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Dynamic Modeling Data Time Series By Using Constant Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity

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Dynamic Modeling Data Time Series By Using Constant Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity

S U Nabila[1,2], M Usman[1,*], Warsono[1], N Indryani[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 Constant Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity (CCC-Garch) model as one of the multivariate time series models is used to model economic variables, especially in stock price data with high volatility characteristics that result in heterogeneous variations. The higher the volatility, the higher the level of uncertainty of the stock returns that can be obtained. The CCC-Garch Multivariate model is the simplest model in its class. The principle of this model is to decompose the conditional covariance matrix into conditional standard deviation and correlation. In this study, we will discuss and determine the best model that can describe the relationship between two vector data timeseries, namely stock return data for companies engaged in mining and construction in Indonesia, namely United Tractor Tbk (UNTR) and Petrosea Tbk (PTRO) where the data is the daily stock return data for the period July 2015 to August 2020. Several models that involve modeling the mean and variance with CCC-GARCH parameterization are applied to data such as the VAR (1) -Garch (1,1), VAR (2) -Garch (1) model., 1), VAR (3) Garch (1,1) and VAR (4) -Garch (1,1). The result was that the VAR (1) -Garch (1,1) model was selected as the best model with the criteria for selecting the AICC, SBC, AIC and HQC models. The dynamic behavior of both UNTR and PTRO stock return variables is explained by Granger Causality and Impulse Response. Furthermore, the forecasting of this data was carried out for some time in which the VAR (1) - Garch (1,1) model which was selected as the best model was only suitable for forecasting in a short time.

Keyword: *Multivariate Timeseries*, *Vector Autoregressive* (VAR), Volatility, *CCC-Garch, forecasting*

1.   Introduction

Volatility can be interpreted as a measure of the difference between the current price of an asset and its past average price. Volatility is the standard deviation of returns, which measures the distribution of returns from the mean value. 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 [1]. In the applied field, especially financial economics, volatility is a statistical measure of fluctuation in the price of a security or commodity during a certain period [2]. Risk and return are positively related to each other, and must

have a positive relationship between expected return and uncertain return volatility and then have a negative relationship between unexpected volatility and real return. The latter relationship occurs when an unexpected increase in volatility increases the return which causes a decrease in stock prices [3]. There are many studies that conduct research on volatility and the effects of volatility, especially in the economic and financial fields, including those conducted by Mascaro and Meltzer [4], Evans [5], Belongia [6], Engle and Susmel [7], Karolyi [8] and Serletis and Shahmoradi [9]. Cronin et al [10] who discussed financial growth. Dimitrious et al [11] found a significant negative effect between volatility and stock returns. Meanwhile, Baker et al. [12] found that the relationship between stocks that have a high level of volatility is very influential on returns. From these results it was found that volatility testing has a significant effect on stock returns. Volatility modeling using statistical methods is also carried out in order to obtain an overview, correct interpretation and approximate accurate forecasting results. This is done to be a reference in determining the right decisions in a security. One of the statistical modeling that can be applied is modeling using methods in time series analysis.

According to Box and Jenskin [13] the application of time series modeling is very useful for forecasting in the economic and financial fields. An important part of time series analysis is the selection of an opportunity model that fits the data. An important part of time series analysis is the selection of an opportunity model that fits the data. Each observation of x_t in the time series analysis is a realization of the random variable X_t. According to Brockwell and Davis [14], 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.

At the beginning of the development of time series data modeling, especially the univariate time series only involved modeling the mean, for example the autoregressive model (AR), the Moving Average (MA) model, the Autoregressive Moving Average (ARMA) and the Autoregressive Integrated Moving Average (ARMA). Meanwhile, in timeseries multivariate data modeling which of course involves more than one variable, simultaneous analysis of timeseries data is carried out in order to obtain accurate conclusions without leaving an important element, namely the existence of other variables other than only depending on the time factor alone. In building a simultaneous model, each variable will depend on one another so that the form of modeling with the univariate time series model will no longer be appropriate. Sims [15] developed the Vector Autoregressive System (VAR) approach as an alternative to the simultaneous equation approach ([14], [16]). The application of the use of the Vector Autoregressive (VAR) model itself has been widely used, such as by Stock and Watson [17], Sharma et al [18], Zuhroh et al [19] and Warsono et al [20]. Warsono et al [21] performed modeling and forecasting on PTBA and HRUM data with a Vector Autoregressive (VAR) model involving the exchange rate variable as an exogenous variable. Kesumah et al [22] performed dynamic modeling of stock prices data.

Besides mean modeling, modeling which includes variance in the model (error modeling) is also interesting to study. Modeling involving variance modeling was developed to handle the heteroscedasticity tendency caused by the high volatility characteristic of economic data. The first model that involves error modeling is the Conditional Heteroscedasticity (ARCH) model introduced by Engle [23]. In 1986, Bollerslev [24] developed a general form of the ARCH model known as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model for univariate time series data. The GARCH model fundamentally changes many modeling approaches in the economic and financial fields, through efficient modeling of volatility. The univariate GARCH model does not consider information about the simultaneous factors of the variables under study. Therefore, Bollerslev, Engle and Wooldridge [25] proposed to develop a univariate GARCH model to become a multivariate GARCH model. The Vector GARCH model is a direct generalization of the univariate GARCH model. Each conditional variance is a function of the conditional lag of the variance as well as the cross-product lag of all components ([26], [27]). M-GARCH has several models, such as VECH, Baba-Engle-Kraft-Kroner (BEKK), Dynamic Conditional Correlation (DCC) and Constant Conditional Correlation (CCC).

