PAPER NAME

2021 1751 Warsono_Indryani_2021_J._Phys.__Conf._Ser._1751_012014 Dynamic Modeling Data Return by Usi

AUTHOR

Warsono Warsono

WORD COUNT

6307 Words

CHARACTER COUNT

30416 Characters

PAGE COUNT

15 Pages

FILE SIZE

1.6MB

SUBMISSION DATE

Jan 1, 2023 5:12 PM GMT+7

REPORT DATE

Jan 1, 2023 5:12 PM GMT+7

● 29% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 22% Internet database
- Crossref database
- 17% Submitted Works database

- 25% Publications database
- Crossref Posted Content database

● Excluded from Similarity Report

- Bibliographic material
- Cited material
- Manually excluded sources

- Quoted material
- Small Matches (Less then 10 words)

PAPER • OPEN ACCESS

Dynamic Modeling Data Return by Using BEKK-GARCH (Study: PT. Indofarma Tbk (INAF) and PT. Kimia Farma Tbk (KAEF) from June 2015 to July 2020)

View the article online for updates and enhancements.

Dynamic Modeling Data Return by Using BEKK-GARCH (Study: PT. Indofarma Tbk (INAF) and PT. Kimia Farma Tbk (KAEF) from June 2015 to July 2020)

N Indryani[1,2], M Usman[1,*], Warsono[1], S U Nabila[1,2], Widiarti[1], D Kurniasari[1].

[1] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Lampung,
Jl. Sumantri Brojonegoro no 1, Bandar Lampung, Indonesia
[2] Graduate Students of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Lampung, Jl. Sumantri Brojonegoro no 1, Bandar Lampung, Indonesia

email: usman_alfha@yahoo.com*

Abstract. The Vector Autoregressive (VAR) model is a statistical model that can be used for modeling multivariate time series data which is commonly applied in the fields of finance, management, business and economics. However, economic data, especially return values, have quite high data fluctuations, so we need to add the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model in the analysis to obtain efficient results. This study will discuss the formation of the best model for multivariate time series data, namely return data of PT. Indofarma Tbk. (INAF) and PT. Kimia Farma Tbk. (KAEF) from June 2015 to July 2020, where data retuned for the two variables tended to have a high volatility shock at some time and low volatility at other times which characterizes the data as having an ARCH effect so that the GARCH model will be used in this analysis, namely the BEKK-model. GARCH. This model proposes a new parameterization which is easily given a restriction, namely the requirement that H_t must be positive for all values of ε_t and x_t in sample room. Based on the selection of the best model using the AICC, HQC, AIC and SBC criteria, it is found that the VAR (1) -GARCH (1,1) model is the best model for the data used. Then this research will also examine the behavior and relationship between INAF and KAEF based on Granger Causality and Impulse Response. In addition, based on the forecasting results of the VAR (1) -GARCH (1,1) model, it shows that this model is good for short-term forecasting.

Keywords: Forecasting, *Vector Autoregressive* (VAR), GARCH, BEKK-GARCH

1. Introduction

Time series data is data that is observed based on time in a certain period. According to Brockwell and Davis, the time series model with observational data $\{x_t\}$ is a specification of the shared distribution of a sequence of random variables $\{X_t\}$ where $\{x_t\}$ is postulated as the realization [1]. In time series analysis, there are several models such as autoregressive (AR), moving average (MA) models or a combination of the two models, namely the Autoregressive moving average (ARMA). The three models are time series analysis which involves modeling the mean. This analysis is commonly used in

economics, finance, and capital markets [2]. In the capital market game, investors are investing with the aim of getting profits in the future [3]. As for this benefit, investors must analyze the stock price by looking at the return of the stock price to make buy and sell decisions in investing [4]. Stock return itself is the level of profit enjoyed by investors for an investment they do [5]. Investors will get profits or capital gains when the return value is positive, whereas if the return value is negative, the investor will get a loss or capital loss. Therefore, making decisions must be good in order to avoid losses, so we need to do an appropriate analysis, namely time series analysis. However, usually an investor does not only invest in one company but several companies so that there is not only one stock return data that needs to be analyzed so that investors know the stock return movements of all the companies that they invest in. So, in this case the univariate time series analysis can no longer be relied upon, but instead will use multivariate time series analysis. Multivariate time series analysis was developed by Tiao and Box by analyzing time series from several time series data simultaneously [6]. This analysis is widely discussed in several literatures and is often used in forecasting in various fields such as finance, economics, geography, and capital markets [7; 8]. The model that is commonly used and effective in forecasting multivariate time series data is Vector Autoregressive (VAR). VAR was developed by Sims [9] as an alternative to the simultaneous equation approach [10; 1]. The application of the use of the Vector Autoregressive (VAR) model itself has been widely used, such as by Stock and Watson, Sharma et. al., Warsono et. al., and Kesumah et. al. who performed dynamic modeling of stock prices data [11; 12; 13; 14].

Return is one of the factors that motivates investors to invest and tends to have variants that change over time [15]. The fluctuation and risk of stock returns are illustrated by the volatility of the data. Volatility is a statistical measurement for the fluctuation in the price of an investment during a certain period which plays an important role in the fields of investment, securities valuation and risk management [16]. Volatility has been widely used in various studies, especially in the fields of economics and finance, including research by Mascaro and Meltzer; Belongia; Engle and Susmel; Karolyi; and Engel and Gizycki [17; 18; 19; 20; 21]. Lopez and Walter evaluated the VaR covariance matrix using constant, historical, EWMA, GARCH and implied volatility models [22]. If there is a wide range of price fluctuations in a short period of time, this indicates high volatility and low volatility if prices move slowly [23]. The difference in volatility fluctuation indicates that the variance of the residual is variable or not constant, so it is called heteroscedasticity [24; 25].

Heteroscedasticity data requires an additional method, namely Autoregressive Conditional Heteroscedasticity (ARCH) to overcome heterogeneous variants. Meanwhile, for multivariate time series data that has heteroscedasticity, the Multivariate Autoregressive Conditional Heteroscedasticity (Multivariate-ARCH) was introduced by Engle, Granger and Kraft to make it more efficient [26]. This model was later extended or generalized by Bollerslev, Engle and Woolridge to become Multivariate-GARCH which involves variance modeling or error modeling [27]. The Multivariate-GARCH model is practical and relatively easy to use in estimating volatility and is considered the basis for dynamic volantility models [28]. Research that uses the Multivariate GARCH includes Francq and Zakoian in their research on asset prices and risk management which crucially depends on the conditional covariance structure of portfolio assets [29]. As well as Bumi, which examines and compares the retun volume of Indonesian stocks with Malaysia and Singapore [30]. A further development was built on the CCC-GARCH model by Bollerslev [31]. The BEKK GARCH model introduced by Baba, et. al. was further developed by Engle and Kroner [32; 33]. In analyzing the effects of the volatility of stock returns, the BEKK GARCH method tends to be more profitable than the GARCH model in general [34]. Engle and Kroner proposed a parametric model with positive precision constraints thus providing an effective model for modeling volantility [33]. BEKK GARCH is known for its ease of obtaining a positive definite variance-covariance matrix and its efficiency in reducing the number of parameters estimated. According to Rahman and Serletis, BEKK GARCH is used to estimate covariance conditions, and can also be used to estimate conditional correlations indirectly [35]. Some researchers who have conducted research related to the BEKK GARCH model are Caporin and McAleer, Xinjun and Minhui, and Hongfei and Lou [36; 37; 38].

