Jurnal Varian
Vol. 6, No. 1, Oktober 2022, Hal. 49–60
e-ISSN: 2581-2017

EGARCH Model Prediction for Sale Stock Price

Ismail Husein[1], Machrani Adi Putri Siregar[2], Rima Aprilia[3], Arya Impun Diapari Lubis[4],
[1,2]Department of Mathematics Universitas Islam Negeri Sumatera Utara Medan, Indonesia

Article Info

Article history:

Received : 06-02-2022
Revised : 10-20-2022
Accepted : 11-13-2022

Keywords:

Modelling;
Prediction;
Heteroskedasticities;
Stock price.

ABSTRACT

Stock is an investment in the capital market that is very promising for investors. Investors can also get high returns from the shares invested. However, this stock price is not always stable, it can go up and down drastically. The purpose of this study is to predict stock prices because they often experience instability. The method used in this research is using the Exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model with the Quasi Maximum Likelihood (QML) method. The result of this research is the implementation of this model. The EGARCH model used is the stock price index model that is formed, namely the autoregressive integrated moving average (ARIMA) (0, 1, 2) EGARCH (1.4). The conclusion from the results of the research that predictions using the ARIMA model (0, 1, 2) EGARCH (1, 4) is the best model in accommodating the asymmetric nature of the volatility of the stock price index. The results of this egarch model show more optimal prediction results seen from an error of 3% compared to other modes such as the arch model and the GARCH model.

Accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: https://doi.org/10.30812/varian.v6i1.1975

Corresponding Author:

Ismail Husein
Department of Mathematics, Universitas Islam Negeri Sumatera Utara Medan, Indonesia
Email: husein_ismail@uinsu.ac.id

A. INTRODUCTION

Capital Market is a securities trading activity and public offering. Securities trading issued is related to public companies, agencies, and other jobs related to it (**?**). Samsul defines the capital market as a place or means of meeting the needs and supply of long-term monetary instruments. Overall, the capital market is a method for framing capital and accumulating reserves aimed at expanding public cooperation in supporting assets for the development of national development assets (Samsul, 2006). The capital market is also a well-organized forum for trading securities, also known as the Stock Exchange. According to Nasarudin, the stock exchange is a forum/means to bring together investors with companies that trade securities so that there is a sale and purchase offer (Nasarudin et al., 2014). Article 1 paragraph 4 of the capital market law states that the stock exchange is a legal place for trading securities according to law. The stock exchange operator must be an individual who already has a business license from Bapepam (UUPM Article 6 paragraph 1). Stock is an investment in the capital market that is very promising for investors. Return is the value of profits or losses obtained from investments within a certain period of time (Zulfikar and Si, 2016) (Husein and Widyasari, 2022). Shares are evidence of participation owned by individuals or institutions given by a company in the form of a limited liability company (PT) in the form of securities (Sunariyah, 2006) (Husein et al., 2022). With this stock, many companies will find it easy to get funds so as to encourage the economy to be better. Investors can also get high profits from the shares invested. However, this stock price is not always stable, it can go up and down drastically. To avoid this, stock price predictions are needed. This is the reason for researchers to raise stock prices as the object of research (Husein et al., 2021).

Research using stock prices is usually done to find a model of the stock. The model of the stock being searched for can be used to predict stock prices on the following day, month, and year (Rizal and Soraya, 2018). By predicting stock prices, investors can consider decisions to sell or buy shares in order to get the desired profit. Stock price prediction is a process of analyzing the price of a stock and also determining the price of a stock in the future (Prakoso, 2019). Stock prices can be used as investments that are quite valuable, but not always the investments made can provide benefits (Poerwanto and Fajriani, 2020). To avoid this, it is necessary to predict stock prices. Similar research on stock price predictions that have existed before, was carried out by Wibowo, et al. with the title "Modeling Banking Stock Return Using Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)". Research conducted by Wibowo, et al. shows that the visible EGARCH model has the relevant parameters ARIMA([2],0,[2]) EGARCH(1,1), ARIMA([2,4],0,[2,4]) EGARCH(1,1) and ARIMA([4],0,[4]) EGARCH(1,1) (Wibowo et al., 2017). Amelia (2017) with the title "Modeling Volatility Using the Egarch Method in the Jakarta Islamic Index" research conducted by Amelia shows that the best GARCH univariate model is EGARCH (3.3) (Amelia, 2017). Furthermore, Kartika researched on "Exponential EGARCH Modeling Using the Quasi Maximum Likelihood Method". this study shows forecasting using the ARIMA model (0,1,1) egarch (1,4) produces stock price values that are close to the actual data (Kartika, 2020)