In this study, we will discuss the best model that can describe the relationship between two vector data timeseries, namely stock returns of companies engaged in mining and construction in Indonesia, namely United Tractor Tbk (UNTR) and Petrosea Tbk (PTRO) where data is data. daily stock returns

for the period July 2015 to August 2020. As a basis for the study of the Constant Conditional Correlation-Generalized Autoregressive Conditional (CCC-Garch) model is used to explain the dynamic relationship between UNTR and PTRO stock return data from July 2015 to August 2020. In addition, in this paper This study will also discuss some of the characteristics of the Multivarite Garch process including the Granger Causality effect, the meaning of impulses from the variable and the forecasting will be carried out in this study.

2. Time Series Modeling

2.1 Vector Autoregressive (VAR) model

The VAR model is often used to determine the habits of the variables simultaneously over time [18]. VAR model was introduced by Sims [15] as a tool to analyze macroeconomic data. VAR model treats all involved variables symmetrically. 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:

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

where Y_t is nx1 vector observation at time t, φ_i is nxn matrix parameters, $n \times n$, $i = 1,2,\ldots,p$, with p is length of lag, and a_t is vector shock.

2.2 Estimation of Parameter VAR, Maximum Likelihood Estimation (MLE)

According to Tsay [27], let a_t in VAR(p) model has multivariate normal distribution. Where $z_{h:q}$ is an observation at $t = h$ to $t = q$. Then the likelihood conditional function can be written as follows:

$$L(Y_{1:p}, \beta, \Sigma_a) = \Pi_{t=p+1}^{T} p(Y_{(p+1):T}|Y_{1:p}, \beta, \Sigma_a) \tag{2}$$

The log-likelihood function is:

$$l(\beta, \Sigma_a) = c - \frac{T-p}{2} \log \log (|\Sigma_a|) - \frac{1}{2} \sum_{t=p+1}^{T} tr(a_t' \Sigma_a^{-1} a_t) l(\beta, \Sigma_a)$$

$$= c - \frac{T-p}{2} \log \log (|\Sigma_a|) - \frac{1}{2} tr\left(\Sigma_a^{-1} \sum_{t=p+1}^{T} a_t a_t' \right)$$

So that MLE of VAR(p) is:

$$L(\hat{\beta}, \hat{\Sigma}_a | z_{1:p}) = (2\pi)^{-\frac{k(T-p)}{2}} |\hat{\Sigma}_a|^{-\frac{T-p}{2}} exp\,exp\left[-\frac{k(T-p)}{2} \right] \tag{3}$$

2.3 GARCH (Generalized Autoregresive Conditional Heteroscedastic)

GARCH model is an extension of ARCH (Autoregresive Conditional Heteroscedastic). This model was developed to avoid the high order of the ARCH Model, and to choose a simpler model, so that the variance is always positive. The univariate GARCH model can be written as follows:

$$X_t = \delta + \sum_{i=1}^{p} \phi_i X_t + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_t \tag{4}$$

$$\varepsilon_t = N(0, \sigma_t^2)$$

$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

Where X_t is conditional mean [28].

The multivariate GARCH model is defined as follows:

$$r_t = \mu_t + a_t \tag{6}$$

$$\mathbf{a}_t = H_t^{\frac{1}{2}} z_t$$

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

2.4 Model Constant Conditional Correlation *(CCC)*

The CCC model was proposed by Bollerslev [29] and is the simplest model in its class. It is based on the decomposition of the conditional covariance matrix into conditional standard deviations and correlations. Then, the conditional covariance matrix is stated as follows:

$$H_t = D_t R D_t$$

model CCC-GARCH(p,q) is written as follows :

$$\sigma_{it}^2 = \omega_i + \sum_{j=1}^{p} \alpha_{ij} \varepsilon_{i,t-f}^2 + \sum_{j=1}^{q} \beta_{ij} \sigma_{i,t-f}^2 \tag{7}$$

where α_{ij} is coefficient ARCH(p) and β_{ij} is coefficient GARCH(p,q). Accoding to Kring et al [30] compared to model such as BEKK, DCC and DVEC model CCC has less parameters.

2.5 Stationarity of Model

The main assumption so that the VAR model can be formed is stationarity [21]. Stationary means that there are no drastic changes to the data. Data fluctuations are around a constant average value, independent of timing and the variance of these fluctuations. Stationarity is divided into 2, namely:

1. Stationary within the ballpark

2. Stationary in variance [31].

Several methods to check the data stability include plotting and analytically using the Augmented Dickey Fuller test (ADF test) ([14], [32], [33], [34]). If after carrying out the ADF test the data is not stationary, a differencing process is carried out until it reaches the stability.

3.   Results and Discussion

The data used in this research is stock return data of companies engaged in mining and construction, namely PT. United Tractors. Tbk (UNTR) and PT. Petrosea. Tbk (PTRO) where the data is daily data from 23 July 2015 to 12 August 2020. The data sources are idnfinancial.com and the Indonesia Stock Exchange (BEI).
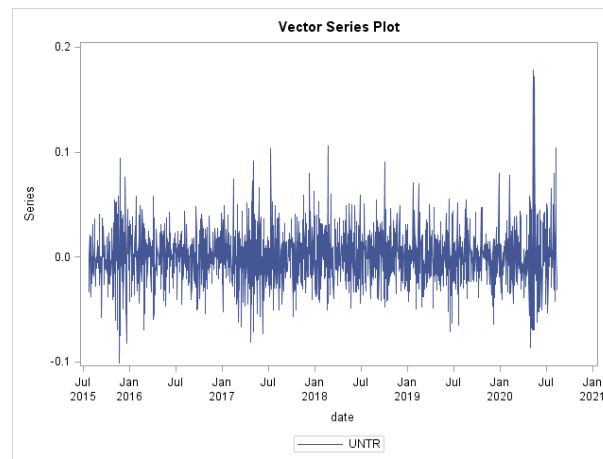