So that in this study we will be modeling the best model selection from stock price return data from Indonesian pharmaceutical companies, namely PT. Indofarma Tbk. (INAF) and PT. Kimia Farma Tbk. (KAEF) from June 2015 to July 2020. This study will apply modeling involving mean and error modeling, namely the VAR-BEKK GARCH model so that a model is formed that can describe the dynamic model of the two variables. In addition, this study will also examine the behavior and relationship of the two variables based on the Granger Causality test and Impulse analysis of each variable.

2. Statistical Model

Time series analysis is an analysis for data in a past time period which is useful for obtaining forecasts of future conditions. However, if there are several observations from several variables that will be analyzed simultaneously, the analysis used is the Multivariate Time Series analysis. The model that is often used in Multivariate Time Series analysis is the Vector Autoregressive Moving Average (VARMA). The VARMA model explains the relationship between observations and errors of a variable at a certain time with observations and errors in the variable itself and other variables at the previous time. Here are some classifications of the VARMA model, namely:

2.1. Vector Autoregressive Model (VAR)

The VAR model is often used to determine the habits of the variables simultaneously over time [12]. VAR model was introduced by Sims as a tool to analyze macroeconomic data. VAR model treats all involved variables symmetrically [9]. In the VAR model, a vector consists of two or more variables and on the right side contains the lag vector of the dependent. The VAR (p) model can be written as follows:

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-1} + a_t \qquad (1)$$

where Y_t is nx1 vector at time t, φ_i is nxn matrix, $i = 1,2,\ldots,p$, where p is lag length, and a_t is vector shock. By using backshift operator, we have

$$(1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p)Y_t = a_t \qquad (2)$$

where $B^j Y_t = Y_{t-j}$ where $j = 1, 2, \ldots, p$. and $\varphi_p = [\varphi_{lm}{}^s]$ is kxk matrix and $s = 1,2,\ldots p$.

2.2. Generalized Autoregresive Conditional Heteroscedastic (GARCH)

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is a development of Autoregressive Conditional Heteroscedasticity (ARCH). This model was developed to avoid the high order of the ARCH model, and to choose a simpler model, thus ensuring that the variance is always positive. The GARCH model can be written as follows:

$$X_t = \delta + \sum_{i=1}^{p} \phi_i X_t + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_t$$
$$\varepsilon_t = N(0, \sigma_t^2)$$
$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Where X_t is *conditional mean* [39].

Model GARCH multivariate is defined as follows:

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \mathbf{a}_t$$
$$\mathbf{a}_t = H_t^{\frac{1}{2}} z_t$$

where, $\mathbf{r}_t$: nx1 vector data at time t.
$\quad\quad\mathbf{a}_t$: nx1 vector of mean-corrected data at time t.
$\quad\quad\boldsymbol{\mu}_t$: nx1 vector of expected value of the conditional $\mathbf{r}_t$
$\quad\quad\mathbf{H}_t$: nxn matrix of conditional variance $\mathbf{a}_t$ at time t.
$\quad\quad z_t$: nx1 vector of $\varepsilon \sim iid$

2.3. BEKK GARCH

This model was first proposed by Baba, Engle, Kraft, and Kroner and then further developed by Engle and Kroner [32; 33]. Although two of the original originators no longer joined, the new parameterization is still given the acronym BEKK. Engle and Kroner proposed a new parameterization that is easily restrictive of the requirement that H_t be positive for all values of ε_t and x_t in the sample space [33]. This model can be written in the following equation:

$$H_t = C_0^{*'}C_0^* + \sum_{k=1}^{K} \quad C_{1k}^{*'}x_t x_t' C_{1k}^* + \sum_{k=1}^{K} \quad \sum_{i=1}^{q} \quad A_{1k}^{*'}\varepsilon_{t-1}\varepsilon_{t-1}' A_{1k}^* +$$

$$\sum_{k=1}^{K} \quad \sum_{i=1}^{q} \quad G_{1k}^{*'}H_{t-1}G_{1k}^* \tag{3}$$

where C_0^*, A_{1k}^* and G_{1k}^* are nxn matrix parameters where C_0^* triangular, C_{1k}^* is Jxn matrix parameters, and summation by the limit K determines the general state of the process. This explains that the above equation will be positive for sure in weak conditions.

When the model GARCH(1,1) with K=1 and if there is no exogenous effect, model (3) becomes:

$$H_t = C_0^{*'}C_0^* + A_{11}^{*'}\varepsilon_{t-1}\varepsilon_{t-1}' A_{11}^* + G_{11}^{*'}H_{t-1}G_{11}^* \tag{4}$$

Model (4) can be translated into vector and diagonal representations as follows:

$$H_t = [h_{11,t} \ h_{12,t} \ . \ h_{22,t}]$$
$$H_t = [c_{11}^0 \ 0 \ c_{12}^0 \ c_{22}^0][c_{11}^0 \ c_{12}^0 \ 0 \ c_{22}^0]$$
$$+[a_{11} \ a_{21} \ a_{12} \ a_{22}][\varepsilon_{1(t-1)} \ \varepsilon_{2(t-1)}][\varepsilon_{1(t-1)} \ \varepsilon_{2(t-1)}][a_{11} \ a_{12} \ a_{21} \ a_{22}] +$$
$$[g_{11} \ g_{21} \ g_{12} \ g_{22}][h_{11(t-1)} \ h_{12(t-1)} \ h_{21(t-1)} \ h_{22(t-1)}][g_{11} \ g_{12} \ g_{21} \ g_{22}] \tag{5}$$