To predict stock prices can be seen from the volatility. Volatility is a condition when data moves up and down, it can even move to extremes. Volatility is usually produced by the standard deviation of returns which has important implications in calculating risk (Ariefianto, 2012). In stock price prediction, volatility is used to measure the risk level of stock price selection by looking for volatility modeling. To measure volatility, there are several models that can be used, with this model we can predict stock prices, including the ARCH (Autoregressive Conditional Heterocedasticity) model. This model is described by Engle (1982) in his article on the ARCH model used to measure the estimated means and variance of inflation in the UK (United Kingdom) due to the emergence of volatility clustering or heteroscedasticity. However, this ARCH model has a drawback, namely the higher the lag , the model is not feasible to use, resulting in limited lag that can be used. To minimize the shortcomings in the ARCH model, Bollerslev (1986) developed a GARCH (Generalized Autoregressive Conditional Heterocedasticity) model which has a more flexible lag level. Bollerslev uses GARCH in calculating the stock price index and exchange rate (Engle, 1982). However, this GARCH model also has weaknesses in dealing with the asymmetry phenomenon in volatility. Based on this, the Asymmetric GARCH model was developed to overcome the shortcomings of the GARCH model. The development of the GARCH model includes EGARCH, TGARCH, ARCH-M, etc. These models can be used to predict stock prices in various companies listed on the stock exchange. To be able to use the Asymmetric GARCH model, a method is needed. Methods that can be used include the QML (Quasi Maximum Likelihood) method. the Quasi Maximum Likelihood (QML) method is an estimation method that is carried out on variations in model parameters. The QML method can be used as a time series analysis whose error values do not follow the normal distribution. QML estimation uses the maximum likelihood method as the basis so that the calculation of quasi-variations is the same as the values obtained from the maximum likelihood method (Saida et al., 2016). To find the best model for prediction by using EGARCH model to see the efectifity from this model.

B. LITERATURE REVIEW

1. Time Series Analysis

a. Meaning of time series

Time series data is data that has been observed on an object for several periods. This data is usually presented with monthly, quarterly, weekly and daily period data. An example can be seen through the notation in the following regression equation (Nuryanto and Pambuko, 2018):

$$Y_t = b_0 + b_1 x_t + \ldots + u_t \tag{1}$$

b. Stationary Test

In testing the consistency of the movement of the data used statistical testing. There are several tests that are used to test statistically, including the Augmented Dickey-Fuller (ADF) test (Wardhono et al., 2019). Augmented Dickey-Fuller is a method to test the stationary level of a data. Stationary testing of the data used is done by seeing whether there is a unit root in the model (Inlistya, 2017).

The Augmented Dickey-Fuller test can be tested with the following hypothesis:

$H_0 : |\varphi| = 1$ (non-stationary data)

$H_1 : |\varphi| < 1$ (stationary data)

Test statistics

$$T = \frac{\varphi_1 - 1}{SE(\varphi_1 - 1)} \tag{2}$$

DOI: https://doi.org/10.30812/varian.v6i1.1975

c. White Noise Test

There is a process $\{a_t\}$ is a process of white noise if the process is a sequence of uncorrelated random variables from a fixed distribution with a constant mean, $E(a_t) = \mu_a$ which is assumed to be equal to zero, constant variance $Var(a_t) =$, and covariance . Therefore it is called a white noise process $\sigma_a^2 \gamma_k = Cov(a_t, a_{t+k}) = 0\{a_t\}$ is a stationary with (Kuntoro, 2015):

d. Heteroscedasticity

Heteroscedasticity is the variance of data that is not stable or constant. Heteroscedasticity can occur due to transitions that are not detected in the regression model, such as the transition of the value of a stock's price caused by bad news about the company selling its shares, thus giving the effect of changes in the level of data accuracy. Cross section data, often experience Heteroscedasticity Disorders as well as time series data (time series) (Pratisto, 2004). Heteroscedasticity can symbolically be written as follows:

$$E(u_i^2) = \sigma_i^2, \quad i = 1, 2, \ldots, n \tag{3}$$

The symbol of the u_i shows the disturbance factor (error)

The effect of heteroscedasticity can be seen by the graphical method. The way this method works is by checking the condition of the scatter plot between the value of a prediction of a related variable and the remainder. If in the scatter plot it is found that the plot makes a pattern, the patterns can be: wavy, funnel, and enlarge and then decrease, then the data can be said to be heteroscedasticity.

e. EGARCH Models

The EGARCH model is a variant of the ARCH/GARCH model. This EGARCH model is also an ARCH model that accommodates asymmetric fluctuations to exponential volatility.