(a)
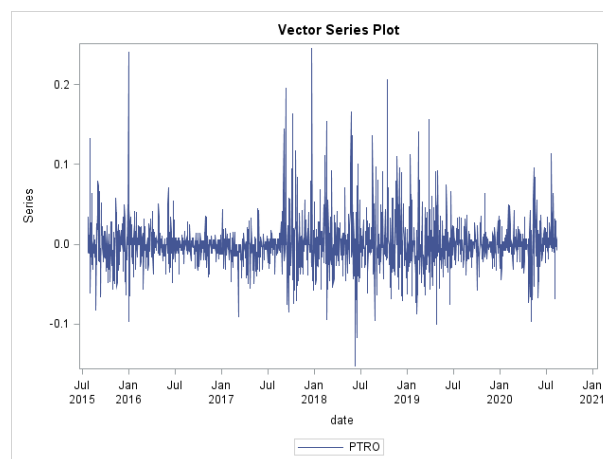
(b)

Figure 1. Plot Variables UNTR and PTRO from July 2015 – August 2020.

In Figure 1 (a), it can be seen that the UNTR fluctuation from the beginning of the period to March 2020 was relatively stable, but in the period April 2020 to June 2020 there was a very extreme shock then stabilized again until the end of the period. Whereas in Figure 1 (b), it can be seen that PTRO experienced extreme fluctuations in several periods, namely in the January 2016 period, extreme shocks occurred during the period August 2017 to June 2019 then fluctuated stably until the end of the period. This indicates that the characteristic of volatility occurs in UNTR and PTRO. However, the overall trend from UNTR and PTRO in the other periods has a constant mean for each lag. Stationarity in mean or variance can also be identified using the ACF and PACF plots.
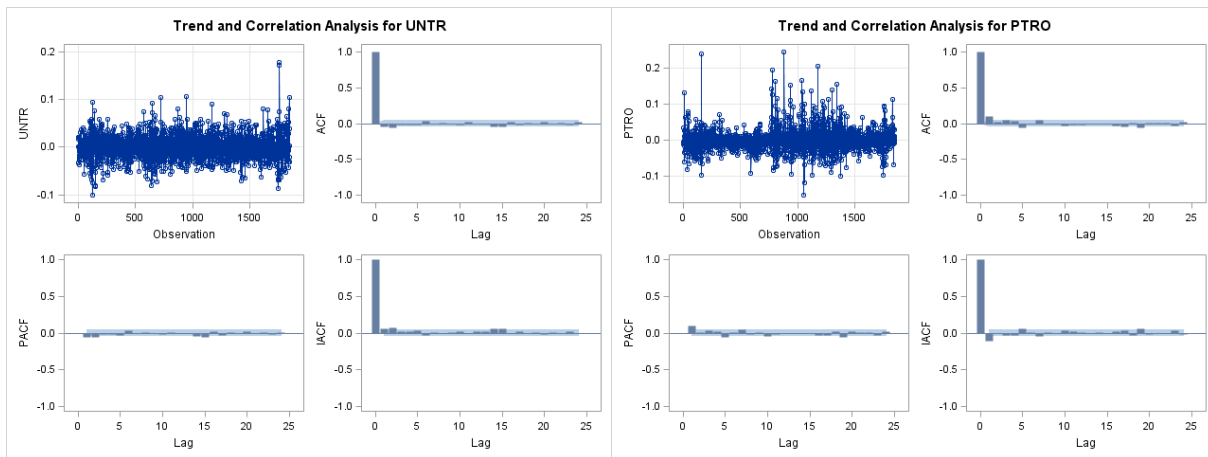
Figure 2. Plot of Trend, autocorrelation, partial autocorrelation function and invers autocorrelation for data return of UNTR and PTRO.

Based on the ACF and PACF plots from UNTR and PTRO in Figure 2 it shows that the autocorrelation value for all lags is around zero which identifies that the data is stationary in mean or variance. In order to strengthen this assumption, Augmented Dicky Fuller testing needs to be done.

Table 1. Augmented Dicky Fuller Unit Root tests.

Variable	Type	Rho	Pr < Rho	Tau	Pr < Tau
UNTR	Zero Mean	-2190.6	0.0001	-33.07	<.0001
	Single Mean	-2192.4	0.0001	-33.08	<.0001
	Trend	-2192.4	0.0001	-33.07	<.0001
PTRO	Zero Mean	-1606.4	0.0001	-28.33	<.0001
	Single Mean	-1607.5	0.0001	-28.33	<.0001
	Trend	-1612.6	0.0001	-28.36	<.0001

The Augmented Dickey Fuller (ADF) test was performed and shown in table 1. Focus attention on the Zero Mean value of the UNTR and PTRO variables, the p-value <.0001 or less than the significant level of 0.05, so there is sufficient evidence to reject H_0, it can be said that UNTR and PTRO variables are stationary. So that another assumption that must be proven is that the error range is heterogeneous by looking at the conditional variance of the data.

