International Journal of Sciences: Basic and Applied Research (IJSBAR)

ISSN 2307-4531
(Print & Online)

http://gssrr.org/index.php?journal=JournalOfBasicAndApplied

Comparison of BEKK GARCH and MEWMA Methods on IDX Composite and Exchange Rate Volatility

Dara Agustina[a*], I Made Sumertajaya[b], Farit Mochamad Afendi[c]

[a,b,c]IPB University, Jl. Raya Dramaga, Babakan, Dramaga District, Bogor City, West Java, Indonesia
[a]Email: agustinadara@apps.ipb.ac.id

Abstrac

At the beginning of 2020, the world was busy with a new virus namely COVID-19. In Indonesia, COVID-19 virus was first identified on March 2nd, 2020. This global pandemic made several impacts. One of the impact is on Country's Economy that can be seen in the decline of IDX Composite and the weakening of US Dollar exchange rate to Rupiah. The movement of IDX Composite and US Dollar exchange rate to Rupiah often increases and decreases every day. This condition can be caused by volatility due to fluctuation. There are several methods to cover the volatility of multivariate data, one of them can be approached using Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model. In addition to the GARCH model, there is another approach that can also be used to cover volatility data, that is Multivariate Exponential Weighted Moving Average (MEWMA) model. Based on the analysis results of the three training data, it was found that the RMSE of the BEKK GARCH method was greater than the RMSE of the MEWMA method and VAR(2)-MEWMA that be used on the three training data had the consistently volatility predict of IDX Composite return and US Dollar exchange rate to Rupiah return. MEWMA method can be said to have a better predictive ability, so VAR(2)-MEWMA is used to model IDX Composite return data and US Dollar exchange rate to Rupiah return data from November 2019 to August 2021 and is used to predict the volatility of the next month on September 2021. MEWMA model's ability is quite good in predicting the volatility of IDX Composite return data and US Dollar exchange rate to Rupiah return data.

Keywords: Return; IDX Composite; Exchange Rate; BEKK GARCH; MEWMA.

----

* Corresponding author.

1. Introduction

At the beginning of 2020, the world was busy with a new virus namely COVID-19. This virus has become a global pandemic that is very disturbing to the world community. COVID-19 virus has spread to almost every country in the world since it first appeared in China on December 31th, 2019. In Indonesia, COVID-19 virus was first identified on March 2nd, 2020. With the global pandemic, it has provided several impacts, one of the impact is on Country's Economy that can be seen in the decline of IDX Composite and the weakening of US Dollar exchange rate to Rupiah. IDX Composite is one of the stock market indexes that be used by the Indonesia Stock Exchange. Meanwhile, US Dollar exchange rate to Rupiah is the value or price of the US Dollar which is measured or expressed in Rupiah. Based on data accessed at www.Investing.com, in the past year, the mean of IDX Composite was 5,427.20 points and the mean of US Dollar exchange rate to Rupiah was Rp. 14,432.00. After the announcement of COVID-19 cases, IDX Composite has decreased, as well as US Dollar exchange rate to Rupiah has weakened. IDX Composite has decreased to 3,937.63 points on March 24th, 2020, where previously IDX Composite had a fairly high value on December 27th, 2019, which was 6,329.31 points. Meanwhile, US Dollar exchange rate to Rupiah has weakened to Rp. 16,575.00 on March 23rd, 2020, where previously US Dollar exchange rate to Rupiah was Rp. 13,572.00 on January 24th, 2020. The movement of IDX Composite and US Dollar exchange rate to Rupiah often increases and decreases every day. This condition can be caused by volatility due to fluctuation. Volatility is a change that shows the condition of the instability of a value. There are several methods to cover the volatility of multivariate data, one of them can be approached using Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model. Currently, the MGARCH model has been developed into several models, one of which is the Baba, Engle, Kraft and Kroner (BEKK) model. The BEKK GARCH model can be used when the data has a different correlation at any time and when there are quite a lot of observed data conditions [1]. In addition to the GARCH model, there is another approach that can also be used to cover volatility data, that is Multivariate Exponential Weighted Moving Average (MEWMA) model.

Rosyida (2016) in a study entitled "Modeling VARIMA-BEKK GARCH Multivariate Time Series on the US Dollar Exchanage Rate to Rupiah and IDX Composite" conducted a study with the aim of modeling and predicting the US Dollar exchange rate to Rupiah and IDX Composite using VARIMA-BEKK GARCH model. The forecast results obtained are that the model can describe the pattern of the data that be used. In addition to the GARCH model, there is another approach that can also be used to capture data volatility, that is Multivariate Exponential Weighted Moving Average (MEWMA) model. Wororomi, J.K (2016) in a study entitled "Development of a Model-Based MEWMA Control Diagram for Non-Random Observation" developed MEWMA control chart that was able to increase the sensitivity of conventional MEWMA control charts to the effects of non-random data patterns. The results obtained are the MEWMA control chart based on the model is sensitive to small spikes in the data.

The movement of IDX Composite and US Dollar exchange rate to Rupiah can be seen from the return value. Where in IDX Composite data, the highest return value occurred on March 9th, 2020, which was –0.0658 and in US Dollar exchange rate to Rupiah data, the highest return value was on March 19th, 2020, which was 0.0457. Based on this background, considering that both of IDX Composite and US Dollar exchange rate to Rupiah experienced a fairly high spike around March 2020 after the identification of COVID-19 cases in Indonesia, a model that can capture this volatility is needed. In this study, to capture the volatility of IDX Composite and US Dollar exchange rate to Rupiah, BEKK GARCH and MEWMA model will be used.

