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The Effect of the COVID-19 Pandemic on Stock Prices with the Event Window Approach: A Case Study of State Gas Companies, in the Energy Sector

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ABSTRACT

Stock price data at State Gas Company is defined as the time-series data comprising varying volatility and heteroscedasticity. One of the best models used to solve the problem of heteroscedasticity is the GARCH (generalized autoregressive conditional heteroscedasticity) model. Therefore, this study aims to build the most suitable model for predicting the 186 days before and 176 days after the Covid-19 pandemic, as well as to provide recommendations to reduce the impact of daily stock price movements. Data were obtained by examining the daily stock price data in Indonesian National Gas Companies from 2019 to 2020. The study also discusses the Event Window, with the best model identified as AR (1) -GARCH (1,1). The result showed that an error of less than 0.0015 is AR (1) - GARCH (1,1), provided the best model for price forecasting of Indonesian National Gas Companies.

Keywords: Stock Price, Heteroscedasticity, GARCH Model, Event Window
JEL Classifications: C5, O42, Q4, Q47

1. INTRODUCTION

Forecasting is an estimation or prediction of a future occurrence by evaluating previous circumstances' information and data. Based on this instance, financial analysts as information mediators play an extensive role by examining useful data related to earnings and stock forecasts (Jahangir, 2013; Chunhui et al., 2013). They are also regarded as intermediaries because they carry out a retrospective analysis of the company's personal and financial information to predict future occurrences. Estimates made by financial analysts and the associated management aids to evaluate and assess companies as well as improve the quality of their financial reporting, which is a forecast of the expected revenue in the subsequent year (Beaver et al., 1980).

Forecasting is classified into three types of methods based on time, namely short, medium, and long term (Montgomery et al., 2008). Short-term is adopted for daily, weekly, and monthly forecasting. Specifically, it aids the administration to make certain decisions regarding human resources, inventory control, and cash flow management (Fildes and Goodwin, 2007; Fama et al., 2005; Liu et al., 2020). Several studies relating to forecasting has been carried out, such as market models (Neslihanoglu et al., 2017), a country's recession, which is the major activity carried out by numerous economic institutions (Fornaro, 2016; Morana, 2017), volatility using the GARCH model (1,1) (Chia et al., 2016; Tsung-Han and Yu-Pin, 2013). The public presumes that volatility is similar to market risks.

The least stock price in the market is increased by volatility. Therefore, in order to realize capital gains, investors need to purchase these stocks as a long-term investment (Planning, National and Indonesia, 2020). The highest volatility depicts maximum uncertainties or returns. This situation is commonly referred to as the "Risk and Return Tradeoff."

The COVID-19 pandemic did not only affect the health sector, it also eroded the global economy, including Indonesia (Baig et al., 2020), (Chen et al., 2020), (Just and Echaust, 2020), (Ortmann et al., 2020), (Singh, 2020). It affected the exchange rate, as well as caused a decline in the Composite Stock Price Index (IHSG), which eventually went into freefall. Furthermore, everything was beyond predictions and difficult to control. Prior to the confirmation of the first phase of COVID-19 in the country, the IHSG was at the level of 6244 (24 January), which was reduced to 5942 (20 February) and 5,361 (2 March). On March 12, when the WHO declared COVID-19, a global pandemic, the IHSG fell to 4.2 percent or 4937 during the Thursday session, a level that had not occurred in almost four years. Conversely, on March 13, stock trading was halted for the first time since 2008 due to the pandemic. (Planning et al., N.d.,2020)

