



## Analysis of Some Variable Energy Companies by Using VAR(p)-GARCH(r,s) Model: Study From Energy Companies of Qatar over the Years 2015–2022

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### ABSTRACT

In this study, the nature of the weekly stock price relationships of several Qatar energy companies, namely the weekly stock price of Qatar Fuel Company (QFLS), Qatar Gas Transport Company (QGTS), and Qatar Electricity and Water Company (QEWG), will be discussed. The duration of data weekly stock price is from January 2015 to April 2022. This study aimed to obtain the best model for the weekly stock price relationship of the three companies QFLS, QGTS, and QEWG. The multivariate time series analysis method will be used to evaluate the data. From the analysis using multivariate time series modeling, the best model is VAR(3)-GARCH(1,1). Based on this best model, further analysis is carried out, namely Granger causality, impulse response function (IRF), and forecasting for the next 12 periods. The Granger causality test found that the QFLS has Granger causality on the QGTS (unidirectional), while the QGTS and QEWG variables have bidirectional Granger causality. The IRF analysis indicated that if there is a shock of 1 standard deviation in QFLS, then QFLS and QEWG will fluctuate for the first 6 weeks and move toward equilibrium from the 7<sup>th</sup> week onwards, while the impact on QGTS can be ignored. Suppose there is a shock of 1 standard deviation in the QGTS. In that case, the QFLS and QEWG will respond by fluctuating for the first 6 weeks, and at the 7<sup>th</sup> week and move toward equilibrium, while the impact on QGTS can be ignored; and if there is a shock of 1 standard deviation in QEWG, then QFLS and QEWG will respond negatively and fluctuating for the first 6 weeks, and at the 7<sup>th</sup> week toward equilibrium, while the impact on QGTS is negligible. Forecasting for the next 12 periods shows that the farther the forecasting period, the larger the standard error. This indicates that the farther the period is, the more unstable it is.

**Keywords:** Multivariate Time Series, VAR(p)-GARCH(r,s), Granger Causality, Impulse Response Function, Forecasting

**JEL Classifications:** C53, Q4, Q47

## 1. INTRODUCTION

Multivariate time series data modeling discusses the interrelationships between variables based on the concept of time lag (Lutkepohl, 2005; 2020; Tsay, 2014; Basu et al., 2019; Hamzah et al., 2020). The application of statistics, modeling data multivariate time series,

has made a lot of the development of the research in the field of economics and social sciences (Chamalwa and Bakari, 2016; Zhang et al., 2016; Keng et al., 2017; Bulteel, 2018; Dumitrescu et al., 2019; Lutkepohl, 2020). One of the purposes of a multivariate time series data analysis is to find a model and to express a structured time relationship between some of the variables discussed and then

to be able to do forecasting of one or more variables. To analyze quantitatively analyze data in multivariate time series involving more than one variable, one can use the Vector Autoregressive (VAR) method, vector error correction model (VECM), or VAR Moving Average method. (Chamalwa and Bakari, 2016; Warsono, et al., 2019a; 2019b; 2020; Sekanabo, et al., 2022; Aregghan et al., 2022). The development of the application of time series analysis, especially multivariate time series, has been widely used in studies in various fields of science. One of the multivariate time series models is the Vector Autoregression (VAR) model, which is one of the most successful in its application. It is a natural progression from a univariate time series model to a multivariate time series model. VAR models have proven particularly useful for describing dynamic behavior in economics, finance, and social sciences.

VAR model is widely used in many studies, especially in the fields of economics, energy, finance, and business. Many researchers have conducted the VAR model applications on macroeconomic variables (Robertson and Tallman, 1999; Wei, 2006; Tsay, 2010). The VAR model plays an important role as one of the data analysis methods, especially in the fields of economics and finance (Hamilton, 1994; Kirchgassner and Wolters, 2007; Tsay, 2010; 2014; Wei, 2019). If the variables discussed had an autoregressive conditional heteroscedasticity (ARCH) effect, then the modeling data can be used in the VAR-GARCH or VARMA-GARCH models (Abounoori et al., 2016; Virginia et al., 2018; Lin et al., 2020). Sims (1980) introduced the VAR model as an alternative in macroeconomic analysis. The VAR model has a simpler model structure with a minimal number of variables where all the variables are endogenous, with the independent variables being the lag of the variables involved in the modeling. VAR models are often used to describe the behavior of variables over time. This model often assumes that the present value is a function of previous values and random error (Fuller, 1985). This model is easy to analyze from multivariate time series data, flexible, easy to estimate, and usually fits very well with the data (Fuller, 1985; Lutkepohl, 2005; Juselius, 2006). VAR models based on the normal distribution are usually popular for describing the behavior of time series macroeconomic data (Juselius, 2006). In the p-order VAR model, VAR(p), each component of the  $Z_t$  vector depends linearly on its own lag up to the p-th period as well as on the lag of the other variables up to the p-th lag (Lutkepohl, 2005; Wei, 2006; Kirchgassner and Wolters, 2007). VAR models are very useful for describing and explaining the behavior of multivariate time series data and also for prediction or forecasting (Lutkepohl, 2005; Wei, 2006). Forecasting is the main goal in multivariate time series data analysis. Forecasting by using the VAR model is simple because it can be conditional on future conditions in the model. Furthermore, the VAR model can also be used for structural analysis. In the structural analysis, certain assumptions on the causal structural data under investigation are applied and the results due to the causal effect of an unexpected shock or innovation on a specific variable are examined. These causal effects are usually inferred in Granger causality and IRFs (Hamilton, 1994; Lutkepohl, 2005; Wei, 2006; Tsay, 2010).

The VAR model is designed for stationary data that do not contain trends. The stochastic trend in the data indicates that there are

long-run (long-term) and short-run (short-term) components in multivariate time series data. Research on stochastic trends in economic variables continues to grow, so in 1981, Granger developed the concept of cointegration (Granger, 1981). Johansen and Juselius (1990) developed the concept of VECM). VECM offers an easy working procedure to separate the long-term and short-term components of the data generation process. We can ask the question of how to build the possible relationship for multivariate time series data. That is how a possible approach to building a data modeling of two or more multivariate time series data. In such a system where each variable will depend on one another, the univariate modeling form will no longer be appropriate. Sims (1980) developed the VAR System (VAR) approach as an alternative to the simultaneous equation approach (Basu et al., 2019; Kilian and Lutkepohl, 2019; Wei, 2019). Starting from a stationary autoregressive form, all the variables involved are assumed jointly endogenous. So in a VAR model of order p ( $V(p)$ ), each component of the  $Z_t$  vector depends linearly on its own lag up to the lag value of the p-th period (Kirchgassner and Wolters, 2007; Hamilton, 1994; Brockwell and Davis, 2002; Wilms et al., 2017a; 2017b; Dias and Kapetanios, 2018; Wei, 2019).

In this study, data on weekly stock prices of QFLS, QGTS, and QEWC over the year January 2015 to April 2022 will be discussed. This study aims to find the best multivariate time series modeling that fits the data weekly stock price of QFLS, QGTS, and QEWC. Once the best model is found, then further analysis such as Granger causality, IRF, and forecasting for the next 12 periods (weeks) will be conducted.

## 2. STATISTICAL MODELING

In this study, a modeling analysis of the weekly stock price of three Qatari energy companies, namely QFLS, qatar transport company (QGTS), and QEWC, will be discussed. The data QFLS, QGTS, and QEWC are taken from January 2015 to April 2022. In the current study, we analyzed the data QFLS, QGTS, and QEWC as a set of vector time series observations: and let

$$Z_t = \begin{bmatrix} QFLS_t \\ QGTS_t \\ QEWC_t \end{bmatrix} \text{ is a vector observation at time } t. \quad (1)$$

This type of vector time series observation will be analyzed using the multivariate time series method. Before modeling the data, the assumptions of the multivariate time series analysis will be checked. In the time series modeling analysis, it is assumed that the data are stationary. Therefore, before a model is constructed, it is necessary to check whether the data meet the stationary assumption. In addition, it is necessary to check whether the data have an autocorrelation and have an ARCH effect. There are two approaches to checking the stationary data that are used: the first is by plotting the data, and subsequently analyzing the behavior of the plot of the data; the second is by using the Augmented Dickey-Fuller (ADF) test with the null hypothesis that the data are nonstationary (Tsay, 2010; Virginia et al., 2018; Warsono et al., 2019a; 2020). If the data are nonstationary, then

the data are transformed using a process of differentiation, such that the data become stationary (Wei, 2006; Montgomery et al., 2008). The Portmanteau Q test and Lagrange multiplier test (LM test) were used to check the existence of ARCH effect. If ARCH effects exist in the data, then the GARCH model will be used to model the residuals of vector observation  $Z_t$ . Many time series in practice that involve more than one variable are best considered components of some vector-valued multivariate time series,  $\{Z_t\}$  whose specification includes not only the serial dependence of each component  $\{Z_{it}\}$ , but also interdependence between different components  $\{Z_{it}\}$  and  $\{Z_{jt}\}$  [Brockwell and Davis, 2002]. VAR process provides a very useful class of models in multivariate time series for describing the dynamics of an individual time series. The pth order VAR, VAR(p), is formulated as follows:

$$Z_t = \Phi_o + \Phi_1 Z_{t-1} + \Phi_2 Z_{t-2} + \dots + \Phi_p Z_{t-p} + \varepsilon_t, \tag{2}$$

where  $Z_t$  is a vector observation at time t as given in (1),  $\Phi_o$  is a  $3 \times 3$  constant matrix,  $\Phi_1, \Phi_2, \dots, \Phi_p$  are the  $3 \times 3$  coefficient parameters for  $Z_{t-1}, Z_{t-2}, \dots, Z_{t-p}$ , respectively, and is the vector white noise.

