COMPARISON OF SYMMETRIC AND ASYMMETRIC GARCH MODELS IN THE FUTURES CONTRACT OF ROBUSTA COFFEE IN JAKARTA FUTURES EXCHANGE

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Abstract- Futures exchange is growing rapidly in various countries and has become one of the supports for the economic development of the country. However, research on investment in this field in Indonesia is limited. This study compares the symmetric and asymmetric GARCH models to investigate the volatility of the futures price data of Robusta coffee in the Jakarta Futures Exchange. It used the GARCH, EGARCH, and GJR-GARCH models. Meanwhile, the data used were robusta coffee prices, covering spot prices, March contract prices, and September contract price for the 2016-2019 period. The results of the study indicate that the GARCH (1,1) is the most suitable model for the three Robusta coffee prices.

Index Terms**-** Futures, Robusta Coffe, GARCH, Asymetric GARCH

I. Introduction

A futures exchange is a place that facilitates the sale and purchase of futures contracts for a number of agricultural, plantation, mining, and other types of commodities at a predetermined price and at a specified time in the future for the delivery (Hull, 2008). In the futures market, trading is based on a standardized contract called a futures contract. In the futures exchange, there are two important roles, namely the hedger and the speculator. The hedger group is the party that takes advantage of the existence of a futures exchange to manage risks due to price fluctuations of the commodities. Meanwhile, the speculator group is the party that takes advantage of commodity price fluctuation on the stock exchange for profit. Predicting in this futures market can result either in profit or loss. The potential profit of the speculation is proportional to the risks that have to be faced, depending on the skill of the speculator in predicting price fluctuation.

In the financial sector, there are many time series that have high volatility and diversity which differ at each point in time. According to (Enders, 1995), time-series data with non-constant variations are called time series data with heteroscedasticity. It can be solved using the Autoregressive Conditional Heteroscedastic (ARCH) model. The ARCH model was introduced by Engle (1982). This model was later developed by Bollerslev (1986) and called the GARCH model. Several studies on economic data indicate that returns have asymmetric volatility in which there are differences in volatility movements towards an increase or decrease in asset prices. Research conducted by Arifin et al (2017) on data on three stock assets in Indonesia using the GARCH and EGARCH models showed that the EGARCH model was better. Another study by Julia et al (2018) revealed the comparison of the GARCH model and some asymmetric EGARCH models, namely EGARCH and TGARCH for modeling the return of the Composite Stock Price Index (IHSG). It showed that the asymmetric GARCH model is better than the GARCH model. Therefore, the researcher is interested in applying the symmetrical and asymmetric GARCH models in the case of the futures exchange in Indonesia.

Jakarta Futures Exchange (JFX) is the first futures exchange in Indonesia. One of the commodities currently dominating the transactions at JFX is Robusta Coffee. Indonesia is the 4th world's largest coffee producer after Brazil, Vietnam, and Colombia. Besides, the increase in popularity of the coffee business will increase the coffee trade between farmers and traders or coffee entrepreneurs which can attract more investors. Therefore, the researcher is interested in using the commodity price data of robusta coffee in JFX. This study aims to compare the symmetric and asymmetric GARCH models to investigate the volatility of the futures price data for the Robusta coffee in the Jakarta Future Exchange. It used the GARCH, EGARCH, and GJR-GARCH models

II. Materials And Methods

2.1 Return

Investors invest to get return assets from the results of the investment. According to (Tsay, 2010), suppose P_t represents the asset price at time t, then to find the log return if represents the asset price at t-time, the log return can be calculated with the following equation:

$$R_t = \ln(1 + R_t) = \ln\frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1}$$

P_{t-1} shows the asset price at the end of the period $t - 1$.

2.2 Stationary Test

Stationer time series data have a constant mean and variance (Cryer, 2008). One of the data stationary tests is the Augmented Dickey-Fuller (ADF) test. The model to be tested is:

$$\Delta Y_t = aY_{t-1} + \emptyset_1 \Delta Y_{t-1} + \cdots + \emptyset_k \Delta Y_{t-p+1} + \varepsilon_t$$

Y_t represents the time series data in the t-period and k lag order of the auto-regression process. The Dickey-Fuller test has the following hypothesis.

