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Dynamic modeling and forecasting stock price data by applying AR-GARCH model

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Abstract:
The aims of this study are to obtain the best model, to estimate parameters, and to predict the adjusted closing stock prices of Elnusa Tbk from January 2015 to December 2018, which is categorized in BEI as mining sector in Indonesia.Application of AR-GARCH model comes to be the solution to overcome the high volatility and heterogeneous variance that can often be the issues in many financial and economic time series data. The best model which fits to the data is AR(1)-GARCH(1,1) model.The model can be applied soundly to predict the following 30 days stock prices that can a consideration for investors to put or call the firm's stocks.

Keywords:*Volatility, AR, GARCH model, forecasting.*

I INTRODUCTION

Financial analysts are the intercessor of data and information as they conduct retrospective analysis towards firm private and financial forecast to generate future information. Forecast conducted by financial analyst could help the firm to evaluate and value at the firm to improve the quality of their financial reporting as forecasting to the expected amount of earnings that raised on the current year (Beaver et al., 1980).

Nowadays, many economics and statistical analysis are used to forecast the future market condition (Pankratz,1991; Dzikevičius and Šaranda, 2011; Virginia et al, 2018). Forecasting of volatility in oil market has received much attention in the researches by both academicians and a practitioner during recent years (Day and Lewis , 1992; Mirmirani and Li, 2004; Kang et al., 2009; Mohammadi and Su, 2010). The oil as a commodity plays an important role in the world economy in many ways, and its price affects a number of macroeconomic factors like inflation, economic growth and employment (Papapetrou, 2001; Lardic and Mignon, 2006; Rafiq et al., 2009; Wei et al., 2010).

The dynamic of oil price during the last decades have been characterised by high volatility or variances and were associated with underlying fundamentals of oil markets and world economy (Askari and Krichene, 2008). The oil price volatility according to Ross (1989) as an indicator of the flow of information in a market. The volatility, information and risk spreading between markets and assets have been investigated and confirmed by manyresearchers (Engle et al., 1990; Caporale et al , 2006; Li, 2007; Yazdanfar, 2015). Public suppose that the volatility as the same as the risk in the market. The lowest volatility in share price would raise the lowest share price movements in the market. In the low volatility share price conditions to received a capital gain, investors have to hold the share as a long-term investment. The highest the volatility in the market, the highest the uncertainty or return. Thecondition of volatility and highest return is commonly known as “Risk and Return Tradeoff”. When the daily volatility of a share price is high, there could arise high increase or decrease of share prices which provides a space for trading in order to receive gain by the differences of the opening and closing share prices, which can be called as “High Risk High Return” (Hull, 2015; Kongsilp and Mateus, 2017). Some investors who usually plan a strategic trading, they would like to choose the high volatility, while some investors who tend to invest for long-term investment, they would prefer to choose a low volatility as the share price would increase in the future (Chan and Wai-Ming, 2000; Tsung-Han and Yu-Pin, 2013). The situation could also follow the theory of risk and return trade-off as known as “high risk, high return”. Volatility is also considered as the fundamental to asset pricing and important information for investment (Hull, 2015; Kongsilp and Mateus, 2017).

The aim of this study are to know the dynamic of share price and forecast the future price based on the best model chosed in the oil company of Elnusa TBK (ELSA). There are many papers has been published about the price volatility of share price.Most of reseachers agreed that volatility can be approximated in many share price market in the world, but there are many difference models that can be applied. One of the model that commonly used for modeling the volatility is Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model (Gokcan, 2000)

II LITERATURE REVIEW AND STATISTICAL MODELLING

Volatility is a situation where prices tend to move up and down unstable and sometimes even move to an extreme, so that the variance is not constant. To overcome this, Engle (1982) developed the Autoregressive Conditional Heteroscedasticity (ARCH) model which was originally used to analyze inflation behavior in England. Engle explained that models with time series data with high volatility tend to contain heteroscedasticity problems. The estimation method used by Engle (1982) is the Maximum Likelihood (ML) with the ARCH model and compares it to the estimated OLS model. The estimation results show that the ARCH-ML model is able to provide results with better variant predictions compared to the OLS method.