### 2.1. (ADF) Test

The ADF test checks the stationary data with the null hypothesis that the data are nonstationary (Fuller, 1985; Wei, 2006; Warsono et al., 2020). The ADF test with lag-p is formulated as follows (Zivot and Wang, 2006; Tsay, 2010):

$$Z_{it} = c_{it} + \beta Z_{it-1} + \sum_{j=1}^{p-1} \alpha_j \Delta Z_{it-j} + \varepsilon_{it}, \tag{3}$$

where  $c_{it}$  is a constant function at time t,  $\Delta Z_{it} = Z_{it} - Z_{it-1}$  is the difference of a series of  $Z_{it}$ , and  $\varepsilon_{it}$  is the white noise. The ADF test (or tau test) statistic is formulated as follows:

$$\tau\text{-test} = \frac{\hat{\beta} - 1}{std(\hat{\beta})} \tag{4}$$

Reject the null hypothesis if the  $P < 0.05$  (Tsay, 2010; Brockwell and Davis, 2002).

### 2.2. Information Criterion AICC

The AICC is a criterion for selecting the best model. AICC is an estimate of the quality of the statistical model; by comparing several proposed models, the model with the smallest AICC value is selected as the best model among the models offered. The calculation process is as follows: let a linear model with k coefficient of parameters and let  $\hat{\sigma}_k^2$  be the likelihood estimator of variance, and calculated as follows:

$$\hat{\sigma}_k^2 = \frac{RSS_k}{T}, \tag{5}$$

where  $RSS_k = \sum_{t=1}^k (X_t - \bar{X})^2$  is the residuals sum of squares under

the model with k coefficient parameters. The AICC is defined as follows:

$$AICC = \ln \hat{\sigma}_k^2 + \frac{T+k}{T-k-2} \tag{6}$$

where T is the sample size (Shumway and Stoffer, 2006).

### 2.3. Testing for White Noise

To check whether errors (residuals) are white noise, Q-statistic (or Box–Pierce test) or Ljung–Box test will be used (Ljung and Box, 1978). The Q-statistic ( $Q_{BP}$ ) tests the null hypothesis that the errors (residuals) are white noise. The Q-statistic is calculated as follows:

$$Q_{BP} = T \sum_{j=1}^k \hat{\rho}_j^2, \tag{7}$$

where  $\hat{\rho}_j$  is the autocorrelation estimate at lag j, and T is the sample size. Under the null hypothesis, the  $Q_{BP}$  statistic is asymptotically the Chi-squares distribution with k degrees of freedom,  $\chi^2(k)$ .

### 2.4. Testing Zero Cross Correlations

The basic idea in multivariate time series analysis modeling is to test the existence of linear dynamic dependence in the data. The null hypothesis to be tested is  $H_0: \rho_1 = \rho_2 = \dots = \rho_m = 0$  against the alternative hypothesis  $H_a: \rho_i \neq 0$  for some i,  $1 \leq i \leq m$ , where m is a positive integer. The test statistic is the multivariate Ljung-Box test statistics and defined as follows:

$$Q_k(m) = T^2 \sum_{s=1}^m \frac{1}{T-s} tr(\Gamma'_s \Gamma_0^{-1} \Gamma_s \Gamma_o^{-1}) \tag{8}$$

Where  $tr(A)$  is the trace of matrix A and T is the sample size. Under the null hypothesis that  $\Gamma_s = 0$  for  $s > 0$  and the condition that  $Z_s$  is normally distributed,  $Q_k(m)$  is asymptotically distributed chi-square with  $mk^2$  degrees of freedom (Tsay, 2014).

### 2.5. Test for Normality Distribution

Some methods are available to check the normality of the errors (residuals). Some methods are commonly used to check whether the errors (residuals) are normally distributed: (1) check the histogram of the residuals; (2) check the Q–Q plot of the data or error (residuals); and (3) use the statistical test, the Jarque–Bera (JB) test, with the null hypothesis that the data are normally distributed (Brockwell and Davis, 2002; Tsay, 2010). The JB test is calculated as follows:

$$JB = \frac{T}{6} \left[ S^2 + \frac{(K-3)^2}{4} \right], \tag{9}$$

where T is the sample size, S is the expected skewness, and K is the expected excess kurtosis.

### 2.6. Testing for ARCH Effect

The GARCH model is developed based on the assumption that the variances are heteroscedastic. The concept of ARCH was first introduced by Engle (1982), and later, the GARCH model was developed by Bollerslev (1986). Before we apply the ARCH or

GARCH model for the QFLS, QGTS, and QEWC data, first, we test the ARCH effects in the residuals (error). If there is ARCH effect, we use the ARCH or GARCH model for vector observation  $\{Z_t\}$  data. To test the ARCH effects, we used the LM test with the null hypothesis that there is no ARCH effect. The null hypothesis is rejected if the P-value is  $<0.05$ . To perform the LM test, the residuals model is first built as follows:

$$\varepsilon_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \dots + \gamma_p \varepsilon_{t-p}^2 + u_t \tag{10}$$

From model (10), we estimate the R-square ( $R^2$ ) value and then calculate the LM test. The LM test is defined as follows:

$$LM = T \cdot R^2 \tag{11}$$

where T is the sample size, and  $R^2$  is the R-square computed from the model (10). Under the null hypothesis, the LM test approximately has a Chi-squares distribution with p degrees of freedom,  $\chi^2(p)$  (Zivot and Wang, 2006).

### 2.7. Constant Conditional Correlation-GARCH Model

One of the approaches of the multivariate GARCH model is the Constant Conditional Correlation (CCC)-GARCH model. CCC-GARCH model was introduced by Bollerslev (1990), who proposed a representation where the conditional correlation matrix is assumed to be constant. Under this assumption, the conditional covariance matrix  $H_t$  is defined as follows:

$$H_t = D_t R D_t$$

Where

$$D_t = \text{diag}(\sigma_{1,1,t}^{1/2}, \sigma_{2,2,t}^{1/2}, \sigma_{3,3,t}^{1/2})$$

$$R = \begin{bmatrix} 1 & \rho_{1,2} & \rho_{1,3} \\ \rho_{1,2} & 1 & \rho_{2,3} \\ \rho_{1,3} & \rho_{2,3} & 1 \end{bmatrix}$$

and  $\rho_{i,j}$  is the CCC between  $\varepsilon_{it}$  and  $\varepsilon_{jt}$ . The representation is known as the CCC- model. Thus,

$$h_{i,j,t} = \rho_{ij} \sqrt{\sigma_{i,it} \cdot \sigma_{j,j,t}}$$

And  $\sigma_{i,i,t}$  can be modeled independently as the case of univariate GARCH model, for example, like the simple GARCH(1,1) model,

$$\sigma_{i,i,t} = ci + \alpha_i \sigma_{i,i,t-1} + \beta_i \varepsilon_{i,t-1}^2, i = 1, 2, 3. \tag{12}$$

### 2.8. Test for Granger Causality

In this section, the question to be investigated is whether the value of a variable can help forecast another value of a variable  $Z_{jt}$ . If it cannot, then we say that  $Z_{it}$  is not Granger causality  $Z_{jt}$ . To test that  $Z_{it}$  is Granger causality  $Z_{jt}$ , we construct the following steps:

$$Z_{jt} = \alpha_0 + \alpha_1 Z_{jt-1} + \alpha_2 Z_{jt-2} + \dots + \alpha_p Z_{jt-p} + \theta_1 Z_{it-1} + \theta_2 Z_{it-2} + \dots + \theta_p Z_{it-p} + u_t \tag{13}$$

By Ordinary Least Squares we conduct an F-test of the null hypothesis,

$$H_0: \theta_1 = \theta_2 = \dots = \theta_p = 0.$$

We calculate the Sum of Square Residuals (RSS) of (13),

$$RSS_1 = \sum_{t=1}^T u_t^2$$

Under the null hypothesis, model (13) can be written as:

$$Z_{jt} = \gamma_0 + \gamma_1 Z_{jt-1} + \gamma_2 Z_{jt-2} + \dots + \gamma_p Z_{jt-p} + a_t \tag{14}$$

We calculate the Sum of Square Residuals (RSS) of (14),

$$RSS_0 = \sum_{t=1}^T a_t^2$$

The test statistic is given by:

$$S = \frac{T(RSS_0 - RSS_1)}{RSS_1} \tag{15}$$

S asymptotically has chi-square distribution with p degrees of freedom. We reject the null hypothesis if  $P < 0.05$ . (Hamilton, 1994).

### 2.9. Impulse Response Function

There is an approach to exploring the relationship between variables in studying the structure of a VAR(p) model. We are often interested in the effect of changes in one variable on another variable in a multivariate time series model. VAR(p) model can be written in the vector MA( $\infty$ ) as follows (Hamilton, 1994; Tsay, 2014; Wei, 2019):

$$Z_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \dots$$

The matrix  $\Psi_s$ , has the interpretation

$$\frac{\partial Z_{t+s}}{\partial \varepsilon_t} = \Psi_s \tag{16}$$

That is the row i, column j element of  $\Psi_s$  indicates the effect of one unit standard deviation increase in the jth variable innovation at date t ( $\varepsilon_{jt}$ ) for the value of the ith variable at time t+s ( $Z_{it+s}$ ), holding all other innovations constant. The plot of the row i, column j element of  $\Psi_s$ ,

$$\frac{\partial Z_{it+s}}{\partial \varepsilon_{jt}} \tag{17}$$

as a function of s is called Impulse Response Function (IRF) (Hamilton, 1994, Tsay, 2010; 2014; Wei, 2019).