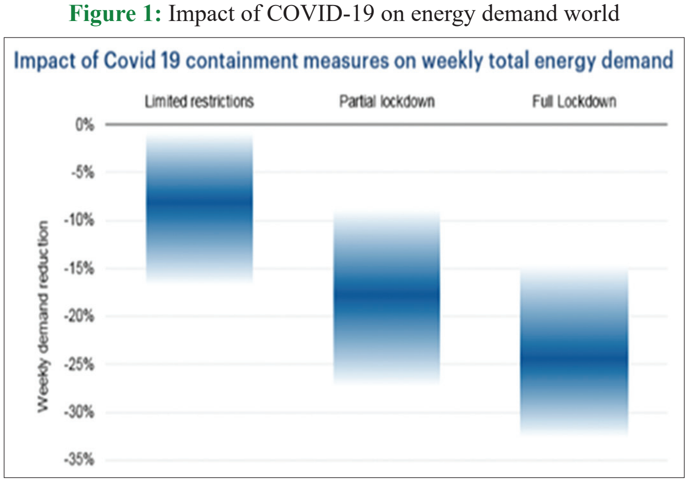
In addition, all human activities were restricted in order to curb the spread of the virus. Several countries adopted partial and simultaneous restriction policies, which had an impact on energy demand.

Countries with full lockdown policies experienced lesser energy demand than those with partial lockdown rules. In 2020, a 6% decline was predicted in the previous year. This is presumed as the worst condition in 70 years after the second world war. Indonesia is one of the nations with limited restriction policies, which also impacted energy demand (Ibrahim et al., 2018).

However, supposing the daily volatility of energy is high, there tends to be either an enormous increase or decrease in stock price, thereby leading to the provision of trade benefits, which is referred to as "High-Risk High-Returns" (Hull, 2015; Zali et al., 2018; Lyócsa et al., 2020, (Ayinde et al., 2019). Investors that usually adopt strategic trading plans prefer high volatility (risk taker). On the contrary, those that tend to invest long-term prefers low volatility because stock prices are bound to increase in the future (risk of harm) (Chan and Wai-Ming, 2000; He et al., 2020; Lin et al., 2019). Several economic and statistical studies are currently used to predict market conditions (Dzikevičius and Šaranda, 2011; Gontijo et al., 2020).

Numerous studies have been carried out to discuss the effect of energy on economic growth and price forecasting. Tehran and Seyyedkolaee (2017), (Shinkevich et al., 2019) researched the relationship between oil price volatility and economic growth in Iran, an oil-exporting country. They also reviewed the impact of oil price volatility on domestic economic growth. Meanwhile, Vijayalakshmi et al. (2014) investigated the effect of price forecasts on the deregulated wholesale spot electricity market.

Figure 1: Impact of COVID-19 on energy demand world



Weron and Misiorek (2006; 2008) studied the modeling of load forecasting and electricity prices. However, volatility in the stock market simply means the difference between an explosive increase or decrease in stock prices where there are moments when it goes up and down. Subsequently, when it is high, it implies that the stock price rises and falls significantly within one second. Volatility (price changes) in the capital market notably affects the return on investment. This circumstance also in accordance with risk and return trade-off theory known as "high-risk high-return." It is also considered as the basis for pricing assets and the acquisition of relevant information related to investment (Kongsilp and Mateus, 2017).

2. METHODOLOGY AND DATA

In this study, the data used was obtained from the stock price of State Gas Compan, the largest state-owned company in Indonesia. They are involved in the transmission and distribution of natural gas. Its business activities include planning, development, and management of downstream natural gas, processing, transportation, storage and trading, construction, production, as well as the supply, and distribution of artificial gas, etc (State Gas Company, 2020), (Ali et al., 2020), (Arafah et al., 2018), (Fadol, 2020), (Faizah and Husaeni, 2018), (Farhat et al., 2014), (Kapitonov and Voloshin, 2017).

The ability of the GARCH (p, q) model to fit properly is the main objective of this methodology. A brief introduction of this model and its equations, which are reported in full, before introducing the econometric considerations that need to be applied in this process are stated as follows.