(a)

(b)
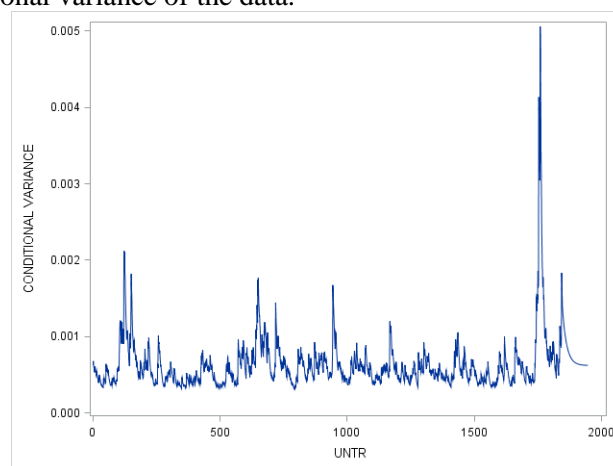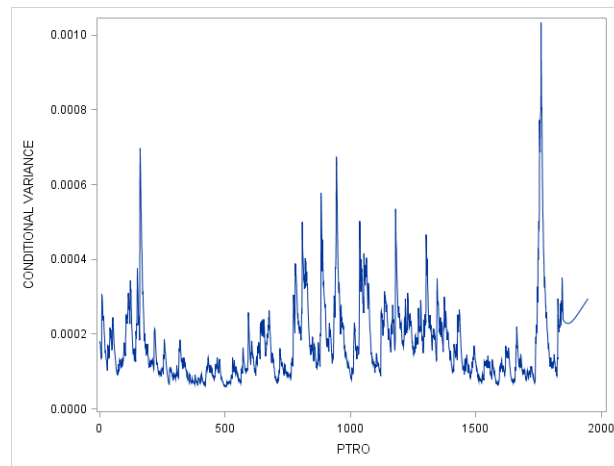
Figure 3. Vollatility Plot Conditional Variance for return data of UNTR and PTRO.

The conditional variance of the UNTR variable in Figure 3 (a) underwent a relatively stable trend change at the beginning of the period until the 1700th period then experienced an extreme shock until the 2000th period, while in the same time period the PTRO variable in Figure 3 (b) experienced changes in trend that were more varied at the beginning of the period to the 300th period, a high shock then stabilized until the 800th period PTRO experienced a high shock until the 1500th period and the highest fluctuation of conditional variance between 1700 and 2000 periods. it is clear that both UNTR and PTRO identify features of high volatility. This volatility state is one indication of the occurrence of heterogeneous error or heterogeneity (heteroscedasticity). So that modeling using M-GARCH, especially CCC-GARCH model is carried out. The white noise test was carried out and shown in Table 2, the variables UNTR and PTRO have a p-value (<0.001) which is less than the significance level $\alpha = 0.05$ which means that it has enough evidence to reject H_0, so it can be concluded that the data is heteroscedastic, which means the residuals from the data have the same residuals. Thus, modeling using M-GARCH can be done.

Table 2. Univariate Model White Noise Diagnostics

Variable	Durbin Watson	Normality		ARCH	
		Chi-Square	Pr > ChiSq	F Value	Pr > F
UNTR	2.00484	909.25	<.0001	8.83	0.003
PTRO	2.0372	1026.38	<.0001	30.86	<.0001

3.1 VAR(p) Model

The most important part of analyzing data using time series methods is to ensure that the assumption of stationarity is fulfilled. Therefore, the stationarity test is carried out before modeling using the time series method. If the data is not stationary, the diffencing process is carried out until the data is stationary, but when the data is stationary, modeling using timeseries methods can be done. After the stationary assumptions are met, the mean modeling with VAR modeling can be done. To determine the best VAR model, several model selection criteria are used as shown in Table 3.

Table 3. Criteria AICC, HQC, AIC and SBC for VAR(1)-VAR(4).

Criteria	Model			
	VAR(1)	VAR(2)	VAR(3)	VAR(4)

AICC	-14.4275	-14.4282	-14.4312	**-14.431**
HQC	**-14.4231**	-14.4194	-14.418	-14.414
AIC	-14.4275	-14.4282	-14.4312	**-14.431**
SBC	**-14.4156**	-14.4043	-14.3953	-14.383

Before doing variance modeling, the mean modeling was carried out using VAR modeling. To get the best model that fits the data, several VAR (p) models are applied to the daily return data of UNTR and PTRO stock prices such as VAR (1), VAR (2), VAR (3) and VAR (4). The selection of the best models from these models is based on several criteria for selecting the best models, namely AICC, HQC, AIC and SBC. The best model is the model that has the minimum criteria value. Based on table 3, there are 2 best candidate models, namely the VAR (1) and VAR (4) models where the criteria for HQC = -14.4231 and SBC = -14.4156 indicate the minimum value for the VAR model (1) while the criteria for AICC = -14.431 and AIC = -14,431 indicates the minimum value for the VAR model (4) so that the VAR (1) and Var (4) models can be considered the best models. Apart from looking at the criteria for selecting the best model, schematic representation is shown to make sure the best model is chosen. Based on table 4, there are two significant parameters (AR1) in the VAR model (1) and five significant parameters in the VAR model (4). Table 5 shows the Schematic representation of the estimated Garch parameters (1,1), there are six significant parameters in the Var (1) Garch (1,1) model, while in the Var (4) Garch (1,1) model, no variables are found. significant. So that the Var (1) -Garch (1,1) model is the best model.

Table 4. Schematic Representation of parameter for VAR(1) and VAR(4).