In the EGARCH model (p, q) can be formulated as:

$$\ln \sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{4}$$

where is the constant of the model parameter $EGARCH(p, q)$. $\alpha_0, \alpha_i, \beta_j$

2. Parameter Estimation

a. Quasi Maximum Likelihood Method

QML is a predictive method on parameter variances. utilization of the maximum likelihood method is still used as the basis for estimating the quasi maximum likelihood (QML) method.

The likelihood function is written as:

$$L(\varepsilon_1, \ldots, \varepsilon_T | \vartheta) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\varphi\sigma_t^2}} \exp\left(-\frac{\varepsilon_t^2}{2\varphi\sigma_t^2}\right) \tag{5}$$

By utilizing the natural logarithm conditions, the log likelihood function can be arranged as follows (provided that the constants are ignored):

$$l_t(\vartheta) = \frac{1}{2T} \left(\sum_{t=1}^{T} l_t(\vartheta) \right) \tag{6}$$

where

$$l_t(\vartheta) = -\left(\ln \sigma_t^2(\vartheta) + \frac{\alpha_t^2}{\alpha_t^2(\vartheta)} \right) \tag{7}$$

C. RESEARCH METHOD

1. The Research Sources and Variables

That research variables are properties or properties or values of individuals, items or actions that have certain variations determined by the analyst to concentrate on and then reach conclusions (Sugiyono, 2013). The research data source is the subject of the data source obtained (Arikunto, 2019). The data used is the stock price index data on a daily basis. Data is available at the Indonesia Stock Exchange office, when data collection is hindered due to the COVID-19 condition, data collection is carried out through the IDX official website. The data collection period is 1 July 2020 to 30 June 2021. The variable of the data used in this study is the stock price return data.

2. Data Analysis Techniques

The research carried out was assisted by using EViews 10 software. The steps taken to analyze the data were as follows:

1. Make stock data into return data.
2. There are several tests used to test statistician, including the Augmented Dickey-Fuller (ADF) test (Wardhono et al., 2019). Performing the Augment Dickey Fuller (ADF) test to perform a statistical test. If the data is not stationary, then differencing is done.
3. Identify the ARIMA model by looking at the AR and MA orders on the ACF and PACF correlogram lags in the data. ACF and PACF are used to identify the time series model and to determine the stationary of the data (Inlistya, 2017).
4. ARIMA model parameter estimation
5. The verification of the model is to test the independence of the residuals and test the normality of the residuals.
6. Residual independence test can be seen on the probability value that meets the criteria, which is more than $\alpha = 0.05$ or the Q-stat lag value of 12, 24, and 36 on the residual correlogram of the ARIMA model.
7. The residual normality test is carried out by using the Jarque-Bera test, it meets the requirements if the probability value is more than $\alpha = 0.05$.
8. See the effect of heteroscedasticity by performing the Lagrange Multiplier test. Meets the criteria if the LM value is greater than 0.01.
9. Identify the EGARCH model.
10. By using the quasi-maximum likelihood method, parameter estimation in the EGARCH model is carried out.
11. Choose the best EGARCH model.

D. RESULTS AND DISCUSSION

1. Description of data

The data used is stock price return data which consists of 241 observations

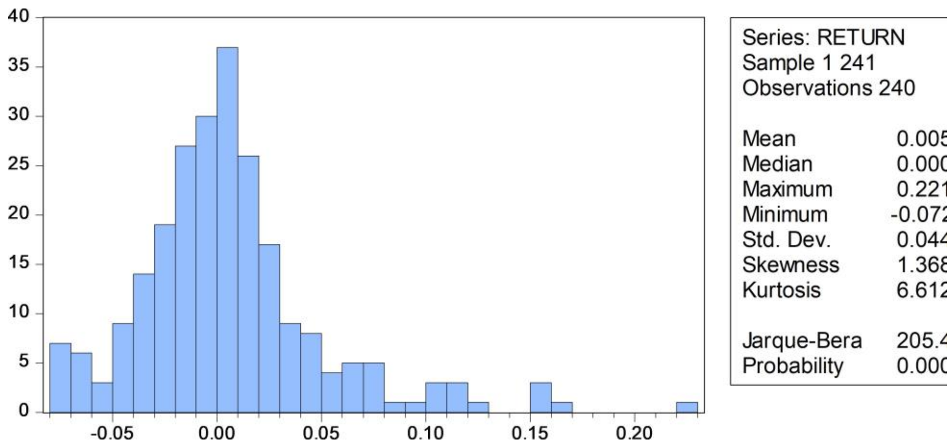


Figure 1. Histogram and descriptive statistics of stock price log-return

The level of the stock price index log-return has a positive mean value, this indicates that the data has increased, a positive skewness indicates that the data is skewed to the right, then the value of kurtosis which is higher than 3 means that the data These have early symptoms of heteroscedasticity.