Bollerslev (1986) generalized the ARCH model developed by Engle (1982) but is more general in nature. This is done by incorporating elements of past residuals and residual variants in the Autoregressive equation. The model is called Generalized Autoregressive Conditional Heteroscedasticity (GARCH). Using inflation data in America with the autoregressive equation, Bollerslev (1986) tries to re-evaluate inflation with the ARCH model from Engle. The results show that incorporating residual variance elements in the equation produces better regression than the ARCH model. In addition to modeling, the GARCH model can also be used for forecasting.

The data used in this study are the data share price of oil from the company Elnusa Tbk over the years 2015 to 2018. Elnusa TBK is one of the national companywhich mastering the service in the sectors of Seismic service, drilling and management of oil fields. Elnusa TBK provide oil and gas serviceswith a global alliance strategy for world class oil and gas companies (Elnusa Tbk, 2016). In the time series data analysis, there are some assumptions to be examined. The initial step is to check the stationarity data by evaluating the graph of the data and by using Augmented Dicky Fuller (ADF) test (Tsay, 2005; Warsono et al., 2019).

Let $ELSA_1$,$ELSA_2$,$ELSA_3$, …., $ELSA_n$ be the series of data from Elnusa Tbk and $\{ELSA_t\}$ follows the AR(p) model with mean μ. The mathematical equation can be presented as follows:

$$ELSA_t = \mu + \gamma_1 ELSA_{t-1} + \sum_{k=1}^{p-1} \gamma_k \Delta ELSA_{t-1} + \varepsilon_t, \quad (1)$$

where $\gamma_i$is defined asthe parameters and ε_t is the white noise with mean 0 and variance σ_ϵ^2. This test is conducted through the calculation of the value of τ (tau) statistic as follows (Virginia et al., 2018):

$H_0 = \gamma_1 = 0$ (non-stationary)

$H_1 = \gamma_1 < 1$ (stationary)

ADF Test:

$$\tau = \frac{\gamma_i}{\widehat{Se}_{\gamma_1}}. \quad (2)$$

Brockwell and Davis (2002), and Tsay (2005) stated that if $\tau < -2.57$ or if $P < 0.05$ at $\alpha = 0.05$, then we reject H_0.

Autocorrelation Function (ACF) and White Noise Test

Montgomery et al (2008) argued the residuals of time series cosnsisting of uncorrelated and has a stable variance is defined as white noise. It is supported by Brockwell and Davis (2002) that normal distribution of coefficient in sample autocorrelation at lag k in a large sample with mean 0 and variance 1/T, where T is the observation number.

Equation (3) presents

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

Equation (3) examines the hypothesis of H_0: $\rho_k = 0$ against H_1: $\rho_k \neq 0$ for the lag k autocorrelation by using the following test statistic:

$$Y = \frac{r_k}{\sqrt{1/T}} = r_k\sqrt{T}. \quad (4)$$

If $|Y| > Y_{\alpha/2}$ and p-value < 0.05, We reject H_0. Wei (2006) added the statistic equation (4) can implement ACF and PACF (Partial Autocorrelation Function). The very slow decrease of ACF indicates a non stationary time series data. Box-Pierce (1970) statistic is applicable to solve the problem of time series indicated as jointly evaluating autocorrelation of white noise by using as follows:

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

K is defined as degree of freedom and $Q_{BP}$is chi-squares under null hypothesis that the time series is white noise (Montgomery et al., 2008). if $Q_{BP} > x_{\alpha,K}^2$ and p-value < 0.05, we reject $H_{0,}$ indicating the data is not white noise.

Differencing is used when the series is still non stationary by transforming the series to be stationary. The next step when it satisfies the stationary data, the estimated order of autoregressive moving average (ARMA) can be set by using ACF and PACF.

ARCH Effect Test

Engle (1982) introduced the model of autoregressive conditional heteroscedasticity (ARCH) which can model the volatility with conditional heteroscedasticity. Unlike the traditional econometric models, the ARCH and GARCH estimates a non-constant variance that is dependent on fluctuations in the past. GARCH model is a further development of the ARCH model and is the most widely used dynamic model to estimate volatility (Bollerslev, 1986). The selection of best ARMA model can convey the availability of ARCh effect by using the Lagrange multiplier (LM) test (Virginia et al., 2018).