$H_0 :\ a = 0$ or non-stationary data

$H_1 :\ a < 0$ or stationary data

Statistics Test

$$\tau^* = \frac{\hat{a}}{se(\hat{a})}$$

If the value of $|\tau^*|$ is higher than the critical value of τ Dickey-Fuller with the degree of freedom (n) and significance level (α), then, H_0 is rejected, thus it can be said that the data are stationary.

2.3 Autoregressive Integrated Moving Average (ARIMA)

The identification of the ARIMA model (p, d, q) was performed after the data are stationary. If the data are not differencing (the data have been stationary), then d will be 0 and if the data become stationary after the first differencing, then d will be 1 and so on. Cryer (2008) formulates some general ARIMA models:

a.ARIMA Model (0,0,q) or MA(q)

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_q \varepsilon_{t-q}$$

b.ARIMA Model (p,0,0) or AR(p)

$$Y_t = \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \phi_q Y_{t-p} + \varepsilon_t$$

c.ARIMA Model (p,0,q) or ARMA(p, q)

$$Y_t = \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_q \varepsilon_{t-q}$$

where :

ϕ = *autoregressive* parameter

θ = *moving average* parameter

p = *autoregressive level*

q = *moving level*

ε_t = residual

2.4 Ljung-Box Test

The Ljung-Box test is an error autocorrelation test of the ARMA model that has been formed. The test hypothesis covers:

$H_0 :\ \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (there is no autocorrelation)

H_1 : at least one $\rho_k \neq 0$ for k = 1,2,…,k (there is autocorrelation)

Statistic Test

$$Q = n(n+2)\sum_{k=1}^{K}\frac{\hat{r}_k^{\,2}}{n-k}$$

The decision on the residual autocorrelation hypothesis is if the value of $Q \leq X^2_{[\alpha;K-p-q]}$ at the significance level of α or the p-value of the Q test statistic is higher than the α value, then H is not rejected meaning that there is no autocorrelation.

2.5 Heteroscedasticity Test

The time series model covers an error process which is usually denoted by ε_t. One of the assumptions that should be met is the assumption of homoscedasticity in which variance of the residuals does not change with changes in one or more independent variables. Meanwhile, if the residual variance is not constant, the residual is heteroscedasticity. The AutoRegressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test is to determine the presence of heteroscedasticity effects on data.

If $\varepsilon_t = X_t - \mu_t$ is the error of the mean equation, then ε_t^2 is to check the heteroscedasticity or ARCH effect. This test is the same as the F statistics in the linear regression.

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_t^2 + \cdots + \alpha_p\varepsilon_{t-L}^2 + w_t$$

T represents the number of observations and w_t is the error. The hypothesis of the ARCH-LM test is as follows:

$H_0 : \alpha_0 = \alpha_1 = \cdots = \alpha_p = 0$ (no ARCH effect)

H_1: at least one $\alpha_k \neq 0, k = 0,1,2,\dots,p$(there is an ARCH effect)

2.6 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

Financial time series data such as stock price index, return assets, exchange rates, and others tend to fluctuate from time to time. This fluctuation makes the data variability relatively high and time-varying variance. One of the models that can be used is the Autoregressive Conditional Heteroscedasticity (ARCH) model. This model was then developed into Generalized Autoregressive Conditional Heteroscedasticity (GARCH). The GARCH model (p, q) can be seen below (Montgomery et.al, 2007).

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2 + \sum_{j=1}^{q}\alpha_j\varepsilon_{t-j}^2$$

σ_t^2 is *conditional variance*, α_j and ε_{t-j}^2 are components of ARCH, β_i and σ_{t-i}^2 are components of GARCH. In the GARCH model (p,), ε_t is generated by the process of $\varepsilon_t = z_t\sigma_t$ where σ_t the positive root of σ_t^2 and z_t is the *iid* process (*independent and identically distributed*).