Model	Variable/Lag	AR1	AR2	AR3	AR4
VAR(1)	UNTR	.+			
	PTRO	.+			
VAR(4)	UNTR	-+	-.	..	..
	PTRO	.+	..	+.	..
+ is > 2*std error, - is < -2*std error, . is between, * is N/A					

Table 5. Schematic Representation of parameter CCC-GARCH(1,1)

Model	Variable/Lag	GCHC	ACH1	GCH1
VAR(1) GARCH(1,1)	h1	+	+*	+*
	h2	+	*+	*+
VAR(4) GARCH(1,1)	h1	.	..	..
	h2	.	..	..
+ is > 2*std error, - is < -2*std error, . is between, * is N/A				

3.2 Model CCC-GARCH

Because the data contain heteroscedasticity effects, in this study the CCC-GARCH model was used. Based on the results of selecting the best VAR model, the suitable model is VAR (1) CCC-GARCH (1,1) which is selected as the best model.

Model VAR(1) CCC-GARCH(1,1) can be written as follows:

$$[UNTR_t \; PTRO_t] = [-0.04823 \; 0.03682 \; 0.03154 \; 0.10529 \,][UNTR_{t-1} \; PTRO_{t-1}\,] + [\varepsilon_{1,t} \; \varepsilon_{2,t}\,]$$

with *conditional variance* and *correlation* based on parameterization CCC on model GARCH (1,1) :

$$H_t = D_t R D_t$$

$$
\begin{aligned}
H_t &= \left[\sqrt{h_{11,t}}\ 0\ 0\ \sqrt{h_{22,t}}\ \right]\left[1\ \rho_{12}\ \rho_{21}\ 1\ \right]\left[\sqrt{h_{11,t}}\ 0\ 0\ \sqrt{h_{22,t}}\ \right]H_t \\
&= \left[\sqrt{h_{11,t}}\ \rho_{12}\sqrt{h_{11,t}}\ \rho_{12}\sqrt{h_{11,t}}\ \sqrt{h_{22,t}}\ \right]\left[\sqrt{h_{11,t}}\ 0\ 0\ \sqrt{h_{22,t}}\ \right]H_t \\
&= \left[h_{11,t}\ \rho_{12}\sqrt{(h_{11,t}h_{22,t})}\ \rho_{12}\sqrt{(h_{11,t}h_{22,t})}\ h_{11,t}\ \right]H_t \\
&= \left[h_{11,t}\ 0.23533\sqrt{(h_{11,t}h_{22,t})}\ 0.23533\sqrt{(h_{11,t}h_{22,t})}\ h_{22,t}\ \right]
\end{aligned}
$$

where,

$$
\begin{aligned}
\left[h_{11,t}\ h_{22,t}\ \right] &= \ \left[0.00004\ 0.00002\ \right] \\
&+ \left[0.0823\ 0.85969\ 0.13476\ 0.86486\ \right]\left[\varepsilon_{1,t-1}^2\ h_{11,t-1}\ \varepsilon_{2,t-1}^2\ h_{22,t-1}\ \right]
\end{aligned}
$$

Model VAR(1) CCC-GARCH(1,1) can be written as univariate regression as follows:

$$UNTR_t = \ -0.04823\ UNTR_{t-1} + \ 0.03682\ PTRO_{t-1} + \ \varepsilon_{1,t} \qquad (8)$$

$$PTRO_t = \ 0.03154\ UNTR_{t-1} + 0.10529\ PTRO_{t-1} + \ \varepsilon_{2,t} \qquad (9)$$

With *conditional variance* and *correlation*:

$$h_{11,t} = 0.00004 + \ 0.0823\ \varepsilon_{1,t-1}^2 + 0.85969\ h_{11,t-1}$$

$$h_{22,t} = 0.00002 + \ 0.13476\varepsilon_{2,t-1}^2 + \ 0.86486\ h_{22,t-1}$$

$$h_{12,t} = h_{21,t} = Cov\big(\varepsilon_{1,t}, \varepsilon_{2,t}\big)$$

$$= \rho_{12}\sqrt{(h_{11,t}h_{22,t})}$$

$$= 0.23533\sqrt{(h_{11,t}h_{22,t})}$$

To check whether the VAR (1) CCC-GARCH (1,1) model is univariate reliable or not for use, a fit test of the univariate model shown in Table 6.

Table 6. Univariate Model ANOVA Diagnostics.

Variable	Standard Deviation	F Value	Pr > F
UNTR	0.02504	9.61	0.002
PTRO	0.03026	19.35	<.0001

Table 7. Model Parameter Estimate VAR(1).

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
UNTR	AR1_1_1	-0.04823	0.02521	-1.91	0.0559	UNTR(t-1)
	AR1_1_2	0.03682	0.0184	2	0.0456	PTRO(t-1)

PTRO	AR1_2_1	0.03154	0.02279	1.38	0.1666	UNTR(t-1)
	AR1_2_2	0.10529	0.02782	3.79	0.0002	PTRO(t-1)

Table 8. Model Parameter Estimates CCC-GARCH(1,1).

