sim Norm_N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is

$$\mathbf{w} = \frac{\boldsymbol{\Sigma}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}^{-1}\mathbf{1}_N} \tag{4}$$

where $\boldsymbol{\Sigma}^{-1}$ is inverse variance-covariance matrix.

2.3. Time Series Model

Auto Regressive Moving Average (ARMA) models are from statistical models' views. ARMA models are renowned to be strong and efficient in financial statistical model particularly short run prediction. It has been extensively utilized in field of economics and finance. Alternative statistics models are regression methodology, exponential smoothing, Generalized Auto Regressive Conditional Heteroskedasticity (GARCH). Few connected works those has engaged ARMA model for prediction are included. In this project intensive method of building ARIMA models for short run stock value prediction is presented. The results obtained from real life information in contestable the potential strength of ARMA models to produce investors short run prediction that would aid investment process (Khandelwal & Mohanty, 2021).

ARMA is a combination of AR and MA models into a simpler form so that the number of parameters used remains small (Tsay, 2002). For a stochastic process X_t, the general model for the ARMA(*p*,*q*) process can be written as Equation 5

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q}. \tag{5}$$

By using the backshift operator, the ARMA(*p*,*q*) model can be written as follows:

$$\phi_p(B)X_t = \theta_q(B)a_t \tag{6}$$

with $a_t \sim N(0,\sigma^2)$. In addition, the ARMA(p,q) model is formed from stationary AR(p) and invertible MA(q) models.

Autoregressive Integrated Moving Average Model (ARIMA) is the result of combining stationary processes with non-stationary processes that have been made stationary. The general form of the ARIMA(p,d,q) model is (Wei, 2006):

$$\phi_p(B)(1-B)X_t = \theta_q(B)a_t \tag{7}$$

where

$$\phi_p(B) = (1 - \phi_1 B - \cdots - \phi_p B^p) = 1 - \sum_{i=1}^{p} \phi_i B^i$$

$$\theta_q(B) = (1 - \theta_1 B - \cdots - \theta_q B^q) = 1 - \sum_{j=1}^{q} \theta_j B^j$$

$$a_t \sim N(0,\sigma^2).$$

ARIMA estimation model can utilize ACF plots and PACF plots, where the time series must be stationary.

2.4. ARCH/GARCH Model

In general, time series modeling must fulfill the assumption of homoskedasticity (a constant variance). However, financial data such as stock prices, currency rates, inflation rates and others usually show the phenomenon of cluster volatility, which is a period in which their prices show alternating changes for a long period followed by period indicating a stable state. The situation that previously mentioned can cause variance data not constant (heteroskedasticity). To overcome this heteroskedasticity problem, the ARCH and GARCH models are used (Rosadi, 2012).

ARCH (Auto Regressive Conditional Heteroskedasticity) Model

The ARCH model was firstly used to model the residual data volatility, introduced by Engle (1982). The ARCH model assumes that the residual variance at one time point is a function of the residual at another time point. According to Tsay (2002), the general form of the ARCH(p) model are:

$$a_t = \sigma_t \varepsilon_t \tag{8}$$

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_p a_{t-p}^2 \tag{9}$$

where $\varepsilon_t \sim N(0,1), \alpha_0 > 0,$ and $\alpha_i \geq 0 (i = 1,2, \ldots, p)$.

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) Model

Bollerslev (1986) developed the ARCH model into a more general model known as GARCH. This model is used to overcome too large order in ARCH model. In GARCH model, conditional variance are not only influenced by past residuals but by the lag of conditional variance themselves (Ariefianto, 2012). Thus, the conditional variance in GARCH model consists of two components, namely the past component of the squared residual (denoted by degree q) and the past component of the conditional variance (denoted by degree p). Mathematically the GARCH model (p, q) can be made in the following form:

$$a_t = \sigma_t \varepsilon_t \tag{10}$$

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i\, a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{11}$$

where $\varepsilon_t \sim N(0,1), \alpha_0 > 0$, and $\alpha_i, \beta_j \geq 0 (i = 1,2, \ldots, p; j = 1,2, \ldots, q)$, $0 < (\alpha_i + \beta_j) < 1$.