3. Data Analysis

In this study, the data used are daily stock return data from the pharmaceutical sector, namely Indofarma Tbk. (INAF) and Kimia Farma Tbk. (KAEF) from June 2015 to July 2020 obtained from idnfinancial.com and the Indonesia Stock Exchange (IDX) with a plot series distribution form of the two variables can be selected in Figure 1.The use of return data was chosen because it more describes the risk of changes in stock prices itself. It can be seen that INAF retun data has a higher data fluctuation than KAEF. In addition, INAF and KAEF experienced changes in data fluctuations which were quite unstable from January to June 2020. This was based on the COVID-19 pandemic so that pharmaceutical sector stocks attracted the attention of investors. Therefore, time series analysis will be carried out to determine the future stock return forecast in order to determine the risk of the INAF and KAEF stocks. However, in conducting time series analysis, there are assumptions that must be met first, namely stationarity. The method of testing the standard used is the Dickey-Fuller Test, the results of which can be seen in Table 1.
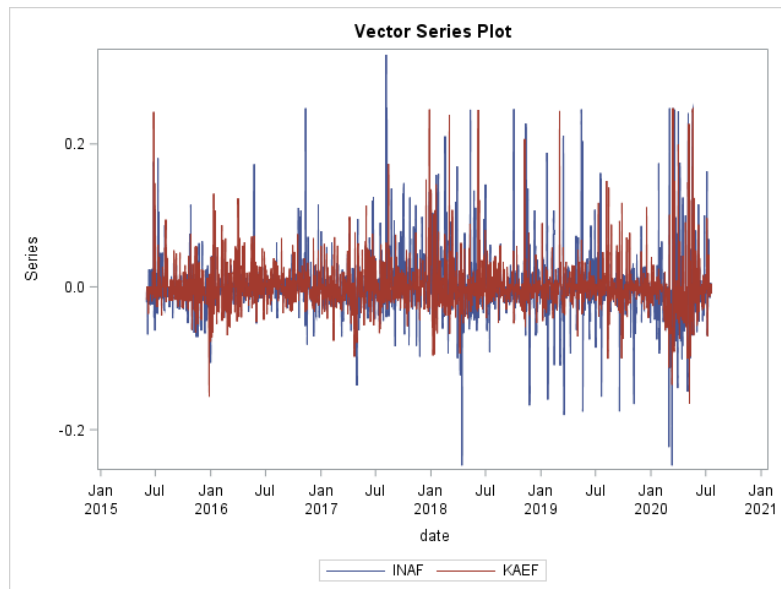
Figure 1. Plot Data Return share price INAF and KAEF from June 2015 - July 2020

In the Augmented Dicky-Fuller test, the H0 test is rejected if Pr <Tau is less than 0.05, and based on Table 1. The Pe <Tau value of each type for all variables, both INAF and KAEF, is <0.0001 which means <0.05. Therefore the decision obtained is to reject H0 or in other words, stationary data [40; 1]. This decision is also in line with the trend graphs from INAF and KAEF which are presented in Figure 2. The trend graph shows that the ACF and PACF values of ADRO and ITMG did not decrease exponentially, which means that the data used in the study were stationary. so that further analysis can be carried out.

Table 1. Dickey-Fuller Unit Root Test

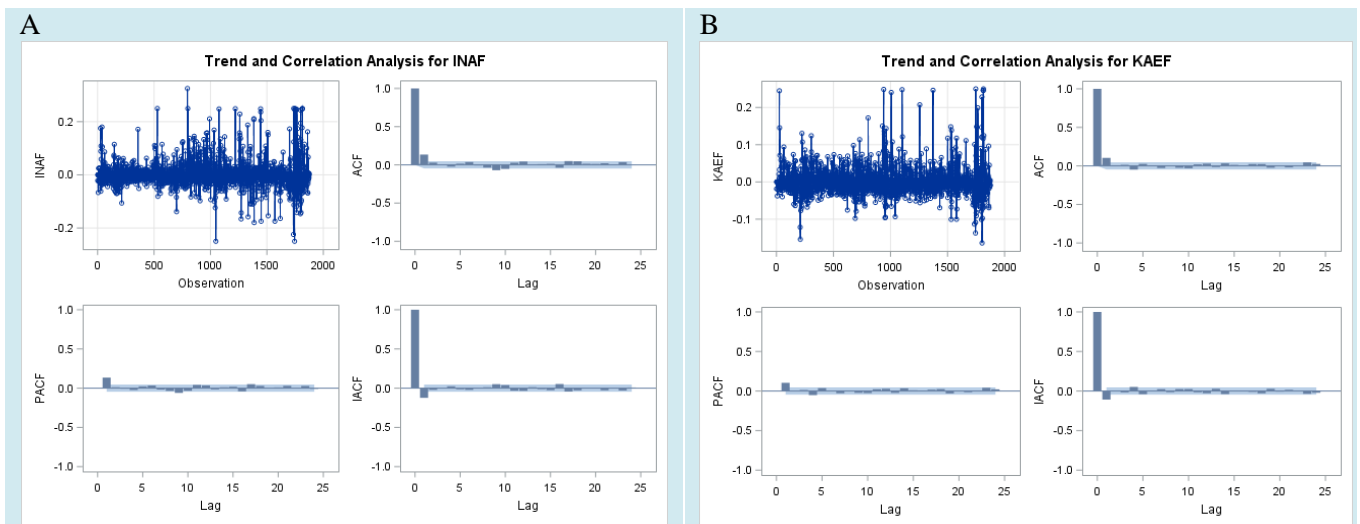| Variable	Type	Rho	Pr < Rho	Tau	Pr < Tau
INAF	Zero Mean	-1576.2	0.0001	-28.06	<.0001
	Single Mean	-1582.4	0.0001	-28.11	<.0001
	Trend	-1582.6	0.0001	-28.10	<.0001
KAEF	Zero Mean	-1682.7	0.0001	-28.99	<.0001
	Single Mean	-1686.3	0.0001	-29.01	<.0001
	Trend	-1689.3	0.0001	-29.03	<.0001

A

B

Figure 2. Plot Trend and Correlation Analysis for (a) INAF and (b) KAEF

Whereas in Figure 3 we can see the form of the volatility of the INAF and KAEF conditional variances. Figure 4 (a) shows that INAF has several high volatility shocks and has low volatility at other times which characterizes that INAF is heteroscedasticity. While the KEAF volatility presented in Figure 4 (b) shows that the volatility is more stable than INAF, but there are still 3 shocks that exceed 0.01 and in the 1700 to 1800 period there is a volatility shock that is not high enough, while in other time periods KAEF is relatively volatile low. So, based on the volatility condition of the KAEF data, it can be seen that the KAEF return data is heteroscedastic. In addition, to further ascertain whether the two data have heteroscedasticity or not, further testing will be carried out, namely the White Noise Test as presented in Table 2.