ARMA(p,q) model

Effects of surprising shocks on the variance are maintained under autoregressive moving average process (ARMA) model of the squared residuals (Bollerslev, 1986). The smallest number of as Aikaike information criterion (AIC) (Akaike, 1973), Schwarz information criterion (Schwarz, 1978) and Hannan–Quinn information criterion

(HQC) (Hannan and Quinn, 1978) are set as selected parameter estimations for the best model of ARMA. In general, the AR(p) model form can be written in Equation (6):

$$ELSA_t = \beta + \Phi_1 ELSA_{t-1} + \Phi_2 ELSA_{t-2} + \Phi_3 ELSA_{t-3} + \cdots + \Phi_p ELSA_{t-p} + \varepsilon_t. \quad (6)$$

MA(q) is presented as follows:

$$ELSA_t = \mu + \varepsilon_t - \lambda_1 \varepsilon_{t-1} + \lambda_2 \varepsilon_{t-2} + \lambda_3 \varepsilon_{t-3} + \cdots + \lambda_q \varepsilon_{t-q}; \varepsilon_t \sim N(0, \sigma^2). \quad (7)$$

Equations (6) and (7)is generally formulated as

$$ELSA_t = \beta + \Phi_1 ELSA_{t-1} + \Phi_2 ELSA_{t-2} + \Phi_3 ELSA_{t-3} + \cdots + \Phi_p ELSA_{t-p} + \varepsilon_t - \lambda_1 \varepsilon_{t-1} - \lambda_2 \varepsilon_{t-2} + \cdots + \lambda_q \varepsilon_{t-q} = \beta + \sum_{i=1}^{p} \Phi_i IE_{t-i} + \varepsilon_t - \sum_{k=1}^{q} \lambda_k \varepsilon_{t-i}, \quad (8)$$

where the variable is at lag t; β indicates the constants of AR(p); Φ_i is the regression coefficient;i = 1,2,3,…,p; p is the order of AR; λ_k denotes the model parameter of MA, k = 1,2,3,…,q; q is the order of MA; and ε_t is the error term at time t.

LM Test

Heteroscedasticity can be an issue involved in time series data that has autocorrelation problem (Engle, 1982). Engle mentioned at the same year that to detect heteroscedasticity, the ARCH effect can use the ARCH-LM test (see Tsay, 2005; Hamilton, 1994; Wei, 2006).

GARCH Model

Many multivariate volatility models have been proposed in the literature, including multivariate stochastic volatility and multivariate generalizations of GARCH models (Tsay, 2014). It was Bollerslev (1986) that initially introduced the generalised autocorrelation conditional heteroscedasticity (GARCH) to avoid the high order of ARCH model. The statistical equation of GARCH is as follows:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{q} \varrho_i \varepsilon_{t-i}^2 + \sum_{k=1}^{p} \varsigma_j \varepsilon_{t-j}^2. \quad (10)$$

Heteroscedasticity of time-varying conditional variance of the GARCH model is on AR and MA, in which q lag from the square residual and the p lag of the conditional variance is equated as GARCH(p,q) (Wang, 2009).

Equation (11) shows the GARCH model as

$$ELSA_t = \beta + \sum_{i=1}^{p} \Phi_i ELSA_{t-i} + \varepsilon_t - \sum_{k=1}^{q} \lambda_k \varepsilon_{t-i}$$
$$\varepsilon_t \sim N(0, var(IE)^2) \quad (11)$$
$$\sigma_t^2 = \varpi + \sum_{i=1}^{q} \varrho_i \varepsilon_{t-i}^2 + \sum_{k=1}^{p} \varsigma_j \varepsilon_{t-j}^2.$$

where $ELSA_t$ is share price data series from Elnusa Tbk, and the β, Φ_i and λ_k are the constant parameters.

III RESULTS AND DISCUSSION

This study uses the data close share price of Elnusa Tbk (Code BEI: ELSA) over the years 2015 to 2018. Figure 1 reveals that the plot data is not stationary. The graph of the data (Figure 1)shows thatthe data Elnusa Tbk are price fluctuate and not moving constantly. Therefore, the share price data of Elnusa Tbk does not always move around a certain number, meaning nonstationary.

