PERIÓDICO TCHÊ QUÍMICA
ARTIGO

MODELAGEM DINÂMICA DE USO DE DADOS DE SÉRIE DE TEMPO MODELO BEKK-GARCH

DYNAMIC MODELING OF TIME SERIES DATA USING BEKK-GARCH MODEL

PEMODELAN DINAMIS DATA DERET WAKTU MENGGUNAKAN BEKK-GARCH MODEL

USMAN, Mustofa[1*]; INDRYANI N[1]; WARSONO[1]; AMANTO[1], WAMILIANA[1]

[1] Universitas Lampung, Faculty of Mathematics and Natural Science, Department of Mathematics, Indonesia
* *Corresponding author*

e-mail:usman_alfha@yahoo.com

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RESUMO

O modelo de média móvel autorregressiva vetorial (VARMA) é um dos modelos usados com frequência na modelagem de dados de séries temporais multivariadas. Nas séries temporais, os dados econômicos, especialmente o retorno de dados, geralmente apresentam altas flutuações em alguns períodos de tempo, de modo que a volatilidade do retorno é instável. No processo de modelagem do retorno de dados dos preços das ações ADRO e ITMG, será considerado o comportamento de alta volatilidade. Os objetivos deste estudo são encontrar o melhor modelo adequado ao retorno de dados do preço das ações das empresas de energia da PT Adaro Energy Tbk (ADRO) e PT Indo Tambangraya Megah Tbk (ITMG), para analisar o comportamento da resposta ao impulso de os dados das variáveis retornam ADRO e ITMG, para analisar o teste de causalidade de granger e para prever os próximos 12 períodos. Com base na seleção do melhor modelo utilizando os critérios AICC, HQC, AIC e SBC, verificou-se que o modelo VARMA (2.2) -GARCH (1.1) é o melhor para os dados deste estudo. Com base no melhor modelo selecionado, são discutidas a resposta ao impulso, o teste de causalidade maior e a previsão para os próximos 12 períodos.

Palavras-chave: *média móvel autorregressiva vetorial, heterocedasticidade condicional autorregressiva generalizada, Modelo BEKK-GARCH, previsão*

ABSTRACT

The Vector Autoregressive Moving Average (VARMA) model is one of the models that is often used in modeling multivariate time series data. In time-series data of economics, especially data return, they usually have high fluctuations in some periods, so the return volatility is unstable. In modeling data return of share prices ADRO and ITMG, the behavior of high volatility will be considered. This study aims to find the best model that fits the data return of share price of the energy companies of PT Adaro Energy Tbk (ADRO) and PT Indo Tambangraya Megah Tbk (ITMG), to analyze the behavior of impulse response of the variables data return ADRO and ITMG, to analyze the granger causality test, and to forecast the next 12 periods. Based on the selection of the best model using the criteria of AICC, HQC, AIC, and SBC, it was found that the VARMA (2.2) -GARCH (1.1) model is the best one for the data in this study. The model VARMA(2,2)-GARCH (1,1) is then written as a univariate model. For the univariate ADRO model, the test statistics F=4,73 and P-value =0,0084, which indicates the model is very significant; and for the univariate ITMG model, the test statistics is F= 5,82 and P-value < 0,0001, which indicates the model is significant. Based on the best model selected, the impulse response, Granger causality test, and forecasting for the next 12 periods are discussed.

Keywords: *vector autoregressive moving average, general autoregressive conditional heteroscedasticity, BEKK-GARCH model, forecasting*

ABSTRAK

Model Vektor Autoregresif Moving Average (VARMA) merupakan salah satu model yang sering digunakan dalam pemodelan data deret waktu multivariat. Pada data deret waktu ekonomi, khususnya data return, biasanya memiliki fluktuasi yang tinggi dalam beberapa periode waktu tertentu, sehingga volatilitas return tidak stabil. Dalam pemodelan data return harga saham ADRO dan ITMG, akan diperhatikan perilaku volatilitas yang tinggi. Penelitian ini bertujuan untuk menemukan model terbaik yang sesuai dengan data return harga saham perusahaan energi PT Adaro Energy Tbk (ADRO) dan PT Indo Tambangraya Megah Tbk (ITMG), untuk menganalisis perilaku impulse response dari variabel data return ADRO dan ITMG, untuk menganalisis uji kausalitas granger, dan untuk meramalkan 12 periode berikutnya. Berdasarkan pemilihan model terbaik dengan menggunakan kriteria AICC, HQC, AIC, dan SBC, didapatkan model VARMA (2.2) -GARCH (1.1) yang terbaik untuk data dalam penelitian ini. Model VARMA (2,2) -GARCH (1,1) kemudian ditulis sebagai model univariat. Untuk model ADRO univariat diperoleh statistik uji F = 4,73 dan P-value = 0,0084 yang menunjukkan model tersebut sangat signifikan; dan untuk model ITMG univariat diperoleh statistik uji F = 5,82 dan P-value <0,0001 yang menunjukkan model tersebut signifikan. Berdasarkan model terbaik yang dipilih, respon impuls, uji kausalitas Granger, dan peramalan untuk 12 periode berikutnya didiskusikan.

Kata Kunci: *vektor autoregressif moving average, bentuk umum autoregresif heteroskedastik bersyarat, model BEKK-GARCH, peramalan.*

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1. INTRODUCTION:

The time-series data is an observation that is collected over time. Over time, observation data is commonly conducted in economics, finance, capital market, business, climates, and the environment. One of the interesting applications of time series data analysis is in the capital market. In the process of buying and selling in the capital market to get profits, investors must carry out a stock price analysis by looking at the return data of these stock prices to decide whether to buy or to sell in investing (Aspara and Indriani, 2017). Investors are interested in entering the Indonesian capital market because Indonesia is known as a country that is rich in natural resources, including mining resources. Therefore, the mining industry is playing an important role in supporting the development of the Indonesian economy.

In multivariate time series analysis, several models can be used, for example, vector autoregressive model (VAR), vector moving average (VMA), or a combination of both models, namely vector autoregressive moving average (VARMA). However, the data return of stock price analysis is usually conducted on several observations from several variables simultaneously, such as for an investor who not only invests in one company but in several companies. The investor needs to know the movement of return shares of all the companies he invests. In this case, the univariate time series analysis can no longer be relied upon, but multivariate time series_analysis will be used instead.

Multivariate time series analysis was developed by Tiao and Box (1981). This analysis has been discussed in several works of literature and is often used to forecast_in various fields such as finance, economics, earth science, and capital markets (Lutkepohl, 2005; Reinsel, 1993). The commonly used and effective model for forecasting multivariate time series data is the Vector Autoregressive moving average (VARMA) (Tsay, 2014). The VARMA model is an extension of the ARMA model in univariate time series data(Lutkepohl, 2005; Wei, 1990). This VARMA model can be used to predict more than one variable simultaneously and see the interrelationships between variables and predict macroeconomic data (Dufour and Pelletier, 2002).

The VARMA modeling process can be carried out if it meets the assumptions of stationary. If the stationary assumptions are not met, then the data must be transformed using a differencing process to make them stationary (Brockwell and Davis, 2002; Wei, 2006; Gujarati and Porter, 2009). The multivariate time series analysis was first used by Quenouille (1957) which was then widely used by researchers such as Hillmer and Tiao (1979), Tiao and Box (1981), Tiao and Tsay (1989), Tsay (1991), Kascha and Trenckler (2011), and Warsono *et al*. (2019a, 2019b).