In this White Noise test, the null hypothesis is that the residual does not have an ARCH effect (data is not heteroscedaticity) and the alternative hypothesis is that the data has an ARCH effect (heteroscedasticity data) with a significance level of $\alpha = 0.05$, H_o will be rejected if the p-value <0.05. Based on Table 2. It is obtained that the Pr> F value of the INAF and KAEF variables is <0.0001 which means <0.05 so we reject H0 which in other words that the data we have contains heteroscedasticity. Therefore, we will include the GARCH model in the VARMA modeling that will be formed, namely the BEKK-GARCH model to overcome the heteroscedasticity characteristic. Furthermore, model testing will be carried out based on the AICC, HQC, AIC and SBC criteria from the VAR (1) -GARCH (1,1), VAR (2) -GARCH (1,1), VAR (3) -GARCH (1) models. 1), VAR (4) -GARCH (1,1), and VAR (5) -GARCH (1,1) to get the best model from the data. Based on the model criteria information presented in Table 3. Where the criteria for selecting the model criteria for AICC, HQC, AIC and SBC show that VAR (1) -GARCH (1,1) has the smallest criterion value compared to other models and the VAR (1) - GARCH model (1,1) has the schematic representation of parameters and GARCH parameters which are presented in Table 4. And Table 5. Thus, the best model for the INAF and KAEF return resized data is the VAR (1) -GARCH (1,1) model.
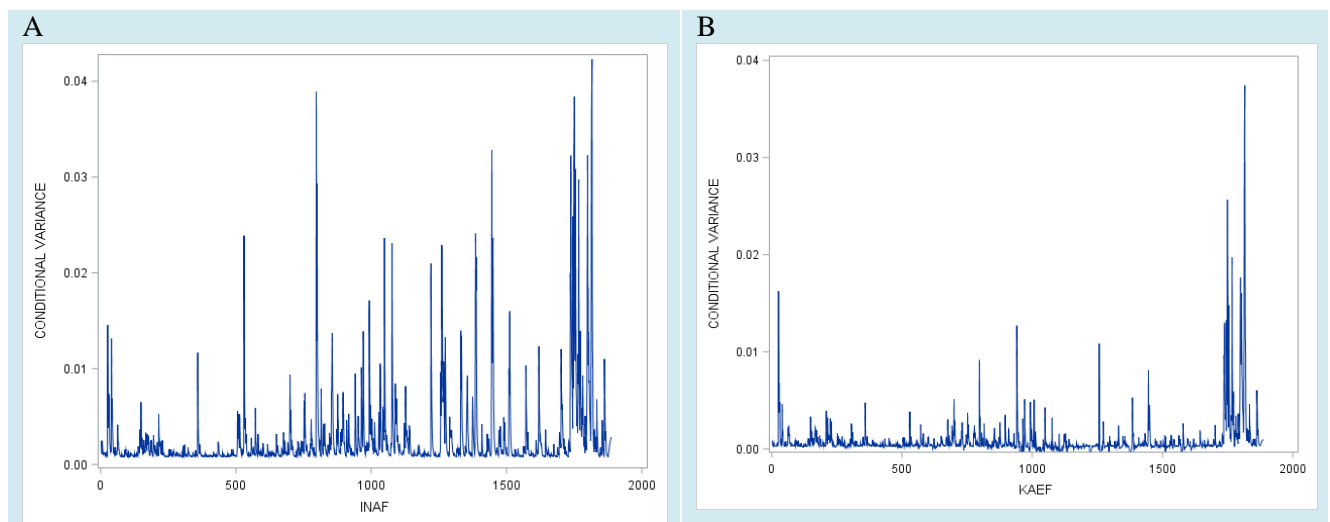

Figure 3. Plot Conditional Variance INAF (a) and KAEF (b)

Table 2. Univariate Model White Noise Diagnostic

Variable	Durbin Watson	Normality		ARCH	
		Chi-Square	Pr > ChiSq	F Value	Pr > F
INAF	1.78116	7573.30	<.0001	153.30	<.0001
KAEF	1.89662	9999.99	<.0001	92.75	<.0001

Table 3. Information Criteria of Models

	VAR(1)-GARCH(1,1)	VAR(2)-GARCH(1,1)	VAR(3)-GARCH(1,1)	VAR(4)-GARCH(1,1)	VAR(5)-GARCH(1,1)
AICC	-21423.7	-21402.4	-21384.8	-21367.8	-21354.5
HQC	-21393.4	-21364.1	-21338.5	-21313.6	-21292.3
AIC	-21424.0	-21402.8	-21385.4	-21368.6	-21355.6
SBC	-21340.9	-21297.7	-21258.1	-21219.2	-21184.0

Table 4. Schematic Representation of Parameter Estimates

Model	Variable/Lag	AR1
VAR (1) – GARCH (1,1)	**INAF**	..
	KAEF	.+

+ is > 2*std error, - is < -2*std error, . is between, * is N/A

Table 5. Schematic Representation of GARCH Parameter Estimates

Model	Variable/Lag	GCHC	ACH1	GCH1
VAR (1) – GARCH (1,1)	**h1**	++	+.	+.
	h2	+	.+	.+

+ is > 2*std error, - is < -2*std error, . is between, * is N/A

Based on the selection of the best model, the VAR (1) -GARCH (1,1) model is obtained as the best model. Therefore, it will be carried out estimating the model parameters presented in Table 6 and the GARCH model parameters presented in the Table. But in Table 7, it is known that there are 2 insignificant parameters ACH1_2_1 and ACH1_1_2, but based on the principle of meaning where the parameter value is greater than 0.05, ACH1_2_1 is still included in the model so that the VAR (1) - GARCH (1,1) model is obtained as follows:

$$[ADRO_t \ ITMG_t] = [0.01412 \ 0.03704 \ -0.03137 \ 0.07178][INAF_{t-1} \ KAEF_{t-1}] + [\varepsilon_{1,t} \ \varepsilon_{2,t}]$$

Conditional mean of model VAR (1) can be written as univariate models as follows:
$$INAF_t = 0.01412 \ INAF_{t-1} + 0.03704 \ KAEF_{t-1} + \varepsilon_{1,t} \qquad (6)$$
$$KAEF_t = -0.03137 \ INAF_{t-1} + 0.07178 \ KAEF_{t-1} + \varepsilon_{2,t} \qquad (7)$$
and *conditional variance* of model GARCH (1,1) with the BEKK GARCH method is:

$$h_{11t} = 0.00036 + (0.58787)^2 \varepsilon_{1(t-1)}^2 + (0.76182)^2 h_{11(t-1)} +$$
$$2(0.58787)(0.05905) \ \varepsilon_{1(t-1)} \ \varepsilon_{2(t-1)} + (0.05905)^2 \varepsilon_{2(t-1)}^2 +$$
$$2(0.76182)(-0.08835) \ h_{12(t-1)} + (-0.08835)^2 \ h_{22(t-1)}$$

$$h_{12t} = 0.00018 + (0.58787)(0.03779)\varepsilon_{1(t-1)}^2 + (0.52986)(0.05905)\varepsilon_{2(t-1)}^2 +$$

$$(0.76182)(-0.03379)h_{11(t-1)} +$$

$$(0.75486)(-0.08835)h_{22(t-1)} + (0.76182)^2 h_{11(t-1)} +$$

$$\{(0.05905)(0.00018) + (0.58787)(0.52986)\}\varepsilon_{1(t-1)}^2 \varepsilon_{2(t-1)}^2 +$$

$$\{(0.01295)(-0.07361) + (0.92956)(1.01948)h_{12(t-1)}$$

$$h_{22t} = 0.00027 + (0.52986)^2\varepsilon_{2(t-1)}^2 + (0.75486)^2h_{22(t-1)} +$$
$$2(0.52986)(0.03779)\,\varepsilon_{1(t-1)}\,\varepsilon_{2(t-1)} + (0.03779)^2\varepsilon_{1(t-1)}^2 +$$
$$2(-0.03379)(0.75486)\,h_{12(t-1)} + (-0.03379)^2\,h_{11(t-1)}$$

The statistical tests of the ADRO_t and ITMG_t models are presented in Table 6. Based on these statistical tests, the INAF_t model has a value of F = 15.91 and a P-Value <0.0001 which means significant and has a coefficient of determination of R-square 0.0084. While KAEF_t has a value of F = 14.30 and P-Value = 0.0002 which means significant and has a coefficient of determination of R-square 0.0076. So it can be said that the two univariate models are feasible to use. Model (6) explains that the return value of KAEF has a positive effect on lag 1 (t-1). Model (7) explains that the INAF return value has a negative effect on lag 1 (t-1). In addition, based on Figure 6, it can be seen that the distribution of prediction error for INAF and KAEF return data tends to approach the normal distribution. Meanwhile, if seen from the patterns of prediction error, it can be seen that KAEF has a more stable prediction error than INAF. However, the prediction error from INAF and KAEF shows high instability compared to other years, namely in 2020.