GARCH Model Parameter Estimates				
Parameter	Estimate	Standard Error	t Value	Pr > |t|
CCC1_2	0.23533	0.02193	10.73	0.0001
GCHC1_1	0.00004	0.00001	3.77	0.0002
GCHC2_2	0.00002	0	3.95	0.0001
ACH1_1_1	0.0823	0.01386	5.94	0.0001
ACH1_2_2	0.13476	0.01934	6.97	0.0001
GCH1_1_1	0.85969	0.02486	34.59	0.0001
GCH1_2_2	0.86486	0.01758	49.2	0.0001

Statistical parameter test for the above model is given in Table 7 and the univariate model test is given in Table 6. Based on the univariate model test in table 6, the univariate modeling of the UNTR variable is significant to the model with a value of F = 9.61 and a value of p = 0.002. In addition, the univariate modeling of the PTRO variable is also significant with a value of F = 19.35 and a value of p <0.0001. So it can be said that the two univarite models are feasible to use. Model 8 explains that the UNTR return value has a negative effect on lag 1 (t-1). Model 9 explains that the PTRO return value has a positive effect on lag 1 (t-1).
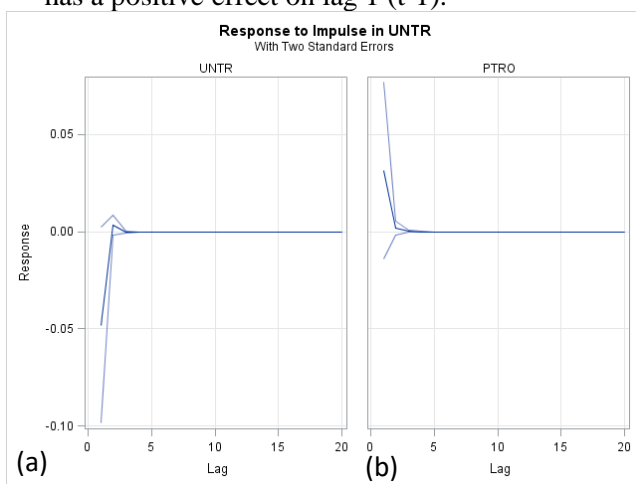
Figure 4. Impulse Response data UNTR.
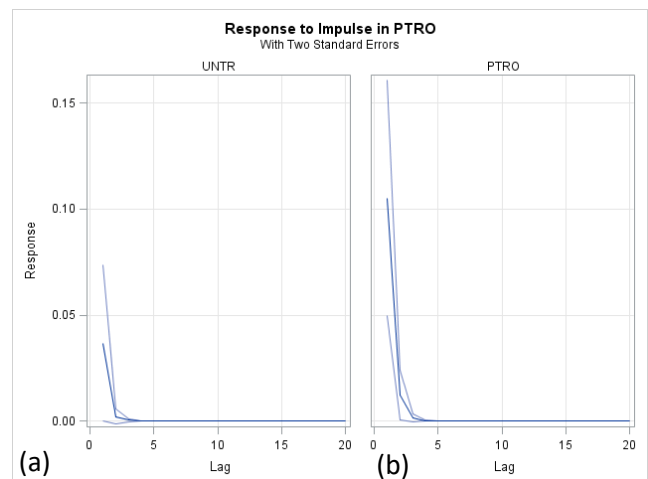
Figure 5. Impulse Response data PTRO.

Table 9. Causality Test for return data of UNTR and PTRO

Test	Group	DF	Chi-Square	Pr > ChiSq
Test 1	Group 1 Variables: UNTR Group 2 Variables: PTRO	1	3.88	0.0489
Test 2	Group 1 Variables: PTRO Group 2 Variables: UNTR	1	0.63	0.4267

The nature of the Garch Multivariate process is demonstrated by Granger Causality and Impulse Response (IRF). Granger Causality is used to test several null hypotheses. Test 1 and Test 2 test the hypothesis where the UNTR and PTRO variables are influenced by themselves and the alternative hypothesis where the UNTR and PTRO variables are influenced by other variables. In table 9 the Granger Causality Test, Test 1 the Chi-Square value = 3.88 and the p-value = 0.0489, as a result we reject the Null hypothesis so that it is concluded that the UNTR variable is not only influenced by itself but is also influenced by other variables, namely the PTRO variable. Then in Test 2 the Chi-Square value = 0.63 and the P value = 0.4267, as a result, we do not have enough evidence to reject the null hypothesis so that the PTRO variable is only influenced by itself and is not influenced by other variables.

Apart from the Granger Causality test, the properties of the multivarite time series analysis are also explained through the IRF interpretation. Estimation of the IRF is used to see the response of a variable to a shock caused by other variables and to see how long the period for the effect of the variable shock after a shock occurs. The horizontal axes in Figures 4 and 5 below show the time periods where one period represents one day. In this case, the author uses a period of 20 days so that the period used in the IRF test is 20 periods. Meanwhile, the vertical axis shows changes in UNTR to a certain shock variable, in this case to itself and to the PTRO variable, where this change is expressed in units of standard deviation (SD). Based on graph 4 (a) the response of the UNTR variable impulse to the shock itself. UNTR is fluctuating in the first lag to lag 4. In the first lag, UNTR has given a negative response of -0.04823 when a shock occurs, namely in the second period the UNTR value itself rises to 0.00349 and in the next period UNTR's response to itself has decreased to negative. The UNTR response to the shock itself reaches an equilibrium point at 0.00002 in the 4th period and in the next period it moves constant at zero. Meanwhile, UNTR's response to PTRO in Figure 4 (b) is fluctuating in the second and third lags. In the first period, UNTR gave a positive response of 0.03682 which then headed for the second period of UNTR's response to PTRO experiencing a shock, decreased to 0.00210 and continued to decline sloping towards the 4th period.