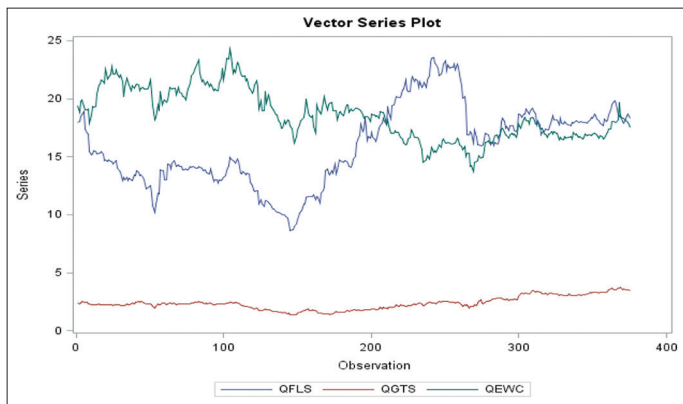
### 2.10. Forecasting

Forecasting will be performed after obtaining the best model for data vector-valued multivariate time series  $\{Z_t\}$ . By using the best model that fits the data, forecasting is carried out directly for the next 12 periods (weeks).

### 3. RESULTS AND DISCUSSION

The data used in this study is weekly stock price data for several energy companies in Qatar, namely QFLS, QGTS, and QEWC data, from January 2015 to April 2022. Figure 1 shows the plot of QFLS, QGTS, and QEWC data. The graph shows that the weekly data on the stock prices of QFLS, QGTS, and QEWC is not stationary; this is also shown in (Figure 2a and b), and (Figure 2c) where the data graph is not stationary and fluctuates. (Figure 2a and b) and (Figure 2c) also show the results of the Autocorrelation Function (ACF) graph where the three data show that ACF decays very slowly, indicating that the data are nonstationary. The ADF test also shows that the data is not stationary. Therefore, to fulfill the assumption of stationary data, a differencing process will be carried out. Data Table 1 shows that the data, after being differentiated, meet the stationary assumption.

**Figure 1:** Plot of data QFLS, QGTS, and QEWC from January 2014 to April 2022



After differencing and the data fulfills the stationary assumption, we check the autocorrelation (Table 2), and the results of the Portmanteau test it shows that there is autocorrelation in the residuals up to lag 24, this shows partially in modeling for each QFLS, QGTS, and QEWC data that requires modeling that involves the concept autoregressive. Based on the multivariate time series modeling from the Portmanteau test regarding the cross-correlation from Tables 3 and 4, the test is significant up to lag 3. Thus, multivariate time series modeling will involve autoregressive vector modeling (VAR) up to lag 3.

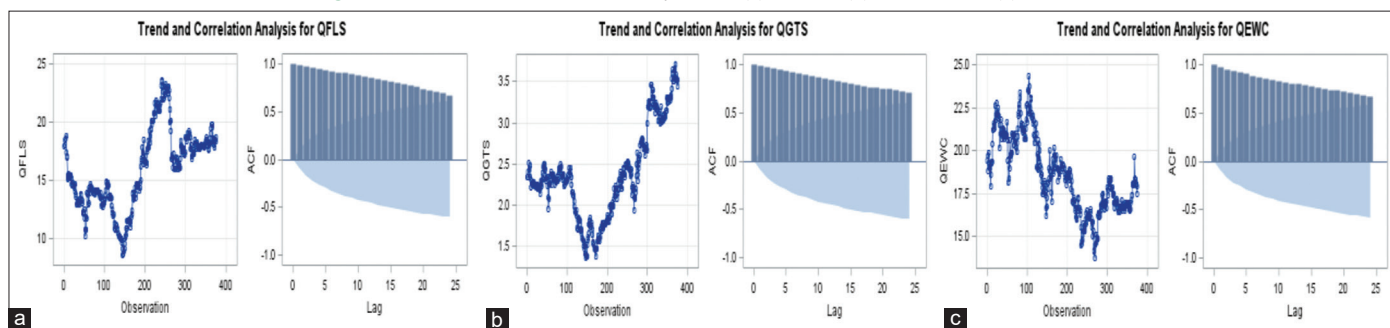
Table 5 shows that the three variables QFLS, QGTS, and QEWC indicate that all three have ARCH effects. LM test up to order 6 is very significant, with  $P < 0.0001$  for the three variables QFLS, QGTS, and QEWC. Based on the ARCH affect test results, the modeling to be built will not only involve modeling with the autoregressive (VAR) model but will also involve GARCH modeling for the residuals (Table 6).

Based on Table 4, schematic representation of cross-correlation, suggested that the model should involve lag 3. From the results of analysis by using eq.(6), AICC, we will compare models which involve lag 3 are VAR(3)-GARCH(1,1), VARMA(3,1)-GARCH(1,1), and VARMA(1,3)-GARCH(1,1). The AICC values from these three model are given in Table 7. From Table 7, the minimum AICC value is the AICC value of model VAR(3)-GARCH(1,1). Therefore, we will use model VAR(3)-GARCH(1,1) for further study.

#### 3.1. VAR(3)- GARCH(1,1) Model

From the results of the analysis, the estimated model of VAR(3)-GARCH(1,1) is as follows:

**Figure 2:** Trend and correlation analysis for (a) QFLS, (b) QGTS, and (c) QEWC



**Table 1:** Dickey-Fuller unit roots test before and after differencing (d=1)

Variable	Type	Before differencing				After differencing (d=1)			
		Rho	P-value	Tau	P-value	Rho	P-value	Tau	P-value
QFLS	Zero mean	-0.14	0.6496	-0.25	0.5957	-362.29	0.0001	-13.44	<0.0001
	Single mean	-3.76	0.5651	-1.36	0.6053	-362.29	0.0001	-13.42	<0.0001
	Trend	-8.10	0.5729	-2.33	0.4145	-364.62	0.0001	-13.45	<0.0001
QGTS	Zero mean	0.40	0.7798	0.72	0.8695	-433.08	0.0001	-14.67	<0.0001
	Single mean	-0.98	0.8876	-0.40	0.9056	-435.61	0.0001	-14.69	<0.0001
	Trend	-4.50	0.8542	-1.51	0.8258	-443.76	0.0001	-14.80	<0.0001
QEWC	Zero mean	-0.18	0.6426	-0.38	0.5459	-487.96	0.0001	-15.60	<0.0001
	Single mean	-7.90	0.2207	-1.97	0.3015	-488.09	0.0001	-15.58	<0.0001
	Trend	-19.58	0.0724	-3.18	0.0909	-488.09	0.0001	-15.56	<0.0001

**Table 2: Autocorrelation for white noise**

Variable	To lag	Chi-square	DF	P-value	Autocorrelations					
QFLS	6	2098.70	6	<0.0001	0.989	0.978	0.966	0.953	0.939	0.926
	12	3906.31	12	<0.0001	0.913	0.901	0.889	0.876	0.864	0.852
	18	5435.17	18	<0.0001	0.838	0.825	0.812	0.798	0.784	0.771
	24	6665.32	24	<0.0001	0.756	0.740	0.726	0.708	0.690	0.672
QGTS	6	2081.17	6	<0.0001	0.987	0.973	0.961	0.949	0.935	0.921
	12	3839.31	12	<0.0001	0.906	0.892	0.877	0.862	0.848	0.836
	18	5323.84	18	<0.0001	0.822	0.810	0.797	0.786	0.776	0.768
	24	6628.13	24	<0.0001	0.760	0.751	0.742	0.733	0.724	0.713
QEWC	6	1965.84	6	<0.0001	0.973	0.953	0.936	0.917	0.902	0.884
	12	3587.31	12	<0.0001	0.870	0.855	0.839	0.827	0.816	0.807
	18	4970.98	18	<0.0001	0.797	0.783	0.771	0.760	0.746	0.737
	24	6146.01	24	<0.0001	0.729	0.719	0.709	0.695	0.681	0.664

**Table 3: Cross correlations of dependent series by variable up to lag 6**

Variable Lag	QFLS			Variable Lag	QGTS			Variable Lag	QEWC		
	QFLS	QGTS	QEWC		QFLS	QGTS	QEWC		QFLS	QGTS	QEWC
0	1.000	0.238	0.345	0	0.238	1.000	0.277	0	0.345	0.277	1.000
1	0.027	0.176	-0.032	1	0.044	-0.021	0.075	1	0.036	0.117	-0.110
2	0.001	0.004	0.035	2	0.033	-0.068	-0.058	2	0.031	-0.011	-0.072
3	0.120	-0.055	0.001	3	0.081	-0.013	0.097	3	-0.021	-0.068	0.028
4	-0.010	0.077	-0.038	4	0.009	0.041	-0.099	4	-0.080	-0.011	-0.048
5	0.018	0.018	-0.002	5	0.026	0.062	0.009	5	0.030	-0.016	0.042
6	-0.025	0.035	-0.025	6	-0.070	-0.028	0.007	6	-0.016	0.043	-0.067

**Table 4: Schematic representation of cross-correlation**

Variable/lag	0	1	2	3	4	5	6
QFLS	+++	•+•	•••	+••	•••	•••	•••
QGTS	+++	•••	•••	•••	•••	•••	•••
QEWC	+++	•+-	•••	•••	•••	•••	•••