2. Methodology

2.1 Return Data

Changes in the price of financial assets over a certain period of time are often also known as the return value of assets expressed as a percentage [2]. The return value is used on the grounds that cause it contains a complete summary of information on an investment asset from most investors and it's easier to handle than asset data when viewed from a statistical points of view. The return value in time series data analysis is the same as performing logarithmic transformation and differentiation. The return data can be assumed to be stationary on variance and mean. The return value can be obtained using equation (1) [3].

$$R_t = \frac{Y_t - Y_{t-1}}{Y_{t-1}} \tag{1}$$

with

R_t : return value in t period

Y_t : t data period

Y_{t-1} : $(t-1)$ data period

2.2 Var model

Vector Autoregressive (VAR) model is a time series model that be used to explain causality between economic variables. The VAR(p) model is a multivariate time series model which is an extension of the Autoregressive or AR(p) model. The VAR(p) model is a system of equations where the estimation of a variable in a certain period depends on the change in the variable itself and other variables involved in the system of equations in the previous periods. The equation of VAR(p) model with order p is shown in equation (2) [4].

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{Y}_{t-p} + \boldsymbol{e}_t \tag{2}$$

description :

$\boldsymbol{Y}_t$: variable vector in the t period $(mx1)$

$\boldsymbol{\Phi}_i$: variable coefficient matrix (mxm)

$\boldsymbol{Y}_{t-i}$: variable vector in the $(t-1)$ period $(mx1)$

$\boldsymbol{e}_t$: residual vector $(mx1)$

p : the long of lag

m : the many of variable

Assuming $\boldsymbol{e}_t$ is normally distributed, the estimation of the VAR(p) model can use the Maximum Likelihood Estimation (MLE) method.

2.3 Bekk garch method

In the principle, Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) method can be generalized in the same way as in the univariate cases. This method consists of two parts, the VAR model and the BEKK GARCH model which are used to explore volatility [5]. In the MGARCH model, the conditional covariance matrix has the form

$$vech(\boldsymbol{\Sigma}_{t|t-1}) = \boldsymbol{\gamma}_0 + \sum_{j=1}^{q} \boldsymbol{\Gamma}_j vech(\boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j}) + \sum_{j=1}^{m} \boldsymbol{G}_j vech(\boldsymbol{\Sigma}_{t-j|t-j-1}) \quad (3)$$

where $\boldsymbol{G}_j$ is also a fixed $\left(\frac{1}{2}m(m+1)x\frac{1}{2}m(m+1)\right)$ coefficient matrix. The parameter space of the MGARCH model has large dimensions in general and needs to be constrained to ensure the uniqueness of the representation and to obtain appropriate properties of the conditional covariance. To reduce the parameter space, the diagonal MGARCH model, where $\boldsymbol{\Gamma}_j$ and $\boldsymbol{G}_j$ in equation (4) are diagonal matrices [6]. Alternatively, the BEKK GARCH model of the following form may be useful.

$$\boldsymbol{\Sigma}_{t|t-1} = \boldsymbol{C}_0^{*\prime}\boldsymbol{C}_0^{*} + \sum_{n=1}^{N}\sum_{j=1}^{q} \boldsymbol{\Gamma}_{jn}^{*\prime}\boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j}\boldsymbol{\Gamma}_{jn}^{*} + \sum_{n=1}^{N}\sum_{j=1}^{m} \boldsymbol{G}_{jn}^{*\prime}\boldsymbol{\Sigma}_{t-j|t-j-1}\boldsymbol{G}_{jn}^{*} \quad (4)$$

description :

$\boldsymbol{C}_0^{*}$: constant matrix (mxm)

$\boldsymbol{\Gamma}_{jn}^{*}$ dan $\boldsymbol{G}_{jn}^{*}$: BEKK GARCH model parameter matrix (mxm)

$\boldsymbol{e}_{t-j}$: residual vector $(mx1)$

$\boldsymbol{\Sigma}_{t-j}$: variance covariance matrix (mxm)

The likelihood function can be maximized with respect to the parameter by using a numerical method. The solution does not exist due to the nonlinear form of the function. With the existence of a unique maximum likelihood estimate, it is important to identify unique parameters, for example in the form of the BEKK model carried out with restrictions. Of course, if the log-likelihood function is used even though the actual distribution of $\boldsymbol{\varepsilon}_t$ is non-normal, then the estimation will only be a Quasi Maximum Likelihood estimate. The quasi maximum likelihood method is an estimation method that is carried out on the variance covariance of parameter model with the residual assumption is violated. Based on the value of the variance covariance formed, a new inference is developed to determine the significance of the model parameter estimator. Quasi maximum likelihood still uses the maximum likelihood method as a basis. Calculation of the quasi variance covariance is also the values generated from the maximum likelihood method [7].

