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Comparative Analysis of EGARCH and TGARCH Models in Stock Price Prediction

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ABSTRACT

Stocks are proof of the value of ownership of a company which are usually sold on the capital market, companies that buy and sell their shares will be easy to find with the existence of the stock market. The fund obtained by the company from investors who invest in several companies. Investors need to understand the models valuation of stock prices because investors have interest with changes in share prices. The purpose of study for looking the difference of the EGARCH model with TGARCH as a comparison which one is better at predicting stock prices. This research is a quantitative study using the EGARCH and TGARCH models by use Quasi Maximum Likelihood (QML) method. It was found that ARIMA (1 0 1) EGARCH (3 4) is a model that shows the best performance based on the smallest AIC value and the significance of all parameters. The ARIMA (1 0 1) EGARCH (3 4) model formed for forecasting returns and volatility is as follows:

$$Y_t = 0.790493_{t-1} + \mu\text{-}0.774343\varepsilon_{t-2} + \varepsilon_t \text{with} ln(\sigma_t^2) = -0.368 - 0.092\left(\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right|\right) + 0.154\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right) + 0.384\, ln(\sigma_{t-1}) + 0.465\, ln(\sigma_{t-2}) + 0.125(\sigma_{t-3}) + 0.141(\sigma_{t-4}).$$

ARIMA (1 0 1) EGARCH (3 4) models also have the MAE (Mean Absolute Error) value is 0.044%.

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1. INTRODUCTION

Stocks are proof of the value of ownership of a company which are usually sold on the capital market. companies that buy and sell their shares will be easy to find with the existence of the stock market. [1]. The fund obtained by the company from investors who invest in several companies. Investors need to understand the models valuation of stock prices because investors have interest with changes in share prices. The fund obtained by the company from investors who invest in several companies [2]. If an investor wants higher rate of return, he must be brave or willing to take risks higher (High risk high return) [3]. Investors need to understand the models valuation of stock prices because investors have interest with changes in share prices [4]. Stocks are also a form of paper listed clearly contains some information including nominal value, company name and followed with the rights and obligations described to any of its holders or shareholders, other than that shares also become one of the assets owned by shareholders who are ready to sell [5]. For investors, stock investment is one of the most investment interest, this is because it can provide a level higher return than bonds and mutual funds. This return income will be later expected for investors, as for income This return consists of dividends and capital gains [6]. Stock price data usually very random (random) and has high volatility or error variance not constant (heteroscedasticity) [7]. In its implementation, by owning shares, it states that the shareholder is also a part owner of the company [8]. A model to measure the estimated mean and variation of UK inflation data which contain volatility namely the Autoregressive Conditional Heteroscedasticity (ARCH) model [9]. In practice, found The weakness of this model is the limited order that can be used. The higher the level of volatility on one financial data, a larger order is also needed to model the variance with this model. Solutions to the weaknesses of the ARCH model are developed by generalizing the ARCH model viz Generalized Autoregressive Conditional Heterocedasticity (GARCH). GARCH has the property of volatility symmetrical (equal) to shocks, both positive and negative. Circulating financial data is not forever have symmetrical volatility, some of them have asymmetrical volatility. It is known with the "leverage effect" or the effect of asymmetry, namely the conditions that occur when the price value moves there is a difference in the magnitude of changes in volatility. Brilliantya et al: The EGARCH and TGARCH Models for Measuring Asymmetric Stock Return Volatility 46 GARCH which has symmetrical characteristics cannot handle the effect of asymmetry. For deal with that, developing asymmetric GARCH models, some of which are Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH). In his research, Maqsood et al., 2017 explained that the asymmetric GARCH model plays an important role in predicting the volatility for daily stock returns [10].

2. RESEARCH METHODE

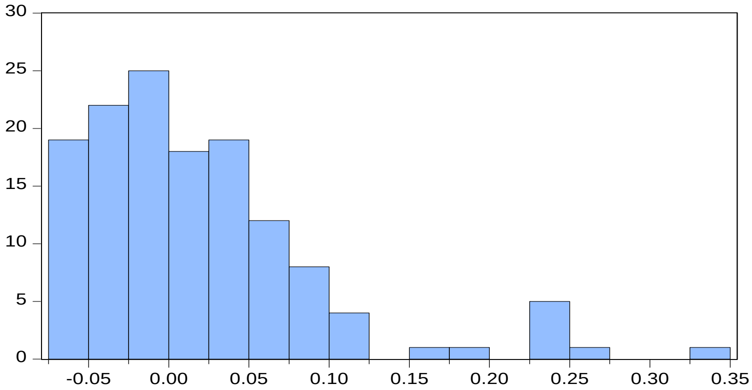
Study variables are individual properties or values, items or actions with certain variations that an analyst decides to focus on and reach conclusions [11]. The research data source is the subject of the data source obtained [12]. Data processing procedures and schemes use Eviews 10 software as follows:

a. Making stock data into return data.
b. Carry out the Augment Dickey Fuller (ADF) test to carry out the stationary test. It is solved by differencing if data have been test is not get stationary
c. Look at the AR and MA orders.
d. Parameter estimation of the Autoregressive integrated moving average model.
e. Model verification.
f. Testing the value of residual independence.
g. the residual value with the jarque-Bera test if the value a = 0.05.
h. Seeing the effect of heteroscedasticity by carrying out the Lagrange Multiplier test. If the LM value > 0.01.
i. Identify the EGARCH model and the TGARCH model.
j. determine parameters in the EGARCH model and the TGARCH model with QML.
k. Choose the best model.

3. RESULT AND ANALYSIS

3.1 Data description

Data used is the price return data consisting of shares out of 137 observations



Series: RETURN	
Sample 1 137	
Observations 136	
Mean	0.018923
Median	0.000000
Maximum	0.340659
Minimum	-0.069444
Std. Dev.	0.076464
Skewness	1.679909
Kurtosis	6.434090
Jarque-Bera	130.7943
Probability	0.000000

Figure 3.1 Histogram and log- *return* descriptive statistics price share

Based on Figure 3.1 above , log- return level index price share own positive mean value , p the indent material data experienced increase , skewness that is positive showing that data sticks out to right , then more kurtosis value tall of 3 means that data own initial symptoms heteroscedasticity .

3.2 Stationarity test

Viewed results from the price log-return plot share under This is as following .

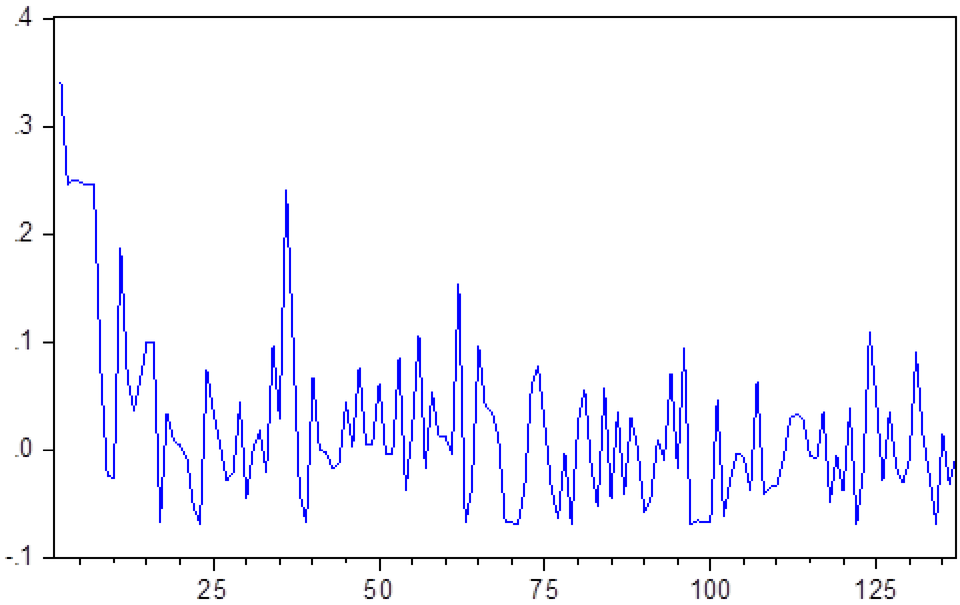


Figure 3.2 Plot Log- *return* price share

In Figure 3.2 _ showing that the data is stationary in the mean, besides it will too done testing stationary with *the dickey fuller augment* test the results are is as following .

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.899135	0.0000
Test critical values:	1% level	-3.479281	
	5% level	-2.882910	
	10% level	-2.578244	

*MacKinnon (1996) one-sided p-values.