2.1. Planning Data

The first stage of time series modeling is identification. It involves the calculation of ACF (autocorrelation function), PACF (partial autocorrelation function), and inverse autocorrelation from the time series data. Dickey and Fuller (1979) stated that supposing a distinction is required, it is relevant to carry out a stationary procedure.

2.2. Testing Stationary Data

The Augmented Dicky Fuller test (ADF) was used to evaluate stationary data, plot time-series graphs, and statistical analysis. However, some of the data tend to be non-stationary, such as price series, because they are not fixed. In addition, they are referred to as a unit-root non-stationary time series (Tsay, 2005). Unit-root is one of the features of certain stochastic processes that cause problems in time series modeling. The ADF test process is reported as follows (Brockwell and Davis, 2002; Tsay, 2005).

x1, x2 …,, xn are time series data and {xt} follows the AR (p) model with mean μ. The model's mathematical expression is stated in equation (1).

$$Xt\left(\mu+\varphi 1Xt-1\right)=\sum_{i=1}^{p-1}\varphi 1\Delta Xt-1+\varepsilon t \quad (1)$$

Where the difference in sequence xt, εt is white noise with 0 mean and variance σ2 (εt ~ WN (0, σ2)). The ADF analysis is a unit-root test that was realized by calculating the statistical value τ as follows:
Ho: ϕ 1 = 1 (non-stationary data).
Ho: ϕ 1 < 1 (stationary data). Statistics.

Statistical test (ADF test):

$$\tau=\frac{\varphi 1}{Se\varphi 1} \quad (2)$$

Therefore, for the significance level (α = 0.05), Ho is rejected supposing τ <−2.57 or P <0.05 (Brockwell and Davis, 2002).

2.3. Checking for White Noise

Subsequently, the use of a time series consisting of uncorrelated observations (data) has a constant variance, which is presumed to be white noise (Montgomery et al., 2008). On the contrary, when these time-series observations are normally distributed, it is referred to as the Gaussian white noise. Furthermore, when the time series is reported as white noise, the distribution of a large sample autocorrelation coefficient at lag k is similar to a normal distribution with 0 mean and a variance of 1/T, where T is the number of observations (Montgomery et al., 2008; Brockwell and Davis, 2002; Pankratz, 1991). The following expressions are reported in Equation (3).

$$r\sim N(0,\tfrac{1}{T} \quad (3)$$

Based on Equation (3), it is possible to test the autocorrelation lag hypothesis k Ho: ρ k = 0 against Ha: ρ k ≠ 0 by using the test statistics reported in Equation (4).

$$Z=\frac{rk}{\sqrt{1/T}}=rk\sqrt{T} \quad (4)$$

Ho is rejected when| Z | > Z $^{\alpha}{}_{/2}$ is on top of α/2 percent of the standard or when P < 0.05. The test statistic realized from Equation (4) is used to evaluate the ACF and PACF (Wei, 2006). However, when the ACF is extremely slow decay, the time series is presumed to be non-stationary.

The aforementioned procedures are carried out, one at a time, specifically, the level of significance applies to autocorrelation and is considered individually. This study evaluates a set of autocorrelations together when the time series is reported as white noise. Therefore, to solve this problem, a statistical expression, adopted from the Box-Pierce statistic (Box-Pierce, 1970), was applied, as shown in Equation (5).

$$Q_{BP}=T\sum_{k=1}^{K}r^2\text{k} \quad (5)$$

It is roughly distributed as chi-squared with degrees of freedom K, under the null hypothesis that the time series is white noise (Montgomery et al., 2008). Ho is rejected supposing Q_BP>X_ (a, K)^2, it was concluded that the time series is not white noise. It is also possible to use the P-value in order to cause Ho to be rejected when P < 0.05.

Subsequently, supposing the data is not stationary, it becomes relevant to carry out the differentiation and transformation processes.

