Available online at http://scik.org
J. Math. Comput. Sci. 11 (2021), No. 2, 2136-2152
https://doi.org/10.28919/jmcs/5453
ISSN: 1927-5307

ARMA-GARCH MODEL FOR VALUE-AT-RISK (VaR) PREDICTION ON STOCKS OF PT. ASTRA AGRO LESTARI.Tbk

TARNO[1,*], DI ASIH I MARUDDANI[1], RITA RAHMAWATI[1], ABDUL HOYYI[1], TRIMONO[1], MUNAWAR[2,3]

[1]Statistics Department, Faculty of Science and Mathematics, Universitas Diponegoro, Jalan Prof. Soedarto S.H. Semarang 50275 Indonesia

[2]Faculty of Mathematics and Science, Syiah Kuala University, Jl. Syech Abd.Rauf, Kopelma Darussalam, Banda Aceh, Aceh 23111, Indonesia

[3]Faculty of Science and Technology, Prince of Songkla University, Pattani Campus, Muang Pattani, 94000 Thailand

Abstract: PT. Astra Agro Lestari Tbk (AALI) is one of the plantation companies with the largest market capitalization in Indonesia. AALI stocks traded on the stock exchange have fairly fluctuating value and volatility of stock returns are not constant (heteroskedastic). One of the risk measurements that can be used to predict the risk of stock investing is Value-at-Risk (VaR). In conditions that are heteroskedastic stock returns, risk prediction can be done with the VaR ARCH/GARCH and VaR ARCH/GARCH combination model. Empirical studies were carried out on AALI stocks for the period of August 2, 2012 until October 1, 2019. The results obtained showed that the best model was ARIMA (0,0,1)-GARCH (1,2) with AIC value of -4.9793 and MSE of 0.00005. At the 95% trust level, the VaR ARCH/ARCH value was -0.3464.

Keywords: stock price; return; heteroscedastic; VaR ARCH / GARCH.

2010 AMS Subject Classification: 62M10, 62P20.

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*Corresponding author
E-mail address: tarno@lecturer.undip.ac.id
Received January 19, 2021

1. INTRODUCTION

In stock asset investments, volatility is associated with the uncertainty of value of stock returns that investors will obtain. Mathematically, volatility is defined as the standard conditional deviation of stock returns (Tsay [11]). The volatility characteristics are strongly influenced by the variance characteristics of stock returns. Generally, there are two characteristics of the variance, the first one is homoskedastic (constant variance), and the second one is heteroskedastic (variance change with time). To properly model the volatility, it is important to understand the variance characteristics of the data return.

To modelling the variance that is not constant, Engle [3] introduced a model named ARCH (Autoregressive Conditional Heteroskedasticity). The ARCH model models the conditional variance by going back to the previous value of the mean model residual value. In 1986, ARCH models were developed further by Bollerslev [2] who presented a Generalized-ARCH Generalized (GARCH) model, where the variance value was modeled not only based on the residual value in the previous period, but also based on the variance of the previous period.

The ARCH/GARCH model has proven to be successful in modeling heteroskedastic variance and are widely used in financial activities for risk analysis also in subsequent decision-making guidance. Zhang et al. [15] introduced the ensemble/combination to the ANN model, which in turn ensemble/combination model can also be applied to the ARCH/GARCH model. In risk management, volatility models are generally used to predict the level of risk from return and the amount of return which might be obtained at a specific time period Engle [4]. A measurement of risk that is often applied in risk management practices is Value at Risk (VaR). Value at Risk is defined as the possibility of the maximum loss risk value that can still be borne by an investor at a certain level of trust and time period (McNeil, Frey, and Embrechts [6]). The VaR idea emerged in an effort to find a better measure of risk after the big financial crisis which caused several banks to go bankrupt, which led to discussion and skepticism about the existing market risk practices.