2.5. Ensemble ARIMA-GARCH

Time series prediction using combination method is a prediction technique that works by combining the output values of several prediction models as a predictive value (Zaier, Shu, Ouarda, Seidou, & Chebana, 2010). The form of the Ensemble ARIMA-GARCH model is firstly done by determining the single ARIMA-GARCH model. The selection of models is generally based on the results of model verification/significance test parameters. Afterwards, each model will obtain $\widehat{X}_t$ and $\widehat{\sigma}_t^2$. The next process is to combine each of $\widehat{X}_t$ and $\widehat{\sigma}_t^2$ using averaging approach. Suppose N is the number of single ARIMA-GARCH models, the predicted values of Ensemble ARIMA-GARCH model are:

$$f(\hat{X}_t) = \frac{1}{N} \sum_{i=1}^{N} \hat{X}_t{}^{(i)}, i = 1,2, \ldots, N \tag{12}$$

and

$$f(\hat{\sigma}_t{}^2) = \frac{1}{N} \sum_{i=1}^{N} \hat{\sigma}_t{}^{2,(i)}, i = 1,2, \ldots, N. \tag{13}$$

2.6. Optimum Method Selection and Evaluation

AIC (Akaike's Information Criterion) can be used to determine the optimum model selection. The optimum model is the model that has the smallest AIC value among other models. The formula to obtain the AIC value is as follows (Rosadi, 2012):

$$AIC = n \ \ln \left(\frac{SSR}{n} \right) + 2k, \tag{14}$$

where, n is the sample size, k is the number of parameter model, and $SSR = \sum_{i=1}^{n} \varepsilon_i{}^2$.

The accuracy of a model in predicting time series data can be evaluated using Mean Square Error (MSE). The MSE formula is defined as follows (Ghani & Rahim, 2019):

$$MSE = \frac{1}{T - T_1} \sum_{t=T_1}^{T} \left(X_t - \widehat{X}_t \right)^2 \tag{15}$$

where T is the total observation, T_1 is the first observation on the out-sample data, and $\hat{X}_t$ is the predicted value. The smaller the MSE, the better the model is used for prediction.

2.7. Value at Risk (VaR) in Stocks Portfolio

Value at Risk (VaR) is a measure of risk that is often used in finance. VaR is defined as the maximum possible value of loss over a certain period of time with a specified level of confidence. Suppose that X_t is a stochastic process which states the value of portfolio returns at period t and X_t follows a certain distribution. The VaR at time (t+1) with confidence level α can be expressed as quantile $(1-\alpha)$ from the $X_{t+1}|X_t$ distribution. VaR equation with the confidence level α is (Jadhav, Ramanathan & Naik-Nimbakar, 2009):

$$VaR_\alpha(X_t) = -\inf\{x \in \mathbf{R} | F_{X_{t+1}|X_t}(x) \geq (1-\alpha)\} \quad (16)$$

It has been said that the VaR value is the quantile value of the distribution of risk values. Therefore, VaR for continuous distribution losses can be expressed as

$$VaR_\alpha(X_t) = E[X_{t+1}|X_t] + z_{1-\alpha}\sqrt{E[X_{t+1}^2|X_t] - \left(E[X_{t+1}^2|X_t]^2\right)} \quad (17)$$

$$VaR_\alpha(X_t) = \mu_{X_{t+1}|X_t} + z_{1-\alpha}\sigma_{X_{t+1}|X_t} \quad (18)$$

where $z_{1-\alpha}$ is quantile $(1-\alpha)$ from the standard Normal distribution.