Figure 3.3 Stationary test results

In Figure 3.3 can seen that data return already stationary in the mean because mark probability = 0.0000 < α= 0.5 or absolute the ADF test value (t-Statistic = -7.899135) it more big from c value test 5% level = -2.882910

3.3 Identification of ARIMA models

For can identify ARIMA model look from ACF and PACF plots. This is the ACF and PACF plots are as following bellow.

Date: 08/07/22 Time: 09:46
Sample (adjusted): 2 137
Included observations: 136 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.435	0.435	26.341	0.000
		2	0.311	0.150	39.923	0.000
		3	0.258	0.098	49.343	0.000
		4	0.220	0.064	56.234	0.000
		5	0.155	-0.001	59.662	0.000
		6	0.101	-0.020	61.130	0.000
		7	0.096	0.022	62.474	0.000
		8	0.152	0.102	65.868	0.000
		9	0.161	0.067	69.688	0.000
		10	0.096	-0.035	71.050	0.000
		11	0.094	0.009	72.391	0.000
		12	0.100	0.017	73.900	0.000
		13	0.084	0.003	74.966	0.000
		14	-0.018	-0.103	75.016	0.000
		15	-0.070	-0.084	75.780	0.000
		16	-0.004	0.050	75.782	0.000
		17	-0.063	-0.075	76.402	0.000
		18	0.013	0.091	76.429	0.000
		19	-0.004	-0.001	76.433	0.000
		20	0.045	0.049	76.761	0.000
		21	0.054	0.013	77.231	0.000
		22	0.074	0.048	78.142	0.000
		23	-0.017	-0.075	78.188	0.000
		24	-0.035	-0.044	78.397	0.000
		25	0.010	0.048	78.415	0.000
		26	0.012	0.030	78.440	0.000
		27	-0.036	-0.047	78.661	0.000
		28	0.043	0.093	78.980	0.000
		29	0.140	0.119	82.395	0.000
		30	0.128	0.020	85.316	0.000
		31	0.155	0.057	89.587	0.000
		32	0.098	-0.039	91.313	0.000
		33	0.068	-0.035	92.159	0.000
		34	0.082	-0.002	93.403	0.000
		35	-0.044	-0.109	93.758	0.000
		36	-0.041	-0.005	94.068	0.000

Figure 3.4 ACF PACF plot at level level

In Figure 3.4 above can is known that mark probability Already not enough from 0.05, p This means data already stationary to variety so that identify the ARIMA model can be is known from Figure 3.4 that the order d = 0 because the data has been stationary at the level level , whereas For determine the order p and q can seen from the same lag AC and PAC intersect the interval line. Same *lag* _ intersect the interval line is 1 and 2 so can determined the tentative arima model , namely ARIMA (0 0 1), ARIMA (1 0 0), ARIMA (1 0 1), ARIMA (0 0 2), ARIMA (2 0 0), ARIMA (1 0 2), ARIMA (2 0 1), ARIMA (2 0 2).

3.4 Estimating the parameters of the arima model

Following This is results from estimate some significant arima models.

Table 3.1 The results of ARIMA model parameters

Model	parameter	Prob.	Decision
ARIMA (0 0 1)	ϕ_1	0.0000	H_0 rejected

ARIMA (1 0 0)	ω_1	0.0000	H_0rejected
ARIMA (1 0 1)	ω_1	0.0000	H_0rejected
	ϕ_1	0.0000	H_0rejected
ARIMA (0 0 2)	ϕ_2	0.0004	H_0rejected
ARIMA (2 0 0)	ω_2	0.0000	H_0rejected
ARIMA (1 0 2)	ω_1	0.0000	H_0rejected
	ϕ_2	0.3284	H_0 accepted
ARIMA (2 0 1)	ω_2	0.0000	H_0rejected
	ϕ_1	0.0000	H_0rejected
ARIMA (2 0 2)	ω_2	0.0000	H_0rejected
	ϕ_2	0.0000	H_0rejected

Based on the table above is known that all models have mark H_0rejected because the data is smaller than 0.05 with the conditions of the hypothesis:
H_0 : the parameter No significant
H_0 : the parameter significant
data using level significant 5% and all parameters significant.

3.5 *Diagnostics checking*

Then diagnostic checking. Below is the result of the test.