2.4 Mewma method

The easiest multivariate volatility model to apply is the Exponential Weighted Moving Mean (EWMA). It's from the EWMA univariate model that written in equation (5).

$$\hat{\sigma}_t^2 = \lambda\hat{\sigma}_{t-1}^2 + (1-\lambda)Y_{t-1}^2 \quad (5)$$

assuming that the weights are known or frequently assigned. While in the multivariate, the model is basically same that following equation (6).

$$\hat{\boldsymbol{\Sigma}}_t = \lambda\hat{\boldsymbol{\Sigma}}_{t-1} + (1-\lambda)\boldsymbol{Y}'_{t-1}\boldsymbol{Y}_{t-1} \quad (6)$$

with the individual element

$$\hat{\sigma}_{t,ij} = \lambda\hat{\sigma}_{t-1,ij} + (1-\lambda)Y'_{t-1,i}Y_{t-1,j} \text{ dimana } i,j = 1,\dots,m \quad (7)$$

The covariance matrix can be predicted by applying equation (6) separately for each asset and asset pair in the portfolio. Implementing the EWMA model is easy, even for a large number of assets. Coupled with the fact that the covariance matrix is guaranteed to be semi definitely positive, it is not surprising that EWMA is often the method of choice. However, there are a few drawbacks, namely the existence of limitations, either because of its simple structure or a single assumption that is usually not expected. In application, it often means that the covariance seems to move excessively but this condition does not become difficult to estimate the parameters using Quasi Maximum Likelihood. Quasi Maximum Likelihood can produce consistent estimates for the mean and variance parameters [8].

2.5 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a measure that is often used to see the difference between the values predicted by a model with the observed values. The RMSE value serves to combine the magnitude of the error in predictions for various data pointss into a single measure of predictive power [9]. The RMSE value is positive and is said to be getting better if it is close to zero. So a model that has a lower RMSE can be said to be better than one that has a higher value. The RMSE value can be calculated using equation (8) [10].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T}(y_i - \hat{y}_i)^2}{T}} \quad (8)$$

description :

y_i : variable value

$\hat{y}_i$: predictive value

T : periode

2.6 Data

The time series data that be used in this study is secondary data. The time series data consists of two variables, namely IDX Composite in points and US Dollar Exchange Rate to Rupiah in rupiah. The IDX Composite data and the US Dollar exchange rate to Rupiah are sourced from the website www.Investing.com. The data that be used is daily data from November 2019 to August 2021. As a validation of model consistency, modeling is carried out using three training data. The first training data is from November 2019 to March 2021. The second training data is from November 2019 to May 2021. The third training data is from November 2019 to July 2021.

3. Result and Discussion

3.1 Identification of IDX Composite and US Dollar Exchange Rate to Rupiah

Identification of data patterns is the first step taken before analyzing time series data. It aims to find out the description of the data under study. One way to identify data patterns is plotting the data. Based on the Figure 1(a), it can be seen that the IDX Composite has a fluctuating data pattern. The mean of IDX Composite during November 2019 to August 2021 was in the range of 5,637.10 points. The highest fluctuation occurred on March 24th, 2021, when COVID-19 was first identified, where the IDX Composite decreased to 3,937.63 points. The emergence of COVID-19 cases did not only affect to IDX Composite, but this condition also affected to US Dollar exchange rate to Rupiah. Based on the Figure 1(b), the information is obtained that the US Dollar exchange rate to Rupiah also has a fluctuating pattern. The mean of US Dollar exchange rate to Rupiah during November 2019 to August 2021 was in the range of Rp. 14,405.75. The highest fluctuation occurred on March 23rd, 2020, not far from the highest fluctuation in the IDX Composite. The exchange rate weakened to Rp 16,575.00. A complete summary of the descriptive statistics for IDX Composite and US Dollar exchange rate to Rupiah data is presented in Table 1.

(a) IDX Composite Development

(b) US Dollar Exchange Rate to Rupiah Development

Figure 1: IDX Composite and US Dollar Exchange Rate to Rupiah Development.

during November 2019 – August 2021

Table 1: Descriptive Statistics of IDX Composite and US Dollar Exchange Rate to Rupiah.

Descriptive Statistics	IDX Composite	Exchange Rate
Mean	5.637,10	14.405,75
Median	5.940,05	14.370,00
Standard Deviation	603,04	509,98
Minimum	3.937,63	13.572,50
Maximum	6.435,21	16.575,00
Skewness	-0,62	1,66
Kurtosis	-0,97	4,16

The movement of IDX Composite and US Dollar exchange rate to Rupiah often increases and decreases which resulted in indication of volatility. One of these movements can be seen from the return value. Based on the Figure 2, IDX Composite return and US Dollar exchange rate to Rupiah return fluctuate around the value of zero. IDX Composite return are figured by a blue graph and US Dollar exchange rate to Rupiah return are figured by an orange graph. The high increase value is indicated by a large return and a positive sign. The sharp decline in value is indicated by a large return and a negative sign. IDX Composite return and US Dollar exchange rate to Rupiah return have different fluctuation during November 2019 to August 2021. The highest fluctuation occurred at the beginning of the COVID-19 identification as described previously. The highest IDX Composite return occurred on March 09th, 2020, which was -0.0658 and the highest US Dollar exchange rate to Rupiah return occurred on March 19th, 2020, which was 0.0457. The two returns in the Figure 2 show an early indication that the variance is not constant during period November 2019 to August 2021. A complete summary of descriptive statistics on IDX Composite return data and US Dollar exchange rate to Rupiah return data are presented in Table 2.