2.8. Backtesting Test

According to Danielsson (2011), backtesting test is a procedure of testing the accuracy of the VaR. Backtesting is done by taking the value of the VaR then comparing it to the actual portfolio return. If the actual return for a certain period is lower than the VaR in the same period, a violation is said to occur. Hence, measuring the quality of VaR forecasting can be done by comparing the number of violations that occur with the number of violations expected or what is more commonly referred to as the Violation Ratio (VR). The VR is calculated by comparing the number of violations v_1 with the expected number of violations. The VR formula is given by following equation:

$$VR = \frac{v_1}{m_0 \times K_u} \quad (19)$$

m_0 is the probability of a suspected violation, and K_u is the length of the test window. If the value of VR = 1, then the number of violations that occur is the same as the expected number of violations (VaR calculation method gives the right risk estimation results). If VR > 1, the violations that occur are greater than the expected number of violations. Meanwhile, VR < 1 indicates that the violations that occurred are fewer than the expected number of violations.

3. MATERIAL AND METHOD

3.1. Data Source

The data used in this study is the return data from the closing price of two stocks listed on Indonesia Stock Exchange (IDX) in plantations and food sector. Those two stocks are PT Indofood CBP Sukses Makmur Tbk (ICBP.JK) and PT Indofood Sukses Makmur Tbk (INDF.JK) for the period of 01/01/2018 to 30/07/ 2021. There are 901 data returns divided into two groups. The first group is in-sample data (881 data), the second group is out-sample data (20 data). Data was obtained from https://finance.yahoo.com/.

3.2. Method of Analysis

The steps taken for data analysis were as follows: (1) The value of stock returns was calculated. (2) The weight of the stocks portfolio was calculated using the MVEP method. (3) The stocks portfolio returns were calculated. (4) The stocks portfolio data were divided into in-sample and out-sample data. (5) Stationarity test in the mean for in-sample data was carried out. (6) The ARIMA model was formed through ACF and PACF plots. (7) The

ARIMA model was verified. (8) The effect of GARCH on the ARIMA model through the Lagrange Multiplier test was identified. (9) The ARIMA-GARCH model was formed. (10) Optimum ARIMA-GARCH model was chosen by comparing the AIC value. (11) The Ensemble ARIMA-GARCH model was formed. (13) The model was evaluated through MSE values. (14) Predicted VaR for the optimum model.

4. RESULTS AND DISCUSSION

In the prediction of return and VaR for stocks portfolio, the first step begins with a time series plot and descriptive statistics from a single stock data. The objective of this is to know the characteristics of the data that will be used to form a stock portfolio, in addition to also see whether there are outliers in the data that will be used to form a stocks portfolio. The time series plot for ICBP.JK and INDF.JK stocks price data is presented as Figure 1.

Based on Figure 1, it can be seen that during the period of 1/01/2018 to 30/07/2021, the movement of ICBP.JK and INDF.JK have a tendency to fluctuate. This condition can be an indication that there is positive correlation. With pearson corellation test, the correlation formed between ICBP.JK and INDF.JK was 0.6879. In stocks portfolios, portfolio return is obtained from the aggregation between ICBP.JK and INDF.JK return. Figure 2 is a time series plot for ICBP and INDF returns.