Table 3.2 Residual independence test results

Model	lag	Q-stat	Decision
ARIMA (0 0 1)	12	23.126	H_0 accepted
	24	30,030	H_0 accepted
	36	40,307	H_0 accepted
ARIMA (1 0 0)	12	7.4116	H_0 accepted
	24	16043	H_0 accepted
	36	25,855	H_0 accepted
ARIMA (1 0 1)	12	5.5003	H_0 accepted
	24	16,042	H_0 accepted
	36	29,133	H_0 accepted
ARIMA (0 0 2)	12	34,172	H_0 accepted
	24	40,243	H_0 accepted
	36	53,607	H_0 accepted
ARIMA (2 0 0)	12	18,843	H_0 accepted
	24	26,756	H_0 accepted
	36	40,741	H_0 accepted
ARIMA (1 0 2)	12	6.7399	H_0 accepted
	24	14,776	H_0 accepted
	36	24,817	H_0 accepted
ARIMA (2 0 1)	12	6.6913	H_0 accepted
	24	14,696	H_0 accepted
	36	25,370	H_0 accepted
ARIMA (2 0 2)	12	13051	H_0 accepted
	24	26,757	H_0 accepted
	36	45.158	H_0 accepted

From table 3.2 you can seen language all arima models fulfil residual assumption with hypothesis :
H_0: happened correlation between *lag*
H_0: no happen *lag*
All model can continue to get residual normality test

Residual normality test

The residual normality test is used to determine whether the residual data are normally distributed. Below is the result of the test.

Table 3.3 Test results residual normality

Model	Jarque fallow	Prob.	Decision
ARIMA (0 0 1)	77.04521	0.000000	H_0rejected
ARIMA (1 0 0)	41.89645	0.000000	H_0rejected
ARIMA (1 0 1)	10.99076	0.004106	H_0rejected
ARIMA (0 0 2)	76.25849	0.000000	H_0rejected
ARIMA (2 0 0)	43.29932	0.000000	H_0rejected
ARIMA (1 0 2)	43.68070	0.000000	H_0rejected
ARIMA (2 0 1)	40.15984	0.000000	H_0rejected
ARIMA (2 0 2)	14.38190	0.000753	H_0rejected

From table 3.3 above is known that all residual models do not normally distributed because mark probability not enough from hose confidence 0.05 ie H_0 rejected with provision as following :
H_0: there is ARCH/GARCH effect
H_1: no exists ARCH/GARCH effect

3.6 Heteroscedasticity

Effect test heteroscedasticity with using *white's* test , follows is results from the heteroscedasticity test performed ,

Table 3.4 The results of the ARIMA model heteroscedasticity test

Model	Prob.	Decision
ARIMA (0 0 1)	0.0000	H_0 accepted
ARIMA (1 0 0)	0.0000	H_0 accepted
ARIMA (1 0 1)	0.0000	H_0 accepted
ARIMA (0 0 2)	0.0000	H_0 accepted
ARIMA (2 0 0)	0.0000	H_0 accepted
ARIMA (1 0 2)	0.0000	H_0 accepted
ARIMA (2 0 1)	0.0000	H_0 accepted
ARIMA (2 0 2)	0.0000	H_0 accepted

In table 3.4 can is known that there is effect heteroscedasticity of the residual due mark probability not enough of 0.05 or accept H_0. For overcome problem heteroscedasticity on the data *return* ARIMA model, then done GARCH modeling namely TGARCH and EGARCH.

3.7 Identification of the EGARCH and TGARCH models

The EGARCH and TGARCH models were formed For overcome problem heteroscedasticity that occurs with ARIMA model, residual was carried out previously state that model is formed own effect heteroscedasticity so formed the EGARCH and TGARCH models for overcome matter such and for determine the best model seen from AIC and SIC values in both models . Following This is results of the early EGARCH models

Table 3.5 AIC/SIC results of EGARCH model

Model	AIC	SIC
EGARCH (1 1)	-2.832332	-2.746665
EGARCH (3 1)	-2.816078	-2687579
EGARCH (2 4)	-2.757279	-2.585946
EGARCH (3 4)	-2.743158	-2.550409

Following This is results of the early TGARCH models .