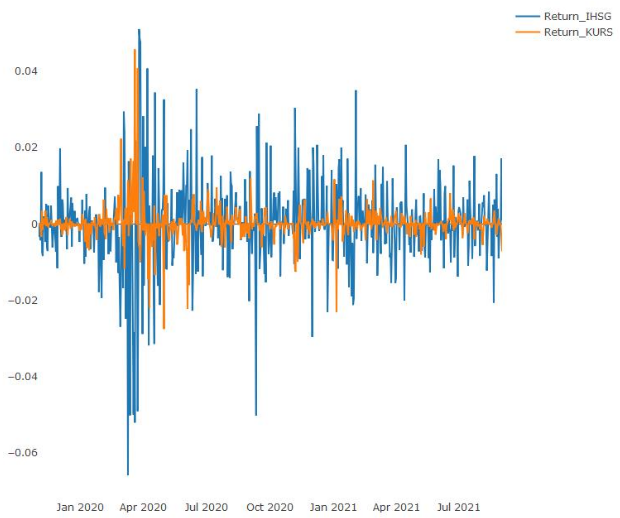


Figure 2: The Development of IDX Composite Return and US Dollar Exchange Rate to Rupiah Return.

Table 2: Descriptive Statistics of IDX Composite Return and US Dollar Exchange Rate to Rupiah Return.

Descriptive Statistics	IDX Composite Return	Exchange Rate Return
Mean	0,00	0,00
Median	0,00	0,00
Standard Deviation	0,01	0,01
Minimum	-0,07	-0,03
Maximum	0,05	0,05
Skewness	-0,43	1,78
Kurtosis	4,15	21,45

3.2 Var modelling

The data that be used in this study start from November 2019 to August 2021. The data is divided into three training data. The first training data starts from November 2019 to March 2021. The second training data starts from November 2019 to May 2021. The third training data starts from November 2019 to July 2021. Modeling is carried out on three conditions of training data as model validation in this study. Before doing the modeling, it is necessary to identify the order of p. Identification of order p using Matrix Partial Autocorrelation Function (MPACF). Based on the identification of MPACF in the three training data, the order of $p = 2$. VAR(2) model is the model that chosen to model the three training return data of IDX Composite and US Dollar exchange rate to Rupiah. The estimation of VAR(2) model uses Maximum Likelihood Estimation (MLE).

VAR(2) Model of The First Training Data

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} 0,0789 & -0,0197 \\ -0,0531 & 0,0345 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} -0,0272 & 0,0140 \\ -0,0177 & 0,1010 \end{pmatrix} \begin{pmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \quad (9)$$

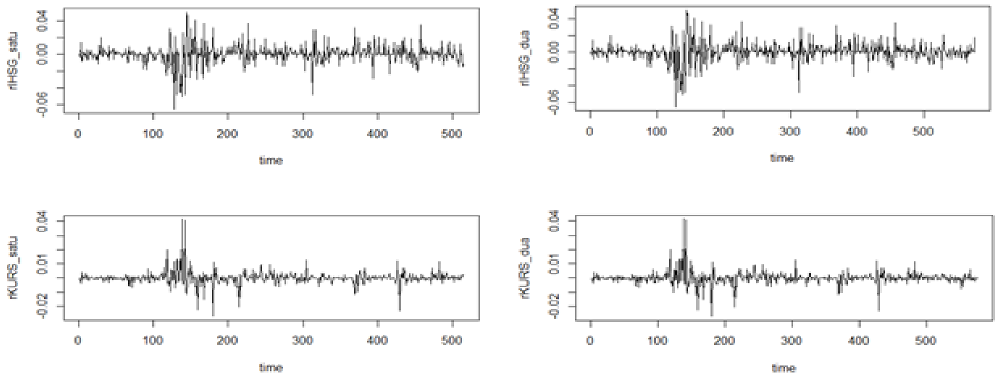
VAR(2) Model of The Second Training Data

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} 0{,}0784 & -0{,}0106 \\ -0{,}0530 & 0{,}0338 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} -0{,}0320 & -0{,}0105 \\ -0{,}0180 & 0{,}0976 \end{pmatrix} \begin{pmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \tag{10}$$

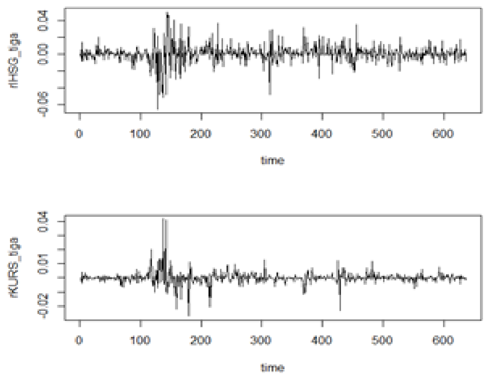
VAR(2) Model of The Third Training Data

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} 0{,}0731 & -0{,}0081 \\ -0{,}0517 & 0{,}0359 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} -0{,}0350 & -0{,}0011 \\ -0{,}0172 & 0{,}0985 \end{pmatrix} \begin{pmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \tag{11}$$

The general assumption of time series is necessary on the VAR(2) model, those are white noise assumption test and normality assumption test. White noise assumption test is using Portmanteau test. This test is conducted to determine whether the model accepts the assumption of residual white noise or not. Based on the test results of the three training data, can be concluded that the VAR(2) model does not accept the white noise residual assumption. This condition is supported by the residual of the VAR(2) model from the three training data that shown in the Figure 3.