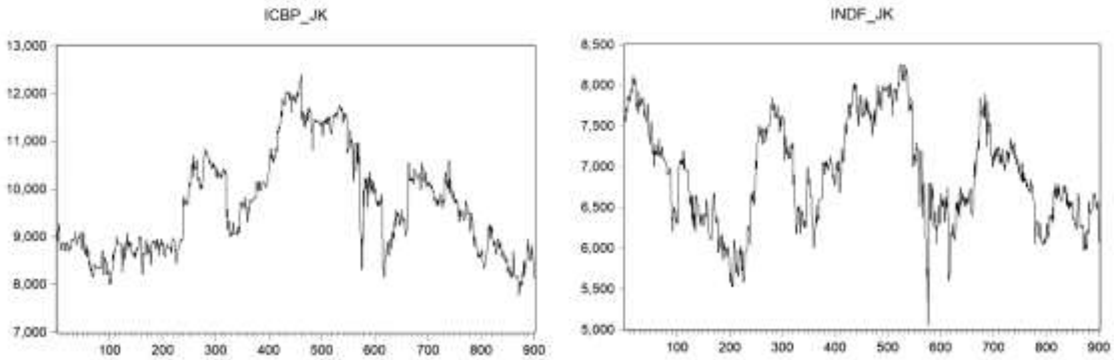

Figure 1. Time Series Plot of ICBP.JK and INDF.JK Stocks Price

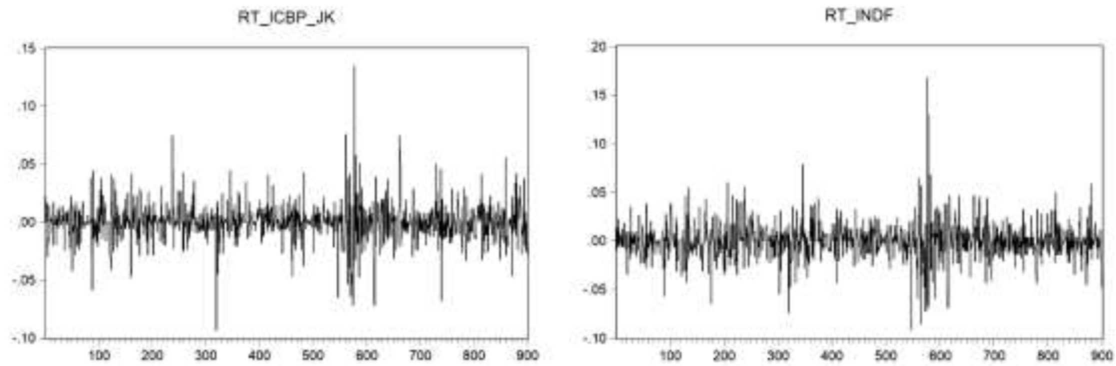

Figure 2. Time Series Plot of ICBP.JK and INDF.JK Returns

Figure 2 shows that there are no outliers visually in ICBP and INDF return data, other than that, the data has a tendency to be stationary because its value spreads around the mean. One method that can be used to form an optimum portfolio weight is the MVEP method.

The weighting results using the MVEP method for ICBP.JK and INDF.JK are 0.4882 and 0.5118 respectively. In other words, the proportion of investment in the portfolio to obtain the maximum profit is 48.82% invested in ICBP, and the remaining 51.18% is invested in INDF. Figure 3 is a time series plot of the portfolio return.

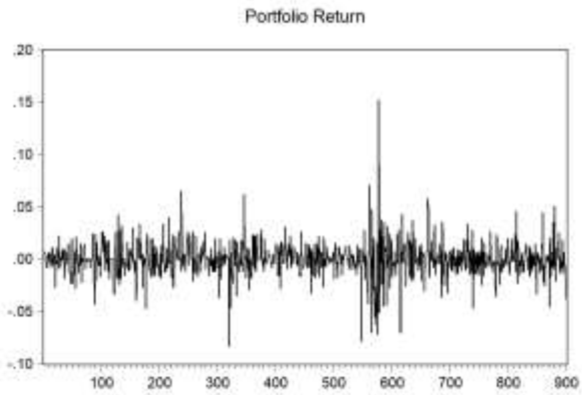

Figure 3. Time Series Plot of the Portfolio Return

The portfolio return plot shows that the data tend to be stationary in mean, because throughout the observation period the data distribution was around the mean value. Formally, data stationarity is tested through the ADF-test, the ADF-test results are presented on Table 1.

Table 1. Stationary Test in Mean for Portfolio Return

ADF Value	Significance Level	p-value	Decision
-23.6448	5%	0.0000	Data is stationary in mean

Referring to Table 1, H_0 for the ADF-test is rejected, this means that the portfolio returns are stationary in mean. Based on ACF and PACF plots for portfolio return data, the possible ARMA models formed are ARMA(1,0), ARMA (2,0), ARMA(0,1), ARMA(1,1) and ARMA (2,1). Table 2 shows the estimated parameter values for the three models.