2.4. Testing the ARCH Effect

This step involves the estimation and examination of parameters, diagnoses, and test residuals, as well as selecting the best model based on certain criteria, such as determining the minimum value of AIC or SC. The residuals obtained from the best ARMA model were examined using the LM test to determine ARCH's effect. Although, when there is an ARCH effect, the data is modeled using the ARCH or GARCH method. The sequence of these models is discovered by plotting the square of the PACF residuals.

2.5. ARCH Model

The basic idea of the least square model assumes that the expected values for all squared errors are similar at some point, and this assumption is referred to as homoscedasticity (Engle, 2001). Meanwhile, the ARCH or GARCH model is based on the heteroscedasticity assumption that the variance is not constant. These models handle heteroscedasticity as a variant that needs to be modeled (Engle, 2001; Bollerslev, 1986). Engle (1982) introduced a time-variance model with an autoregressive conditional heteroscedasticity (ARCH) model using lagged disturbances. ARCH is an autoregression function that presumes that the variance is not constant over time and is also affected by previous data (Arch, 2006). The idea behind this model is to determine the relationship between the current and previous random variables.

2.6. Generalized ARCH (GARCH) Model

The GARCH (Generalized Autoregressive Conditional Heteroscedastic) model is a general form of ARCH. It was built to avoid an extremely high sequence. The GARCH model not only observes the relationship between several residuals, rather it also depends on some previous residuals (Eliyawati, 2014), and it was introduced by Bollerslev (1986), (Hsieh and Ritchken, 2005), (Virginia et al., 2018). The GARCH model with degrees p and q is defined as follows:

$$X_t\,|\,F_{(t-1)}\,|\sim N(0,\sigma^2{}_t) \quad (6)$$

The GARCH model permits conditional variants based on previous lag, and this is reported in Equation (7).

$$\sigma^2{}_t=\omega+\sum_{i=1}^{q}\lambda_{i\varepsilon_{t-i}^2}+\sum_{j=1}^{p}\beta_{j\sigma_{t-j}^2} \quad (7)$$

The present value of the conditional variant is parameterized based on the q and p lags of the squared residual and conditional variant. This is written as GARCH (p, q). Therefore, the conditional variance that varies from the GARCH model is heteroscedastic in accordance with the autoregression and MA (Wang, 2009). This model is reported in equation (8).

$$X_t = \delta + \sum_{i=1}^{p} \varnothing_1 X_{t-i} - \sum_{i=1}^{q} \theta_1 \varepsilon_{t-i} + \varepsilon_t \qquad (8)$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

$$\sigma^2{}_t = \omega + \sum_{i=1}^{q} \lambda_{i\varepsilon_{t-i}^2} + \sum_{j=1}^{p} \beta_{j\sigma_{t-j}^2}$$

x_t is the equation of conditional mean (Bollerslev, 1986).

2.7. Model Selection Criteria

In selecting the ideal model, AIC criteria are used to discover the best predictions, and they are stated as follows:

$$AIC = -2\left(\frac{1}{T}\right) + 2\left(\frac{K}{T}\right),$$

Where,

$$I = -\frac{Td}{2}(In 2\pi) - \frac{T}{2} ln|\Omega|, |\Omega| = \det(\sum_t \varepsilon_t \varepsilon_t' / T)$$

l is the log-likelihood function, k is the number of parameters to be estimated, and T is the number of observations.

2.8. Checking the Event Window

Conceptually, the event window is the short-term deviation of a financial variable from its long-term level (Owens and Wu, 2011). The long and short-term levels depict the respective year and month sequentially. Therefore, the average year and month need to be calculated. In addition, the month's deviation from the mean of the year also needs to be discovered. Subsequently, the deviation is divided by the mean of the year and multiplied by 100 to determine the% deviation (Sahoo et al., 2012). Based on this concept, stock price behavior is compared to determine its average in a year.

3. RESULTS AND DISCUSSION

The data acquired from the stock price of State Gas Company before and after Covid-19 was utilized in this research. Before it was analyzed, a stationary data set was examined, and this was carried out in two ways, namely by (1) determining the data subjectivity plot and assessing whether or not the information is stationary (2) evaluating the stationary data using the ADF test.