(a) First Training Data (b) Second
Training Data



(c) Third Training Data

Figure 3: Residual of VAR(2) Model.

Based on the Figure 3, it can be seen that the residual of VAR(2) model in the three training data fluctuates. This condition can indicate that there is an ARCH effect. Before continuing to another test, it is necessary to test the normality residual assumption. The multivariate normality residual test was performed using the Q-Q Plot correlation coefficient [11]. The hypothesis that be used in the normality test is

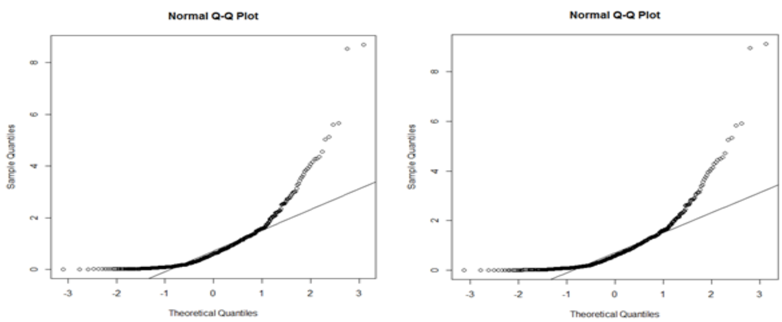
H_0 : residuals are normally distributed multivariate *vs*

H_1 : residuals are not normally distributed multivariate

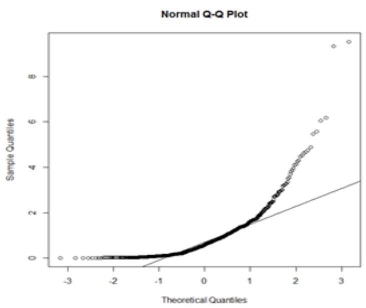
Table 3: Q-Q Plot Correlation Coefficient.

VAR(2) Model	Correlation Coefficient	Critical Points	Decision
First Training Data	0,5639	0,0777	Reject H_0
Second Training Data	0,5500	0,0817	Reject H_0
Third Training Data	0,5364	0,0864	Reject H_0

Based on the Table 3, the correlation coefficient of Q-Q Plot on the three training data has a correlation coefficient value greater than the critical points at a significant level of 0.05. The test results reject the null hypothesis and it can be concluded that the residual of the VAR(2) model in the three training data does not have a multivariate normal distribution. This condition is supported by the Figure 4 which shows that there are some outliers in the Normal Q-Q Plot from the three training data.



(a) First Training Data (b) Second Training Data



(c) Third Training Data

Figure 4: Q-Q Plot Residual of VAR(2) Model.

VAR(2) model has residual that does not accept the white noise and multivariate normal assumptions. Therefore, further tests were carried out on the residual of the model, using the Lagrange Multiplier (LM) test with a significance level of 0.05 to determine the ARCH effects in the VAR(2) model. The hypothesis that be used in the LM test is as follows.

$$H_0: \boldsymbol{\beta_1} = \cdots = \boldsymbol{\beta_q} = \mathbf{0} \text{ : there is no Multivariate GARCH effect}$$

$$H_1: \boldsymbol{\beta_q} \neq \mathbf{0} \text{ : there is Multivariate GARCH effect}$$

Table 4: Lagrange Multiplier Test.

VAR(2) Model	F-test	p-value	Decision
First Training Data	255,4192	0,0000	Tolak H_0
Second Training Data	291,8609	0,0000	Tolak H_0
Third Training Data	328,5131	0,0000	Tolak H_0

Based on the Table 4, the test resulted in the statistical value of LM test on the three training data which had p-value smaller than the 0.05 level of significance. The test results reject the null hypothesis at a significance level of 0.05 and it can be concluded that there is an element of Multivariate GARCH in the residual of the VAR(2) model. Indications of volatility due to these fluctuation can be modeled using a volatility model, the BEKK GARCH model and the MEWMA model as comparisons.

4. Bekk garch modelling

The VAR model that be used is VAR(2). The VAR model has an element of Multivariate GARCH. VAR(2) modeling on the three training data was continued to volatility modeling. The volatility model that be used is Multivariate GARCH with BEKK representation. The BEKK GARCH model is obtained from the residual variance of the VAR(2) model.

BEKK GARCH Model of the First Training Data

$$\boldsymbol{\Sigma}_{t|t-1} = \begin{bmatrix} 0,0103 & 0,3583 \\ 0,0000 & 0,0650 \end{bmatrix} \begin{bmatrix} 0,0103 & 0,3583 \\ 0,0000 & 0,0650 \end{bmatrix} + \begin{bmatrix} 0,5813 & 1,7553 \\ 0,6603 & -1,0273 \end{bmatrix} \boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j} \begin{bmatrix} 0,5813 & 1,7553 \\ 0,6603 & -1,0273 \end{bmatrix} + \begin{bmatrix} 0,0539 & 0,6105 \\ -0,0394 & 0,1709 \end{bmatrix} \boldsymbol{\Sigma}_{t-j|t-j-1} \begin{bmatrix} 0,0539 & 0,6105 \\ -0,0394 & 0,1709 \end{bmatrix} \quad (12)$$