Stock returns are the profits enjoyed by investors from the investment they do (Ang, 2001). Stock returns can also mean the results obtained from stock investment, either profit or loss. Investors will get a profit or capital gain if the return value is positive; by contrast, the investor will get a loss or capital loss if the return value is negative. Volatility has been widely used in various studies, especially in the economic and financial fields, for example, studies by Mascaro and Meltzer (1983), Belongia (1984), Engle, and Susmel (1993), Karolyi (1995), and Engel and Gizycki (1999). Lopez and Walter (2000) evaluate the Value at Risk (VaR) covariance matrix using the constant, historical, EWMA, GARCH, and applied volatility models.

The volatility of the stock returns depicts the fluctuations in the stock return and shows the risk. High fluctuations in stock return will cause the variance not to be homogeneous but heterogeneous instead. Autoregressive Conditional Heteroscedasticity (ARCH) method in analyzing heterogeneous data can be used to cope with this situation. For multivariate time series data with ARCH properties or ARCH effects, the model used is Multivariate Autoregressive Conditional Heteroscedasticity (Multivariate-ARCH), which was introduced by Engle, Granger, and Kraft (1984) and it can be used more efficiently in modeling. Multivariate-ARCH was later generalized by Bollerslev (1986, 1990) to Multivariate-GARCH. This model is a development of time series analysis, which models the mean and involves modeling variance. The Multivariate-GARCH model is practical and relatively easy to use in estimating volatility and considering the basis of a dynamic volatility model (Alexander and Lazar, 2006).

The multivariate GARCH model can dynamically describe the correlation of fluctuation of stock price data. Studies using Multivariate GARCH, among others, were conducted by Francq and Zakoian (2010), researching the price of assets and management risk crucially depending on the conditional covariance structure of the asset portfolio. Further development of the CCC-GARCH model was introduced by Bollerslev (1990).

The BEKK GARCH model was introduced by Baba, Engle, Kraft, and Kroner (1990) and further developed by Engle and Kroner (1995). Engle and Kroner (1995) propose parametric BEKK GARCH models, which provide an effective model for modeling volatility. BEKK GARCH is known for its ease of obtaining a positively definite variance-covariance matrix and its efficiency in reducing the estimated number of parameters. Compared to GARCH in general, BEKK -GARCH is more profitable in analyzing the volatility of return stocks.

BEKK-GARCH is used to estimate conditional covariance and indirectly estimate conditional correlations. Caporin and McAleer (2011) compared the BEKK GARCH and DCC GARCH methods in estimating volatility, where it was concluded that BEKK GARCH provides a more optimal model in volatility modeling. Xinjun and Minhui (2011) used the BEKK GARCH model (1,1) in modeling the volatility effect of the Hu, Shenzhen, and United States (US) stock markets, and the results showed that the risk of the US stock market affected the Hu, Shenzhen stock market. Still, Shenzhen shares do not affect the US stock market. Also, Hongfei and Lou (2010) used the BEKK GARCH model to model global oil prices on industrial output in China with monthly data from January 2001 to December 2009. The research shows that international oil has a significant fluctuating effect on the oil and gas industry. However, it negatively affects the utility industry, tourism, and entertainment industry shares.

This study aims to model the data return of stock price from an Indonesian mining company, PT. Adaro Energy Tbk. (ADRO) and Indo Tambangraya Megah Tbk. (ITMG) from April 2009 to December 2019. Also, this research will apply the BEKK-GARCH model to data modeling and to find the best model that can describe the dynamic model of the two variables.

2. MATERIALS AND METHODS:

2.1 Statistical Models

The Time series analysis method is useful for forecasting future conditions. However, if several observations from several variables will be analyzed simultaneously, the Multivariate Time Series analysis is used. The model frequently used in Multivariate Time Series analysis is Vector Autoregressive Moving Average (VARMA). The VARMA model explains the relationship between observations and errors of-variables at a certain time with observations and errors in the variable itself and other variables at a previous time. Here are some classifications of the VARMA model,

2.1.1 Vector Autoregressive Model (VAR)

The general form of the VAR model with order p, VAR(p) model, or VARMA(p,0) model with K variable can be written as Equation 1.

$$\Gamma_t = \delta + \sum_{i=1}^{p} \Phi_i \Gamma_{t-i} + \varepsilon_t \quad \text{(Eq.1)}$$

where δ is a constant vector of dimension kx1, Φ_i is the i^{th} coefficient of the square matrix of order k of autoregressive parameters, and p is the lag length. According to Tsay (2005), ε_t is kx1 random vector and is assumed to have a multivariate normal distribution.

2.1.2 Vector Moving Average Model (VMA)

Model VMA with order q, VMA(*q*), or VARMA(0,*q*) can be written as Equation 2.

$$\Gamma_t = \delta + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad \text{(Eq. 2)}$$

where δ is kx1 vector constant, ε_t is kx1 random vector and uncorrelated, and θ_j is the i^{th} coefficient of a square matrix of order k of moving average.

2.1.3 Vector Autoregressive Moving Average Model (VARMA)

The VARMA model for multivariate time series data is an extension of the ARMA model used for univariate time series data (Lutkepohl, 2005; Wei, 1990). According to Warsono *et al*. (2019a), the combination of the VAR model with the order p and the VMA model with the order q forms the VARMA(p, q), model. Based on the equations (1) and (2) of multivariate time series data with a dimension k is VARMA (p, q) and can be written as Equation 3:

$$\Gamma_t = \delta + \sum_{i=1}^{p} \Phi_i \Gamma_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad \text{(Eq. 3)}$$

where δ is a constant vector with k dimension, ε_t is kx1 random vector and uncorrelated, and θ_j is the i^{th} coefficient of a square matrix of order k of moving average, Φ_i is the i^{th} coefficient of a square matrix of order k of autoregressive parameters, and p and q are the lag length for the autoregressive and moving average.

2.1.4.Generalized Autoregressive Conditional Heteroscedastic (GARCH)

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model develops the Autoregressive Conditional Heteroscedasticity (ARCH) model. This model was developed to avoid high orders of the ARCH model, and make a model simpler, thus ensuring that variance is always positive. The GARCH model can be written as Equation 4:

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

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

$$\sigma_t^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad \text{(Eq.4)}$$

Where X_t is a conditional mean (Brooks, 2014). The multivariate GARCH model is defined as Equation 5 (Tsay, 2014, Wei, 2019):

$$\mathbf{X}_t = \boldsymbol{\mu}_t + \mathbf{a}_t \quad \text{(Eq.5)}$$

where, $\mathbf{X}_t$: n x 1 vector process at time t, , $\boldsymbol{\mu}_t = E(X_t | F_{t-1})$ is the conditional expectation of X_t given the past information, F_{t-1}, up to time (t-1). and the innovation $\mathbf{a}_t$ is given in Equation 6.

$$\mathbf{a}_t = \mathbf{H}_t^{1/2} \boldsymbol{\varepsilon}_t \quad \text{(Eq.6)}$$

where $\{\boldsymbol{\varepsilon}_t\}$ is a sequence of an independent identically distributed random vector such that $E(\boldsymbol{\varepsilon}_t)=\mathbf{0}$ and $Cov(\boldsymbol{\varepsilon}_t)=\mathbf{I}_n$ and $\mathbf{H}^{1/2}$ denote the positive-definite square root matrix of $\mathbf{H}_t$., where $\mathbf{H}_t$ is the conditional covariance matrix $\mathbf{X}_t$ given information up to time (t-1).