Table 6. Estimation of Parameters Model

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
INAF	AR1_1_1	0.01412	0.02997	2.17	0.0376	INAF(t-1)
	AR1_1_2	0.03704	0.02599	2.45	0.0143	KAEF(t-1)
KAEF	AR1_2_1	-0.03137	0.01580	-1.99	0.0473	INAF(t-1)
	AR1_2_2	0.07178	0.02865	2.51	0.0123	KAEF(t-1

Table 7. Estimation of Parameters Model GARCH

Parameter	Estimate	Standard Error	t Value	Pr > |t|
GCHC1_1	0.00036	0.00004	9.18	0.0001
GCHC1_2	0.00018	0.00003	6.57	0.0001
GCHC2_2	0.00027	0.00003	8.52	0.0001
ACH1_1_1	0.58787	0.04565	12.88	0.0001
ACH1_2_1	0.05905	0.06679	0.88	0.3767
ACH1_1_2	0.03779	0.02270	1.67	0.0961
ACH1_2_2	0.52986	0.04101	12.92	0.0001
GCH1_1_1	0.76182	0.02503	30.43	0.0001
GCH1_2_1	-0.08835	0.04475	-1.97	0.0485
GCH1_1_2	-0.03379	0.01707	-1.98	0.0479
GCH1_2_2	0.75486	0.03136	24.07	0.0001

Table 8. Univariate Model Anova Diagnostics

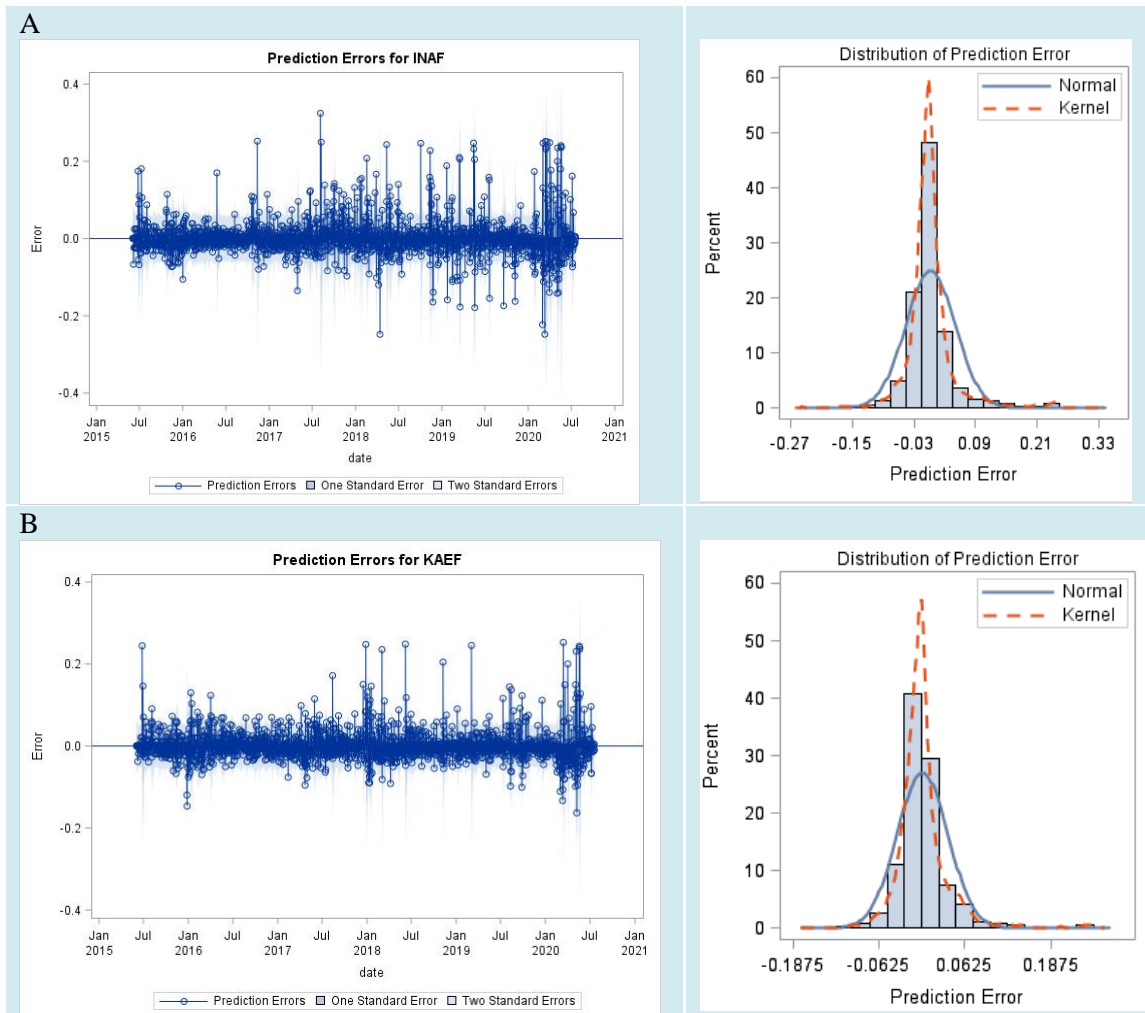| Variable	R-Square	Standard Deviation	F Value	Pr > F
INAF	0.0084	0.04816	15.91	<.0001
KAEF	0.0076	0.03687	14.30	0.0002

Figure 4. Prediction and Distribution of Errors base on model for data of INAF (a) and KAEF(b)

Furthermore, a Granger Causality Test will be carried out which aims to determine the causal relationship between variables [41; 13]The Granger Causality test is based on the Wald test where the Chi-square distribution or F-test is used as an alternative. Based on the results of the Granger Causality test analysis presented in Table 9, it shows that the first test in which INAF is group 1 and KAEF is Group 2, the Chi-square value = 11.23 and P-value = 0.0008, which means the data reject H0. Therefore, it is concluded that the INAF return value is influenced by the KAEF return value. Meanwhile, for the second test with KAEF as group 1 and INAF as group 2, it was obtained Chi-square = 0.57 and P-value = 0.4491, so we don't have enough evidence to reject H0. In other words, it can be concluded that the KAEF return value is not affected by the KAEF return value. In addition to the Granger Causality test, the relationship of variables from the multivariate time series analysis is also explained through the IRF interpretation presented in Figures 5 and 6.