The UNTR response to PTRO reached the equilibrium point in the 5th period and has moved constantly at zero in the following periods. Based on the graph in Figure 5 (a), it shows that in the first period PTRO to the UNTR shock gave a positive response value of 0.03154. The shock that occurred in the second period showed a positive value, causing the PTRO value to drop to 0.00180. Then in the next period the PTRO response to shock drops and reaches the equilibrium point in period 4. Meanwhile, Figure 5 (b) the PTRO impulse response to the shock itself. In the first period PTRO gave a positive response value of 0.10529 and when experiencing a shock in the second period the PTRO response value to itself dropped to 0.01225. The PTRO response to itself reaches the equilibrium point in the 5th period and undergoes a constant movement at zero in the next period.
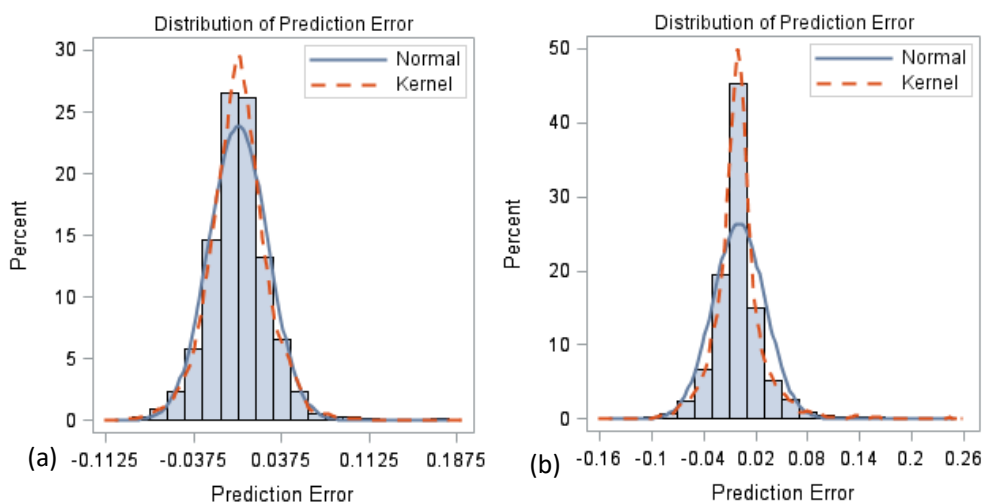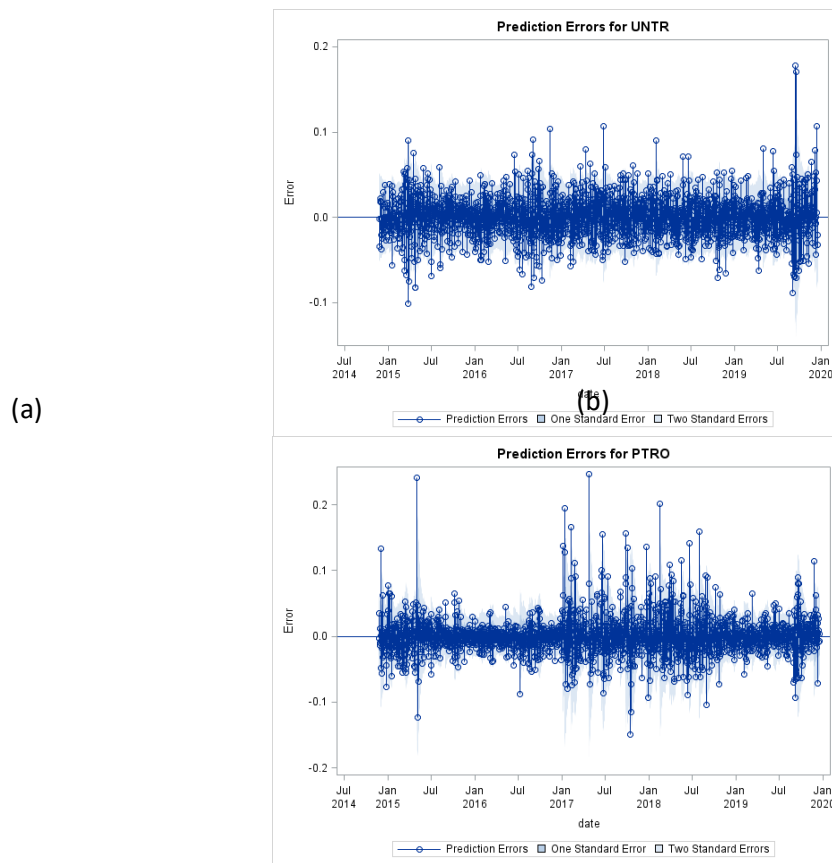

Figure 6. Distribution of error for data return UNTR and PTRO

(a)

(b)

Figure 7. Prediction errors based on model VAR(1)-GARCH(1,1) data return UNTR and PTRO

From Figure 6 (a and b) the pattern of the error distribution for the UNTR and PTRO return data approaches the normal distribution curve. In Figures 7 (a) and 7 (b) the prediction error of the UNTR return shows that the prediction error from day to day does not fluctuate too much and can be said to be quite stable. In contrast to the prediction error pattern, the PTRO data return shows instability of error fluctuation from day to day.

The results of the data return prediction in table 10, the UNTR variable in the first forecast is worth 0.00121, meaning that the UNTR stock price has increased. Then on the second day of forecasting the return value of UNTR of -0.0001 means that TBLA's stock price has decreased or lost, until the 5th day of forecasting the return value of TBLA is close to zero, meaning that UNTR's share price has not changed significantly. Meanwhile, the PTRO variable forecast for the first day of -0.0018 means that PTRO's share price has decreased, then on the second day of forecasting it is -0.0002 until the fifth day the return value is close to zero or there is no change in the PTRO variable share price.

Table 10. Forecasting Data return TBLA and CEKA.