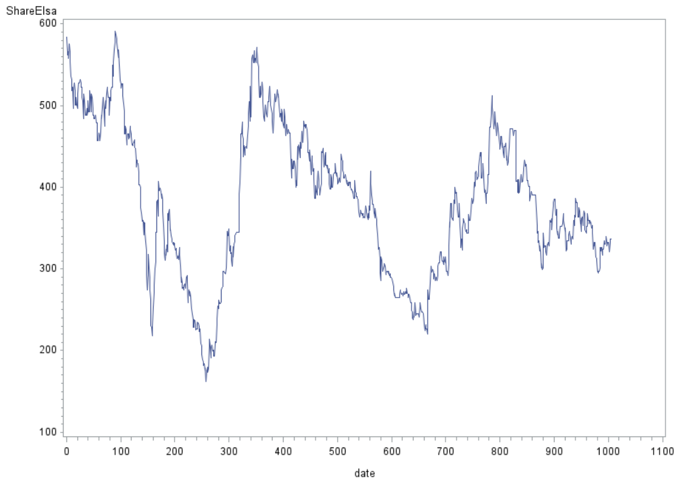

Fig. 1. Data of Elnusa Tbk Share Price from 2015 to 2018

Next we do the ADF, ACF and PACF statistical tests, and check the white noise to see that the data is non stationary.

Table 1
Augmented Dickey-Fuller **(**ADF) Unit Root Tests

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	3	-1.1650	0.4455	-1.1677	0.2223		
Single Mean	3	-11.5554	0.0924	-2.6280	0.0881	3.6236	0.1402
Trend	3	-11.6487	0.3334	-2.5536	0.3020	3.4526	0.4823

Table 2
Parameter Estimates for the Intercept (Constant Value)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	382.0317	2.8575	133.69	<.0001

Table 1 confirms that there is not enough evidence to reject Ho. This is indicated by the ADF test with a value of more than 0.05.Table 2 is an estimation parameter for the intercept (Ho: intercept = 0) which is very significant as indicated by the p-value <0,0001, which means different from zero.

Figure 2 shows an autocorrelation analysis or ACF test that aims to see whether the data is stationary or non-stationary. From this figure it can be seen that ACF decreases slowly. This indicates that Elnusa Tbk data is non-stationary data. Furthermore, white noise behavior is possible to check the stationarity of the data. This test is used to see the hypothesis estimates significantly different from zero or no autocorrelation until a certain lag. In group six (table 3) the white noise hypothesis was strongly rejected with a p value <0,0001, which is the data series from Elnusa Tbk non-stationary.

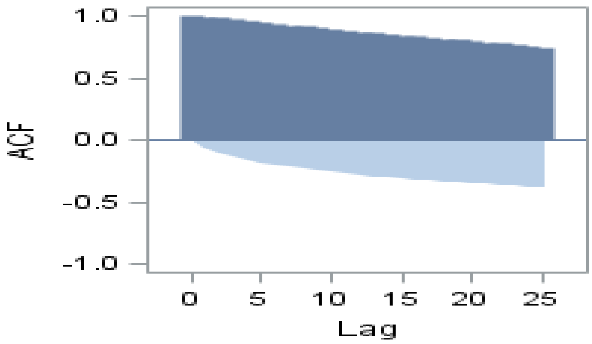

Fig. 2. Correlation Analysis of Elnusa Tbk Data

Table 3
Autocorrelation Check for White Noise of Elnusa Tbk

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5626.04	6	<.0001	0.989	0.980	0.969	0.958	0.946	0.934
12	9999.99	12	<.0001	0.923	0.912	0.900	0.889	0.878	0.866
18	9999.99	18	<.0001	0.857	0.847	0.838	0.829	0.820	0.812
24	9999.99	24	<.0001	0.803	0.795	0.786	0.777	0.767	0.757

Differencing the Data Series of Elnusa Tbk

From the previous test stage that the data is non-stationary, the next step is to change the Elnusa Tbk data to stationary by using differencing with lag = 2 (d = 2). As seen in Figure 3 the behavior of the residual data after differencing is around zero and the ACF plot also decreases rapidly.