2.2. BEKK GARCH

BEKK-GARCH model was first introduced by Baba *et al*. (1990) then developed further by Engle and Kroner (1995). Engle and Kroner (1995) propose a new parameterization that is easily given a restriction. The conditional covariance H_t can be written as in Equation 7.

$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \sum_{i=1}^{q} \mathbf{A}_i' \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}_{t-1}' \mathbf{A}_i + \sum_{i=1}^{p} \mathbf{G}_i' \mathbf{H}_{t-1} \mathbf{G}_i \quad \text{(Eq.7)}$$

Where C is a mxm triangular matrix, A_i and G_i are mxm parameter matrices (Tsay, 2014; Wei, 2019).

The model in Equation 7 is called BEKK(p,q) model.

3. RESULTS AND DISCUSSION:

In this study, the data used is the weekly data return of the stock price of Indonesian mining companies, namely PT Adaro Energy Tbk (ADRO) and PT Indo Tambangraya Megah Tbk (ITMG) from April 2009 to December 2019 obtained from https://www.idnfinancial.com and the Indonesia Stock Exchange (BEI) in the form of a series plot distribution of the two variables that can be seen in Figure 1. However, what is used in the analysis is not in the form of stock price data but return stock prices because the return data better illustrates the risk of changes in stock prices. Therefore, the stock price data is changed into the form of stock price return to form a series of ADRO and ITMG return data series, as shown in Figure 2.

In Figure 2, it can be seen that both ADRO and ITMG return data have high fluctuation so that the application of the GARCH model might be appropriate. However, in conducting time series analysis, some assumptions must be met first, namely stationarity. To check the stationary of the data, the Dickey-Fuller test is used, and the results of the test given in Table 1.

In the Augmented Dicky-Fuller test, Ho is rejected if the p-value <0.05, and based on Table 1, the p-value <0.0001 is obtained for both ADRO and ITMG data, respectively. Therefore, the null hypothesis is rejected r;or in other words, stationary data are attained (Dickey and Fuller, 1979; Brockwell and Davis, 2002). The decision is also following the trend graph of ADRO and ITMG presented in Figure 3; the trend graph shows that the ACF and PACF values of ADRO and ITMG decay very past, which means that the data used in the study are stationary.

From Figure 4, we can see the volatility of the ADRO and ITMG from their conditional variances. Figure 4(a) shows that ADRO has high volatility at some periods and the highest trend changes are around observations 350 and 400. Likewise, for ITMG data presented in Figure 4(b), it appears that there is high volatility in several periods, but the changing ITMG trend tends to be more extreme than ADRO.

From the ARCH effect test results, based on Table 2, the p-value values are 0.0449 and 0.0130 for the ADRO and ITMG data, respectively. Therefore, the null hypothesis is rejected; in other words, ADRO and ITMG data have ARCH effects. Thus, the GARCH model is included in the VARMA modeling formed, and it is, namely as the BEKK-GARCH model. Furthermore, in the process of selecting the best model, the data analysis is performed using several models: VARMA (1.1) -GARCH (1.1), VARMA (1.2) - GARCH (1.1), VARMA(2.1) -GARCH (1,1), and VARMA (2,2) -GARCH (1,1).

Based on the model criteria information presented in Table 3, the AICC and HQC model selection criteria indicate that VARMA (2,2) - GARCH (1,1) has the smallest criterion value, which means the best model. By contrast, based on the AIC criteria, the VARMA (2.1) -GARCH (1.1) model is the best model, and based on the SBC criteria, the VARMA (1.1) -GARCH (1.1) model is the best model. Because there are three best model candidates, these models will be compared using the schematic representation of parameters and GARCH parameters presented in Table 4. and Table 5. From Tables 4 and 5 the best model for ADRO and ITMG stock return data is the model VARMA (2,2) -GARCH (1,1).

***Table 2**. Univariate Model White Noise Diagnostic*

Variables	Durbin Watson	Normality		ARCH	
		Chi-Square	P-value	F-Value	p-value
ADRO	1.99970	132.15	<.0001	4.04	0.0449
ITMG	1.92441	18.44	<.0001	6.21	0.0130

Based on the criterion of selecting the best model by using Information criteria AICC, HQC, AIC, and SBC, the best model that fits the data is VARMA(2,2)-GARCH(1,1) model. The estimated model VARMA(2,2)-GARCH(1,1) is as Equation 8.

$$\Gamma_t = \begin{bmatrix} 0.00379 \\ 0.00782 \end{bmatrix} + \begin{bmatrix} 0.00285 & -0.30001 \\ 0.86976 & -1.19455 \end{bmatrix} \Gamma_{t-1} + \begin{bmatrix} -0.73639 & 0.03952 \\ -3.75264 & 0.65400 \end{bmatrix} \Gamma_{t-2} - \begin{bmatrix} 0.04314 & -0.34157 \\ 0.85100 & -1.14980 \end{bmatrix} \varepsilon_{t-1} - \begin{bmatrix} -0.72864 & 0.02755 \\ -3.88199 & 0.80782 \end{bmatrix} \varepsilon_{t-2} + \varepsilon_t \quad \text{(Eq.8)}$$

Model VARMA(2,2)-GARCH(1,1) can also be written as two univariate regression models as Equations 9 and 10.

$$\mathrm{ADRO}_t = 0.00379 + 0.00285\, ADRO_{t-1} - 0.30001\, ITMG_{t-1} - 0.73639\, ADRO_{t-2} + 0.03952\, ITMG_{t-2} - 0.04314\varepsilon_{1t-1} +$$

$$0.34157\varepsilon_{2t-1} + 0.0.72864\varepsilon_{1t-2} - 0.02755\varepsilon_{2t-2} + \varepsilon_{1t} \quad \text{(Eq.9)}$$

$$\text{ITMG}_t = 0.00782 + 0.86976\, ADRO_{t-1} - 1.194551\, ITMG_{t-1} - 3.75264\, ADRO_{t-2} + 0.65400\, ITMG_{t-2} - 0.85100\varepsilon_{1t-1} + 1.14980\varepsilon_{2t-1} + 3.88199\varepsilon_{1t-2} - 0.807825\varepsilon_{2t-2} + \varepsilon_{12t} \quad \text{(Eq.10)}$$

The conditional variance and covariance-based on the BEKK parameterization of model GARCH (1,1) is as Equations 11, 12, and 13.