The State Gas Company plot data is shown in Figure 1. The graph shows that the data is stationary, however three hundred and sixty-two of them portray an upward trend, which later moved downward to the final information. This behavior confirms that the data realized from the State Gas Company is constant at a certain number. Based on Table 1, the ADF unit-root test statistics for stationary data are reported in accordance with the test (P-value), which shows that the information acquired from the State Gas Company is 0.2097. It is, therefore ascertained that the data is stationary. Meanwhile, Table 2 shows that the test statistic for the intercept (Ho: Intercept = 0) is extremely significant with a P value> 0.0001. This means that its tapping is different from zero. In addition, the correlation analysis of the data is shown in Figure 2. Based on these plots, there is a possibility of determining whether or not the State Gas Company data series is stationary. Therefore, the ACF indicates that the circuit is stationary because it decays extremely rapidly. Table 3 is used to determine the stationary data by checking WhiteNoise.

The White Noise behavior was used to check for data stationarity. This analysis is an approximate statistical test of the hypothesis, which indicates that there is no autocorrelation from the series to a specific break that is significantly different from zero. Although when this is true for all lags, then there is no information about the series. Autocorrelation was examined in six groups (Table 3) in which the hypothesis based on the white noise was strongly detected (P > 0.0001), which is to be expected because the State Gas Company data series (Figure 3) is stationary.

3.1. Identify the Different Series of Data State Gas Companies

Since the data series obtained is not stationary, the next step is to convert it to stationary using differentiation. Conversely, by

Table 1: Augmented Dickey-Fuller unit root test

Type	Data	Lags	Tau	P-value
Mean	PGAS Tbk	2	0,9591	0,2097

Figure 2: State Gas Company data plot

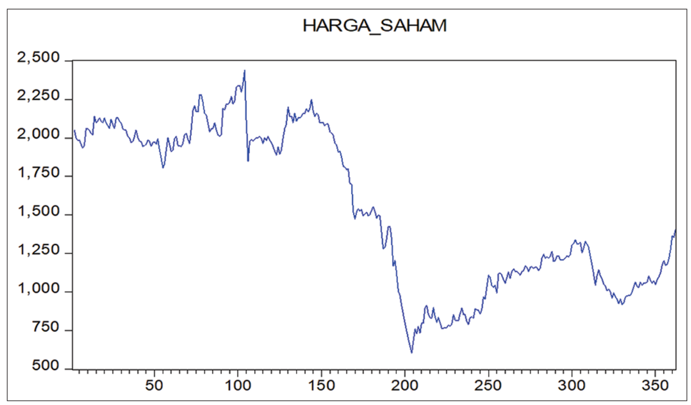


Figure 3: Correlation analysis of State Gas Company data

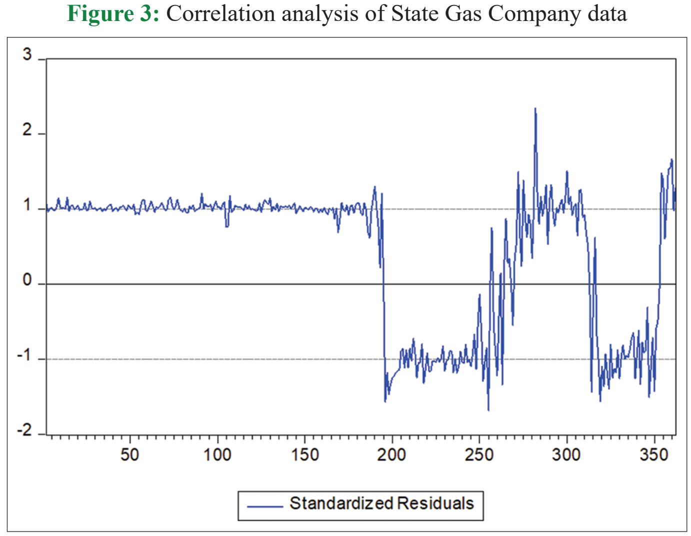


Table 2: Estimated parameters for tapping

Variable	Data	DF	Estimate	Standard Error	t-value	P-value
Intercept	PGAS Tbk	1	0.994	0.994	359.56	0.000