2.7 Asymmetric GARCH

The weakness of the GARCH model is that it cannot capture asymmetric effects. The asymmetric effect is the difference in the changes in volatility when there is a movement in the return value. Some models have been developed to overcome the weaknesses of GARCH including the Exponential GARCH which was introduced by Nelson in 1991. The EGARCH model is expressed in the following equation.

$$log\,\sigma_t^2 = \omega + \sum_{i=1}^{p}\beta_i ln\,\sigma_{t-i}^2 + \sum_{j=1}^{q}\alpha_j\,|z_{t-j}| + \sum_{j=1}^{q}\gamma_j\,z_{t-j}$$

The GJR-GARCH model was proposed by Glosten *et a*l. in 1993 as cited by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2 + \sum_{j=1}^{q}\alpha_j\varepsilon_{t-j}^2 + \sum_{j=1}^{q}\gamma S_j^-\varepsilon_{t-j}^2$$

where S_j^- is a dummy variable which has a value of 1 if ε_{t-j} is negative and 0 if ε_{t-j} is positive. The asymmetric effect can be detected by looking at the coefficient γ on the asymmetric GARCH model. The resulting coefficient $\gamma \neq 0$ showed a significant asymmetric effect (Dutta, 2014).

2.8 Best Model Criteria

In data analysis, commonly some models can represent data. One of the best models among them is selected with several criteria based on error analysis and forecast. One of the error analysis is Akaike Info Criterion (AIC). Meanwhile, based on the forecast, it can use Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Root Mean Square Error (RMSE).

1. Akaike Info Criterion (AIC)

   $\mathrm{AIC} = -2\ln(\mathrm{l}) + 2\mathrm{k}$

dengan

$$l = -\frac{R}{2}\left[1 + \log(2\pi) + \log\left(\frac{\varepsilon'\varepsilon}{R}\right)\right]$$

2. Mean Absolute Deviation

$$\text{MAD} = \frac{1}{T}\sum_{t=1}^{T}\left|Y_t - \widehat{Y_t}\right|$$

3. Mean Square Error

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{Y_t})^2$$

4. Root Mean Square Error

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{Y_t})^2}$$

where T = number of data, Y_t = actual data, $\widehat{Y_t}$ = predicted data. The model is better if the statistic value of AIC, MAD, MSE, and RMSE is smaller.

2.10 Data

This study used daily close price data of the Robusta coffee commodity on the Jakarta Futures Exchange from January 4, 2016, through December 31, 2019. The data covered spot price and contract price data of March and September contracts. Data in the period January 4, 2016 - December 20, 2019, were used to obtain the best modeling, while data in the period of December 21, 2019 - December 31, 2019, were for model validation.

III RESULT

3.1 Data Exploration

This study used daily close price data of the Robusta coffee commodity on the Jakarta Futures Exchange from January 4, 2016, to December 20, 2019. It used a total of 1448 data consisting of three types of Robusta coffee prices, namely the spot price, March contract price, and September contract price.

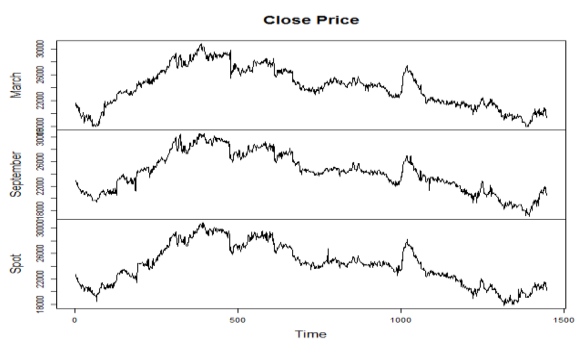

Figure 1 Plot of Robusta Coffee Closing Price

Based on Figure 1, the robusta coffee closing price plot showed up and down trends. Based on the two plots, the pattern tends to be the same in which it started to increase in early 2017 and decreased in early 2018. Based on the Statistics of Indonesian Coffee Commodities in 2016, the coffee land damages in 2018 reaching 158,593 hectares (ha) of the total land area of 1.25 million ha. This may be the cause of the decline in robusta coffee prices in 2018. Then, the return of the daily closing price data was calculated. The descriptive statistics and plots of the Robusta spot return and contract can be seen below.