BEKK GARCH Model of the Second Training Data

$$\boldsymbol{\Sigma}_{t|t-1} = \begin{bmatrix} -0,0009 & -0,0138 \\ 0,0000 & 0,5851 \end{bmatrix} \begin{bmatrix} -0,0009 & -0,0138 \\ 0,0000 & 0,5851 \end{bmatrix} + \begin{bmatrix} 0,6115 & 1,3544 \\ 0,7272 & -0,4913 \end{bmatrix} \boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j} \begin{bmatrix} 0,6115 & 1,3544 \\ 0,7272 & -0,4913 \end{bmatrix} + \begin{bmatrix} 0,0801 & 0,6891 \\ 0,0158 & -0,3073 \end{bmatrix} \boldsymbol{\Sigma}_{t-j|t-j-1} \begin{bmatrix} 0,0801 & 0,6891 \\ 0,0158 & -0,3073 \end{bmatrix} \quad (13)$$

BEKK GARCH Model of the Third Training Data

$$\boldsymbol{\Sigma}_{t|t-1} = \begin{bmatrix} 0{,}0327 & 0{,}2839 \\ 0{,}0000 & 0{,}0090 \end{bmatrix} \begin{bmatrix} 0{,}0327 & 0{,}2839 \\ 0{,}0000 & 0{,}0090 \end{bmatrix} + \begin{bmatrix} 0{,}9141 & 1{,}6856 \\ 0{,}7311 & -1{,}2743 \end{bmatrix} \boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j} \begin{bmatrix} 0{,}9141 & 1{,}6856 \\ 0{,}7311 & -1{,}2743 \end{bmatrix} + \begin{bmatrix} 0{,}0123 & 0{,}8539 \\ 0{,}0017 & -0{,}3579 \end{bmatrix} \boldsymbol{\Sigma}_{t-j|t-j-1} \begin{bmatrix} 0{,}0123 & 0{,}8539 \\ 0{,}0017 & -0{,}3579 \end{bmatrix} \quad (14)$$

5. Mewma modelling

In addition to using the BEKK GARCH model, another model is used as an evaluation, that is the Multivariate Exponential Weighted Moving Average (MEWMA) model. In MEWMA model, a decay factor is needed where the decay factor is determined based on the concept of inverse wishart. Multivariate model can use decay factor values close to -0.1 and univariate model can use decay factor values close to 0.1. Based on the test results, it is known that the parameter in the three MEWMA models are significant because the p-value is close to zero which is less than the 0.05 level of significance.

MEWMA Model of the First Training Data

$$\widehat{\boldsymbol{\Sigma}}_t = 0.9347\widehat{\boldsymbol{\Sigma}}_{t-1} + 0.0653\boldsymbol{e}'_{t-1}\boldsymbol{e}_{t-1} \quad (15)$$

MEWMA Model of the Second Training Data

$$\widehat{\boldsymbol{\Sigma}}_t = 0.9436\widehat{\boldsymbol{\Sigma}}_{t-1} + 0.0564\boldsymbol{e}'_{t-1}\boldsymbol{e}_{t-1} \quad (16)$$

MEWMA Model of the Third Training Data

$$\widehat{\boldsymbol{\Sigma}}_t = 0.9478\widehat{\boldsymbol{\Sigma}}_{t-1} + 0.0522\boldsymbol{e}'_{t-1}\boldsymbol{e}_{t-1} \quad (17)$$

6. Evaluation

Evaluation was conducted to determine the performance of the two methods that be used in the three training data. In this study, the evaluation was carried out by looking at the RMSE value based on the comparison of the estimated value and the actual value of IDX Composite return and US Dollar exchange rate to Rupiah return. Based on the results of the analysis obtained a summary of the RMSE value. The model that has a lower RMSE can be said to be better than one that has a higher value. The RMSE value can be seen in the Table 5.

Table 5: The RMSE Value of IDX Composite Return and US Dollar Exchange Rate to Rupiah Return.

Model	First Training Data		Second Training Data		Third Training Data	
	r_IHSG	r_KURS	r_IHSG	r_KURS	r_IHSG	r_KURS
BEKK GARCH	0,6722	0,0229	1,0144	0,0069	0,9189	0,1027
MEWMA	0,0117	0,0048	0,0113	0,0046	0,0109	0,0044

Based on Table 5, it is found that the RMSE value of the BEKK GARCH method is greater than the RMSE value of the MEWMA method. The RMSE value of the MEWMA method is small and can be said to have a better forecasting ability than the BEKK GARCH method. Based on the three training data used, the RMSE value for the VAR(2)-MEWMA model are not much different. It can be concluded that VAR(2)-MEWMA has a consistent ability to predict the volatility of IDX Composite return and US Dollar exchange rate to Rupiah return. In this study, the IDX Composite return volatility and US Dollar exchange rate to Rupiah return were forecasted for 30 days on September 2021. The data that be used for estimating the parameters of the VAR(2)-MEWMA model is from November 2019 to August 2021. The VAR(2) model is the model chosen to model the IDX Composite return data and US Dollar exchange rate to Rupiah return. The estimation of the VAR(2) model uses Maximum Likelihood Estimation (MLE). The complete estimation results of the VAR(2) model are presented in the Table 6. Hypotheses for parameter significance testing :

$$H_0 : \phi_i = 0 \qquad vs$$

$$H_1 : \phi_i \neq 0$$

Table 6: Estimating and Testing the Significance of VAR(2) Model Parameters.