2. Statistically test

In this study, looking back at the statistical log-return data from the stock price index, the results of the stock price log-return plot are as follows

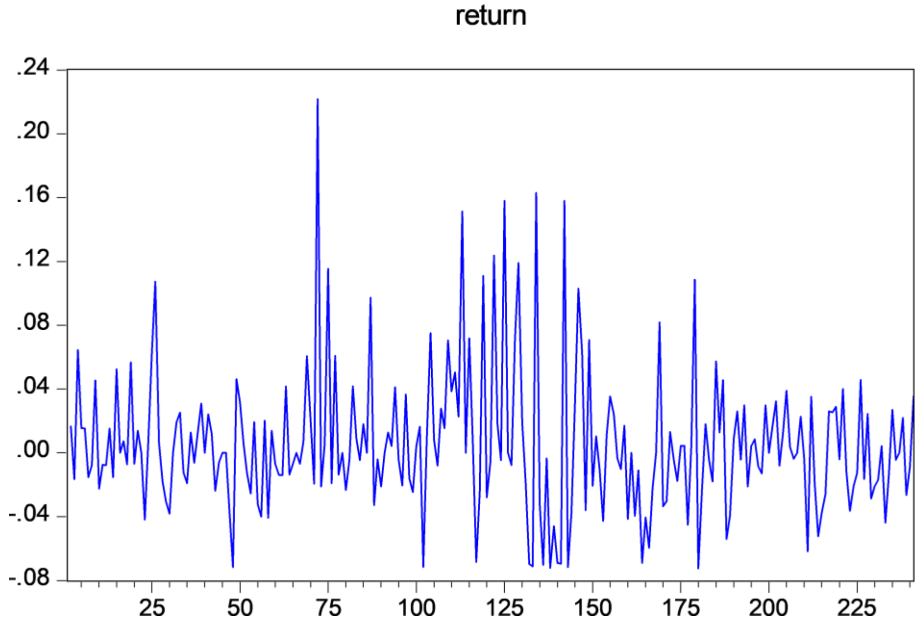


Figure 2. Stock price log-return plot

The statistical data is in the mean, besides that, an augmented dicky fuller test will also be carried out , the results of which are as follows.

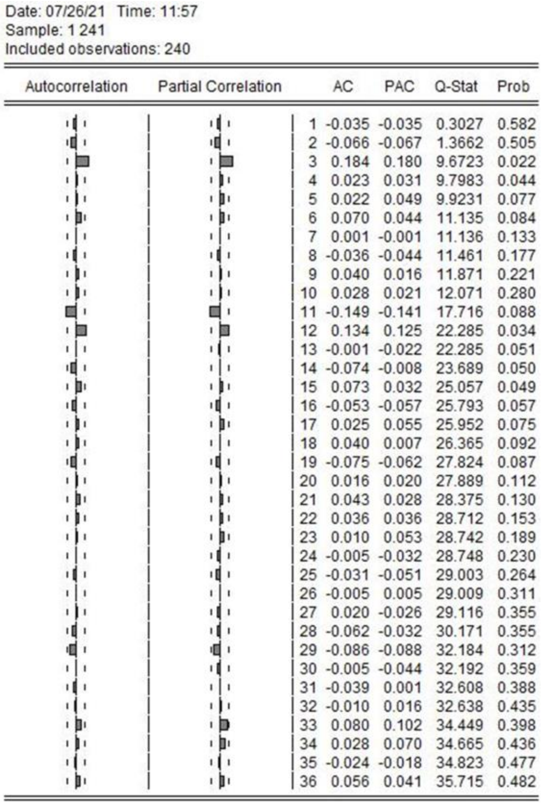
Table 1. Statistician test result

		t-Statistic	Prob*
Augmented Dickey-Fuller test statistic		-15.93616	0.0000
Test critical values:	1% level	-3.457630	
	5% level	-2.873440	
	10% level	-2.573187	

The return data is stationary in the mean because the probability value = 0.0000 ≤ 0.05 or the absolute ADF test value (t-Statistic = -15.93616) is greater than the critical test values 5% level = - 2.873440.