There have been many studies that examine the risk prediction of stock return with non-constant variance. Sun [10] applied the ensemble ARIMA-GARCH model to predict and model stock returns on several equities in the US capital market. Furthermore, Smolovic, Bozovic, and Vujoevi [9] predicted the value of loss risk in the Montenegro stock market using the VaR ARIMA-GARCH model. In this study, the ARIMA-GARCH and ensemble ARIMA-GARCH model was examined and compared to predict the return value on the daily stock price of PT. Astra Agro Lestari, Tbk (AALI) for the period of 3 October 2012 to 1 October 2019. The selection of the best model was based on the criteria of AIC and MSE values. Furthermore, the two models would also be used to predict VaR value. Based on the VaR value, information can be obtained regarding the maximum loss that might occur.

2. THEORETICAL FRAMEWORK

This section will examine theoretical overview of the time series model used in the time series data analysis.

Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Model (AR) is a model with the prediction of the current period value obtained from the regression results of the values of the previous period. In other words, the value of future period is a function of the values of previous periods. For example, $\{X_t\}$ is a stochastic process that states return in period *t*. The AR (*p*) model has the following representations (Wei [13]):

$$X_t = \sum_{i=1}^{p} \emptyset i X_{t-i} + \varepsilon_t \tag{1}$$

where ε_t residuals are white noise with mean 0 and variance σ_a^2, p is a nonnegative integer number that represents the amount of time lag in the AR model, and $X_{t-i}, i = 1.2, .. p$ is the period return value $t - i$.

According to Wei [13], the Moving Average (MA) model also works by regressing values in the previous period to obtain predictive value in the current period. In the MA model, the regressed value is the residual value for the previous period, plus the residual value of the current period. The formula for the MA (q) model is:

$$X_t = \sum_{j=1}^{q} \theta_j \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

Similar to the AR model, ε_t residuals are white noise with mean 0 and variance σ_a^2, and q is a nonnegative integer number that specifies the number of lag time in the MA model.

The development of the ARMA model as a prediction method for financial instrument variables was introduced by Box-Jenkins in 1976. This method works to find the most suitable model for predicting variable values in the future. The ARMA model is a combination of the AR and MA models which assumes volatility is constant and does not change with time or it can be said that this model is homoskedastic. The ARMA model (p; q) is defined as

$$X_t = \emptyset_1 X_{t-1} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

For the case of non-stationary data, the differencing process (d) is carried out to make the data stationary. The modeling process in this case is done using the ARIMA model which equation is

$$\emptyset_p(B)(1-B)^d X_t = \theta_0 + \theta_q(B)\varepsilon_t \tag{4}$$

where

$$\emptyset_p(B) = \left(1 - \emptyset_1 B - \cdots - \emptyset_p B^p\right) \text{ and } \theta_q = (1 - \theta_1 B - \cdots - \theta_q B^q)$$

ARCH/GARCH Model

Not all time series data are homoskedastic, therefore, Engle [3] introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model. ARCH(p) model is a model stating that the value of volatility for a time depends on the p value of previous observations. The ARCH(p) model has the following representations:

$$\begin{gathered} \varepsilon_t = \sigma_t \varphi_t \\ \sigma_t^2 = \varepsilon_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \end{gathered} \tag{5}$$

In Generalized-ARCH (GARCH) model, there is a generalization of the ARCH model to model heteroskedastic volatility, the GARCH model equation is as follows:

$$\sigma_t^2 = \varepsilon_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \tag{6}$$

assuming that innovation φ_t have normal standard distribution.

Ensemble ARIMA-GARCH Model

Time series data prediction using combination method is a prediction technique that works by combining the output values of several prediction models as a predictive value (Zaier et al [14]). The formation of the ensemble ARIMA-GARCH model can be done by determining the members of the combination first. Each combination model will return $\hat{X}_t$. The next process is to combine each $\hat{X}_t$ value using the averaging approach. In the averaging approach, for each member of the combination obtained, the average value is calculated. Suppose N is the number of individual members of the ARMA-GARCH, thus, the predicted value of the ensemble ARIMA-GARCH model is:

$$f(\hat{X}_t) = \frac{1}{N}\sum_{i=1}^{N}\hat{X}_t^{(i)} \quad i = 1,2, \dots N \tag{7}$$

Implementing this combination model approach is quite easy, and this model has proven to be an effective approach to improve the performance of a single model.