Parameter	Estimation Value	Standard Eror	t-value	p-value	Decision
$\hat{\phi}_{1,11}$	0,0683	0,0436	1,5665	0.1177	Terima H_0
$\hat{\phi}_{1,12}$	-0,0166	0,1089	-0,1524	0.8789	Terima H_0
$\hat{\phi}_{1,21}$	-0,0532	0,0174	-3,0575	0.0023**	Tolak H_0
$\hat{\phi}_{1,22}$	0,0380	0,0434	0,8756	0.3816	Terima H_0
$\hat{\phi}_{2,11}$	-0,0340	0,0440	-0,7727	0.4400	Terima H_0
$\hat{\phi}_{2,12}$	-0,0007	0,1080	-0,0065	0.9948	Terima H_0
$\hat{\phi}_{2,21}$	-0,0166	0,0175	-0,9486	0.3432	Terima H_0
$\hat{\phi}_{2,22}$	0,0971	0,0430	2,2581	0.0243**	Tolak H_0

Description :

* : significance on α=10%

** : significance on α=5%

*** : significance on α=1%

If the p-value of a parameter is less than the significance level of α, it is decided to reject the null hypothesis and conclude that the parameter is significant. Based on the Table 6, it is known that in the VAR(2) model, the significant parameters are $\phi_{1,21}$ and $\phi_{2,22}$. The VAR(2) model can be written in a matrix as follows.

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} 0,0683 & -0,0166 \\ -0,0532 & 0,0380 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} -0,0340 & -0,0007 \\ -0,0166 & 0,0971 \end{pmatrix} \begin{pmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \tag{18}$$

or in the form of a non-matrix equation can be written as follows.

$$Y_{1,t} = 0,0683Y_{1,t-1} - 0,0166Y_{2,t-1} - 0,0340Y_{1,t-2} - 0,0007Y_{2,t-2} + e_{1,t} \tag{19}$$

$$Y_{2,t} = -0{,}0532Y_{1,t-1} + 0{,}0380Y_{2,t-1} - 0{,}0166Y_{1,t-2} + 0{,}0971Y_{2,t-2} + e_{2,t} \qquad (20)$$

The evaluation results conclude that the MEWMA method is better than the BEKK GARCH method in estimating the volatility of IDX Composite return and US Dollar exchange rate to Rupiah return. Based on the results of parameter estimation in the MEWMA model, the lambda estimation value is 0.9520 with t-test statistic value of 209.70. If the p-value of the parameter is less than the 0.05 level of significance, it is decided to reject the null hypothesis and conclude that the parameter is significant. Based on the test results, it is known that the parameter in the MEWMA model is significant because the p-value is close to zero which is less than the 0.05 level of significance. The MEWMA model can be written as follows.

$$\widehat{\boldsymbol{\Sigma}}_t = 0.9520\widehat{\boldsymbol{\Sigma}}_{t-1} + 0.0480\boldsymbol{e}'_{t-1}\boldsymbol{e}_{t-1} \qquad (21)$$

The VAR(2)-MEWMA model is used to predict IDX Composite return and US Dollar exchange rate to Rupiah return. The results of the volatility estimation using the VAR(2)-MEWMA model from November 2019 to August 2021 and the volatility forecasting using the VAR(2)-MEWMA model in September 2021 are shown in the Figure 5. forecasting the value in the future period is based on the value of the previous period and related factors [12]. rIHSG Volatility in the Figure 5 is the volatility of the IDX Composite return and rKURS Volatility in the Figure 5 is the return volatility of the US Dollar exchange rate to Rupiah.

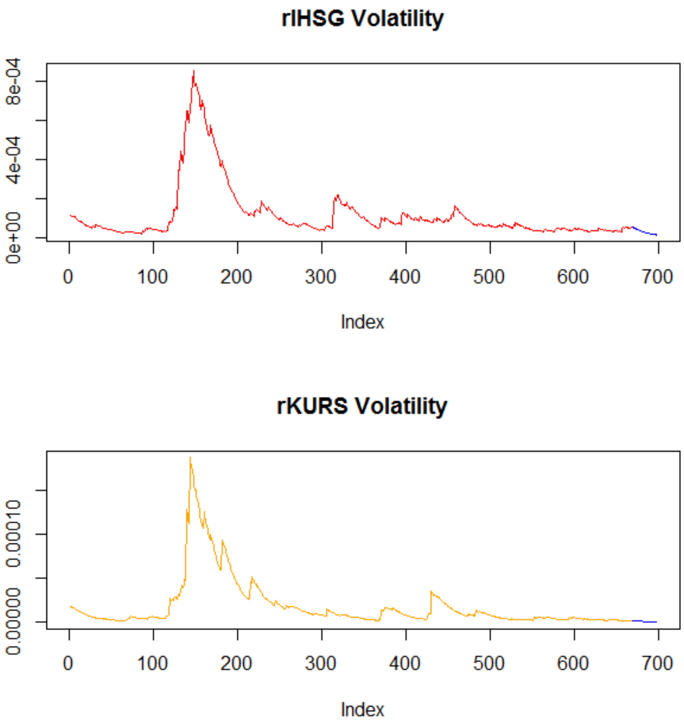


Figure 5: The Volatility of IDX Composite and US Dollar Exchange Rate to Rupiah.