Table 9. Granger Causality Wald Test

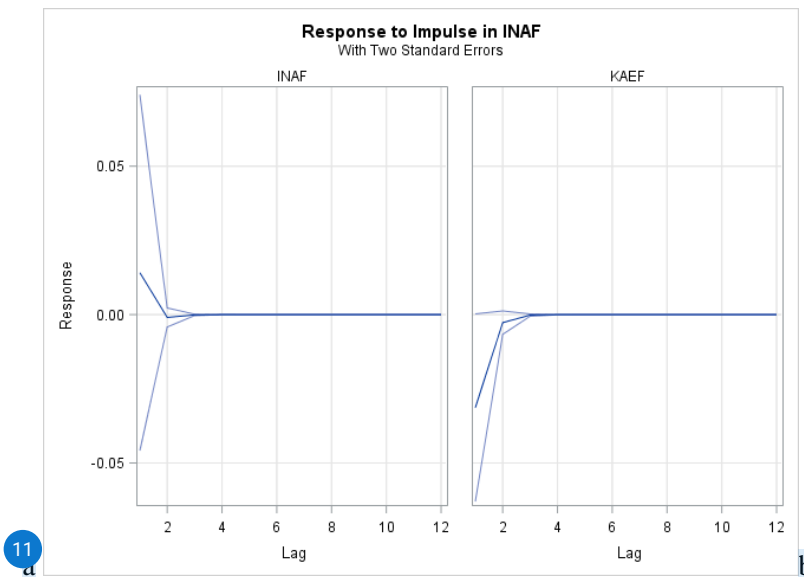| Test	Group	DF	Chi-Square	Pr > ChiSq
1	Group 1 Variabels: INAF	1	11.23	0.0008
	Group 2 Variabels: KAEF			
2	Group 1 Variabels: KAEF	1	0.57	0.4491
	Group 2 Variabels: INAF			

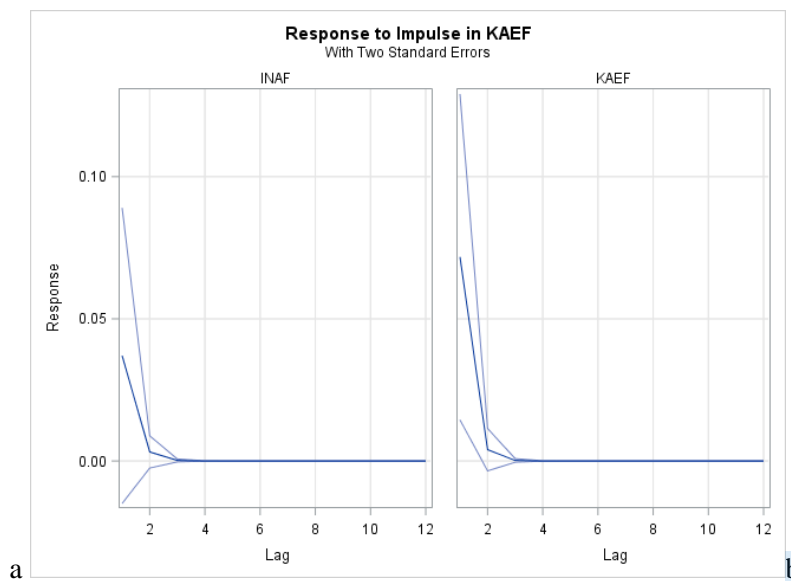**Figure 5.** Response to Impulse in INAF

Figure 6. Response to Impulse in KAEF

Impulse response itself is commonly used in economics to describe the economic reaction from time to time to exogenous impulse. The horizontal axes in Figures 5 and 6 show the time periods where

one period represents one day. While the vertical axis shows changes in a variable to the shock itself and other variables. Figure 5 (a) shows the impulse of INAF on itself. The shock of the INAF standard deviation causes a fluctuating response until the 3rd period then the response goes to zero or stability. Whereas in Figure 5 (b) it can be seen that the fluctuation of the standard deviation tends to increase after receiving a KAEF shock and reaching the equilibrium point in the 3rd period. Meanwhile, Figure 6 (a) depicts the impulse of KAEF's response to INAF shock. The shock from the standard deviation KAEF tends to decrease after receiving a shock from INAF and in the 3rd period it starts to move towards stability. Meanwhile, in Figure 6 (b) the shock from the standard deviation of ITMG caused ITMG to stabilize or move towards zero in the 3rd period.

Table 10. Forecasts for return value of INAF and KAEF

Variable	OBS	Time	Forecast	Standard Error	95% Confidence Limits	
INAF	1876	20JUL2020	-0.00033	0.02844	-0.05607	0.05542
	1877	21JUL2020	-0.00003	0.03314	-0.06498	0.06492
	1878	22JUL2020	-0.00000	0.03686	-0.07225	0.07225
	1879	23JUL2020	-0.00000	0.03994	-0.07828	0.07828
	1880	24JUL2020	-0.00000	0.04254	-0.08338	0.08338
	1881	25JUL2020	-0.00000	0.04478	-0.08776	0.08776
	1882	26JUL2020	-0.00000	0.04672	-0.09157	0.09157
	1883	27JUL2020	0.00000	0.04843	-0.09491	0.09491
	1884	28JUL2020	0.00000	0.04993	-0.09787	0.09787
	1885	29JUL2020	0.00000	0.05128	-0.10050	0.10050
	1886	30JUL2020	0.00000	0.05247	-0.10285	0.10285
	1887	31JUL2020	0.00000	0.05355	-0.10496	0.10496
KAEF	1876	20JUL2020	-0.00063	0.02523	-0.05007	0.04881
	1877	21JUL2020	-0.00004	0.02851	-0.05592	0.05585
	1878	22JUL2020	-0.00000	0.03100	-0.06075	0.06075
	1879	23JUL2020	-0.00000	0.03296	-0.06460	0.06460
	1880	24JUL2020	-0.00000	0.03453	-0.06768	0.06768
	1881	25JUL2020	-0.00000	0.03582	-0.07020	0.07020
	1882	26JUL2020	0.00000	0.03687	-0.07226	0.07226
	1883	27JUL2020	0.00000	0.03774	-0.07397	0.07397
	1884	28JUL2020	0.00000	0.03847	-0.07540	0.07540
	1885	29JUL2020	0.00000	0.03908	-0.07659	0.07659
	1886	30JUL2020	0.00000	0.03959	-0.07759	0.07759