Table 1 Descriptive statistics of robusta coffee price return

Return	Spot	March	September
Mean	-0.000076	-0.000076	-0.000086
Min.	-0.08588	-0.1107	-0.08512
Max.	0.09574	0.07505	0.09511
Skewness	-0.09807	-0.54896	0.3661
Kurtosis	8.46983	7.60895	8.257441
Kolmogorov-Smirnov	0.0000*	0.000*	0.000*

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Based on Table 1, the mean value of the return spot and march contract is higher than that of the september contract. The negative skewness value on the return spot and march contract indicated that the data distribution was the long left tail. Meanwhile, the September contract return was positive, so it has a long right tail. Then, the three returns have a kurtosis value that is not equal to 3. Therefore, based on the skewness and kurtosis values, it illustrates the asymmetry of the normal distribution. These results are supported by the Kolmogorov-Smirnov test result which produces a p-value of less than 5%.

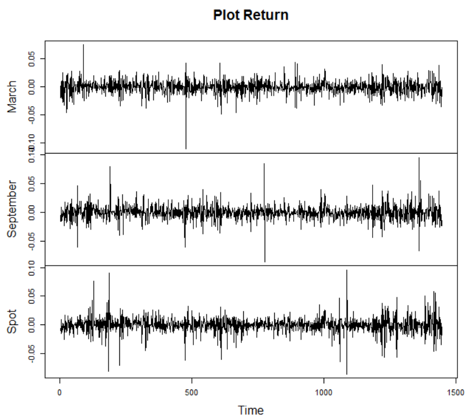

Figure 2 Plot Return of Robusta Coffee

Robusta	p-value
Spot	0.01
March	0.01
September	0.01

Figure 2 is a plot of the return spot and the two contract returns. The plot of the return spot can be used to identify the stationary data. Data are stationary if the observed data do not have a certain movement pattern, or do not contain a trend. Figure 2 shows that there are no more up or down trends. Stationary can be tested using the Augmented Dickey-Fuller (ADF) test. The result of the ADF Test is presented in Table 2.

Table 2 Results of ADF Test

Table 2 shows the result of the data stationary test using the Augmented Dickey-Fuller (ADF) test. Based on the ADF test, the three data were stationary at the significance level of 5%. After the return is declared stationary, the next step is the ARMA modeling.

3.2 ARIMA Model

The initial model used for this study was the ARMA model. The selection of candidate models was based on the order simulation from the ACF and PACF plots. The selected ARIMA model is the one with the smallest AIC value and significance coefficient. Besides, some additional models would be tested for compatibility, where the order p and q were obtained through a trial and error process. Based on those considerations, the best model for each robusta price is as follows:

Table 3 The Best ARIMA Model

Robusta	Model	Parameter	Estimation	p-value
Spot	ARIMA	AR(1)	-0.99028	0.000
	(2,0,4)	AR(2)	-0.67868	0.000
		MA(1)	1.0306	0.000
		MA(2)	0.49894	0.001
		MA(3)	-0.2599	0.000
		MA(4)	-0.16837	0.001
March	ARIMA	MA(1)	0.089001	0.000
	(0,0,3)	MA(2)	-0.19721	0.000
		MA(3)	-0.11281	0.000

September	ARIMA (2,0,1)	AR(1)	0.39393	0.000
		AR(2)	-0.17729	0.000
		MA(1)	-0.37507	0.001

Based on table 3, the best ARIMA model for robusta spot is ARIMA (2,0,1). While the best model for March and September were ARIMA (0,0,3) and ARIMA (2,0,4) respectively. Then, the ARCH LM test was carried out to see heteroscedasticity in the remain model. The null hypothesis of the ARCH LM test is that there is no heteroscedasticity in the remain model.

Table 4 The Result of ARCH-LM test

Robusta	Lag					
	1	2	3	4	5	6
Spot	0.000	0.000	0.000	0.000	0.000	0.000
March	0.000	0.000	0.000	0.000	0.000	0.000
September	0.000	0.000	0.000	0.000	0.000	0.000

Based on Table 4, the result of the heteroscedasticity test at lag 1 - 6 showed a very small p-value. P-value which is smaller than the significance level of 5% means that the null hypothesis is rejected. It means there is heteroscedasticity in the remain models. Heteroscedasticity in the remain of the ARIMA model can be solved using the GARCH model and asymmetric GARCH model.

3.3 GARCH Model

The process of selecting the best GARCH model was carried out by combination simulation of predetermined orders, namely GARCH (1,1), GARCH (1,2), GARCH (2,1), and GARCH (2,2). The ARCH/GARCH model selection was based on the AIC value of each model and the significance of the parameters. The results of the GARCH model for each robusta can be seen in Table 5.