The red color in the rIHSG Volatility starting at index 0 to 670 is the result of estimating the volatility of the IDX Composite return from November 2019 to August 2021. The blue color in the rIHSG Volatility from index 671 to 700 is the result of forecasting the volatility of the IDX Composite return in September 2021. The first time COVID-19 virus was identified which caused a drastic decline in the IDX Composite value occurred on March 24, 2020 or on the 145th data. The extreme conditions due to the identification of COVID-19 can be well predicted using the VAR(2)-MEWMA model as shown in the Figure 9. Based on the Figure 9, it can be concluded that The VAR(2)-MEWMA model well predicts the volatility of the IDX Composite return. The same applies to the estimation and forecasting of exchange rate return volatility. The orange color on the rKURS Volatility from index 0 to 670 is the result of estimating the volatility of the US Dollar exchange rate to Rupiah return from November 2019 to August 2021. The blue color of the rKURS Volatility starting at index 671 to 700 is the result of forecasting the volatility of the US Dollar exchange rate to Rupiah return in September 2021. The first time COVID-19 virus was identified which caused the weakening of the US Dollar exchange rate to Rupiah occurred on March 23, 2020 or in the 144th data. The extreme conditions due to the identification of COVID-19 can also be well predicted using the VAR(2)-MEWMA model as shown in the Figure 9. Based on Figure the 9, it can be concluded that the VAR(2)-MEWMA model well predicts the volatility of US Dollar exchange rate to Rupiah return.

7. Conclusions and Suggestions

The movement of IDX Composite and US Dollar exchange rate to Rupiah often increases and decreases every day. This condition can lead to data volatility due to fluctuation. There are several treatments for the volatility of multivariate data, one of them can be approached using Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model. In addition to the GARCH model, there is another approach that can also be used to capture data volatility, that is Multivariate Exponential Weighted Moving Average (MEWMA) model. Based on the results of the analysis on the three training data, it was found that the RMSE value of the BEKK GARCH method was greater than the RMSE value of the MEWMA method and the three VAR(2)-MEWMA that be used had consistently predict the volatility of IDX Composite return and US Dollar exchange rate to Rupiah return. MEWMA method can be said to have a better predictive ability, so VAR(2)-MEWMA is used to model IDX Composite return data and US Dollar exchange rate to Rupiah return data from November 2019 to August 2021 and is used to predict volatility on September 2021. The results of the volatility estimation using VAR(2)-MEWMA model show that extreme conditions on IDX Composite return and US Dollar exchange rate to Rupiah return due to the identification of COVID-19 can be well estimated using VAR(2)-MEWMA model. Then VAR(2)-MEWMA model is used to predict the volatility of the next month, September 2021. Based on the results of the analysis, it can be concluded that the MEWMA model's ability is quite good in predicting volatility in IDX Composite return data and US Dollar exchange rate to Rupiah return data. Considering that fluctuations in a commodity are not only influenced by internal factors but can also be influenced by external factors such as other economic factors, the next research is expected to include exogenous variables that affect volatility forecasting.

References

[1]. H. Lütkepohl, New Introduction Multiple Time Series Anlysis, Germany: Springer-Verlag Berlin Heidelberg, 2005.

[2]. J. Danielsson, Financial Risk Forecassting, Great Britain: CPI Antony Rowe, Chippenham, Wiltshire,

2011.

[3]. R.S. Tsay, Multivariate Time Series Analysis, United States of America: John Wiley & Sons, Inc, 2002.

[4]. W.W.S. Wei, Time Series Anlysis: Univariate and Multivariate Methods, Second Edition. United States of America: Pearson Education Inc, 2006.

[5]. R.F. Engle and K.F Kroner, "Multivariate Simultaneous Generalized ARCH", Econom Theory, Vol. 11(1) : pp. 122–150, 1995

[6]. T. Bollerslev, R.F Engle and J.M Wooldridge, "A Capital Asset Pricing Model with Time Varying Covariances", Journal of Political Economy, Vol. 96 : pp. 116–131, 1998.

[7]. A. Agresti, Categorical Data Analysis, Second Edition, United States of America: John Wiley & Sons, Inc, 2002.

[8]. T. Bollerslev T and J.M. Wooldridge, "Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances", Econometric Reviews. Vol. 11 : pp. 143–172, 1992.

[9]. R.J. Hyndman and A.B. Koehler, "Another Look at Measures of Forecast Accuracy", International Journal of Forecasting. Vol. 22(4) : pp. 679–688, 2006.

[10]. R.G. Pontius Jr, O. Thontteh, H. Chen, "Components of Information for Multiple Resolution Comparison Between Maps that Share a Real Variabel", Environmental Ecological Statistiks. Vol. 15(2) : pp. 111–142, 2008.

[11]. R.A. Johnson and D.W. Wichern, Applied Multivariat Statistikal Analysis, Sixth Edition, United States of America: Prentice Hall, 2007.

[12]. J.D Cryer and K. Chan, Time Series Analysis With Aplications In R, Second Edition, New York: Springer Science and Business Media, 2008.