$$h_{11t} = 0.00280 + (0.34203)^2\varepsilon^2_{1(t-1)} + (-0.25866)^2 h_{11(t-1)} + 2(0.34203)(-0.47961)\, \varepsilon_{1(t-1)}\, \varepsilon_{2(t-1)} + (-0.47961)^2\varepsilon^2_{2(t-1)} + 2(-0.25866)(0.01295)\, h_{12(t-1)} + (0.01295)^2\, h_{22(t-1)} \quad \text{(Eq.11)}$$

$$h_{12t} = 0.00241 + (0.34203)(0.12135)\varepsilon^2_{1(t-1)} + (003160)(-0.47961)\varepsilon^2_{2(t-1)} + (-0.25866)(-0.00595)h_{11(t-1)} + (0.98885)(0.01295)h_{22(t-1)} + (-0.25866)^2 h_{11(t-1)} + \{(-0.47961)(0.12135) + (0.34203)(003160)\}\varepsilon^2_{1(t-1)}\varepsilon^2_{2(t-1)} + \{(0.01295)(-0.00595) + (-0.25866)(0.98885)h_{12(t-1)} \quad \text{(Eq.12)}$$

$$h_{22t} = 0.00003 + (0.03160)^2\varepsilon^2_{2(t-1)} + (0.98885)^2 h_{22(t-1)} + 2(0.03160)(0.12135)\, \varepsilon_{1(t-1)}\, \varepsilon_{2(t-1)} + (0.12135)^2\varepsilon^2_{1(t-1)} + 2(-0.00595)(0.98885)\, h_{12(t-1)} + (-0.00595)^2\, h_{11(t-1)} \quad \text{(Eq.13)}$$

Statistical tests of the $ADRO_t$ and $ITMG_t$ models are presented in Table 6. Based on these statistical tests, the $ADRO_t$ model has a value of F = 4.73 and P-Value = 0.0084, which means significant and has a coefficient of R-square determination 0.0616. While $ITMG_t$ has a value of F = 5.82 and P-Value <0.0001, which means significant and has a coefficient of determination of R-square of 0.0781. Also, based on Table 7, it is known that the F-test of AR (1), AR (1,2), AR (1,2,3), and AR (1,2,3,4) produces a P-value < 0.05 or in other words, we reject Ho. So we conclude that the residuals are not correlated.

Next, a Granger Causality Test is administered, aiming to determine the causal relationship between variables (Tsay, 2014; Warsono *et al*., 2019a). Granger Causality test is based on a Wald test in which the Chi-square distribution or F-test is used as an alternative. The results of the Granger Causality test analysis presented in Table 8 show that the first test in which ADRO as Group 1 and ITMG as Group 2 obtained Chi-square value = 2.35 and P-value = 0.3081 where the data do not reject Ho. Therefore, it was concluded that the ITMG return value did not influence the ADRO return value. The second test with ITMG as Group 1 and ADRO as Group 2, Chi-square = 0.74, and P-value = 0.6906; consequently, there is not enough evidence to reject Ho. In other words, it can be concluded that the ADRO return value does not influence the ITMG return value. Therefore, it is identified that ADRO and ITMG return values are only influenced by themselves.

***Table 6**. Univariate Model Anova Diagnostics*

Variable	R-square	Standard Deviation	F-value	p-value
ADRO	0.0616	0.06036	4.73	0.0084
ITMG	0.0781	0.05999	5.82	<0.0001

Based on Figure 5, it appears that the distribution of prediction error data return ADRO and ITMG tends to approach the normal distribution. Meanwhile, if seen from the form of prediction error, it can be seen that both ADRO and ITMG have unstable prediction errors throughout the year. However, in ADRO prediction errors, there was a high instability compared to other years, namely during 2015 and 2016.

Figures 6 (a) and 6(b) display the Impulse Response of each variable. The Impulse response itself is commonly used in economics to describe the economic reaction from time to time to the exogenous impulse. Figure 6(a) shows the impulse of ADRO. The shock from the ADRO standard deviation causes the response to fluctuating until the 15th week, and then the response goes to zero or stability. Whereas in Figure 6(b), it can be seen that fluctuations in the standard deviation tend to decrease after being shocked in ADRO, and since the 13th week started moving towards 0. This indicates that ITMG fluctuates following shock in ADRO.

Figure 6(a) illustrates the shock response implant in ITMG. The shock from the ITMG standard deviation causes ADRO to fluctuate until the 10th week and then move towards stability. Whereas in Figure 6(b), the shock from the ITMG standard deviation causes ITMG to stabilize or move towards zero after the 18th week.

The purpose of time series analysis is to forecast future conditions based on previous observational data. Therefore, ADRO and ITMG return forecasting will be formed in the next 12 weeks based on the VARMA (2.2) -GARCH (1.1) model, estimated and presented in Table 9. Based on forecasting results, it is seen that the return values of both ADRO and ITMG still quite volatile but ITMG experienced higher fluctuation compared to ADRO. Hence, the risk of investment is higher than ADRO in the next 12 weeks. Also, based on Figures 7 and 8, it appears that ADRO and ITMG have predictive values and observational data approaching each other; this indicates that the model fits the data.

Meanwhile, the forecasts for ADRO and ITMG plots show that the confidence interval tends to be constant. Even in the ADRO forecast, there is a slight decrease in the confidence interval. This shows that the model used is suitable for data analysis and forecasting.

4. CONCLUSION:

Based on the results of the analysis, the best model for data return of PT Adro Energy Tbk (ADRO) and PT Indo Tambangraya Megah Tbk (ITMG) is VARMA(2,2) -GARCH (1,1). Also, based on the Granger causality test, it is known that ADRO and ITMG do not directly influence each other. In line with forecasting results obtained based on the best model, it is found that the prediction value is close to the observation data, which means that the model fits the data. Thus, it can be concluded that VARMA (2,2) -GARCH (1,1) is suitable for modeling the data return of ADRO and ITMG. It can also be seen that confident intervals forecasting of data return ADRO and ITMG for the next 12 weeks tend to be stable, which means that the model provides good forecasting results.