+ is > 2\*std error, - is < -2\*std error, • is between

**Table 5: Test for ARCH effect**

Variable	Order	Q	P-value	LM	P-value
QFLS	1	353.0531	<0.0001	347.2733	<0.0001
	2	680.3122	<0.0001	347.4005	<0.0001
	3	976.9750	<0.0001	347.9990	<0.0001
	4	1241.6570	<0.0001	348.1778	<0.0001
	5	1478.1629	<0.0001	348.1979	<0.0001
	6	1693.5621	<0.0001	348.8624	<0.0001
QGTS	1	338.6083	<0.0001	333.8252	<0.0001
	2	648.7727	<0.0001	334.1128	<0.0001
	3	928.9561	<0.0001	334.2653	<0.0001
	4	1179.7573	<0.0001	334.4350	<0.0001
	5	1402.6310	<0.0001	334.4529	<0.0001
	6	1596.2300	<0.0001	334.6787	<0.0001
QEWC	1	269.5211	<0.0001	266.3434	<0.0001
	2	465.2711	<0.0001	266.3639	<0.0001
	3	613.0733	<0.0001	266.6047	<0.0001
	4	717.6193	<0.0001	266.9586	<0.0001
	5	801.8029	<0.0001	268.0056	<0.0001
	6	859.0418	<0.0001	269.5999	<0.0001

$$\begin{bmatrix} 0.1099 & 0.7375 & -0.1168 \\ -0.0043 & 0.0117 & -0.0016 \\ -0.0055 & 0.9624 & -0.0656 \end{bmatrix} \begin{bmatrix} QFLS_{t-3} \\ QGTS_{t-3} \\ QEWC_{t-3} \end{bmatrix} \quad (18)$$

and the estimate of CCC-GARCH(1,1) is as follows:

$$\begin{aligned} \sigma_{1t}^2 &= 0.0125 + 0.1940 \varepsilon_{1t-1}^2 + 0.7663 \sigma_{1t-1}^2, \\ \sigma_{2t}^2 &= 0.0040 + 0.02794 \varepsilon_{2t-1}^2 - 0.1356 \sigma_{2t-1}^2, \text{ and} \quad (19) \\ \sigma_{3t}^2 &= 0.0142 + 0.1965 \varepsilon_{3t-1}^2 + 0.7600 \sigma_{3t-1}^2 \end{aligned}$$

Figure 3 and Table 8 show that  $QFLS_t$  was affected significantly by  $QGTS_{t-3}$  and  $QEWC_{t-3}$ .  $QGTS_t$  is affected significantly by  $QFLS_{t-1}$ , and  $QEWC_t$  is affected significantly by  $QGTS_{t-1}$ ,  $QGTS_{t-3}$ ,  $QEWC_{t-1}$ , and  $QEWC_{t-2}$ . Table 8 shows that the effect of  $QEWC_{t-3}$  to  $QFLS_t$  is negative with the estimated parameter of  $-0.1168$ , which means that the value of  $QFLS_t$  will decrease as big as  $-0.1168$  for every increment of one unit of  $QEWC_{t-3}$ , with the assumption that all other values hold constant. The effect of  $QFLS_{t-3}$ ,  $QGTS_{t-3}$  to  $QFLS_t$  are positive. The estimated value of parameter  $QFLS_{t-3}$  is  $0.1099$  this means that the value of  $QFLS_t$  will increase as big as  $0.1099$  for every increment of one unit of  $QFLS_{t-3}$ , with the assumption that all other values hold constant. The estimated value of parameter  $QGTS_{t-3}$  is  $0.7375$  this means that the value  $QFLS_t$  will increase as big as  $0.7375$  for every increment one unit of  $QGTS_{t-3}$ , assuming that all other values hold constant. Table 8 shows that the effect of  $QFLS_{t-1}$  to  $QGTS_t$  is positive, with the estimated value of the parameter is  $0.0298$  this means that the value of  $QGTS_t$  will increase as big as  $0.0298$  for every incremental unit of  $QFLS_{t-1}$ , with the assumption that

$$\begin{bmatrix} QFLS_t \\ QGTS_t \\ QEWC_t \end{bmatrix} = \begin{bmatrix} 0.0037 \\ 0.0000 \\ 0.0066 \end{bmatrix} + \begin{bmatrix} 0.0747 & 0.2175 & -0.0193 \\ 0.0298 & -0.0865 & 0.0097 \\ 0.0594 & 0.7554 & -0.1456 \end{bmatrix} \begin{bmatrix} QFLS_{t-1} \\ QGTS_{t-1} \\ QEWC_{t-1} \end{bmatrix} + \begin{bmatrix} -0.0019 & 0.3516 & -0.0033 \\ 0.0065 & -0.0662 & 0.0001 \\ 0.0596 & 0.0637 & -0.1094 \end{bmatrix} \begin{bmatrix} QFLS_{t-2} \\ QGTS_{t-2} \\ QEWC_{t-2} \end{bmatrix} +$$

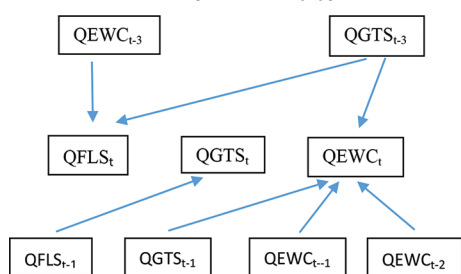
**Table 6: Minimum information criterion based on AICC**

Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	-8.423137	-8.473188	-8.456536	-8.494014	-8.492097	-8.457456
AR 1	-8.459455	-8.449881	-8.440389	<b>-8.474537</b>	-8.447535	-8.412081
AR 2	-8.442628	-8.446048	-8.436864	-8.452341	-8.409439	-8.380424
AR 3	<b>-8.429065</b>	<b>-8.471784</b>	-8.456168	-8.416343	-8.3752	-8.340514
AR 4	-8.406429	-8.45258	-8.414111	-8.374472	-8.342551	-8.313291
AR 5	-8.391898	-8.422344	-8.385843	-8.352417	-8.315632	-8.26821

**Table 7: The comparison AICC of model VAR (3)-GARCH (1,1), VARMA (3,1)-GARCH (1,1), and VARMA (1,3)-GARCH (1,1)**

Information criterion	Model		
	VAR (3)-GARCH (1,1)	VARMA (3,1)-GARCH (1,1)	VARMA (1,3)-GARCH (1,1)
AICC	-8.4040	-8.3446	-8.3833

**Figure 3:** The variables that have significant effect on  $QFLS_t$ ,  $QGTS_t$ , dan  $QEWC_t$  based on the results of test of the parameters given in Table 8 with  $P < 0.05$



all other values hold constant. Table 8 shows that the effect of  $QEWC_{t-1}$  and  $QEWC_{t-2}$  to  $QEWC_t$  are negative, with the estimated values of the parameters are  $-0.1456$  and  $-0.1094$  for  $QEWC_{t-1}$ , and  $QEWC_{t-2}$ , respectively. So the effect of  $QEWC_{t-1}$  to  $QEWC_t$  is negative with the estimated parameter value of  $-0.1456$  this means that the value of  $QEWC_t$  will decrease as big as  $-0.1456$  for every increment of one unit of  $QEWC_{t-1}$ , with the assumption that all other values held constant; and the effects of  $QEWC_{t-2}$  to  $QEWC_t$  is negative with the estimated value of the parameter is  $-0.1094$  this means that the value of  $QEWC_t$  will decrease as big as  $-0.1094$  for every increment one unit of  $QEWC_{t-2}$ , with the assumption that all other values hold constant. Table 6 shows that the effect of  $QGTS_{t-1}$  and  $QGTS_{t-3}$  to  $QEWC_t$  are positive, with the estimated parameters of  $0.7554$  and  $0.9624$  for  $QGTS_{t-1}$  and  $QGTS_{t-3}$ , respectively. So the effect of  $QGTS_{t-1}$  to  $QEWC_t$  is positive, with the estimated value of the parameter is  $0.7554$  this means that the value of  $QEWC_t$  will increase as big as  $0.7554$  for every increment of one unit of  $QGTS_{t-1}$ , with the assumption that all other values held constant; and the effect of  $QGTS_{t-3}$  to  $QEWC_t$  is positive with the estimated value of the parameter is  $0.9624$  this means that the value of  $QEWC_t$  will increase as big as  $0.9624$  for every increment one unit of  $QGTS_{t-3}$ , with the assumption that all other values hold constant. Table 9 shows the parameter estimate of GARCH(1,1) by using CCC, most of the parameters are significant. The estimation of conditional variance for each variable is given in Equation (19).

**3.2. Diagnostic Model**

Table 10 shows that up to lag 4, the Portmanteau test is significant with the value of Chi-Square=20.22 and P-value=0.0166, while the subsequent lags are not significant. This shows that the use of the VAR(3)-GARCH(1,1) model is appropriate (Wei,

2019). Table 11 shows that the univariate models for QGTS and QEWC are significant, with P-values being 0.0170 and 0.0256, respectively. Table 12 shows that the normality test using the JB-test with the null hypothesis that the residuals are normally distributed, was rejected for QFLS, QGTS, and QEWC data. Still, Figure 4 shows that the distribution of residuals is close to the normal distribution for QFLS errors (Figure 4a), closed to the normal distribution for the QGTS error (Figure 4b), and closed to the normal distribution for the QEWC error (Figure 4c). Table 12 also shows an ARCH effect for the QGTS and QEWC variables with P-values  $< 0.0001$  and  $0.0058$ , respectively. So involving the GARCH model for residuals is appropriate (Wei, 2019). Table 13 shows that the modulus values for both roots VAR and roots GARCH characteristic polynomial are less than 1, indicating that the model is stable (Hamilton, 1994; Lutkepohl, 2005).

**3.3. Granger Causality Wald Test**

Table 14 shows the results of the Wald test or Granger causality test. Test 3, Test 4, and Test 6 are significant. So the null hypothesis for test 3, Test 4, and Test 6 are rejected. The nature of Granger causality from Table 14 can be simplified by Figure 5. Figure 5 explains that the variable QGST not only influenced by itself but also influenced by QFLS (Test 3), variable QGST is not only influenced by itself but also influenced by QEWC (Test 4), and variable QEWC is not only influenced by itself but also influenced by QGTS (Test 6). Figure 5 shows unidirectional Granger causality between QFLS and QGTS, and bidirectional Granger causality between variables QGTS and QEWC.