Trend and Correlation Analysis for ELSA(2)

ELS
A(2)

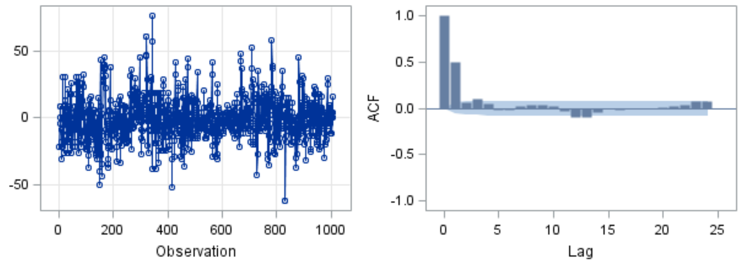

Fig. 3. Residuals and ACF Plotting after Differencing with d = 2 for Elnusa Tbk Data

The Jenkins box methodology is used to examine patterns of autocorrelation to select ARMA candidate models. One useful tool in determining the appropriate ARMA model for this series is the PACF plot (figure 4).

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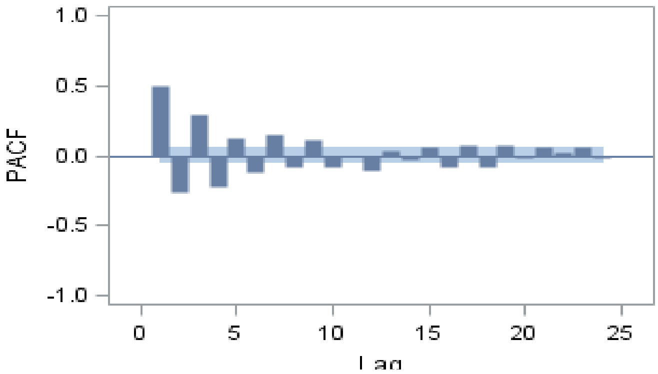

Fig. 4. PACF Plotting after Differencing with *d* = 2 for Elnusa Tbk Data

Table 4
Autocorrelation Check for WhiteNoise of Elnusa Tbk after Differencing (*d* = 2)

To Lag	**Chi-Square**	**DF**	**Pr > ChiSq**	**Autocorrelations**					
6	271.27	6	<.0001	0.502	0.055	0.102	0.053	-0.021	-0.023
12	285.99	12	<.0001	0.021	0.039	0.035	0.028	-0.030	-0.098
18	297.91	18	<.0001	-0.095	-0.048	-0.008	-0.016	-0.010	0.001
24	310.93	24	<.0001	-0.009	0.014	0.025	0.038	0.074	0.070

White noise checking after differencing data (d = 2), shows that changes in Elnusa Tbk data are highly correlated automatically (table 4). This is also supported by the results of the ADF test after differencing (d = 2) shown in table 5 which proves that the hypothesis test 0 (Ho) was rejected significantly because the P and Tau values are both <0,0001 so that the Elnusa Tbk (ELSA) data is now stationary. Thus the AR (1) autocorrelation model for Elnusa Tbk's data may be a good candidate to be adapted to the process.

Table 5
ADF Unit-Root Tests After Differencing (*d* = 2)

Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	3	-796.259	0.0001	-14.86	<.0001		
Single Mean	3	-799.743	0.0001	-14.87	<.0001	110.63	0.0010
Trend	3	-803.463	0.0001	-14.89	<.0001	110.83	0.0010

ARCH Effect Test

The existence of heteroscedasticity in a time series model can be a problem that makes the estimation inefficient. There are some methods to cope this issue, such as the GARCH model. It therefore needs to confirm whether the heteroscedasticity exists or not by using the ARCH-LM test prior to find the best model of the GARCH(p,q).

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Table 6
ARCH-LM Test for Elnusa Tbk Data

Order	Q	Pr > Q	LM	Pr > LM
1	990.977	<.0001	956.639	<.0001
2	1936.45	<.0001	956.639	<.0001
3	2838.41	<.0001	956.639	<.0001
4	3692.35	<.0001	956.906	<.0001
5	4494.95	<.0001	957.098	<.0001
6	5248.25	<.0001	957.119	<.0001
7	5955.7	<.0001	957.129	<.0001
8	6619.95	<.0001	957.137	<.0001
9	7242.66	<.0001	957.137	<.0001
10	7824.44	<.0001	957.166	<.0001
11	8366.56	<.0001	957.181	<.0001
12	8870.81	<.0001	957.193	<.0001

Table 6, shows that H_0 is rejected as the portmanteau (Q) and LM tests calculated from the squared residuals have a very significant p-value ($P < 0.0001$). This indicates that the ARCH effect for the data residuals of Elnusa Tbk is exist and the GARCH(p,q) model in forecasting volatilityneed to be used.