3. Spatial Effect Test

To identify the ARIMA model, it can be seen from the ACF and PACF plots. The results of the Arima plot are as follows.


Date: 07/26/21 Time: 11:57
Sample: 1 241
Included observations: 240

	AC	PAC	Q-Stat	Prob
1	-0.035	-0.035	0.3027	0.582
2	-0.066	-0.067	1.3662	0.505
3	0.184	0.180	9.6723	0.022
4	0.023	0.031	9.7983	0.044
5	0.022	0.049	9.9231	0.077
6	0.070	0.044	11.135	0.084
7	0.001	-0.001	11.136	0.133
8	-0.036	-0.044	11.461	0.177
9	0.040	0.016	11.871	0.221
10	0.028	0.021	12.071	0.280
11	-0.149	-0.141	17.716	0.088
12	0.134	0.125	22.285	0.034
13	-0.001	-0.022	22.285	0.051
14	-0.074	-0.008	23.689	0.050
15	0.073	0.032	25.057	0.049
16	-0.053	-0.057	25.793	0.057
17	0.025	0.055	25.952	0.075
18	0.040	0.007	26.365	0.092
19	-0.075	-0.062	27.824	0.087
20	0.016	0.020	27.889	0.112
21	0.043	0.028	28.375	0.130
22	0.036	0.036	28.712	0.153
23	0.010	0.053	28.742	0.189
24	-0.005	-0.032	28.748	0.230
25	-0.031	-0.051	29.003	0.264
26	-0.005	0.005	29.009	0.311
27	0.020	-0.026	29.116	0.355
28	-0.062	-0.032	30.171	0.355
29	-0.086	-0.088	32.184	0.312
30	-0.005	-0.044	32.192	0.359
31	-0.039	0.001	32.608	0.388
32	-0.010	0.016	32.638	0.435
33	0.080	0.102	34.449	0.398
34	0.028	0.070	34.665	0.436
35	-0.024	-0.018	34.823	0.477
36	0.056	0.041	35.715	0.482

Figure 3. Plot ACF PACF at level level

The ACF value from lag 1 to lag 36 is relatively small, approaching the value 0, but we also see that the value of the probability is relatively greater than 0.05, this means that the data is not statistically related to variance so that it is necessary to do differencing on data. The following is the result of the ACF PACF plot that has been differencing 1 time.

4. Spatial Heterogeneity Test with R and Geoda Software

Residual independence test is used to detect whether there is a correlation between lags. The following are the results of the residual independence test:

Table 2. Residual independence test result

Model	Lag	Q-stat	Decision
ARIMA (0, 1, 1)	12	22.084	H_0 accepted
	24	28.832	H_0 accepted
	36	36.165	H_0 accepted
ARIMA (0, 1, 2)	12	105.46	H_0 accepted
	24	118.70	H_0 accepted
	36	123.92	H_0 accepted
ARIMA (0, 1, 3)	12	79.638	H_0 accepted
	24	88.440	H_0 accepted
	36	93.955	H_0 accepted
ARIMA (1, 1, 0)	12	80.963	H_0 accepted
	24	91.143	H_0 accepted
	36	99.527	H_0 accepted
ARIMA (2, 1, 0)	12	105.44	H_0 accepted
	24	119.85	H_0 accepted
	36	125.17	H_0 accepted
ARIMA (3, 1, 0)	12	78.438	H_0 accepted
	24	87.110	H_0 accepted
	36	92.466	H_0 accepted

DOI: https://doi.org/10.30812/varian.v6i1.1975

all Arima models meet the residual assumptions with the hypothesis:

H_0 : there is a correlation between lag

H_1 : there is no correlation between lags

So that all of these models can be tested for normality of the residuals Residual normality test

The residual normality test is used to determine whether the residual data is normally distributed or not. Here are the results of the residual normality test

Table 3. Residual normality test results

Model	Jarque bera	Prob.	Decision
ARIMA (0, 1, 1)	179.5463	0.000000	H_0 rejected
ARIMA (0, 1, 2)	86.44945	0.000000	H_0 rejected
ARIMA (0, 1, 3)	86.10540	0.000000	H_0 rejected
ARIMA (1, 1, 0)	113.0354	0.000000	H_0 rejected
ARIMA (2, 1, 0)	90.17791	0.000000	H_0 rejected
ARIMA (3, 1, 0)	85.26047	0.000000	H_0 rejected

all model residuals are not normally distributed because the probability value is less than a confidence interval of 0.05, which is rejecting H_0, with the following conditions:

H_0 : presence of ARCH/GARCH effect

H_1 : no effect ARCH/GARCH

Heteroscedasticity

Test the effect of heteroscedasticity using the white test, the following are the results of the heteroscedasticity test carried out,

Table 4. ARIMA model heteroscedasticity test result

Model	Prob.	Decision
ARIMA (0, 1, 1)	0.000000	H_0 accepted
ARIMA (0, 1, 2)	0.000000	H_0 accepted
ARIMA (0, 1, 3)	0.000000	H_0 accepted
ARIMA (1, 1, 0)	0.000000	H_0 accepted
ARIMA (2, 1, 0)	0.000000	H_0 accepted
ARIMA (3, 1, 0)	0.000000	H_0 accepted

There is a heteroscedasticity effect from the residual because the probability value is less than 0.05 or accept H_0. Therefore, to overcome the problem of hateroscedasticity in the ARIMA model data return , GARCH modeling is carried out, namely EGARCH.

5. Identify the EGARCH

The EGARCH model was formed to overcome the heteroscedasticity problem that occurred in the ARIMA model, because the residual test conducted previously stated that the ARIMA model formed had a heteroscedasticity effect, an ARCH/GARCH model was formed to overcome the heteroscedasticity problem, the EGARCH model was formed to address this by looking at The following values of Akaike's Information Criterion (AIC) and Schwarz's Information Criterion (SIC) are AIC/SIC results from the initial EGARCH model.

Table 5. AIC/SIC result from the initial EGARCH model

Model	AIC	SIC
EGARCH (1, 2)	-3.410981	-3.338467
EGARCH (1, 4)	-3.402629	-3.301111
EGARCH (2, 1)	-3.458259	-3.385746
EGARCH (2, 2)	-3.491218	-3.404202
EGARCH (3, 3)	-3.487158	-3.371137

It can be seen from the table that the initial EGARCH model to be used is the model that has the smallest AIC and SIC values, and which has the smallest AIC and SIC values is the EGARCH model (1, 4), so the model used is the EGARCH model (1, 4)

6. EGARCH model parameter estimation

After determining the EGARCH model, then parameter estimation is carried out, here are the results of the EGARCH model parameter estimation.

Table 6. EGARCH model parameter estimation results

Model	Parameter	Prob	Decision
ARIMA(0, 1, 1)	φ_1	0.8504	H_0 accepted
EGARCH (1, 4)	a_0	0.9980	H_0 accepted
	a_1	0.9982	H_0 accepted
	γ_1	0.9998	H_0 accepted
	ϑ_4	0.9995	H_0 accepted
ARIMA(0, 1, 2)	$\varphi_1 2$	0.0078	H_0 rejected
EGARCH (1, 4)	a_0	0.1143	H_0 accepted
	a_1	0.0000	H_0 rejected
	γ_1	0.0007	H_0 rejected
	ϑ_4	0.0000	H_0 rejected
ARIMA(0, 1, 3)	φ_3	0.0176	H_0 rejected
EGARCH (1, 4)	a_0	0.1175	H_0 accepted
	a_1	0.0000	H_0 rejected
	γ_1	0.0040	H_0 rejected
	ϑ_4	0.1262	H_0 accepted
ARIMA(1, 1, 0)	ω_1	0.0000	H_0 rejected
EGARCH (1, 4)	a_0	0.1309	H_0 accepted
	a_1	0.0001	H_0 rejected
	γ_1	0.0533	H_0 accepted
	ϑ_4	0.0000	H_0 rejected
ARIMA(2, 1, 0)	ω_2	0.6714	H_0 accepted
EGARCH (1, 4)	a_0	0.0866	H_0 rejected
	a_1	0.0000	H_0 rejected
	γ_1	0.0140	H_0 rejected
	ϑ_4	0.3107	H_0 accepted
ARIMA(3, 1, 0)	ω_3	0.0097	H_0 rejected
EGARCH (1, 4)	a_0	0.0756	H_0 accepted
	a_1	0.0000	H_0 rejected
	γ_1	0.0018	H_0 rejected
	ϑ_4	0.1162	H_0 accepted

There is no model whose all parameters reject H_0 therefore to determine the best model to be used is to look at the smallest AIC and SIC values from the above model, and it can be seen that the model that has the smallest AIC and SIC values is ARIMA (0, 1, 2) EGARCH (1, 4) models.