Table 3: Checking white noise on State Gas Company data

To lag	P-value	AC	Pac	Q-Stat	Prob.
1	<0,0001	0.994	0.994	359.56	0.000
2	<0,0001	0.987	−0.078	715.02	0.000
3	<0,0001	0.981	0.110	1067.4	0.000
4	<0,0001	0.975	−0.048	1416.3	0.000
5	<0,0001	0.968	−0.028	1761.5	0.000
6	<0,0001	0.961	−0.075	2102.5	0.000
7	<0,0001	0.953	−0.013	2439.0	0.000
8	<0,0001	0.945	−0.064	2770.6	0.000
9	<0,0001	0.937	−0.032	3097.2	0.000
10	<0,0001	0.928	−0.029	3418.5	0.000
11	<0,0001	0.919	0.005	3734.5	0.000
12	<0,0001	0.910	−0.002	4045.4	0.000
13	<0,0001	0.901	−0.015	4350.9	0.000
14	<0,0001	0.892	0.056	4651.5	0.000
15	<0,0001	0.884	−0.026	4947.2	0.000
16	<0,0001	0.875	0.041	5238.1	0.000
17	<0,0001	0.866	−0.047	5524.0	0.000
18	<0,0001	0.857	−0.061	5804.4	0.000
19	<0,0001	0.846	−0.086	6078.8	0.000
20	<0,0001	0.836	0.036	6347.5	0.000
21	<0,0001	0.826	−0.024	6610.6	0.000
22	<0,0001	0.817	0.077	6868.7	0.000
23	<0,0001	0.808	−0.038	7121.6	0.000
24	<0,0001	0.797	−0.035	7368.8	0.000
25	<0,0001	0.788	0.050	7610.9	0.000
26	<0,0001	0.778	−0.037	7847.6	0.000
27	<0,0001	0.767	−0.058	8078.5	0.000
28	<0,0001	0.756	−0.051	8303.4	0.000
29	<0,0001	0.745	0.012	8522.6	0.000
30	<0,0001	0.734	−0.005	8736.1	0.000
31	<0,0001	0.723	−0.046	8943.8	0.000
32	<0,0001	0.712	0.009	9145.6	0.000
33	<0,0001	0.701	0.059	9342.2	0.000
34	<0,0001	0.691	0.027	9533.7	0.000
35	<0,0001	0.681	−0.006	9720.1	0.000
36	<0,0001	0.670	−0.043	9900.9	0.000

using the result from the differentiation as well as lag = 2 (d = 2), the State Gas Company data was obtained to be stationary. This is evident in residual data behavior after differentiation, which was approximately zero, as shown in Figure 3. Furthermore, this is also evident in the ACF plot's behavior, which was reported to decrease rapidly (Figure 3).

3.2. Testing the ARCH Effect

One of the key assumptions of ordinary least squares regression (OLS) is that the errors have similar variance (homoscedasticity). Although, when it is not constant across samples, the data is presumed to be heteroscedastic. This is because the OLS assumes constant variance, while the presence of heteroscedasticity makes its application inefficient for estimation. The models that take heteroscedasticity into account need to be applied to make the data more efficient. In regression analysis, a general linear model (GLM) is used to eradicate this issue. Conversely, during the time series analysis, several methods, such as the GARCH model, were applied. Therefore, before using this model, it is necessary to