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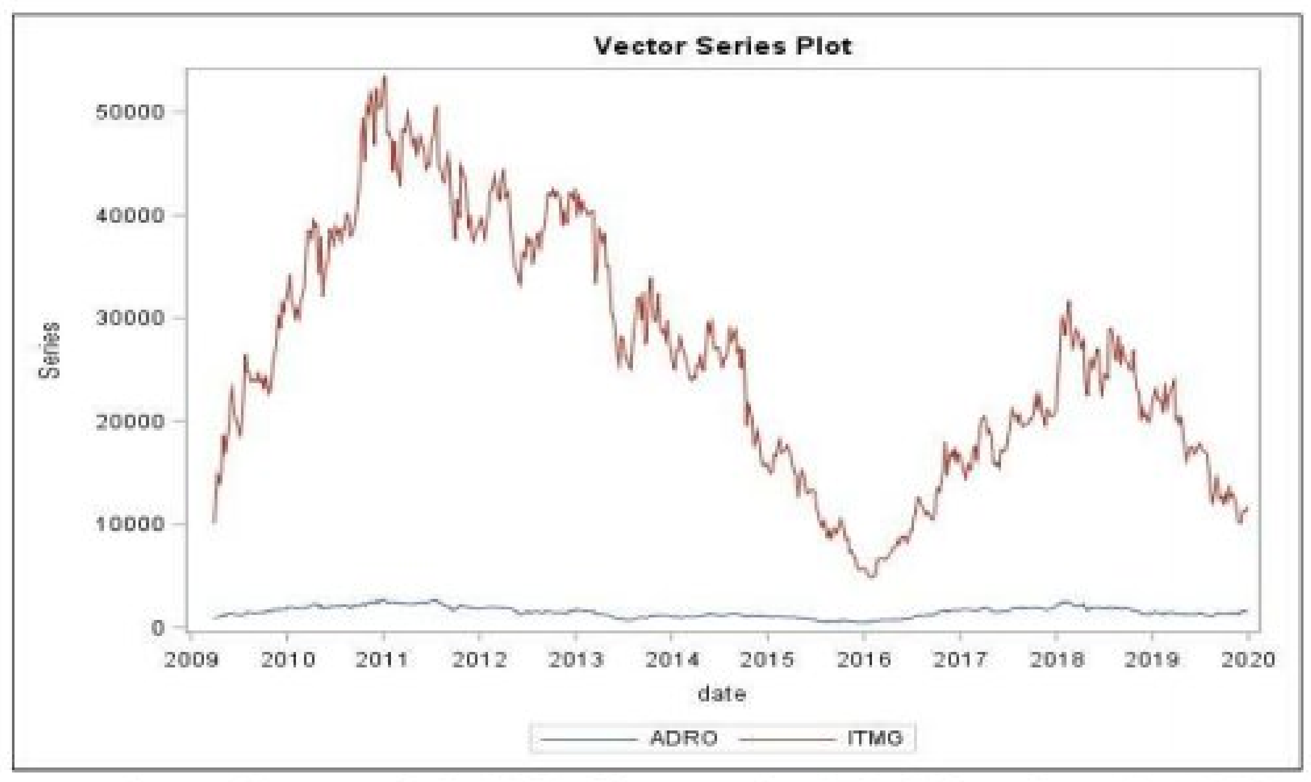


Figure 1. Plot data stock price of ADRO and ITMG April 2009 to December 2019

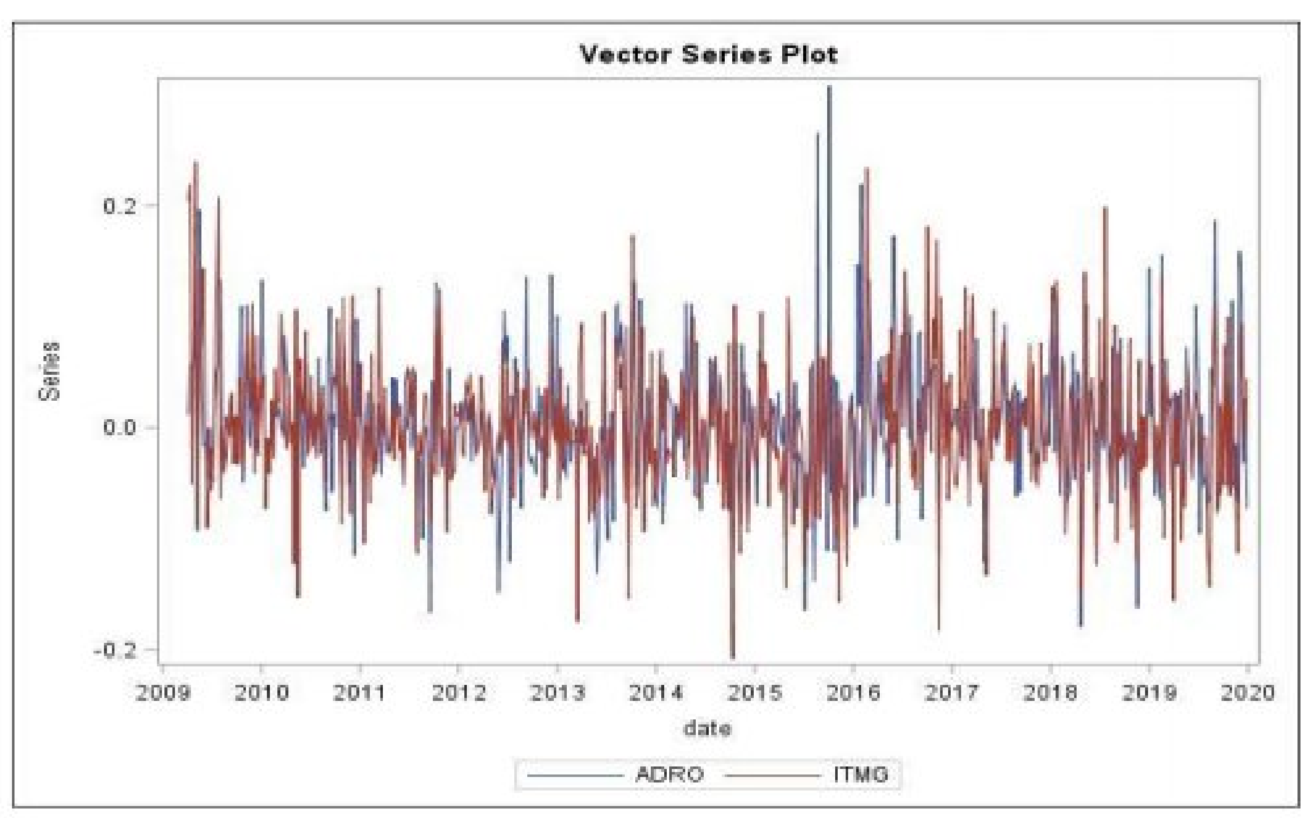


Figure 2. Plot data return stock price of ADRO and ITMG from April 2009 to December 2019