Table 2. Estimated Parameter of ARMA Model

Models	Parameters	Estimates	Prob
ARMA (1,0)	ϕ_1	0.00229	0.8858
ARMA (2,0)	ϕ_1	0.00224	0.8922
	ϕ_2	-0.11547	0.0000
ARMA (0,1)	θ_1	0.00300	0.8521
ARMA (1,1)	ϕ_1	-0.68960	0.0000
	θ_1	0.75143	0.0000
ARMA (2,1)	ϕ_1	-0.54121	0.0002
	ϕ_2	-0.10112	0.0000
	θ_1	0.55181	0.0004

The parameter estimation of ARIMA model resulting that the parameters in ARMA(1,1) and ARMA(2,1) models are significant at the level α = 5%. Meanwhile, for the ARMA(1,0), ARMA(2,0) and ARMA(0,1) model the parameters formed are not significant, because the Prob value for each parameter is greater than α = 5%. Therefore, the models that meet the model verification are ARMA(1,1) and ARMA(2,1).

Furthermore, for each model that passes the model verification, a residual assumption test will be conducted which includes tests of normality, independence, and homoskedasticity test.

Table 3. Residual tests for ARMA models

Models	Residual Test		
	Normality	Independency	Homoskedasticity
ARMA (1,1)	×	✓	×
ARMA (2,1)	×	✓	×

The results of the model residual test shown in Table 3 conclude that the assumptions of normality and homoskedasticity are not fulfilled. The only assumption fulfilled is the residual independence assumption. The unfulfilled homoscedasticity assumption indicates that the residual variance of each model is not constant. Therefore, it needs to be modeled with the ARCH/GARCH model. Based on the model verification for ARCH/GARCH model through the signification test parameter, at the significance level α = 5%, it was found that there were 11 models that passed the verification, those are ARMA(1,1)-ARCH(1), ARMA(1,1)-GARCH(1,1), ARMA(1,1)-GARCH(1,2), ARMA(1,1)-GARCH(2,2), and ARMA(2,1)-ARCH(2).

The optimum model for portfolio returns prediction is chosen based on the AIC value, provided that the optimum model is the model with the smallest AIC value. The AIC value for each model can be seen in Table 4.

Table 4. Evaluation of ARIMA-GARCH Model

Models	AIC
ARMA(1,1)-ARCH(1)	-5.4051
ARMA(1,1)-GARCH(1,1)	-5.4549
ARMA(1,1)-GARCH(1,2)	-5.4625
ARMA(1,1)- GARCH(2,2)	-5.4684
ARMA(1,2)- ARCH(2)	-5.4560

It is known that the optimum model is ARMA(1,1)- GARCH(2,2) because it has the smallest AIC of -5.604. Representations of the ARMA(1,1)- GARCH(2,2) model are as follows:

$$\hat{X}_t = 0.6399\,\phi_1 + a_t - 0.7312 a_{t-1} \tag{20}$$

$$\hat{\sigma}_t^2 = 3.08 \times 10^{-6} + 0.2070 a_{t-1}^2 - 0.1975 a_{t-2}^2 + 1.350 \sigma_{t-1}^2 - 0.3704 \sigma_{t-2}^2 \tag{21}$$

For every ARMA-GARCH models that are signed, the Ensemble ARMA-GARCH Ensemble model can be formed. The ARIMA-GARCH Ensemble model formula for mean prediction can be written as Equation 22.

$$f(\hat{X}_t) = \frac{1}{5}\sum_{i=1}^{5} \hat{X}_t^{(i)} \tag{22}$$

Whereas the Ensemble ARMA-GARCH for variance prediction is formulated by Equation 23.

$$f(\hat{\sigma}_t) = \frac{1}{5}\sum_{i=1}^{5} \sigma_t^{(i)}. \tag{23}$$

The results of portfolio return prediction and its variance values using the ARMA(1,1)-GARCH(2,2) and Ensemble ARMA-GARCH models are shown in Table 5.