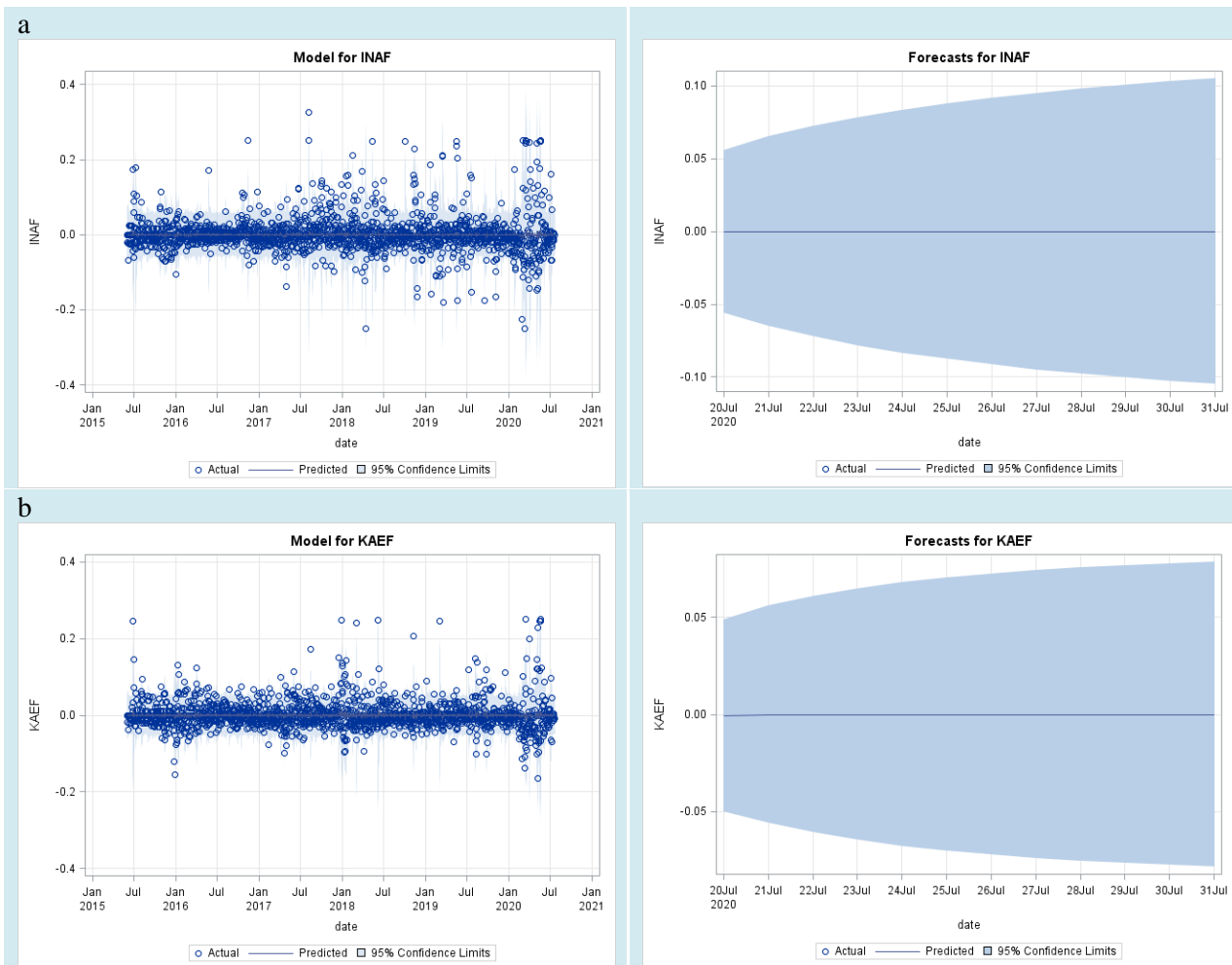| 1887 | 31JUL2020 | 0.00000 | 0.04002 | -0.07843 | 0.07843 |

Figure 7. Model and estimation and forecasting data returns INAF (a) and KAEF (b)

As it is known that the purpose of time series analysis is to obtain forecasts of future conditions based on previous observational data. Therefore, forecasting of INAF and KAEF return data will be formed in the next 12 days based on model VAR (1) -GARCH (1,1) which is presented in Table 10. Based on the forecast results it can be seen that the return value of both INAF and KAEF in the first 2 days of forecasting gives a negative value, which means that the share value has decreased or lost to investors, while from the 3rd to 12th day forecasting it gives a value of 0 (zero) which means that there is no significant change in the stock price of both INAF and KAEF. In addition, based on Figure 7, it can be seen that ADRO and ITMG have predicted values and the observational data are close to each other, this indicates that the model is fit with the data. Meanwhile, in the plot forecasts for INAF and forecasts for KAEF, it can be seen that the confidence interval tends to increase, this shows that the model used is suitable and good for analyzing and forecasting short-term data.

4. Conclusion

Based on the analysis that has been done, the best model in forecasting and modeling PT Indofarma Tbk daily stock return data. (INAF) and PT. Kimia Farma Tbk. (KAEF) from June 2015 to July 2020 is a VAR (1) -GARCH (1,1) model. The selection of the best model uses several model selection criteria,

namely AICC, HQC, AIC and SBC where all the criteria produce the smallest VAR (1) -GARCH (1,1) value. In addition, based on the granger causality test, it is known that the INAF stock return variable is not only influenced by itself but is also influenced by the KAEF variable, while the KAEF variable is only influenced by itself. Then based on the forecasting results obtained based on the model that has been formed, it is found that the prediction values are close to each other with the observational data which means the model is fit with the data. It can also be seen that the confident interval of forecasting INAF and KAEF data for the next 12 days tends to increase. Thus, it can be concluded that VAR (1) - GARCH (1,1) is suitable for modeling INAF and KAEF return data for the short term.

References

[1] Brockwell and Davis 2002 *Introduction to Time Series Analysis and Forecasting* (New York : Springer)

[2] Box G E P and Jenkins G M 1976 *Time Series Analysis: Forecasting and Control* 1 (San Fransisco : Holden-Day)

[3] Tandelilin E 2010 *Portofolio dan Investasi Teori dan Aplikasi* 1 (Yogyakarta : Kanisius)

[4] Aspara R H and Indriani A 2017 Analisis Pengaruh Crude Oil Price, Earning per Share, Price to Book Value, return on assets dan debt to equity ratio terhadap harga saham perusahaan batubara yang terdaftar di Bursa Efek Indonesia Periode 2012-2016 *Diponegoro Journal of Management* Vol. 6(**4**) pp 885-905

[5] Ang R 2001 *Buku Pintar Pasar Modal Indonesia* (Jakarta : Mediasoft)

[6] Tioa G C and Box G E P 1981 Multiple Time Series Modeling With Application *Journal of the American Statistical Association* Vol. 76 pp 802-816

[7] Lutkepohl H 2005 *New Intoduction to Multiple Time Series Analysis* (Berlin : Springer-Verlag)

[8] Reinsel G C 1993 *Element of Multivariate Time Series Analysis* (New York : Springer-Verlag)

[9] Sims C A 1980 Macroeconomics and reality *Econometrica* Vol. 48(**1**) pp 1-48

[10] Kirchgassner G and Wolters J 2007 *Introduction to Modern Time Series Analysis* (Berlin : Pearson Education, Inc)

[11] Stock J H and Watson M W 2001 Vector Autoregressive *Journal of Economic Perspectives* 2001, Vol. 15 4 pp 101-115

[12] Sharma A G et al 2018 Relatiionship between crude oil prices and stock market: Evidence from India *International Journal of Energy Economics and Policy* Vol. 8(**4**) pp 331-337

[13] Warsono et al 2019 Vector Autoregressive with Exogenous Variable Model and Its Application in Modeling and Forecasting Energy Data: Case Study of PTBA and HRUM Energy *International Journal of Energy Economics and Policy* Vol. 9(**2**) pp 390-398

[14] Kesumah F S D et al 2020 Dynamic Model of Forecasting Stock Price *Journal of Engineering and Applied Sciences* Vol. 15(**6**) pp 6815-6828

[15] Tandelilin E 2001 *Analisis Investasi dan Manajemen Portofolio (*Yogyakarta : BPFE)

[16] Firmansyah 2006 *Analisiis Volatilitas Harga Kopi Internasional* (Jakarta : Usahawan)