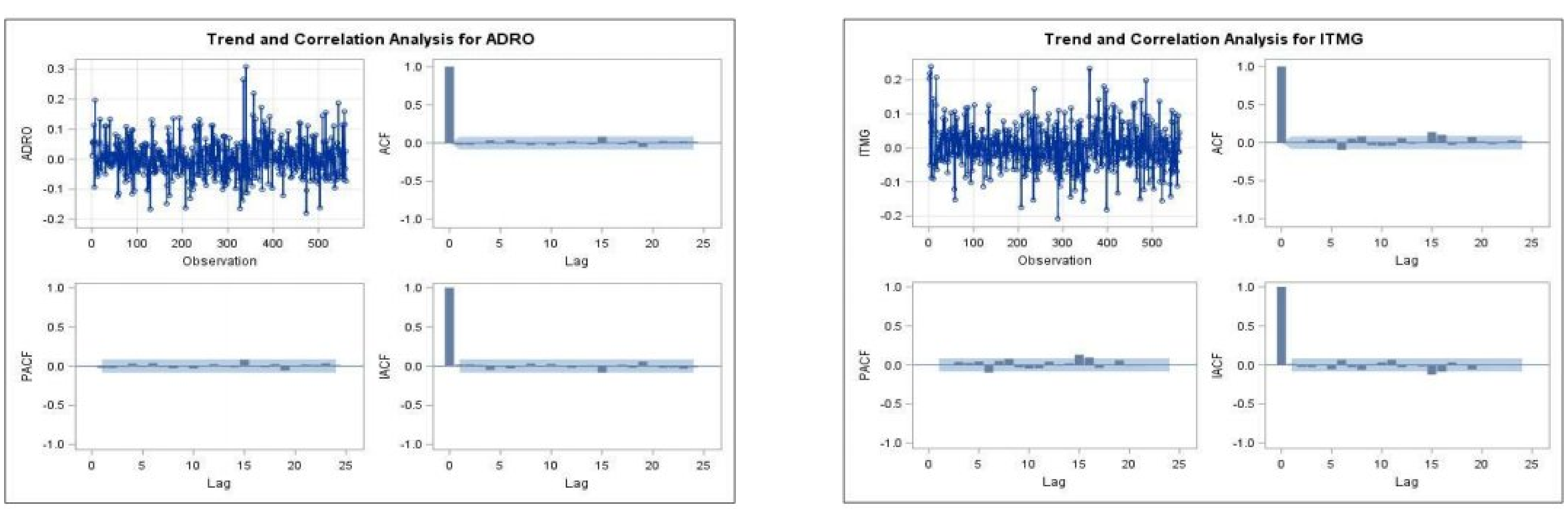


Figure 3. Plot Trend and Correlation Analysis for (a) ADRO and (b) ITMG

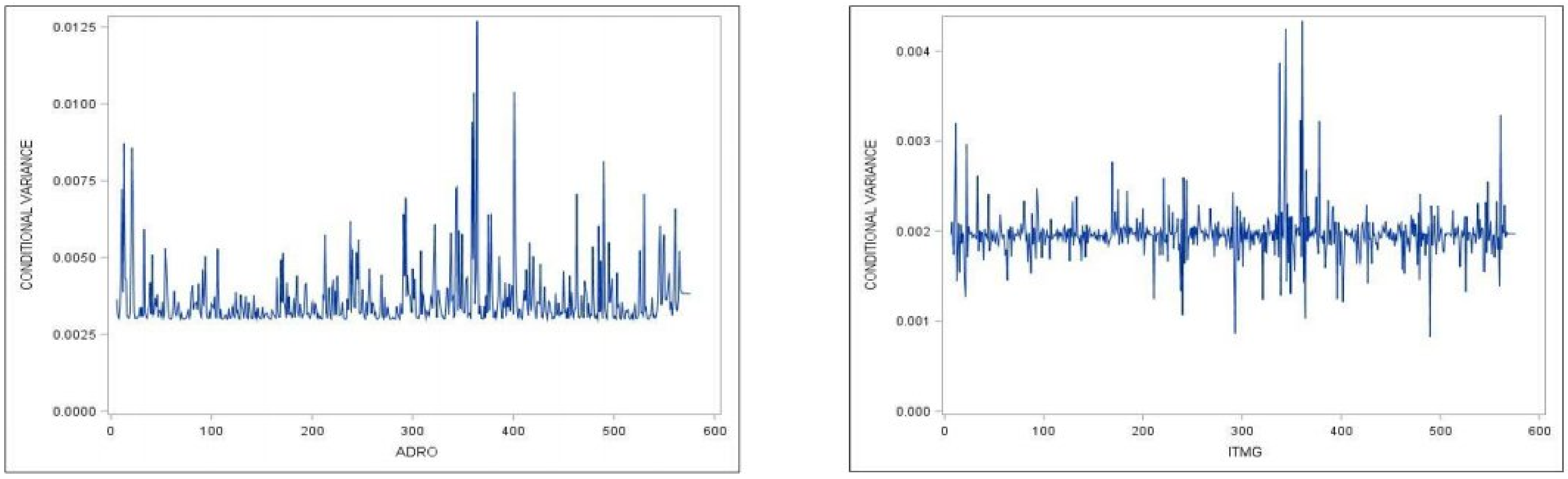
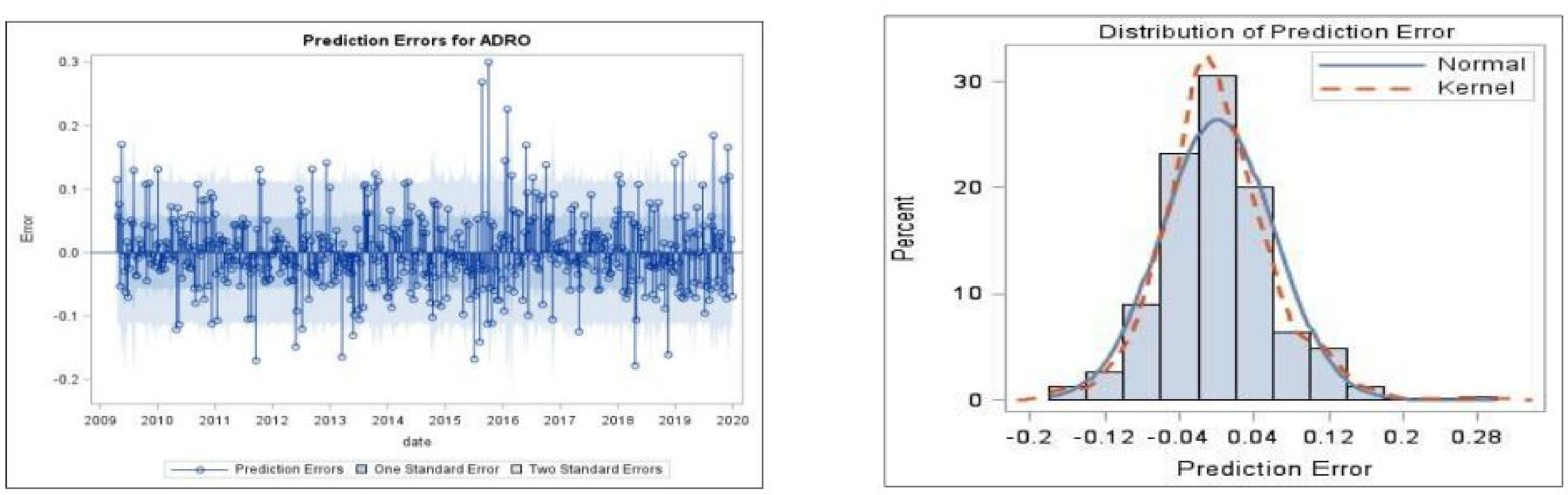
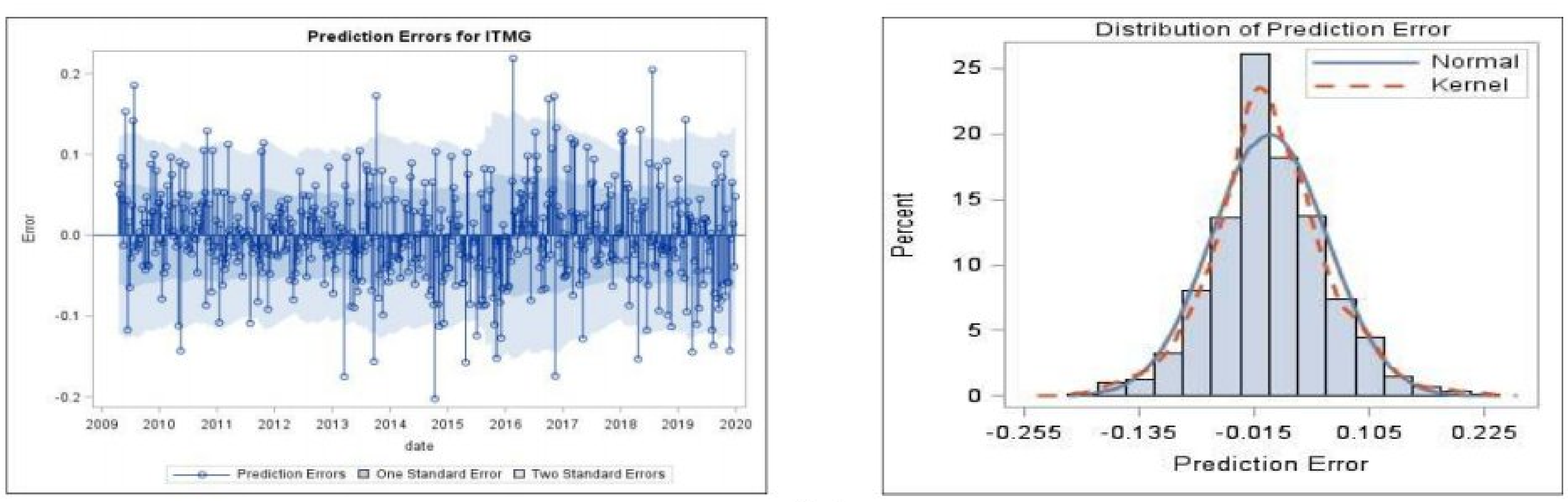