AR(p)–GARCH(p,q) Model

Table 7 shows that the parameter estimate for AR(1) is very significant with t-value is -496.98 and p-value is <0.0001, indicating difference with zero, whereas the other parameters have a significance of p-value <0.05. This resultsshows that to perform the next prediction and study analysis, the best model that should be used is AR(1)–GARCH(1,1).

Table 7
Parameter Estimates of the AR(1)–GARCH(1,1) Model

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	583.5191	665.6471	0.88	<.0001
AR1	1	-0.9996	0.002011	-496.98	<.0001
ARCH0	1	8.5157	2.5841	3.30	0.0011
ARCH1	1	0.0442	0.009297	4.75	<.0001
GARCH1	1	0.8921	0.0265	33.65	<.0001

Thus, according to the analysis results of AR(1)–GARCH(1,1), the model estimation can be presented as follows:

- Mean Model AR(1):

$$ELSA_t = 583.5191 - 0.9996\, ELSA_{t-1}, \quad (12)$$

- and the variance model, GARCH(1,1):

$$\sigma_t^2 = 8.5157 + 0.0442\varepsilon_{t-1}^2 + 0.8921\sigma_{t-1}^2. \quad (13)$$

From the model estimate of AR(1), on average, holding all variables constant, $ELSA_t$ is 583.5191. On average, if $ELSA_{t-1}$ increases 1 unit, then $ELSA_t$ decreases by 0.9996 and all variables are constant.

Table 8
Statistical Estimation of GARCH for Elnusa Tbk Data

SSE	134782.0250	**Observations**	1006
MSE	133.9782	**Uncond Var**	133.7572

Log Likelihood	-3874.5062	**Total R-Square**	0.9837
SBC	7783.5811	**AIC**	7759.0124
MAE	8.1198	**AICC**	7759.0724
MAPE	2.1816	**HQC**	7768.3475
		Normality Test	820.4382
		Pr > ChiSq	<.0001

Furthermore, according to the data analysis results of the AR(1)–GARCH(1,1) model, as shown in Table 8, the R-square is 0.9837, indicating that the variable explained 98.37% by the model. Likewise, MSE = 133.9782, allowing to compute the root mean square error (RMSE). An RMSE of 11.575 is significantly small compared with the forecasting of stock prices Elnusa Tbk(F-ELSA) in Table 9, showing that the model has a good prediction ability. In addition, in Table 8, MAE = 8.1198 has a relatively very small statistic from the forecasting of stock prices Elnusa Tbk(F-ELSA) in Table 9, whereas the accuracy of forecasting is very good as a representative of a very small mean absolute percentage error (MAPE) of 2.1816.

Table 9
Prediction of Data Share Price of Elnusa Tbk for 30 Days

Obs	Forecast	Std Error	95% Confidence Limits	
1007	337.5763	13.9151	310.3032	364.8493
1008	336.4428	15.3933	306.2725	366.6132
1009	337.4225	22.9523	292.4369	382.4080
1010	336.0349	24.3223	288.3640	383.7058
1011	336.8942	30.0883	277.9222	395.8662
1012	335.4497	31.2300	274.2401	396.6593
1013	336.2821	35.9746	265.7732	406.7910
1014	334.8249	36.9487	262.4067	407.2431
1015	335.6512	41.0472	255.2001	416.1022
1016	334.1911	41.9044	252.0600	416.3222
1017	335.0161	45.5573	245.7254	424.3068
1018	333.5554	46.3295	242.7513	424.3596