Table 5 The best GARCH model

Parameter	Spot	March	September
	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
ω	0.000066	0.000064	0.000068
	(0.000)	(0.000)	(0.000)
α_1	0.387601	0.408370	0.485760
	(0.000)	(0.000)	(0.000)
β_1	0.255707	0.129625	0.107781
	(0.000)	(0.009)	(0.000)
AIC	-6.0311	-6.2568	-6.1739

Based on the significance of the parameters and the smallest AIC, the best GARCH model for robusta is GARCH (1,1). Table 5 shows the predicted values for the GARCH model parameters (1,1) for robusta spot, march, and september. All parameter values were less than 5%. The result of the residual test on the three selected models showed no autocorrelation and heteroscedasticity.

3.4 Asymmetric GARCH

The GARCH model assumes that there is no difference in the effect of volatility when there is a negative or positive movement. There was an indication that returns have asymmetric volatility. Thus, to detect an asymmetric effect on the return volatility behavior, several GARCH asymmetric models are specified with the best order model that has been obtained in the symmetric model. They were EGARCH and GJR-GARCH models in which the best asymmetric GARCH model with the smallest AIC criteria would be selected.

Table 6 The Best Asymmetric Model

Parameter	Spot GJR-GARCH(1,1)	March EGARCH(1,1)	September EGARCH(1,1)
ω	0.00007	-5.959710	-5.759374
	(0.000)	(0.000)	(0.000)
α_1	0.47627	0.009153	-0.018357
	(0.000)	(0.815)	(0.616)
β_1	0.164695	0.340790	0.357774
	(0.000)	(0.000)	(0.000)
γ	0.012616	0.712626	0.0847718
	(0.9131)	(0.000)	(0.000)
AIC	-6.0494	-6.2723	-6.2348

Table 6 shows the most appropriate estimation result of the asymmetric model. The coefficient γ indicates the presence of an asymmetric effect. It showed the estimated value of $\gamma \neq 0$ with positive and significant at the significance level of 5% for March and September. Meanwhile, the spot is not significant at the 5% level. Then, based on the residual test, the three models have no autocorrelation and heteroscedasticity up to the 6th lag.

3.5 Selection of the Best Model

Based on the result of the study, the symmetric GARCH model presents a better model than the asymmetric GARCH model. It can be seen from the significance level of the parameters. The objective of the selected model is for simulation, so it requires a good model in terms of forecasting. Therefore, model validation was carried out by calculating the MAD, MSE, and RMSE values. The data used for validation were data from the period of December 21, 2019, to December 31, 2019. The comparison result of the MAD, MSE, and RMSE values can be seen in the following table.

Table 7 Summary of the Validation Result

Robusta	Model	MAD	MSE	RMSE
Spot	GARCH(1,1)	0.0280	0.0012	0.0350
	GJR-GARCH(1,1)	0.0284	0.0013	0.0357
March	GARCH(1,1)	0.0072	0.0001	0.0098
	EGARCH(1,1)	0.0074	0.0001	0.0099
September	GARCH(1,1)	0.0685	0.0098	0.0988
	EGARCH(1,1)	0.0687	0.0098	0.0988

Based on the table above, the validation result for robusta spot showed that the MAD, MSE, and RMSE value of the GARCH(1,1) is smaller than GJR-GARCH (1,1). Then, in the march contract, the MAD and RMSE value in GARCH (1.1) is smaller than EGARCH (1.1). Similar to the september contract, the MAD value on GARCH (1,1) is smaller than MAD value of the EGARCH (1.1). Therefore, the best model based on validation in forecasting for robusta spot returns, march contracts, and september contracts is the GARCH (1,1).

IV CONCLUSION

The high fluctuation of the return data results in the residual of the ARMA model with autocorrelation and non-homogeneous. To solve this problem, simultaneous modeling was carried out using the ARMA model for its mean function and using GARCH/EGARCH/GJR-GARCH model for its conditional variance function. The selected model was then obtained by looking at the significance of the parameters and the validation. The selected model for the spot price, March contract, and September contract is the GARCH (1,1).

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