Figure 4. Plot Conditional Variance ADRO (a) and ITMG (b)

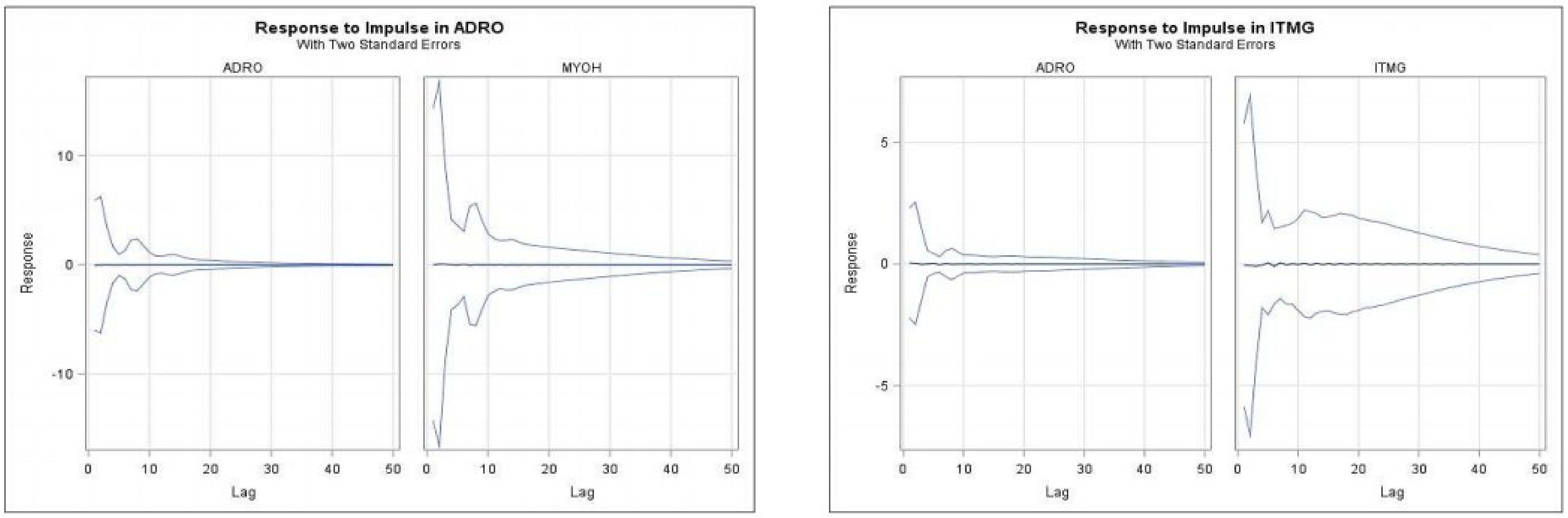


(a)



(b)

Figure 5*.* Prediction and Distribution of Errors base on t
he model for data of ADRO (a) and ITMG (b)



(a) (b)

Figure 6. Respond to Impulse in ADRO (a) in ITMG (b)

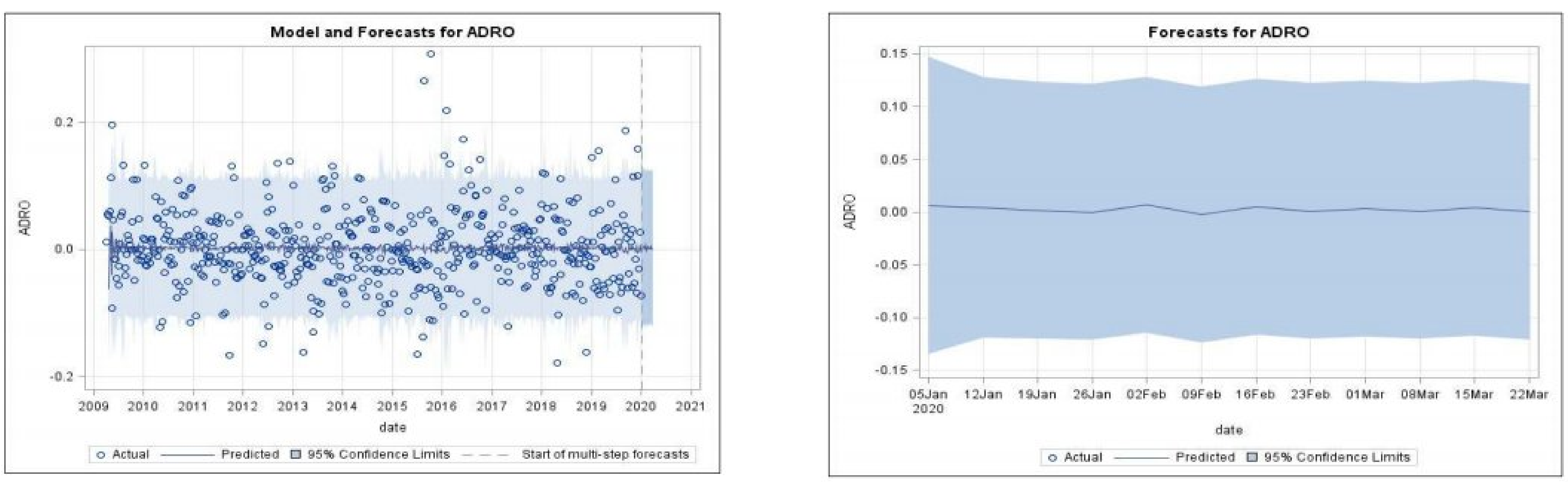


Figure 7. Model and forecast of data return ADRO for the next 12 weeks.