ARIMA-GARCH Value at Risk

Value-at-Risk (VaR) is defined as the maximum risk value that can occur at a certain level of trust α with $\alpha \in (0,1)$ (Tse [12]). For a stochastic process $\{X_t\}$, calculated VaR value in period *t* is the predictive value for the time period *t + 1* or $\hat{X}_{t+1}$. Calculated VaR value at a level of trust, for instance α = 0.95, means that there is 0.95 chance that the risk which will be obtained at time *t + 1* will be less than the VaR value. Mathematically, it can be written as

$$P(X_{t+1} \le VaR_\alpha | X_t) = \alpha$$

$$F_{X_{t+1}|X_t}\big(VaR_\alpha(X_t)\big) = \alpha$$

$$VaR_\alpha(X_t) = F^{-1}_{X_{t+1}|X_t}(\alpha)$$

Using quantile method, the VaR value of the stochastic process $\{X_t\}$ can be determined as follows:

$$V\hat{a}R_\alpha(X_t) = E\,[X_t|X_{t-1}] + \Phi^{-1}(\alpha)\sqrt{Var(X_t|X_{t-1})} \tag{8}$$

$$= \mu_{X_t|X_{t-1}} + \Phi^{-1}(\alpha)\sigma_{X_t|X_{t-1}} \tag{9}$$

with $\sigma_{X_t|X_{t-1}}$ obtained from ARCH/GARCH model.

Best Model Selection

In this study, the selection of the best model is done by comparing the value of Akaike Information Criteria (AIC), Schwarz's Bayesian Information Criterion (SBC), and Hannan-Quinn Information Criterion (HQC) which refers to Akaike [1] and Schwarz [8]. AIC, SBC and HQC values can be calculated based on the following equation:

$$AIC = -2\ln(L) + 2k, \tag{10}$$

$$SBC = -2\ln(L) + \ln(L)\,k, \tag{11}$$

$$HQC = -2\ln(L) + 2\ln(\ln(T))\,k, \tag{12}$$

where L : Value of the likelihood function obtained from the parameter estimation

T : The amount of data used in modeling

k : Number of parameters estimated for each model

Models with AIC, SBC and HQC values can be seen as the best model compared to other models.

Model Evaluation

Model performance in prediction can be evaluated using two measures namely Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) (Ghani and Rahim [5]). The MSE formula is

$$MSE = \frac{1}{T-T_1}\sum_{t=T_1}^{T}\left(X_t - \hat{X}_t\right)^2 \tag{13}$$

and, the formula for MAPE is

$$MAPE = \frac{1}{T-T_1}\sum_{t=T_1}^{T}\left\|\left(\frac{X_t-\hat{X}_t}{X_t}\right)x100\right| \tag{14}$$

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

3. RESEARCH METHOD

The steps of data analysis in this study were as follows:

1. Calculated the value of stock returns from stock closing price data

2. Tested the stationarity in mean using the Augmented Dickey Fuller Test. If the data were not stationary in mean, differencing process was performed.
3. Identified suitable ARIMA models through ACF and PACF plots.
4. Performed parameter estimation and tested the significance of ARIMA model parameters.
5. Verified the ARIMA model, this verification process included a residual independence test and a residual normality test.
6. Identified the effects of ARCH / GARCH through the Lagrange Multiplier test. If there were no effects, then the process was continued by calculating the ARIMA Combination value.
7. Identified ARCH/GARCH models for each ARIMA model through the associated ACF and PACF residual plots.
8. Verified the ARIMA-GARCH Model which include the independence test and the residual normality test.
9. Identified the effects of ARCH / GARCH through the Lagrange Multiplier test.
10. Chose the best ARIMA-GARCH model by comparing the values of AIC, SBC, and HQC
11. Modeled the Ensemble ARIMA-GARCH.
12. Calculated the prediction of VaR ARIMA-GARCH and VaR Ensemble ARIMA-GARCH.

4. MAIN RESULTS

In this section, we provide complete data analysis to calculation of VaR prediction for stock price returns. Note that we analyzed historical single asset data for our modeling in Section 3.

Data Description

The data used in this study is the closing price data of PT. Astra Agro Lestari Tbk from the period of 3 October 2012 to 1 October 2019 (1741 data). The data is divided into in-sample data from the period of 3 October 2012 to 29 August 2019 (1719 data), and out-sample data from 2 September 2019 to 1 October 2019 (22 data).