Table 4: LM ARCH test data for State Gas Company

Testing for ARCH interference based on OLS residue				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.969870	0.060801	15.95163	0.0000
WGT_RESID^2(−1)	0.067770	0.052845	1.282444	0.2005
R-squared	0.004573	Mean dependent var		1.040270
Adjusted R-squared	0.001792	S.D. dependent var		0.496404
S.E. of regression	0.495959	Akaike info criterion		1.440894
Sum squared resid	88.05921	Schwarz criterion		1.462483
Log likelihood	−257.3608	Hannan-Quinn criter.		1.449478
F-statistic	1.644662	Durbin-Watson stat		1.994044
Prob (F-statistic)	0.200517			

check for the presence of heteroscedasticity, and the ARCH LM test is also be used.

Table 4 shows that the Q statistic is calculated based on the squared residual and is used to test for nonlinear effects (e.g., GARCH effect). The null hypothesis (Ho) is tested against Ha, as shown in Table 4:

Ho: OLS State Gas Company's residual data is white noise (or no ARCH effect was detected).

Against Ha: State Gas Company's OLS residual data is not white noise (or there is an ARCH effect).

Based on Table 5, it was discovered that AR (1) -GARCH (1,1) has a probability of 0.0070 and 0.0015. This is because the RMSE is extremely large, and this means that the model has better predictability. This is also supported by the forecasting and real value graph, which are extremely close (Figure 2). The Means Absolute Error (MAE) of 0.094 (Table 5) is also relatively small compared to the predicted stock price (H-1) (Table 6). The MAPE is 0.010 (Table 6), which is relatively small, indicating an ideal prediction accuracy.

In accordance with the Portmanteau Q test statistics and LM test, Ho was accepted because the P-value in Table 5 is P > 0.0001 (0.0015> 0.0001). It was therefore concluded that GARCH affects data acquired from the State Gas Company. This was also supported by the conditional variance behavior (Figure 3). Therefore, a model is needed to solve the issue of heteroscedastic variance. In this instance, the ARCH or GARCH model is used to explain the behavior of the data.

3.3. Windows Event Analysis

However, during the pandemic, from March to November, it was evident that the stock price was below its average in 2020. This has an AC value from the windows event test on the first day which was 0.917 till the 36th test when 0.101 was realized and kept

Table 5: GARCH State Gas Company estimated data statistics

Testing the GARCH Estimate				
	Coefficient	Std. Error	t-Statistic	Prob.
C	454.0191	246.7424	1.840053	0.0658
RESID(−1)^2	0.704713	0.261167	2.698325	**0.0070**
GARCH(−1)	0.301634	0.094929	3.177472	**0.0015**
R-squared	−0.620968	Mean dependent var		1534.529
Adjusted R-squared	−0.620968	S.D. dependent var		511.2199
S.E. of regression	650.8711	Akaike info criterion		14.48315
Sum squared resid	1.53E+08	Schwarz criterion		14.52624
Log likelihood	−2610.209	Hannan-Quinn criter.		14.50028
Durbin-Watson stat	0.005715			

Table 6: State Gas Company MAPE data statistics

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HARGA_SAHAM(−1)	0.959112	**0.010591**	90.56202	0.0000
D (HARGA_SAHAM(−1))	0.135679	0.051696	2.624555	0.0091
D (HARGA_SAHAM(−2))	−0.145159	0.051653	−2.810270	0.0052
C	85.10233	22.21289	3.831214	0.0002
INCPTBREAK	−41.47803	10.97470	−3.779423	0.0002
BREAKDUM	37.57067	48.86662	0.768841	0.4425
R-squared	0.991423	Mean dependent var		1530.531
Adjusted R-squared	0.991302	S.D. dependent var		511.4746
S.E. of regression	47.70278	Akaike info criterion		10.58447
Sum squared resid	800995.3	Schwarz criterion		10.64951
Log likelihood	−1888.621	Hannan-Quinn criter.		10.61034
F-statistic	8138.011	Durbin-Watson stat		1.975206
Prob (F-statistic)	0.000000			