7. Diagnostic Checking model EGARCH

Residual randomness test

Based on the results of the residual randomness test using the ACF and PACF correlograms, nothing significant until the 36th lag, so it can be seen that the residual value of the ARIMA model (0, 1, 2) EGARCH (1, 4) is random.

Table 7. Test Lagrange Multiplier Model EGARCH

Model	LM	Prob.	Decision
ARIMA (0, 1, 2) EGARCH (1, 4)	0.3150	0.3129	H_0 rejected

The probability value is 0.3129, where the value is greater than the confidence interval value of 0.05 so that we reject H 0 so it can be concluded that the resulting model is ARIMA (0, 1, 2) EGARCH (1, 4) which is estimated to be free from the effect of heteroscedasticity, namely:

$$Y_t = Y_{t-1} + \mu - 0.130606\varepsilon_{t-2} + \varepsilon_t$$

DOI: https://doi.org/10.30812/varian.v6i1.1975

with

$$\ln(\sigma_t^2) = -0.004 - 0.161\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right| + 0.237\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + 0.461\ln(\sigma_{t-1}) + 0.187\ln(\sigma_{t-2}) + 0.215(\sigma_{t-3}) + 0.109(\sigma_{t-4})$$

Based on the known ARIMA (0, 1, 2) model, we can see that this model is a model for the stock price return index that has been transformed back into the form of a stock price index.

8. Stock Price Prediction

To find out whether this model is feasible to use in predicting stock prices, it is necessary to first look at the error value, which can be seen in the following figure.

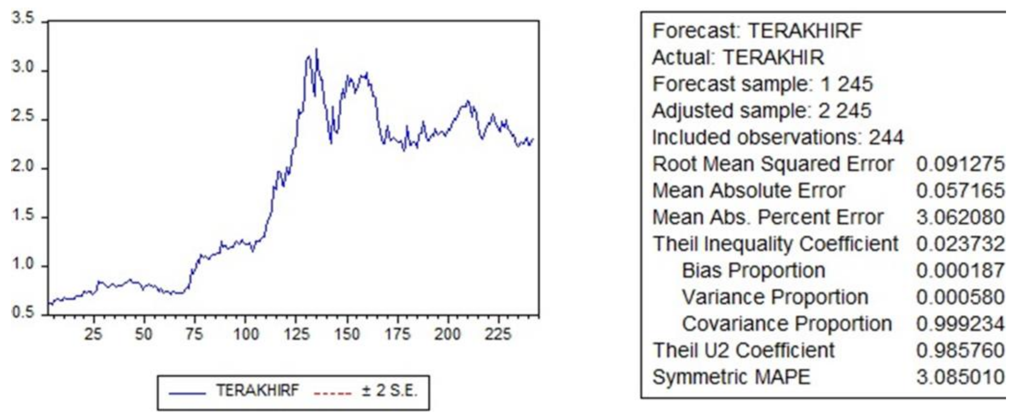


Figure 4. Model feasibility prediction result

The result of the prediction of the feasibility of the model used in predicting stock prices at PT. ANEKA TAMBANG T, bk. It can be seen from the figure that the MAPE error rate (mean abs percent error) is 3.06%.

Predictions are made for the next month from the data used, namely from the beginning of July 2020 to the end of June 2021. The results of the forecasting of the stock price index are as follows.

Table 8. Model feasibility prediction results

Date	Actual Data	Prediction results
16-06-2021	2.320	2.334648
17-06-2021	2.330	2.345889
18-06-2021	2.230	2.238753
21-06-2021	2.200	2.223282
22-06-2021	2.260	2.273208
23-06-2021	2.250	2.253351
24-06-2021	2.250	2.261178
25-06-2021	2.300	2.308584
28-06-2021	2.240	2.243076
29-06-2021	2.220	2.237104

In this study, from the prediction results from the stock data obtained, it can be concluded that there was an increase in the stock price of PT ANEKA TAMBANG T, bk. There was a continuous increase in prices as we can see on 1/7/2021 and continued to increase until 30/7/2021. So that it can be a reference for investors to see volatility as a reference, they can buy shares or sell them as a market strategy.In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2, 5]. The discussion can be made in several sub-chapters.