**3.4. Impulse Response Function**

Figure 6 shows that if there is a shock of 1 standard deviation in QFLS, then the stock prices of QFLS, QGTS, and QEWC will respond. (Figure 6a) shows the mean response of QFLS to a shock 1 standard deviation of QFLS. (Figure 6a) shows that there were quite large price fluctuations until the 5<sup>th</sup> week, the 5<sup>th</sup> to 7<sup>th</sup> week, the fluctuations decreased, and after the 7<sup>th</sup> week, the price was stable. In the 1<sup>st</sup> week, there was a change in the QFLS price with an average change of 0.0747 with a standard deviation of 0.0541. In the 2<sup>nd</sup> week, there was a change in price with an average change of 0.0089 and with standard deviation is 0.0574. In the 3<sup>rd</sup> week, there was a change in price with an average change of 0.1207 and standard deviation is 0.0575. In the 4<sup>th</sup> week, there was a change in price with an average change of 0.0334 and standard deviation of 0.0185. In the 5<sup>th</sup> week, there

**Table 8: Model parameter estimates and test VAR (3)**

Equation	Parameter	Estimate	Standard error	t-value	P-value	Variable
QFLS	CONST1	0.00375	0.02270	0.17	0.8690	1
	AR1_1_1	0.07469	0.05418	1.38	0.1689	QFLS (t-1)
	AR1_1_2	0.21753	0.36612	0.59	0.5528	QGTS (t-1)
	AR1_1_3	-0.01928	0.05366	-0.36	0.7196	QEWG (t-1)
	AR2_1_1	-0.00193	0.05863	-0.03	0.9738	QFLS (t-2)
	AR2_1_2	0.35160	0.38256	0.92	0.3587	QGTS (t-2)
	AR2_1_3	-0.00329	0.05684	-0.06	0.9539	QEWG (t-2)
	AR3_1_1	0.1099	0.05696	1.93	0.0543	QFLS (t-3)
	AR3_1_2	0.7375	0.3755	1.96	0.0503	QGTS (t-3)
QGTS	AR3_1_3	-0.1168	0.0541	-2.16	0.0315	QEWG (t-3)
	CONST2	0.00004	0.00307	0.01	0.9897	1
	AR1_2_1	0.0298	0.00566	5.27	0.0001	QFLS (t-1)
	AR1_2_2	-0.08648	0.05967	-1.45	0.1481	QGTS (t-1)
	AR1_2_3	0.00971	0.00701	1.38	0.1671	QEWG (t-1)
	AR2_2_1	0.00652	0.00738	0.88	0.3771	QFLS (t-2)
	AR2_2_2	-0.06617	0.05835	-1.13	0.2575	QGTS (t-2)
	AR2_2_3	0.00001	0.00685	0.00	0.9983	QEWG (t-2)
	AR3_2_1	-0.00431	0.00798	-0.54	0.5892	QFLS (t-3)
QEWG	AR3_2_2	0.01176	0.05256	0.22	0.8231	QGTS (t-3)
	AR3_2_3	-0.00158	0.00664	-0.24	0.8118	QEWG (t-3)
	CONST3	0.00663	0.02165	0.31	0.7594	1
	AR1_3_1	0.05945	0.05088	1.17	0.2434	QFLS (t-1)
	AR1_3_2	0.7554	0.36100	2.09	0.0371	QGTS (t-1)
	AR1_3_3	-0.1456	0.05308	-2.74	0.0064	QEWG (t-1)
	AR2_3_1	0.05964	0.04968	1.20	0.2306	QFLS (t-2)
	AR2_3_2	0.06371	0.33087	0.19	0.8474	QGTS (t-2)
	AR2_3_3	-0.1094	0.05238	-2.09	0.0374	QEWG (t-2)
	AR3_3_1	-0.00548	0.05039	-0.11	0.9134	QFLS (t-3)
	AR3_3_2	0.9624	0.33541	2.87	0.0043	QGTS (t-3)
	AR3_3_3	-0.06562	0.04711	-1.39	0.1645	QEWG (t-3)

**Table 9: CCC-GARCH (1,1) Model parameter estimates**

Parameter	Estimate	Standard error	t-value	P-value
GCHC1_1	0.01254	0.00561	2.23	0.0261
GCHC2_2	0.00403	0.00081	4.98	0.0001
GCHC3_3	0.01425	0.00821	1.74	0.0835
ACH1_1_1	0.19405	0.05701	3.40	0.0007
ACH1_2_2	0.27938	0.08579	3.26	0.0012
ACH1_3_3	0.19652	0.06084	3.23	0.0013
GCH1_1_1	0.76633	0.05493	13.95	0.0001
GCH1_2_2	-0.13566	0.14788	-0.92	0.3595
GCH1_3_3	0.76000	0.07411	10.26	0.0001

**Table 10: Portmanteau test for cross-correlation of residuals**

Up to lag	DF	Chi-square	P-value
4	9	20.22	0.0166
5	18	23.66	0.1666
6	27	28.58	0.3813
7	36	32.72	0.6252
8	45	39.12	0.7184
9	54	45.61	0.7847
10	63	49.74	0.8880
11	72	59.46	0.8546
12	81	67.10	0.8661

**Table 11: Univariate model ANOVA diagnostics**

Variable	R-square	Standard deviation	F-value	P-value
QFLS	0.0235	0.46906	0.97	0.4676
QGTS	0.0538	0.06868	2.28	0.0170
QEWG	0.0507	0.48601	2.14	0.0256

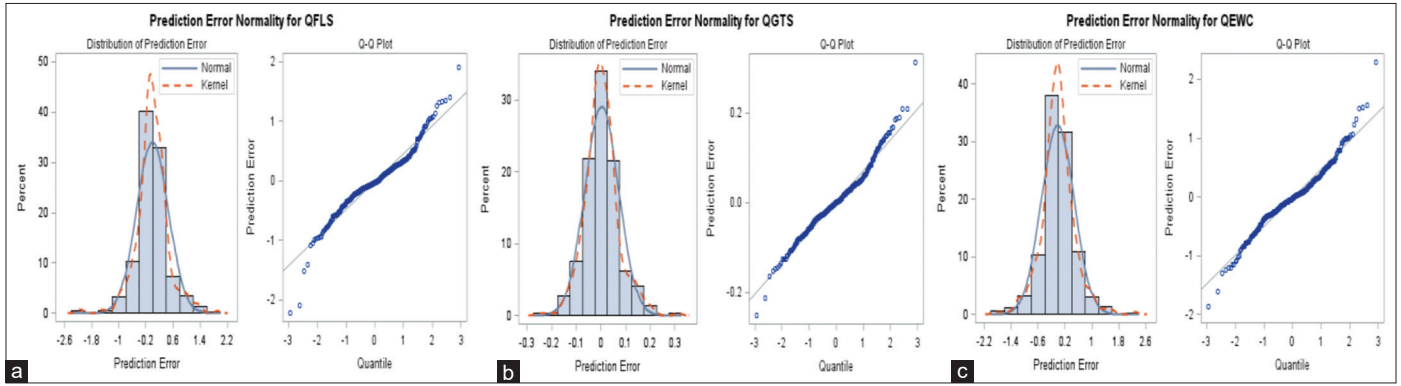
**Table 12: Univariate model white noise diagnostics**

Variable	Durbin watson	Normality		ARCH	
		Chi-square	P-value	F-value	P-value
QFLS	2.11381	175.52	<0.0001	0.09	0.7654
QGTS	2.00726	67.27	<0.0001	29.04	<0.0001
QEWG	2.00379	89.39	<0.0001	7.69	0.0058

was a change in price with an average change of -0.0024, and a standard deviation of 0.0162. In the 6<sup>th</sup> week, there was a price change with an average change of 0.0118 and standard deviation is 0.0164. From the 7<sup>th</sup> week onwards, the price goes to equilibrium. (Figure 6b) shows the response of QGTS if there is a shock of 1 standard deviation in QFLS, Figure shows that the stock price of QGTS is only slightly affected until the 3<sup>rd</sup> week, and the effect is negligible. (Figure 6c) shows the mean response of QFLS to a shock 1 standard deviation of QEWG. (Figure 6c) shows that there were quite large price fluctuations until the 5<sup>th</sup> week, the fifth to 7<sup>th</sup> week the fluctuations decreased and after the 7<sup>th</sup> week, the price was stable. In the 1<sup>st</sup> week, there was a change in the QEWG price with an average change of 0.0594 and with standard deviation is 0.0508. In the 2<sup>nd</sup> week, there was a change in the QEWG price with an average change of 0.0779 and with standard deviation is 0.0492. In the 3<sup>rd</sup> week, there was a change in the QEWG price with an average change of -0.0113 and with standard deviation is 0.0508. In the 4<sup>th</sup> week, there was a change in the QEWG price with an average change of 0.0216, and a standard deviation of 0.0156. In the 5<sup>th</sup> week, there was a change in the QEWG price with an average change of 0.0109 and with standard deviation is 0.0110. In the 6<sup>th</sup> week, there was a change in the QEWG price