[17] Mascaro A and Meltzer A H 1983 Long and short-term interest rates in rislky world *Journal Monet Econ* Vol. 12 pp 485-518

[18] Belongia M 1984 Money growth variability and GNP *Federal Reserve Bank of St, Louis* Vol. 66 pp 23-31

[19] Engle R F and Susmel R 1993 Common volatility in international equity markets *Journal of Business and Economic Statistics* Vol. 11 pp 167-176

[20] Karolyi A 1995 A mutivariate GARCH model of international oil price on China ese stock market-empirical analysis based on industry data *Financial Research* Vol. 356(**2**) pp 173-187

[21] Engle J and Grizycki M 1999 Value at Risk on the stability an forecasting of the variance covariance matrix *Reserve Bank of Australia Research Discussion Papper* Vol. 4

[22] Lopez J A and Walter C A 2000 Evaluating covariance matrix forecast in a Value at Risk framework *Working Paper Federal Reserve Bank of San Fransisco*

[23] Mamtha D and Srinivasan K S 2016 Stock market volatility-conceptual perspective through literature survey *Mediterranean Journal of Social Sciences* Vol. 7(**1**) pp 208-212

[24] Nachrowi D and Usman H 2006 *Pendekatan Populer dan Praktis Ekonometrika untuk Analisis Ekonomi dan Keuangan* (Jakarta : Badan Penerbit Universitas Indonesia)

[25] Ghozali I 2009 *Ekonometrika* (Semarang : Badan Penerbit Universitas Diponegoro)

[26] Engle R F, Granger C W J and Kraft D 1984 Combininf competing forecast of inflation based on a bivariate ARCH model *Journal of Economic Dynamics and control* Vol. 8 pp 151-165

[27] Bollerslev T, Engle R F and Wooldridge J M 1988 A Capital asset pricing model with time varying covariances *Journal of Political Economy* Vol. 96 pp 116-131

[28] Alexander C and Lazar E 2006 Normal micture GARCH (1,1): Aplication to exchange rate modeling *Journal of Applied Econometrics Economic Review* Vol. 39 pp 885-905

[29] Francq C and Zakoian J M 2010 *GARCH Model (*New York : John Wiley)

[30] Bumi O C 2013 Volatilitas return saham di Indonesia: Pola dan perbandingan dengan Malaysia dan Singapura *Journal of Economic Suervey* Vol. 6(**1**, pp 61-74

[31] Bolllerslev T 1990 Modelling the coherence in short-run nominal exchange rate: A multivariate Generalized ARCH Model *Riview of Economics and Statistics* Vol. 72 pp 498-505

[32] Baba Y et al 1990 *Multivariate Simultaneous Generalized ARCH. Unpublishe Manuscript (*San Diego : University of California)

[33] Engle R F and Kroner K F 1995 Multivariate Simultaneous Generalized ARCH *Econometric Theory* Vol. 11 pp 122-150

[34] Li S 2015 Volatility Spillovers in the CSI300 futures and spot markets in China: Empirical Study Based on Discrate Wavelet Transform and VAR-BEKK-Bivariate GARCH Model *Information Technology and Wuantitative Management* Vol. 55 pp 380-387

[35] Rahman S and Serletis A 2012 Oil price uncertainly and the canadian economy: Evidence from a VARMA, GARCH-in-Mean, asymetric BEKK Model *Energy Economics* Vol. 34(**2**) pp. 603-610

[36] Caporin M and McAller M 2011 Do we really need voth BEKK and DCC? A tale of two multivariate GARCH Model *Journal of Economic Surveys* Vol. 10 pp. 1-20

[37] Xinjun W and Minhui L 2011 Shanghai, deep, the US stock market volatility spillover relationship base on termaru BEKK-GARCH (1,1) Model *Shandong Social Sciences* Vol. 24(**11**) pp 158-162

[38] Hongfei J and Luo K 2010 The shadow of international oil price on China ese stock market-empirical analysis based on industry data. *Financial Research* Vol. 356(**2**) pp 173-187

[39] Brooks C 2014 *Introductory Econometrics for Finance (*New York : Cambridge University Press)

[40] Dickey D A and Fuller W A 1979 Distribution of the eatimator for autoregressive time series with a unit root *Journal of the American Statistical Association* Vol. 10 pp 1-20

[41] Tsay R S 2014 Multivariate Time Series Analysis: With R and Financial Applications (Hoboken, New Jersey: John Wiley & Sons, Inc)

● **29% Overall Similarity**

Top sources found in the following databases:

- 22% Internet database
- Crossref database
- 17% Submitted Works database

- 25% Publications database
- Crossref Posted Content database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	S U Nabila, M Usman, Warsono, N Indryani, Widiarti, D Kurniasari. "Dyn... Crossref	**10%**
2	Universitas PGRI Yogyakarta on 2022-12-19 Submitted works	**4%**
3	researchgate.net Internet	**3%**
4	documentation.sas.com Internet	**2%**
5	D B Nugroho. "Comparative analysis of three MCMC methods for estim... Crossref	**<1%**
6	eprints.utm.my Internet	**<1%**
7	econjournals.com Internet	**<1%**
8	University of Birmingham on 2018-09-16 Submitted works	**<1%**

9 morethingsjapanese.com
Internet
<1%

10 Dandi Jia, Qiang Gao, Hui Deng. "Stock Market Prediction Based on Ti...
Crossref
<1%

11 econjournals.com
Internet
<1%

12 sumo.dlr.de
Internet
<1%

13 University of Macedonia on 2022-05-31
Submitted works
<1%

14 De La Salle University on 2022-12-01
Submitted works
<1%

15 pasca.unila.ac.id
Internet
<1%

16 Higher Education Commission Pakistan on 2013-12-11
Submitted works
<1%

17 irep.iium.edu.my
Internet
<1%

18 University of Brighton on 2015-05-05
Submitted works
<1%

19 pcl.physics.uwo.ca
Internet
<1%

20 eshare.stust.edu.tw
Internet
<1%

21 iopscience.iop.org

Internet

<1%

---

22 R N Putri, M Usman, Warsono, Widiarti, E Virginia. "Modeling Autoregr...

Crossref

<1%

---

23 SDM Universitas Gadjah Mada on 2022-12-16

Submitted works

<1%

---

24 jurnal.feb.unila.ac.id

Internet

<1%

---

25 Christian Francq, Jean-Michel Zakoian. "GARCH Models", Wiley, 2019

Crossref

<1%

---

26 Grey Systems, Volume 2, Issue 2 (2012-08-18)

Publication

<1%

---

27 Royal Holloway and Bedford New College on 2008-09-03

Submitted works

<1%

---

28 knepublishing.com

Internet

<1%

---

29 coursehero.com

Internet

<1%

---

30 ssbfnet.com

Internet

<1%

● **Excluded from Similarity Report**

- Bibliographic material
- Cited material
- Manually excluded sources

- Quoted material
- Small Matches (Less then 10 words)

EXCLUDED SOURCES

N Indryani, M Usman, Warsono, S U Nabila, Widiarti, D Kurniasari. "Dynamic ...
Crossref
79%

repository.lppm.unila.ac.id
Internet
79%