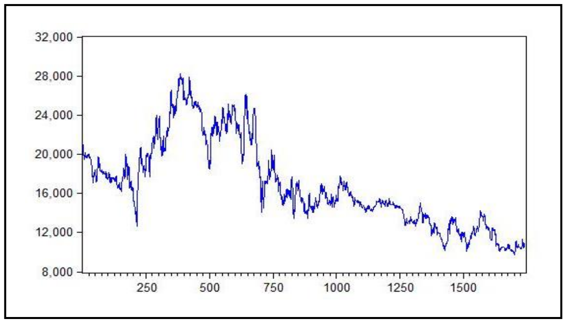

Fig. 1. The AALI stock price plots

Fig. 1 is a time series plot of the AALI stock daily closing price. Based on the plot, in the observation period, the data is not stationary in mean because the value fluctuated from time to time. Fig. 2 is an illustration of the time series plot of the AALI stock daily return value. Based on the plot formed, in the time period of observation the data has been stationary in mean and variance because the values are both constant and there were no fluctuations.

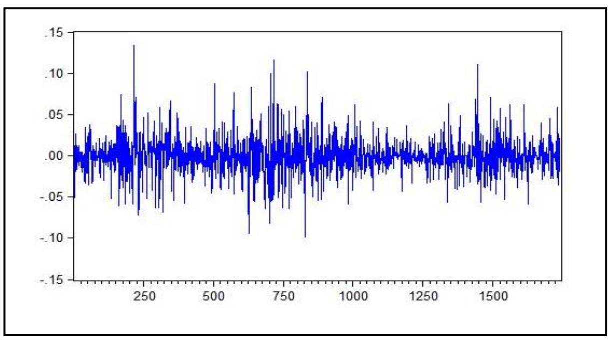

Fig. 2: Time series plots of AALI stock return

The Table 1, presents descriptive statistics from INDF in-sample data, this table can help to find out the characteristics of the data.

Table 1: Descriptive Statistics of Data Return of PT. Indofood Tbk. (INDF)

Parameters	Values
Number of observations	1719
Average	-0.0004
Standard deviation	0.0220
Skewness	0.5271
Kurtosis	6.8742

In Table 1, the stock skewness return value of 6.8742 is greater than the normal distribution kurtosis of 3. This explains that the distribution curve is leptokurtosis, which means there is an extreme value in the data.

Time Series Modeling

The first step in modeling time series for stock returns is to test the stationarity. Based on Fig. 2, the data has been stationary in mean. Formally, stationarity in the mean was tested through the ADF test, and stationarity in the variant was tested through the Box-Cox test. The ADF test and Box-Cox test results are presented in the following table.

Table 2: Stationarity Test in Average for return of AALI

ADF Value	Significance Level	p-value	Decision
-37.6534	5%	0.0000	*H_0 rejected, data is stationary*

Table 3: Stationarity Test in Variance for return of AALI

Estimate λ	Lower	Upper	Rounded Value
1.01	0.83	1.22	1

From Table 2, H_0 on the ADF test is rejected, so it is clear that AALI's data return is stationary in mean. From Table 3, the Rounded Box-value in Box-Cox transformation is equal to 1, indicating that the AALI data return is stationary in variance.