**Figure 4:** Prediction error normality for data (a) QFLS, (b) QGTS, and (c) QEWC



**Table 13: Roots of AR and roots of GARCH characteristic polynomial**

Roots of AR characteristic polynomial						Roots of GARCH characteristic polynomial					
Index	Real	Imaginary	Modulus	Radian	Degree	Index	Real	Imaginary	Modulus	Radian	Degree
1	0.5056	0.0000	0.5056	0.0000	0.000	1	0.9697	0.0000	0.9697	0.0000	0.000
2	0.2209	0.1668	0.2769	0.6470	37.068	2	0.4125	0.0000	0.4125	0.0000	0.000
3	0.2209	-0.1668	0.2769	-0.6470	-37.068	3	0.0703	0.0000	0.0703	0.0000	0.000
4	0.0227	0.4989	0.4994	1.5252	87.388	4	-0.0372	0.0470	0.0600	2.2412	128.408
5	0.0227	-0.4989	0.4994	-1.5252	-87.388	5	-0.0372	-0.0470	0.0600	-2.2412	-128.408
6	-0.2104	0.4654	0.5108	1.9954	114.329	6	-0.1160	0.2218	0.2504	2.0526	117.608
7	-0.2104	-0.4654	0.5108	-1.9954	-114.329	7	-0.1160	-0.2218	0.2504	-2.0526	-117.608
8	-0.3647	0.0938	0.3766	2.8899	165.577	8	-0.1572	0.2603	0.3041	2.1142	121.133
9	-0.3647	-0.0938	0.3766	-2.8899	-165.577	9	-0.1572	-0.2603	0.3041	-2.1142	-121.133

**Table 14: Granger causality wald test**

Test	Variable	Null hypothesis granger causality	DF	Chi-square	P-value
Test 1	Group 1 variables: QFLS Group 2 variables: QGTS	QFLS is influenced only by itself, and not by QGTS.	3	2.00	0.5734
Test 2	Group 1 variables: QFLS Group 2 variables: QEWC	QFLS is influenced only by itself, and not by QEWC.	3	2.31	0.5115
Test 3	Group 1 variables: QGTS Group 2 variables: QFLS	QGTS is influenced only by itself, and not by QFLS.	3	14.68	0.0021
Test 4	Group 1 variables: QGTS Group 2 variables: QEWC	QGTS is influenced only by itself, and not by QEWC.	3	7.90	0.0480
Test 5	Group 1 variables: QEWC Group 2 variables: QFLS	QEWC is influenced only by itself, and not by QFLS.	3	1.61	0.6580
Test 6	Group 1 variables: QEWC Group 2 variables: QGTS	QEWC is influenced only by itself, and not by QGTS.	3	10.55	0.0144

with an average change of  $-0.0055$  and with standard deviation is  $0.0103$ . From the 7<sup>th</sup> week onwards, the price goes to equilibrium.

Figure 7 shows that if there is a shock of 1 standard deviation in QGTS, then the stock prices of QFLS, QGTS, and QEWC will respond. (Figure 7a) shows the mean response of QFLS to a shock 1 standard deviation of QGTS. (Figure 7a) shows a fairly large QFLS price fluctuation due to the shock on QGTS until the 6<sup>th</sup> week, the 7<sup>th</sup> week, the fluctuation decreased and led to a price balance. In the 1<sup>st</sup> week, there was a change in the QFLS price with an average change of  $0.2175$  and the standard deviation is  $0.3661$ , there was a change in price with an average change of  $0.3345$  with a standard deviation of  $0.3796$ . In the 3<sup>rd</sup> week, there was a change in price with an average change of  $0.7213$  and with standard deviation is  $0.3697$ . In the 4<sup>th</sup> week, there was a change in price with an average change of  $-0.1005$  and a standard deviation of  $0.0892$ . In the 4<sup>th</sup> week, there was a change in price with an average change of  $0.0242$  and a standard deviation of  $0.0766$ . In

the 6<sup>th</sup> week, there was a change in price with an average change of  $0.0115$  and with standard deviation of  $0.0730$ . From the 7<sup>th</sup> week onwards, the price goes to equilibrium. (Figure 7b) shows the response of QGTS if there is a shock of 1 standard deviation on QFLS. (Figure 7b) shows that the QGTS stock price is only slightly affected until the 3<sup>rd</sup> week and its effect is small and can be negligible. In the 1<sup>st</sup> week, there was a change in the QGTS price with an average change of  $-0.0865$  with a standard deviation of  $0.0597$ . In the 2<sup>nd</sup> week, there was a change in the QGTS price with an average change of  $-0.0449$  with a standard deviation of  $0.0577$ . In the 3<sup>rd</sup> week, there was a change in price with an average change of  $0.0318$ , and a standard deviation of  $0.0524$ . From the 4<sup>th</sup> week onwards, the effect weakens and the price goes to equilibrium. (Figure 7c) shows the mean response of QEWC to the shock 1 standard deviation of QGTS. (Figure 7c) shows that QEWC price fluctuations were quite large until the 6<sup>th</sup> week, the 7<sup>th</sup> week the fluctuations decreased and after the 7<sup>th</sup> week the prices were stable. In the 1<sup>st</sup> week, there was a change in the QEWC price with an

average change of 0.7554 and a standard deviation of 0.3610. In the 2<sup>nd</sup> week, there was a change in the QEWC price with an average change of -0.0986 and a standard deviation of 0.3258. In the 3<sup>rd</sup> week, there was a change in the QEWC price with an average change of 0.8876, and a standard deviation of 0.3322. In the 4<sup>th</sup> week, there was a change in the QEWC price with an average change of -0.1684 and a standard deviation is 0.1244. In the 5<sup>th</sup> week, there was a change in the QEWC price with an average change of -0.0498 and a standard deviation of 0.0808. In the 6<sup>th</sup> week, there was a change in the QEWC price with an average change of -0.0134, and the standard deviation is 0.0549; and from the 7<sup>th</sup> week onwards the price goes to equilibrium.

**Figure 5:** The granger causality Wald test

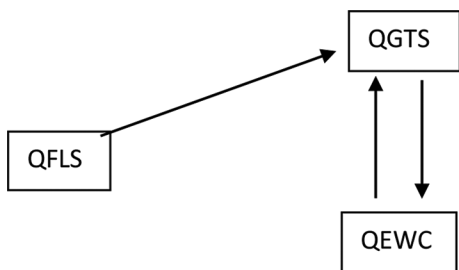
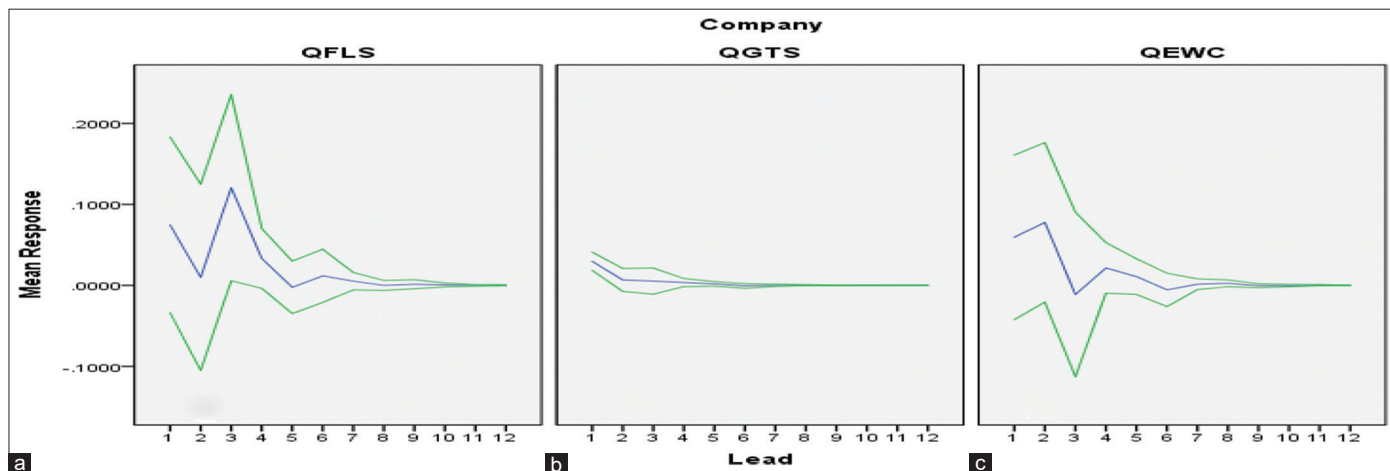
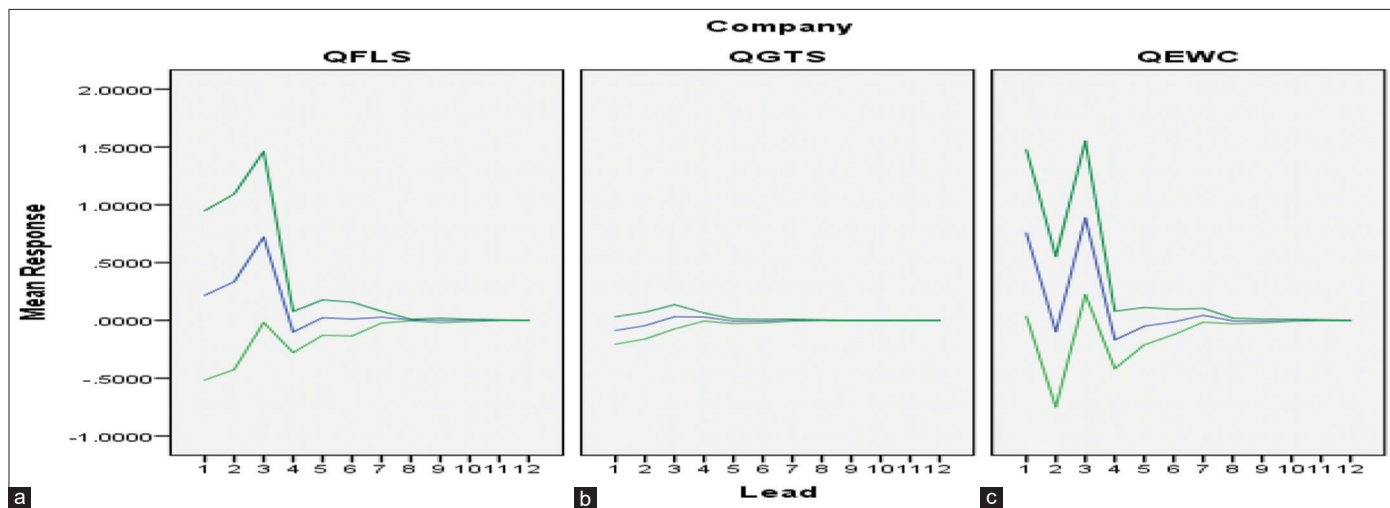