Table 5. Portfolio Return Prediction

Date	ARMA(1,1)- GARCH(2,2)		Ensemble ARMA-GARCH	
	$\hat{X}_t$	$\hat{\sigma}_t^2$	$\hat{X}_t$	$\hat{\sigma}_t^2$
02/07/2021	-0.005370	0.000778	-0.005430	0.000691
05/07/2021	-0.003709	0.000419	-0.003769	0.000332
06/07/2021	-0.000743	0.000345	-0.000803	0.000258
07/07/2021	-0.001483	0.000276	-0.001543	0.000189
08/07/2021	-0.001349	0.000227	-0.001409	0.000140
09/07/2021	-0.000936	0.000204	-0.000996	0.000117
12/07/2021	-0.001440	0.000212	-0.001500	0.000125
13/07/2021	-0.003359	0.000344	-0.003419	0.000257
14/07/2021	-0.003261	0.000279	-0.003321	0.000192
15/07/2021	-0.001121	0.000246	-0.001181	0.000159
16/07/2021	-0.001043	0.000213	-0.001103	0.000126
19/07/2021	0.000106	0.000212	0.000046	0.000125
21/07/2021	0.000293	0.000197	0.000233	0.000110
22/07/2021	0.001102	0.000210	0.001042	0.000123
23/07/2021	-0.000868	0.000255	-0.000928	0.000168
26/07/2021	0.000618	0.000245	0.000558	0.000158
27/07/2021	-0.000113	0.000214	-0.000173	0.000127
28/07/2021	0.000546	0.000204	0.000486	0.000117
29/07/2021	0.000936	0.000199	0.000876	0.000112
30/07/2021	0.002387	0.000267	0.002327	0.000180

Accuracy is an important element in the prediction of time series data, a good prediction model should have high degree of accuracy. The higher the accuracy of a model, the closer the predicted value to the actual value. In this study, prediction accuracy was measured using MSE values. MSE values are presented in Table 6.

Table 6. Comparison of MSE Value

Model	MSE
ARMA(1,1)-GARCH(2,2)	1.9282×10^{-6}
Ensemble ARMA-GARCH	1.3231×10^{-6}

Based on Table 6, models with smallest MSE value is Ensemble ARMA-GARCH. Accordingly, this model is the optimum model to predict portfolio return.

Basically, stocks portfolio investment still contains an element of risk of loss, so it is important for investors to know the estimated risk of loss in the coming period. Predicted losses using the VaR method with 95% of confidence level in the stock portfolio are presented in Table 7.

Table 7. Stock Portfolio Risk Prediction Using VaR

Date	$\widehat{VaR}_{95\%}$	Date	$\widehat{VaR}_{95\%}$
02/07/2021	-0.0197	16/07/2021	-0.0268
05/07/2021	-0.0202	19/07/2021	-0.0239
06/07/2021	-0.0193	21/07/2021	-0.0241
07/07/2021	-0.0179	22/07/2021	-0.0225
08/07/2021	-0.0188	23/07/2021	-0.0207
09/07/2021	-0.0177	26/07/2021	-0.0237
12/07/2021	-0.0208	27/07/2021	-0.0218
13/07/2021	-0.0244	28/07/2021	-0.0201
14/07/2021	-0.0177	29/07/2021	-0.0219
15/07/2021	-0.0246	30/07/2021	-0.0213

Backtesting procedure was used to test the accuracy of VaR in predicting the risk of loss. Through the procedure, violation ratio (VR) obtained is equal to 0. It can be concluded that in VaR calculation period (02/07/2021 to 30/07/2021) there was no actual loss value that was greater than the predicted VaR value. So, it can be said that VaR has very good accuracy in predicting the risk of loss for stock portfolio.