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Obs	Forecast	Std Error	95% Confidence Limits	
1019	334.3801	49.6540	237.0600	431.7003
1020	332.9193	50.3615	234.2126	431.6260
1021	333.7440	53.4316	229.0199	438.4681
1022	332.2832	54.0878	226.2731	438.2932
1023	333.1079	56.9535	221.4811	444.7346
1024	331.6471	57.5676	218.8166	444.4775
1025	332.4718	60.2644	214.3558	450.5878
1026	331.0110	60.8433	211.7602	450.2618
1027	331.8358	63.3974	207.5792	456.0923
1028	330.3750	63.9463	205.0425	455.7075
1029	331.1998	66.3777	201.1019	461.2976
1030	329.7391	66.9006	198.6162	460.8619
1031	330.5638	69.2250	194.8853	466.2424
1032	329.1031	69.7251	192.4444	465.7619
1033	329.9280	71.9552	188.8983	470.9576
1034	328.4673	72.4350	186.4972	470.4374
1035	329.2921	74.5812	183.1157	475.4685
1036	327.8315	75.0428	180.7503	474.9126

Behaviour of the Forecasting Model For Elnusa Tbk of AR(1)–GARCH(1,1)

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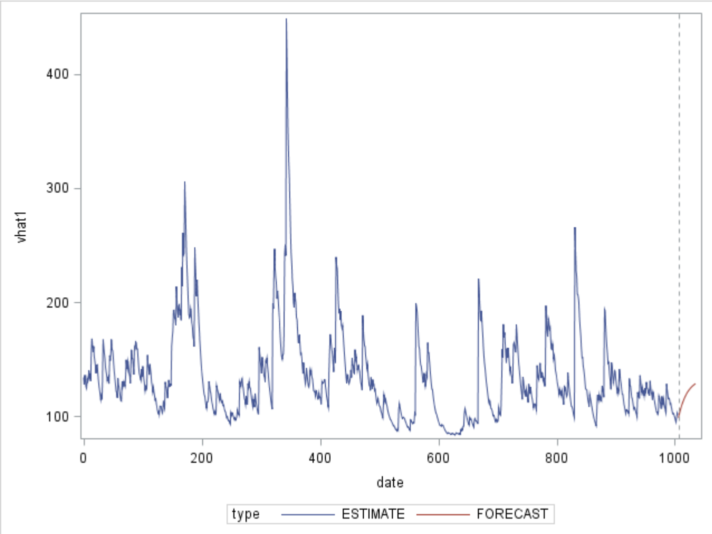

Fig. 5. Volatility of the AR(1)–GARCH(1,1) Model of Elnusa Tbk Data

The Figure 5 depicts the conditional variance of Elnusa Tbk along with its prediction for 30 days later. The graph illustrates very volatile. The forecasting trend of the risk however shows an indication of an increasing pattern as shown by the red line [40-42].