Figure 8 shows that if there is a shock of 1 standard deviation in QEWC, the stock prices of QFLS, QGTS, and QEWC will respond. (Figure 8a) shows the mean response of QFLS to a shock of 1 standard deviation from QEWC. (Figure 8a) shows a fairly large QFLS price fluctuation due to the shock in QEWC until the 6<sup>th</sup> week, the 7<sup>th</sup> week, the fluctuation decreased and goes to equilibrium. In the 1<sup>st</sup> week, there was a change in the QFLS price with an average change of -0.0193 and a standard deviation of 0.0536. In the 2<sup>nd</sup> week, there was a change in price with an average change of 0.0001 and a standard deviation of 0.0563. In the 3<sup>rd</sup> week, there was a change in price with an average change of -0.1119, and a standard deviation of 0.0535. In the 4<sup>th</sup> week, there was a price change with an average change of 0.0131, and a standard deviation of 0.0134. In the 5<sup>th</sup> week, there was a change in price, with an average change of 0.0067, and a standard deviation of 0.0103. In the 6<sup>th</sup> week, there was a change in price with an average change of -0.0101, and a standard deviation of 0.0099; and from the 7<sup>th</sup> week onwards, the price goes to equilibrium. (Figure 8b) shows the response of QGTS if there is a shock of 1 standard deviation in QEWC, (Figure 8b) shows that the stock price of QGTS is only slightly affected and the effect can be ignored. (Figure 8c) shows the mean response of QEWC to the shock 1 standard deviation of QEWC. (Figure 8c) shows a fairly

**Figure 6:** Response of (a)QFLS, (b)QGTS and (c)QEWC to impulse in QFLS with two standard errors



**Figure 7:** Response of (a) QFLS, (b) QGTS and (c) QEWC to impulse in QGTS with two standard errors



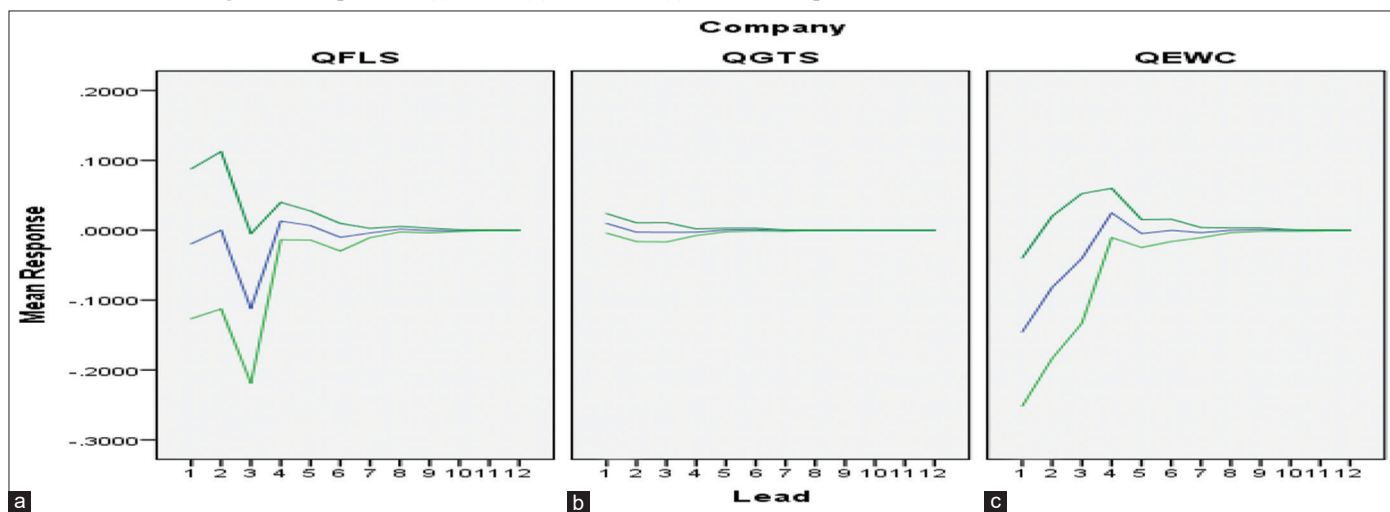
large QEWC price fluctuation until the 5<sup>th</sup> week. In the 6<sup>th</sup> week, the fluctuation decreases and after the 7<sup>th</sup> week, the price is stable. In the 1<sup>st</sup> week, there was a change in the QEWC price with an average change of  $-0.1456$  and a standard deviation of  $0.0531$ . In the 2<sup>nd</sup> week, there was a change in the QEWC price with an average change of  $-0.0820$  and a standard deviation of  $0.0509$ . In the 3<sup>rd</sup> week, there was a change in the QEWC price with an average change of  $-0.0404$  and a standard deviation of  $0.0464$ . In the 4<sup>th</sup> week, there was a change in the QEWC price with an average change of  $0.0248$  and a standard deviation of  $0.0177$ . In the 5<sup>th</sup> week, there was a change in the QEWC price with an average change of  $-0.0047$  and a standard deviation of  $0.0100$ ; from the 6<sup>th</sup> week onwards, the price goes to equilibrium.

### 3.5. Forecasting

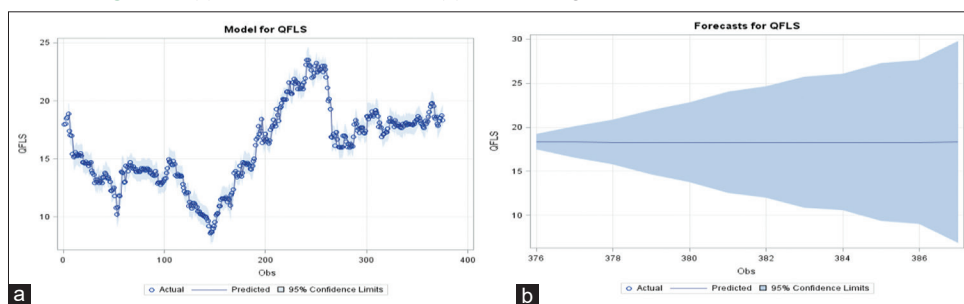
The VAR(3)-GARCH(1,1) model is the best model and fits to the data of QFLS, QGTS, and QEWC. (Figure 9a) shows that the

QFLS model shows that the predicted value and the real data value are very close to each other. This indicates that the model obtained is reliable and can be used for further analysis, especially for forecasting QFLS. (Figure 10a) shows that the QGTS model shows that the predicted value and the real data value are very close to each other. This indicates that the model obtained is reliable and can be used for further analysis, especially for forecasting QGTS. (Figure 11a) shows that the QEWC model shows that the predicted value and the real data value are very close to each other. This shows that the QEWC model obtained is reliable and can be used for further analysis, especially for forecasting QEWC. The forecasting value for QFLS for the next 12 weeks from Tabled 15 and 16 and (Figure 9b) shows the forecasting value is relatively constant at around  $18.30$ . The further away the forecasting is, the greater the standard error value (Table 16), and the farther the forecasting, the greater the confidence interval (Figure 9b). From Table 15, the proportion and prediction error covariances for QFLS

**Figure 8:** Response of (a)QFLS, (b)QGTS and (c)QEWC to impulse in QEWC with two standard errors



**Figure 9:** (a) Model for QFLS, and (b) Forecasting for QFLS for the next 12 weeks



**Figure 10:** (a) Model for QGTS, and (b) Forecasting for QGTS for the next 12 weeks

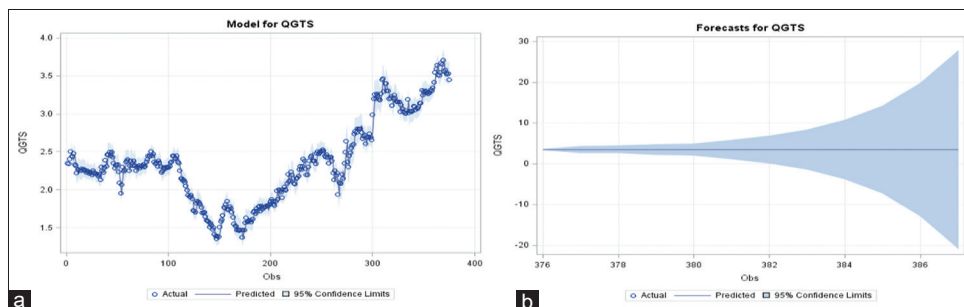


Figure 11: (a) Model for QEWC, and (b) forecasting for QEWC for the next 12 weeks