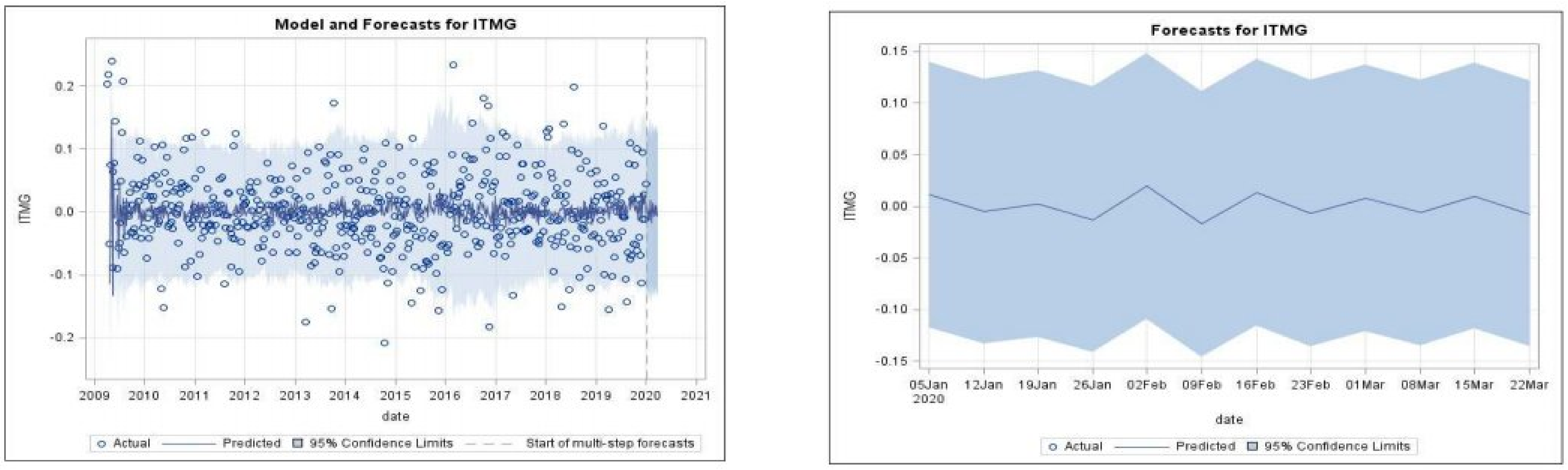


Figure 8. Model and forecast of data return ITMG for the next 12 weeks.

***Table 1**. Dickey-Fuller Unit Root Test*

Variable	Type	Rho	P-value	Tau	P-value
ADRO	Zero Mean	-597.04	0.0001	-17.25	<.0001
	Single Mean	-600.74	0.0001	-17.28	<.0001
	Trend	-601.06	0.0001	-17.27	<.0001
ITMG	Zero Mean	-574.97	0.0001	-17.37	<.0001
	Single Mean	-576.30	0.0001	-17.37	<.0001
	Trend	-583.21	0.0001	-17.43	<.0001

***Table 3**. Information Criteria of Models*

Criterion	VARMA(1,1)-GARCH(1,1)	VARMA(1,2)-GARCH(1,1)	VARMA(2,1)-GARCH(1,1)	VARMA(2,2)-GARCH(1,1)
AICC	-5345.11	-5337.36	-5359.50	-5368.11
HQC	-5311.34	-5297.57	-5319.70	-5322.40
AIC	-5346.82	-5339.80	-6361.94	-5371.40
SBC	-5255.94	-5231.65	-5253.78	-5245.94

***Table 4**. Schematic Representation of Parameter Estimates*

Model	Variable/Lag	C	AR1	AR2	MA1	MA2
VARMA(1,1)-GARCH(1,1)	ADRO	•	+*		+*	
	ITMG	•	**		**	
VARMA(2,1)-GARCH(1,1)	ADRO	•	••	•	••	
	ITMG	•	•*	••	••	
VARMA(2,2)-GARCH(1,1)	ADRO	•	••	•	••	++
	ITMG	•	••	••	••	-+

Note: + 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
VARMA(1,1)-GARCH(1,1)	H1	++	+•	**
	H2	*+	-•	**
VARMA(2,1)-GARCH(1,1)	H1	++	++	••
	H2	*•	-•	•-
VARMA(2,2)-GARCH(1,1)	H1	++	++	••
	H2	••	-•	•+

Notes: + is > 2*std error, - is < -2*std error, • is between, * is N/A

***Table 7**. Univariate Model AR Diagnostics*

Variable	AR1		AR2		AR3		AR4	
	F-value	p-value	F-value	p-value	F-value	p-value	F-value	p-value
ADRO	0.01	0.9175	0.22	0.8003	0.26	0.8575	0.45	0.7752
ITMG	0.73	0.3924	0.41	0.6658	0.78	0.5060	0.77	0.5442

***Table 8.** Granger Causality Wald Test*

Test	Group	DF	Chi-Square	p-value
1	Group 1 Variable: ADRO Group 2 Variable: ITMG	2	2.35	0.3081
2	Group 1 Variable: ITMG Group 2 Variable: ADRO	2	0.74	0.6906

***Table 9**. Forecasts for the return value of ADRO and ITMG*

Variable	Obs.	Time	Forecast	Standard Error	95% Confidence Interval	
ADRO	562	Sun, 5 Jan 2020	0.00593	0.07218	-0.13554	0.14740
	563	Sun, 12 Jan 2020	0.00417	0.06318	-0.11966	0.12801
	564	Sun, 19 Jan 2020	0.00137	0.06236	-0.12085	0.12359
	565	Sun, 26 Jan 2020	-0.00020	0.06204	-0.12179	0.12140
	566	Sun, 2 Feb 2020	0.00671	0.06202	-0.11484	0.12826
	567	Sun, 9 Feb 2020	-0.00235	0.06199	-0.12385	0.11914
	568	Sun, 16 Feb 2020	0.00473	0.06198	-0.11674	0.12621
	569	Sun, 23 Feb 2020	0.00077	0.06196	-0.12067	0.12221
	570	Sun, 1 Mar 2020	0.00286	0.06193	-0.11853	0.12425
	571	Sun, 8 Mar 2020	0.00067	0.06191	-0.12067	0.12201
	572	Sun, 15 Mar 2020	0.00383	0.06189	-0.11747	0.12512
	573	Sun, 22 Mar 2020	0.00007	0.06186	-0.12118	0.12132
ITMG	562	Sun, 5 Jan 2020	0.01113	0.06555	-0.11733	0.13960
	563	Sun, 12 Jan 2020	-0.00497	0.06565	-0.13364	0.12371
	564	Sun, 19 Jan 2020	0.00242	0.06576	-0.12647	0.13131
	565	Sun, 26 Jan 2020	-0.01277	0.06587	-0.14188	0.11633
	566	Sun, 2 Feb 2020	0.01935	0.06582	-0.10965	0.14836
	567	Sun, 9 Feb 2020	-0.01708	0.06579	-0.14603	0.11188
	568	Sun, 16 Feb 2020	0.01364	0.06594	-0.11560	0.14289
	569	Sun, 23 Feb 2020	-0.00669	0.06592	-0.13590	0.12252
	570	Sun, 1 Mar 2020	0.00765	0.06586	-0.12143	0.13673
	571	Sun, 8 Mar 2020	-0.00611	0.06577	-0.13503	0.12280
	572	Sun, 15 Mar 2020	0.00999	0.06570	-0.11878	0.13876
	573	Sun, 22 Mar 2020	-0.00730	0.06564	-0.13595	0.12136