Table 7: The Average Abnormal Return Windows Event After Covid-19

Checking Windows Events After Covid-19						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|*******	.|*******	1	0.917	0.917	305.92	0.000
.|******|	.|* |	2	0.873	0.203	583.99	0.000
.|******|	.|** |	3	0.876	0.343	865.06	0.000
.|******|	.|. |	4	0.845	−0.056	1126.9	0.000
.|******|	.|* |	5	0.831	0.148	1380.8	0.000
.|******|	*|. |	6	0.801	−0.147	1617.6	0.000
.|******|	.|. |	7	0.774	0.041	1839.1	0.000
.|***** |	.|. |	8	0.758	−0.040	2052.4	0.000
.|***** |	.|. |	9	0.725	−0.046	2248.0	0.000
.|***** |	.|. |	10	0.700	−0.014	2431.1	0.000
.|***** |	.|. |	11	0.677	−0.030	2602.6	0.000
.|***** |	*|. |	12	0.637	−0.096	2755.1	0.000
.|**** |	.|. |	13	0.620	0.065	2900.0	0.000
.|**** |	.|. |	14	0.610	0.062	3040.4	0.000
.|**** |	.|* |	15	0.593	0.083	3173.5	0.000
.|**** |	.|. |	16	0.574	−0.015	3298.7	0.000
.|**** |	.|. |	17	0.549	−0.023	3413.6	0.000
.|**** |	.|. |	18	0.527	−0.056	3519.9	0.000
.|**** |	*|. |	19	0.493	−0.151	3612.8	0.000
.|*** |	.|. |	20	0.475	0.068	3699.7	0.000
.|*** |	.|. |	21	0.458	−0.056	3780.6	0.000
.|*** |	.|. |	22	0.432	0.037	3852.8	0.000
.|*** |	*|. |	23	0.406	−0.092	3916.8	0.000
.|*** |	.|. |	24	0.383	0.022	3973.8	0.000
.|*** |	.|* |	25	0.380	0.108	4030.0	0.000
.|** |	*|. |	26	0.350	−0.094	4077.9	0.000
.|** |	*|. |	27	0.305	−0.093	4114.5	0.000
.|** |	.|. |	28	0.294	0.042	4148.6	0.000
.|** |	.|. |	29	0.272	−0.060	4177.7	0.000
.|** |	.|. |	30	0.243	−0.012	4201.1	0.000
.|** |	*|. |	31	0.213	−0.151	4219.1	0.000
.|* |	.|. |	32	0.188	0.061	4233.1	0.000
.|* |	.|. |	33	0.178	0.036	4245.8	0.000
.|* |	.|. |	34	0.156	0.045	4255.6	0.000
.|* |	.|. |	35	0.126	−0.046	4262.0	0.000
.|* |	*|. |	36	0.101	−0.082	4266.1	0.000

declining (Table 7). The percentage shows there is a possibility of a small event window due to the decline in stock price movements till December 2020.

4. CONCLUSION

In this study, the data from the State Gas Company of the Energy Sector was examined using the AR (p) -GARCH (p, q) time series analysis model. The results showed that the information is stationary. Furthermore, the differencing process was used with lag = 2 (d = 2) to convert the time series data to stationary. Conversely, by testing the effect of ARCH using the Q and LM tests, it was concluded that the GARCH model had an effect on the data realized from the State Gas Company. Based on this situation, AR (p) - GARCH (p, q) model was adopted.

The best model for the data acquired from State Gas Company is the AR (1) - GARCH (1,1) model. This is significant, and the R-squares are identified as 0.62 for the firm's model data. This prediction model's application is quite good based on the MAPE (the Mean Absolute Percentage Error) criterion for forecasting State Gas Company data that realized 0.094%. The model also needs to be used for forecasting in the next 176 days.

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