Table 3.6 AIC/SIC results of TGARCH model

Model	AIC	SIC
TGARCH (1 1)	-2.745621	-2.659954
TGARCH (2 1)	-2.731564	-2.624482

TGARCH (2 2)	-2.736764	-2.608265
TGARCH (4 2)	-2.733544	-2.562212

can seen from both early EGARCH and TGARCH models were used is a model that has the smallest AIC/SIC value , and the smallest value is namely EGARCH (3 4) and TGARCH (4 2). So that model will _ used For overcome problem heteroscedasticity .

3.8 Parameter estimation of the EGARCH and TGARCH models

After do determination of the EGARCH and TGARCH models, next done parameter estimation , follows is results from parameter estimation of the EGARCH model.

Table 3.7 EGARCH results of estimating model parameters

Model	AIC	SIC
ARIMA (0 0 1) EGARCH (3 4)	-2.792916	-2.557333
ARIMA (1 0 0) EGARCH (3 4)	-2.729795	-2.493069
ARIMA (1 0 1) EGARCH (3 4)	-2.860899	-2.602652
ARIMA (0 0 2) EGARCH (3 4)	-2.719266	-2.483684
ARIMA (2 0 0) EGARCH (3 4)	-2.798008	-2.560126
ARIMA (1 0 2) EGARCH (3 4)	-2.717086	-2.458839
ARIMA (2 0 2) EGARCH (3 4)	-2.844235	-2.584727

Based on Table 3.7 is obtained that ARIMA (1 0 1) EGARCH (3 4) is an EGARCH model that has the smallest AIC value with all parameters have a p-value < 0.05 so all parameters on ARIMA (1 0 1) EGARCH (3 4) are significant . So the best EGARCH model For measure and predict stock return volatility is ARIMA (1 0 1) EGARCH (3 4).

Tabel 3.8 TGARCH results of estimating model parameters

Model	AIC	SIC
ARIMA (0 0 1) TGARCH (4 2)	-2.380664	-2.187915
ARIMA (1 0 0) TGARCH (4 2)	-2.489336	-2.295651
ARIMA (1 0 1) TGARCH (4 2)	-2.476434	-2.261229
ARIMA (0 0 2) TGARCH (4 2)	-2.408026	-2.215277
ARIMA (2 0 0) TGARCH (4 2)	-2.566078	-2.371447
ARIMA (1 0 2) TGARCH (4 2)	-2.484679	-2.269473
ARIMA (2 0 1) TGARCH (4 2)	-2.519209	-2.302952
ARIMA (2 0 2) TGARCH (4 2)	-2.509528	-2.293272

Based on Table 3.8 is obtained that ARIMA (2 0 0) TGARCH (4 2) is a TGARCH model that has the smallest AIC value with all parameters have a p-value < 0.05 so all parameters on ARIMA (2 0 0) TGARCH (4 2) are significant . So the best EGARCH model For measure and predict stock return volatility is ARIMA (2 0 0) TGARCH (4 2).

Table 4.9 Comparison of the best EGARCH and TGARCH models

Model	AIC	SIC
ARIMA (1 0 1) EGARCH (3 4)	-2.860899	-2.602652
ARIMA (2 0 0) TGARCH (4 2)	-2.566078	-2.371447

Based on Table 3.9 can concluded that ARIMA (1 0 1) EGARCH (3 4) has more performance _ Good than ARIMA (2 0 0) TGARCH (4 2) because the ARIMA (1 0 1) EGARCH (3 4) model has all parameters are significant and the values of AIC and SIC are more small .

4. CONCLUSION

Based on analysis on stock daily return data it was found that there was asymmetric volatility in data returns so that modeling was carried out using EGARCH and TGARCH because they could overcome the asymmetric effects contained in the data. In this study it was found that ARIMA (1 0 1) EGARCH (3

4) is a model that shows the best performance by value of AIC where is it the smallest and the significance of all parameters.

The ARIMA (1 0 1) EGARCH (3 4) model formed for forecasting returns and volatility is as follows:

$Y_t = 0.790493_{t-1} + \mu$-0.774343$\varepsilon_{t-2} + \varepsilon_t$with$ln(\sigma_t^2) = -0.368 - 0.092\left(\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right|\right) + 0.154\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right) + 0.384\, ln(\sigma_{t-1}) + 0.465\, ln(\sigma_{t-2}) + 0.125(\sigma_{t-3}) + 0.141(\sigma_{t-4})$.

ARIMA (1 0 1) EGARCH (3 4) models also have the MAE (Mean Absolute Error) value is 0.044%.

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