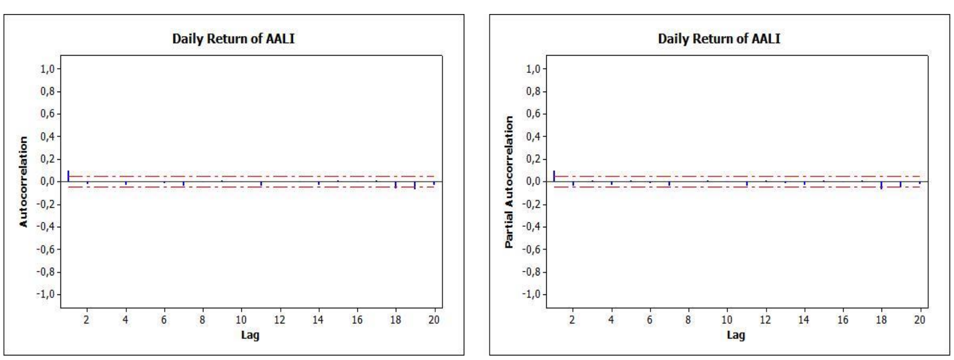

Fig. 3: ACF and PACF plot daily return of AALI

Based on Fig. 3, the ACF and PACF plots experienced cut off in lag 1, this shows that the ARIMA models formed for AALI daily return data are ARIMA (1,0,0), ARIMA (0,0,1), and ARIMA (1,0,1). Estimation for the three ARIMA models are done using the maximum likelihood (ML) method, the estimation results can be seen in the following table

Table 4: Parameters estimates for ARIMA models

Model		Estimates	p-value
ARIMA (1,0,0)	ϕ_1	0.0973	0.0000
ARIMA (0,0,1)	θ_1	0.103818	0.0000
	ϕ_1	-0.3281	0.0507
ARIMA (1,0,1)	θ_1	0.4280	0.0086

The coefficient value of the ARIMA (1,0,0) and ARIMA (0,0,1) model parameters presented in table 4 is significant at the 5% significance level. In the ARIMA model (1,0,1) there is a coefficient value of the parameter which is not significant. Therefore, it can be concluded that at a level of α = 5%, the models that can be used for further analysis are ARIMA (1,0,0) and ARIMA (0,0,1). After parameter estimation, the model verification was then performed which included normality test, independence test, and ARCH / GARCH residual effect test. The test results are as follows:

Table 5: Residual test for ARIMA models

Models	Residual Test		
	Normality	Independency	Homoskedasticity
ARIMA (1,0,0)	x	✓	x
ARIMA (0,0,1)	x	✓	x

Referring to Table 5, the residual value for each model is independent. The normality assumptions of the five models do not meet, but these assumptions can be ignored. While the assumption of homoskedasticity is not fulfilled, so the five models will be modeled in the ARCH/GARCH model. The ARCH/GARCH effect test using Lagrange-Multiplier test, resulting there is an

ARCH/GARCH effect on the ARIMA (1,0,0) and ARIMA (0,0,1) models. Based on the ACF and PACF plots of the squared residuals for each model, the ARIMA-GARCH model formed is ARIMA(1,0,0)-ARCH(1), ARIMA (1,0,0)-ARCH(2), ARIMA(1,0,0)-GARCH(1,1), ARIMA(1,0,0)-GARCH(1,2), ARIMA(1,0,0)-GARCH(2,1), ARIMA(1,0,0)-GARCH(2,2), ARIMA(0,0,1)-ARCH(1), ARIMA(0,0,1)-ARCH(2), ARIMA(0,0,1)-GARCH(1,1), ARIMA (0,0,1)-GARCH(1,2), ARIMA(0,0,1)-GARCH(2,1) and ARIMA(0,0,1)-GARCH(2,2).

For each ARIMA-GARCH model, the model parameters are estimated using the Maximum Likelihood (ML) method. After the parameter estimation value is obtained, the parameter signification test is performed to determine whether there is a model whose parameter is not significant. Based on the signification test parameter, there are parameters in the ARIMA(1,0,0)-GARCH (2,2) and ARIMA (0,0,1)-GARCH (2,2) models which are not significant. Therefore, the two models are not used for further analysis. Furthermore, for each ARIMA-GARCH model that passes the parameter signification test, an evaluation of the model includes a comparison of the AIC, SBC, and HQC values. In addition, a residual test was also conducted to determine whether the residual variance in the model was constant. The results of the model evaluation can be seen in the following table:

Table 6: ARIMA-GARCH Model Evaluation

Models	AIC	SBC	HQC
ARIMA(1,0,0)-ARCH(1)	-4.8516	-4.8420	-4.8480
ARIMA(1,0,0)-ARCH(2)	-4.9089	-4.8994	-4.9054
ARIMA(1,0,0)-GARCH(1,1)	-4.9749	-4.9622	-4.9702
ARIMA(1,0,0)-GARCH(1,2)	-4.9790	-4.9631	-4.9731
ARIMA(1,0,0)-GARCH(2,1)	-4.9729	-4.9602	-4.9682
ARIMA(0,0,1)-ARCH(1)	-4.8519	-4.8424	-4.8484
ARIMA(0,0,1)-ARCH(2)	-4.9105	-4.8979	-4.9058
ARIMA(0,0,1)-GARCH(1,1)	-4.9754	-4.9627	-4.9707
ARIMA(0,0,1)-GARCH(1,2)	-4.9793	-4.9635	-4.9735
ARIMA(0,0,1)-GARCH(2,1)	-4.9764	-4.9605	-4.9705

Table 7: Residual tests for ARIMA-GARCH models

Models	Residual Test		
	Normality	Independency	Homoskedasticity
ARIMA(1,0,0)-ARCH(1)	x	✓	✓
ARIMA(1,0,0)-ARCH(2)	x	✓	✓
ARIMA(1,0,0)-GARCH(1,1)	x	✓	✓
ARIMA(1,0,0)-GARCH(1,2)	x	✓	✓
ARIMA(1,0,0)-GARCH(2,1)	x	✓	✓
ARIMA(0,0,1)-ARCH(1)	x	✓	✓
ARIMA(0,0,1)-ARCH(2)	x	✓	✓
ARIMA(0,0,1)-GARCH(1,1)	x	✓	✓
ARIMA(0,0,1)-GARCH(1,2)	x	✓	✓
ARIMA(0,0,1)-GARCH(2,1)	x	✓	✓

According to the results of the evaluation and verification of ARIMA- GARCH models from tables 6 and 7, the variance value of each model has been constant. Based on the AIC, SBC, and HQC values, the best model is ARIMA(0,0,1)-GARCH(1,2). Representation of ARIMA(0,0,1)-GARCH (1,2) model is as follows:

$$\hat{X}_t = \varepsilon_t + 0.0732\varepsilon_{t-1};\ \ \varepsilon_t \sim N(0, \hat{\sigma}_t^2);$$

$$\hat{\sigma}_t^2 = 7.19\ \times\ 10^{-5} + 0.1723\varepsilon_{t-1} - 0.0936\varepsilon_{t-2} + 0.9092\sigma_{t-1}^2$$

The results of prediction on the out-sample data in the period of 2 September 2019-1 October 2019 (22 periods) using the ARIMA(0,0,1)-GARCH(1,2) model are as follows:

Table 8: Prediction Using ARIMA(0,0,1)-GARCH(1,2) Model

Period	$\hat{X}_t$	$\hat{\sigma}_t^2$
Sep 2, 2019	0.0000	0.0003
Sep 3, 2019	0.0000	0.0003
Sep 4, 2019	0.0002	0.0002
Sep 5, 2019	-0.0005	0.0002
Sep 6, 2019	-0.0003	0.0002
Sep 9, 2019	0.0000	0.0002
Sep 10, 2019	-0.0004	0.0002
Sep 11, 2019	0.0011	0.0002
Sep 12, 2019	-0.0001	0.0002
Sep 13, 2019	-0.0012	0.0002
Sep 16, 2019	0.0011	0.0002
Sep 17, 2019	0.0015	0.0003
Sep 18, 2019	0.0042	0.0008
Sep 19, 2019	-0.0011	0.0004
Sep 20, 2019	-0.0019	0.0005
Sep 23, 2019	0.0001	0.0004
Sep 24, 2019	-0.0009	0.0004
Sep 25, 2019	-0.0025	0.0006
Sep 26, 2019	0.0021	0.0005
Sep 27, 2019	0.0002	0.0004
Sep 30, 2019	-0.0014	0.0005
Oct 01, 2019	0.0016	0.0005

Modeling Ensemble ARIMA-GARCH

Based on the ARIMA-GARCH modeling in the previous section, ten significant models were obtained. The formation of the Ensemble ARIMA-GARCH model is as follows:

The ensemble ARIMA-GARCH for mean:

$$f(\hat{X}_t) = \frac{1}{10}\sum_{i=1}^{10} \hat{X}_t^{(i)} \tag{15}$$

The ensemble ARIMA-GARCH for variance prediction

$$f(\hat{\sigma}_t^2) = \frac{1}{10}\sum_{i=1}^{10}(\hat{\sigma}_t^2)^{(i)} \tag{16}$$

The mean and variance prediction results for using the Ensemble ARIMA-GARCH model is as follows:

Table 9: Prediction using Ensemble ARIMA-GARCH Model

Period	$f(\hat{X}_t)$	$f(\hat{\sigma}_t^2)$
Sep 2, 2019	0.00001	0.00031
Sep 3, 2019	0.00000	0.00030
Sep 4, 2019	0.00019	0.00029
Sep 5, 2019	-0.00058	0.00028
Sep 6, 2019	-0.00036	0.00027
Sep 9, 2019	0.00001	0.00026
Sep 10, 2019	-0.00039	0.00025
Sep 11, 2019	0.00117	0.00028
Sep 12, 2019	-0.00005	0.00026
Sep 13, 2019	-0.00134	0.00029
Sep 16, 2019	0.00121	0.00030
Sep 17, 2019	0.00164	0.00033
Sep 18, 2019	0.00464	0.00081
Sep 19, 2019	-0.00109	0.00061
Sep 20, 2019	-0.00211	0.00052
Sep 23, 2019	0.00009	0.00045
Sep 24, 2019	-0.00093	0.00041
Sep 25, 2019	-0.00278	0.00057
Sep 26, 2019	0.00220	0.00059
Sep 27, 2019	0.00027	0.00046
Sep 30, 2019	-0.00151	0.00046
Oct 01, 2019	0.00175	0.00049

Comparison of the ARIMA-(0,0,1)-GARCH(1,2) with the Ensemble ARIMA-GARCH

Comparison between ARIMA(0,0,1)-GARCH(1,2) model and ensemble ARIMA-GARCH model aims to choose the best model that will be used for Value-at-Risk prediction, the comparison of these two models includes comparison of MAPE values and MSE values.

Table 10: Comparison of MAPE and MSE value

Model	MSE	MAPE
ARIMA(0,0,1)-GARCH(1,2)	0.00005	2.3331%
Ensemble ARIMA-GARCH	0.00039	2.3464%

Based on comparison of MAPE values and MSE in table 10, the best model is ARIMA(0,0,1)-GARCH(1,2) because it has smaller MAPE and MSE values than the Ensemble ARIMA-GARCH model.

VaR Prediction

It is known that the best model for prediction is ARIMA(0,0,1)-GARCH(1,2). Based on the predicted output of mean and variance values, values of $\hat{\mu}_t$ = 0.0016 and $\hat{\sigma}_t^2$ = 0.0005 for the prediction of VaR values with level of trust α = 95% for period $t + 1$ (Oct 2, 2019):

$$V\hat{a}R_{95\%}^{t+1} = \hat{\mu} + \sqrt{\hat{\sigma}_t^2}\Phi^{-1}(5\%)$$

$$V\hat{a}R_{95\%}^{t+1} = 0.0016 + \sqrt{0.0005} - 1.6449$$

$$V\hat{a}R_{95\%}^{t+1} = -0.03464$$

So, the maximum risk value that might occur in the period of October 2019 is 0.03464.

5. CONCLUSION

According to the results and discussion, it can be concluded that the best time series model for predicting AALI returns for the period of 3 October 2012 to 1 October 2019 is ARIMA(0,0,1)-GARCH (1,2), with the representation model:

$$\hat{X}_t = \varepsilon_t + 0.0732\varepsilon_{t-1}; \tag{17}$$

$$\hat{\sigma}_t^2 = 7.19 \times 10^{-5} + 0.1723\varepsilon_{t-1} - 0.0936\varepsilon_{t-2} + 0.9092\sigma_{t-1}^2 \tag{18}$$

By using the model in equation (17) to predict the VaR values, the prediction of VaR values for the period of 2 October 2019 is 0.03464.

ACKNOWLEDGEMENT

This paper is officially funded by grant of Faculty of Science and Mathematics, Universitas Diponegoro in 2019 with contract number 4861/UN7.5.8/PP/2019.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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