Variable	Obs	Time	Forecasts			
			Forecast	Standard Error	95% Confidence Limits	
UNTR	1849	13-Aug-20	0.00121	0.0364	-0.0701	0.07256
	1850	14-Aug-20	-0.0001	0.03588	-0.0704	0.0702
	1851	15-Aug-20	0	0.03533	-0.0693	0.06925
	1852	16-Aug-20	0	0.03481	-0.0682	0.06823

	1853	17-Aug-20	0	0.03431	-0.0673	0.06725
PTRO	1849	13-Aug-20	-0.0018	0.02765	-0.056	0.05241
	1850	14-Aug-20	-0.0002	0.02818	-0.0554	0.05508
	1851	15-Aug-20	-2E-05	0.0285	-0.0559	0.05585
	1852	16-Aug-20	0	0.02882	-0.0565	0.05649
	1853	17-Aug-20	0	0.02914	-0.0571	0.05711
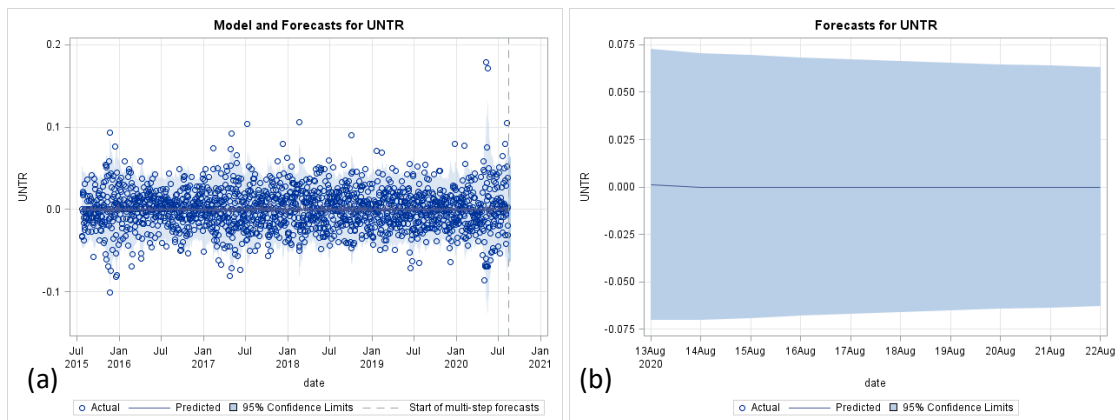
Figure 8. (a and b) Model and forecasting for the next 10 days of data return UNTR.
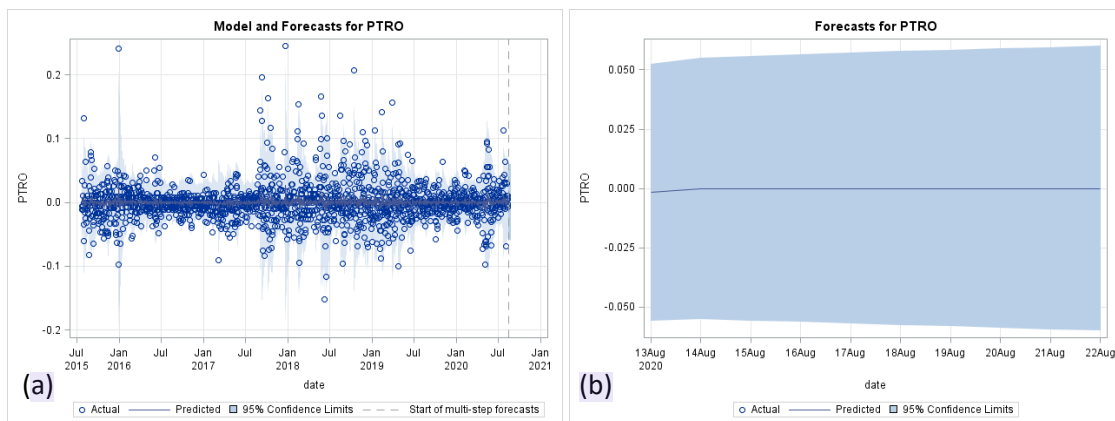
Figure 9. (a and b) Model and forecasting for the next 10 days of data return PTRO.

Model images for UNTR and PTRO return data are shown in Figures 8 (a) and 9 (a) which show the predicted or forecasting values close to each other, which indicates that the model used fits the data.

All the predicted values for UNTR and PTRO return data fall into the 95% confidence interval which can be seen in Figures 8 (b) and 9 (b). The incident interval in Figure 8 (b) has decreased until August 17th. Meanwhile, the Confident interval in Figure 9 (b) has increased until August 17th. This indicates that the VAR (1) CCC-GARCH (1,1) model is suitable for modeling UNTR and PTRO return data for the short term, but if it is used to make long-term predictions, it will produce predictions leading to a zero value, so the model is not suitable to be used for long term predictions.

4. Conclusion

Based on the research and studies that have been done, where this study focuses on determining the best model for modeling the return data of PT. United Tractors. Tbk (UNTR) and PT. Petrosea. Tbk (PTRO) where data is daily data from 23 July 2015 to 12 August 2020. We can conclude that the best model that can be formed to model data is the VAR (1) CCC-GARCH (1,1) model which was selected based on several selection criteria the best models are AICC, AIC, SBC and HQC. Where there is 1 variable that is not significant in the model but can still be included in the model by considering the meaningfulness of the estimate obtained. In addition, based on the Granger Causality test, the variable return of UNTR's stock price is not only influenced by himself but also influenced by the PTRO variable but not by the PTRO variable which is only influenced by himself.

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