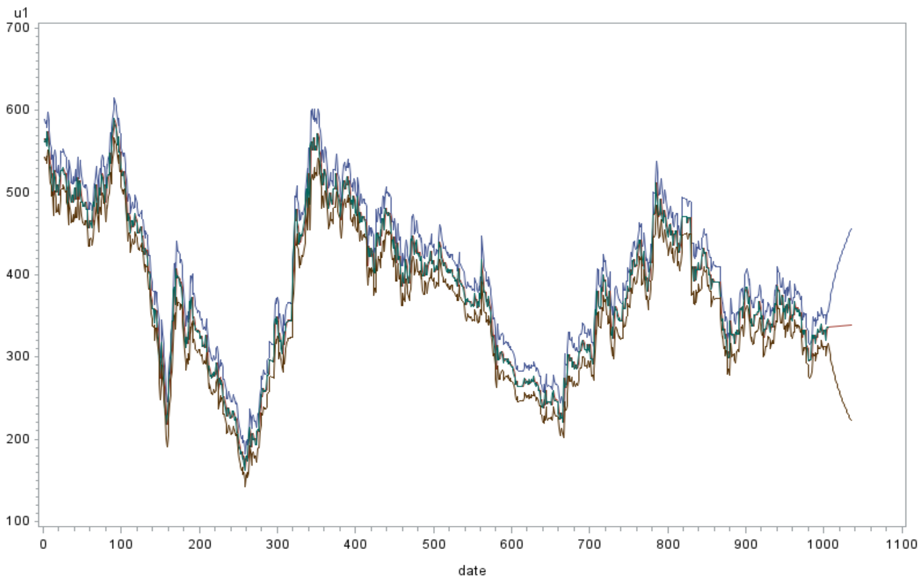

Fig. 6. Forecasting Elnusa Tbk Plot with its Confidence Interval

The aim of this study is to identify the best time in making investment decisions on Elnusa Tbk (ELSA) after computing the best model with the smallest residual value for AR(1)–GARCH(1,1). Figure 6 suggests that the prediction share prices for 30 days experience a gradual upside trend, and it also supports the forecasting with its upper and lower limits. The graph illustrates that the prediction has an increasing pattern with a slow movement as shown in the red line. The risk however is high as presented with the blue line (upper limit) and brown line (lower limit).

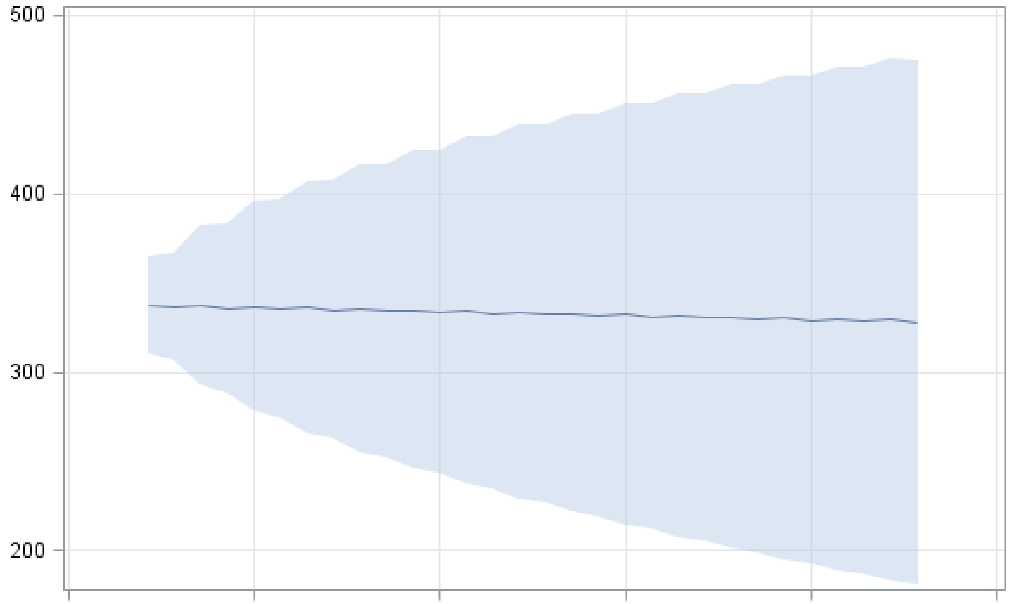

Fig. 7. Forecasting Elnusa Tbk Share Price for the Next 30 Days

Figure 7 supports the data in Figure 6, showing that the stock price of ELSA gradually decreases. The forecast in this study however only for short-term period as we can see the risk for longer period increases significantly over time.

According with the data forecasting of the AR(1)–GARCH(1,1) model, which has the ability to accurately predict with a lower error level (< 0.0001), investors can decide the timing for their investments on ELSA. In this case, by analysing the trend, which shows a moderate upside pattern, investors should sell stocks on ELSA.

IV CONCLUSION

In this study the daily data share price of Elnusa Tbk is used over the years 2015-2018. The data are studied by using time series modeling AR(p)-GARCH(p,q). From the analysis it is found that the data of Elnusa Tbk are non-stationary. To make the data stationary, the differencing process is conducted with lag = 2 (d = 2) and the time series data then become stationary. From the test of ARCH effects by using Q test and LM, it concludes that the data of Elnusa Tbk have ARCH effects. Based on this situation, the AR(p)-GARCH(p,q) model are used to model the data.

The best model for all data of Elnusa Tbk is AR(1)- GARCH(1,1). The models is significant and the R-squares is identified as 0.9837 for the model data of Elnusa Tbk, the application of these model for forecasting are quite good based on the criteria of MAPE (the Mean Absolute Percentage Error) for the forecasting of data for Elnusa Tbk as 2.1816%. The model is also used for forecasting for the next 30 days (date).

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