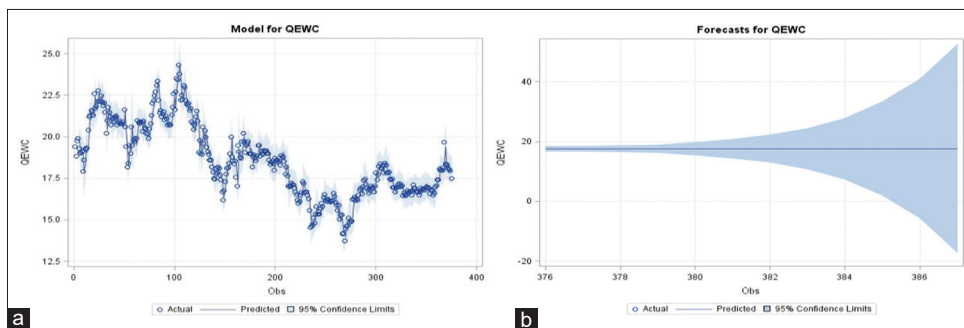


Table 15: Proportions of prediction error covariances by variable

Variable	Lead	QFLS	QGTS	QEWC	Variable	Lead	QFLS	QGTS	QEWC	Variable	Lead	QFLS	QGTS	QEWC
QFLS	1	1.0000	0.0000	0.0000	QGTS	1	0.0610	0.9390	0.0000	QEWC	1	0.1277	0.0500	0.8221
	2	0.9989	0.0006	0.0003		2	0.0987	0.8976	0.0036		2	0.1258	0.0538	0.8203
	3	0.9967	0.0029	0.0003		3	0.0991	0.8968	0.0039		3	0.1265	0.0543	0.8190
	4	0.9805	0.0084	0.0109		4	0.1001	0.8955	0.0043		4	0.1249	0.0657	0.8093
	5	0.9803	0.0085	0.0111		5	0.1005	0.8948	0.0046		5	0.1252	0.0659	0.8087
	6	0.9802	0.0086	0.0111		6	0.1006	0.8946	0.0046		6	0.1253	0.0660	0.8086
	7	0.9801	0.0086	0.0112		7	0.1006	0.8946	0.0046		7	0.1253	0.0660	0.8086
	8	0.9801	0.0086	0.0112		8	0.1006	0.8946	0.0046		8	0.1253	0.0660	0.8086
	9	0.9801	0.0086	0.0112		9	0.1006	0.8946	0.0046		9	0.1253	0.0660	0.8086
	10	0.9801	0.0086	0.0112		10	0.1006	0.8946	0.0046		10	0.1253	0.0660	0.8086
	11	0.9801	0.0086	0.0112		11	0.1006	0.8946	0.0046		11	0.1253	0.0660	0.8086
	12	0.9801	0.0086	0.0112		12	0.1006	0.8946	0.0046		12	0.1253	0.0660	0.8086

data, it appears that the forecasting value for the next 3 weeks is only influenced by itself (QFLS), namely 100%, 99.9%, and 99.7% for the 1<sup>st</sup> week, 2<sup>nd</sup> week, and 3<sup>rd</sup> week of forecasting, respectively. For the fourth to the 12<sup>th</sup> week, the effect of QFLS on itself is 98%, the effect of QGTS on QFLS is 1%, and the effect of QEWC on QFLS is 1%. This is consistent with the results in Figure 3, which has a significant effect  $QFLS_t$ . The forecasting value for QGTS for the next 12 weeks in Table 16 and (Figure 10b) show the forecasting value is relatively constant at around 3.44. The further away the forecasting is, the greater the standard error value (Table 16), and the farther the forecasting, the greater the confidence interval (Figure 10b). From Table 15, the proportion and prediction error covariances for QGTS data, it appears that the forecasting value of QGTS in the 1<sup>st</sup> week, is influenced by itself (QGTS) by 93.9% and influenced by QFLS by 6.1%. The QGTS forecasting value in the 2<sup>nd</sup> week was by itself by 89.76% and by QFLS by 9.87%; The QGTS forecasting value in the 3<sup>rd</sup> week is influenced by QGTS itself by 89.68% and influenced by QFLS by 9.91%. For the fourth to the 12<sup>th</sup> week, the effect of QGTS on itself is 89.48%, the effect of QFLS on QGTS is 10.06%. This is consistent with the results given in Figure 3, which has a significant effect  $QGTS_t$ . The forecasting value for QEWC for the next 12 weeks from Table 16 and (Figure 11b) show the forecasting value is relatively constant at around 17.50. The further away the forecasting is, the greater the standard error value (Table 16), and the farther the forecasting, the greater the confidence interval (Figure 11b). From Table 15, the proportion and prediction error covariances for QEWC data, it appears that the forecasting value of QEWC in the 1<sup>st</sup> week, is influenced by itself (QEWC) by 82.03%, influenced by QFLS by 12.58%, and influenced by QGTS by 5.38%; QEWC forecasting value in the 2<sup>nd</sup> week is influenced by itself (QEWC) by 82.21%, influenced

Table 16: Forecast for the next 12 weeks of QFLS, QGTS, and QEWC

Variable	Obs	Forecast	Standard error	95% Confidence limit	
QFLS	376	18.31609	0.44935	17.43539	19.19680
	377	18.33199	0.91979	16.52924	20.13473
	378	18.28423	1.29942	15.73741	20.83105
	379	18.27913	1.85359	14.64616	21.91210
	380	18.28268	2.32455	13.72664	22.83872
	381	18.28727	2.93600	12.53281	24.04173
	382	18.28888	3.23457	11.94924	24.62852
	383	18.29218	3.80337	10.83771	25.74666
	384	18.29595	3.95181	10.55054	26.04136
	385	18.29988	4.58045	9.32236	27.27741
	386	18.30373	4.74444	9.00479	27.60267
	387	18.30758	5.86649	6.80948	29.80568
QGTS	376	3.44080	0.06879	3.30598	3.57562
	377	3.44330	0.45958	2.54255	4.34406
	378	3.44585	0.49399	2.47764	4.41406
	379	3.44374	0.65772	2.15464	4.73284
	380	3.44324	0.76665	1.94065	4.94584
	381	3.44391	1.20137	1.08927	5.79854
	382	3.44418	1.74374	0.02651	6.86185
	383	3.44423	2.49807	-1.45191	8.34036
	384	3.44437	3.71314	-3.83325	10.72199
	385	3.44458	5.50796	-7.35082	14.23997
	386	3.44477	8.38744	-12.99431	19.88385
	387	3.44495	12.51007	-21.07433	27.96422
QEWC	376	17.50203	0.44654	16.62683	18.37722
	377	17.53680	0.47810	16.59974	18.47385
	378	17.49462	0.62883	16.26215	18.72710
	379	17.49553	0.74011	16.04494	18.94612
	380	17.50211	1.15204	15.24414	19.76007
	381	17.51256	1.66508	14.24907	20.77605
	382	17.51584	2.36897	12.87274	22.15894
	383	17.52054	3.53499	10.59209	24.44900
	384	17.52641	5.24659	7.24329	27.80953
	385	17.53225	7.98712	1.87778	33.18671
	386	17.53773	11.90312	-5.79195	40.86741
	387	17.54328	17.88814	-17.51684	52.60340

by QFLS by 12.77%, and influenced by QGTS by 5%; QEWC forecasting value in the 3<sup>rd</sup> week is influenced by itself (QEWC) by 81.90%, influenced by QFLS by 12.65%, and influenced by QGTS by 5.43%; For the fourth to the 12<sup>th</sup> week, the effect of QEWC on itself is 80.93%, the effect of QFLS on QEWC is 12.49%, and the effect of QGTS on QEWC is 6.57%. This is in accordance with the results in Figure 3, where  $QGTS_{t-1}$ ,  $QGTS_{t-3}$ ,  $QEWC_{t-1}$  and  $QEWC_{t-2}$  have a significant effect on  $QEWC_t$ .

#### 4. CONCLUSION

In this study, the weekly stock price of QFLS, QGTS, and QEWC of Qatar over the years January 2015 to April 2022. The data come from the Qatar Stock Market. The data are studied by using multivariate time series analysis modeling. From the preliminary study, the data exhibit nonstationary cross-correlation and ARCH effects. After the process of differentiating, the data are stationary. Based on the preliminary study, the model VAR(p)-GARCH(r,s) is applied to the data. For GARCH(r,s) model, the estimation of the parameters used CCC-GARCH(r,s) model is applied to the data. The best model and fit to the data vector observation  $Z_t = (QFLS_t, QGTS_t, QEWC_t)'$  are VAR(3)-GARCH(1,1) model. The model is reliable and sound based on the diagnostic analysis of the model. The Granger causality analysis showed that QFLS has Granger causality on QGTS (unidirectional), while QGTS and QEWC have bidirectional Granger causality to each other, namely, QGTS has Granger causality to QEWC and QEWC has Granger causality to QGTS. From the analysis of IRF it was found that: If there is a shock 1 standard deviation on QFLS, QFLS itself and QEWC give a response fluctuate with the mean positive within the first 6 weeks and start from week 7<sup>th</sup> and on the impact is weaken toward a balanced. But the shock 1 standard deviation of QFLS, the impact on QGTS is small and can be negligible. If there is a shock 1 standard deviation on QGTS, then QFLS and QEWC give a response fluctuate with the mean positive within the first 6 weeks and start from week 7<sup>th</sup> and on the impact is weaken toward a balanced. But the shock 1 standard deviation of QGTS, the impact on QGTS itself is small and can be negligible; and If there is a shock 1 standard deviation on QEWC, QFLS and QEWC itself give a response fluctuate with the mean negative within the first 6 weeks and start from week 7<sup>th</sup> and on the impact is weaken toward a balanced. But the shock 1 standard deviation of QEWC, the impact on QGTS is small and can be negligible. From the forecasting results for the next 12 periods, the closing price for QFLS, QGTS, and QEWC is almost constant, around 18.30, 3.44, and 17.50, respectively. but The farther away the forecasting period is, the greater the standard error. This indicates that the farther away the forecasting period is, the more unstable it is.

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