4. CONCLUSION

Based on the analysis results and discussion, it is concluded that the optimum investment weight in the stocks portfolio are 48.82% of investment funds is allocated for investment in ICBP.JK stock, and the remaining 51.18% is allocated for INDF.JK stock. The optimum model that can be used to predict the value of portfolio returns is Ensemble ARMA-GARCH model with MSE is 1.3231 × 10-6. By using VaR, the prediction of loss risk for the period of 30/07/2021 with confidence level α = 95% is -0.0213. Through the backtesting procedure, VaR is proven to have very good accuracy in predicting risk, this is proved by the value of the violation ratio (VR) obtained which is equal to 0.

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REFERENCES

Ariefianto, D. M. (2012). *Econometrics Essence and Applications with EViews*. Jakarta: PT. Gelora Aksara Pratama.

Bollerslev. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31, 307-327. doi: 10.1016/0304-4076(86)90063-1

Daniel, W. W. (1989). *Applied Nonparametric Statistics*. Subtitles by Alex Tri Kantjono Widodo. Jakarta: Gramedia.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Ination. *Journal of Econometrica*, 50(4), 987-1008. doi: 10.2307/1912773

Faulina, R., & Suhartono (2013). Hybrid ARIMA-ANFIS for Rainfall Prediction in Indonesia. *International Journal of Science and Research (IJSR)*, 2(2), 159-162. doi: 10.31219/osf.io/vw8rx

Ghani, I. M. Md, & Rahim, H.A. (2019). Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices. *IOP Conf. Ser.: Mater. Sci. Eng*. 548012023. doi: 10.1088/1757-899X/548/1/012023

Husnan, S. (1998). *Elementary Portfolio Theory and Security Analysis. Second Edition.* Yogyakarta: UPP-AMP YKPN.

Jadhav, D., Ramanathan, T.V., & Naik-Nimbakar, U.V. (2009). Modified Estimators of the Expected Shortfall. *Journal of Emerging Market Finance*, 8(2) : 87-107. doi: 10.1177/097265270900800201

Kaya, P., & Guloglu, B. (2017). Modeling and Forecasting the Markets Volatility and VaR Dynamics of Commodity. *Journal of BRSA Banking and Financial Markets*, 11(1), 9-49.

Lai, K. (2016). Selecting an Optimal Portfolio for Investment in Stocks in India: A Sectoral Approach. *Pacific Business Review International*, 8(9).

Maruddani, D.A.I. (2019). *Value at Risk for Risk Measures on Stock Investment*. Ponorogo: Wade Group.

Radovic, M., Radukic, S., & Njegomir, V. (2018). The Application of the Markowitzs Model in Efficient Portfolio Forming on the Capital Market in the Republic of Serbia. *Economic Themes*, 56(1), 17-34. doi: 10.2478/ethemes-2018-0002

Rosadi, D. (2012). *Econometrics and Applied Time Series with EViews*. Yogyakarta: Andi Offset.

Siaw, R.O., Hene, E.D.O., & Evans, T. (2017). Investment Portfolio Optimization with GARCH. *ELK Asia Pacific Journal of Finance and Risk Management*, 8(2). doi: 10.16962/EAPJFRM/issn. 2349-2325/2015

Tsay, R. S. (2002). *Analysis of Financial Time Series*. New York: John Willey and Sons, Inc.

Wei, W.W.S. (2006). *Time Series Analysis, Univariate and Multivariat Methods*. Canada: Addison Wesley Publishing Combany.

Wabomba, M.S., Mutwiri, M.P., & Fredrick, M. (2016). Modelling and Forecasting Kenyan GDP Using Autoregressive Integrated Moving Average (ARIMA) Models. *Science Journal of Applied Mathematics and Statistics*. 4(2), 64-73. doi: 10.11648/j.sjams.20160402.18

Zaier, I., Shu, C., Ouarda, T., Seidou, O., & Chebana, F. (2010). Estimation of ice thickness on lakes using artificial neural network ensembles. *Journal of Hydrology*, 383, 330-340. doi: 10.1016/j.jhydrol.2010.01.006

Zhang, W., Zhang, S., & Zhao, P. (2019). On Double Value at Risk. *Journal of Risk*. 7(31) doi: 10.3390/risks7010031