E. CONCLUSION AND SUGGESTION

Based on the results and discussion it can be concluded that Implementation of the EGARCH model on the price index of PT. ANEKA TAMBANG, Tbk. years 2020-2021 using the Quasi Maximum Likelihood method are as follows, $Y_t = Y_{t-1} + \mu - 0.130606\varepsilon_{t-2} + \varepsilon_t$ with $\ln(\sigma_t^2) = -0.004 - 0.161 \left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right| + 0.237 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + 0.461\ln(\sigma_{t-1}) + 0.187\ln(\sigma_{t-2}) + 0.215(\sigma_{t-3}) + 0.109(\sigma_{t-4})$. The results of the study provide stock price predictions using the ARIMA model (0, 1, 2) EGARCH (1, 4) is the best model in accommodating the asymmetric nature of the volatility of the stock price index of PT. ANEKA TAMBANG, Tbk

REFERENCES

Amelia, N. (2017). Pemodelan volatilitas menggunakan metode egarch pada jakarta islamic index. *Jurnal Humaniora Teknologi*, 3(1).

Ariefianto, M. D. (2012). Ekonometrika: esensi dan aplikasi dengan menggunakan eviews.

Arikunto, S. (2019). Prosedur penelitian suatu pendekatan praktik.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the econometric society*, pages 987–1007.

Husein, I., Suhada, A., Chetthamrongchai, P., Peressypki, A. P., Nurrohkayati, A. S., Hoang Ca, V., Huynh Tan, H., Grimaldo Guerrero, J. W., and M Kavitha, M. (2021). Scheduling for a container supply chain to minimize costs using the meta-innovation approach. *Industrial Engineering and Management Systems*, 20(4):662–671.

Husein, I. and Widyasari, R. (2022). Algorithm symmetric 2-dlda for recognizing handwritten capital letters. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 21(2):389–402.

Husein, I., Zein, A., and Sabrina, L. (2022). Mustahiq (zakat recipient) determination application with analytic hierarchy process model. *Sinkron: jurnal dan penelitian teknik informatika*, 7(4):2462–2468.

Inlistya, V. A. (2017). *Perbandingan Metode Antara GJR-GARCH Dan EGARCH Pada Analisis Volatilitas Indeks Saham Syariah Indonesia*. PhD thesis, Institut Teknologi Sepuluh Nopember.

Kartika, W. D. (2020). *Pemodelan Exponential GARCH menggunakan metode Quasi Maximum Likelihood: Studi kasus harga saham PT. Telkom Tbk*. PhD thesis, Universitas Islam Negeri Maulana Malik Ibrahim.

Kuntoro, H. (2015). *Teori dan Aplikasi Analisis Seri Waktu*. Zifatama Publisher.

Nasarudin, M. I. et al. (2014). *Aspek hukum pasar modal Indonesia*. Kencana.

Nuryanto, N. and Pambuko, Z. B. (2018). Eviews untuk analisis ekonometrika dasar: Aplikasi dan interpretasi. *UNIMMA PRESS*, pages 978–602.

Poerwanto, B. and Fajriani, F. (2020). Resilient backpropagation neural network on prediction of poverty levels in south sulawesi. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 20(1):11–18.

Prakoso, B. H. (2019). Implementasi support vector regression pada prediksi inflasi indeks harga konsumen. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 19(1):155–162.

Pratisto, A. (2004). Cara mudah mengatasi masalah statistik dan rancangan percobaan dengan spss 12. *Jakarta: PT. Elex Media Komputindo*.

Rizal, A. A. and Soraya, S. (2018). Multi time steps prediction dengan recurrent neural network long short term memory. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 18(1):115–124.

Saida, M. D. N., Sudarno, S., and Hoyyi, A. (2016). Pemodelan return indeks harga saham gabungan menggunakan threshold generalized autoregressive conditional heteroscedasticity (tgarch). *Jurnal Gaussian*, 5(3):465–474.

Samsul, M. (2006). Pasar modal dan manajemen portofolio.

Sugiyono, D. (2013). Metode penelitian pendidikan pendekatan kuantitatif, kualitatif dan r&d.

Sunariyah (2006). *Pengantar Pengetahuan Pasar Modal*. UPP STIM TKPN.

Wardhono, A., Indrawati, Y., Qoriah, C. G., and Nasir, M. A. (2019). *Analisis data time series dalam model makroekonomi*. Pustaka Abadi.

Wibowo, N. M., Sugito, S., and Rusgiyono, A. (2017). Pemodelan return saham perbankan menggunakan exponential generalized autoregressive conditional heteroscedasticity (egarch). *Jurnal Gaussian*, 6(1):91–99.

Zulfikar, S. and Si, M. (2016). Pengantar pasar modal dengan pendekatan statistika. *CV Budi Utama*.

.