Investment and Margin Risk Analysis of Robusta Coffee Futures Contract at Jakarta Futures Exchange

Puspa Renggani1*, I Made Sumertajaya1, Farit Mochamad Afendi1, and Retno Budiarti2
1Department of Statistics, IPB University
2Department of Mathematics, IPB University

*E-mail: puspa_renggani@apps.ipb.ac.id

Abstract. Futures trading is developing rapidly in various countries and has become one of the supports for economic growth. However, studies on investment in futures contracts in Indonesia, particularly in measuring risk are still limited. This study aims to calculate the maximum potential loss on investment and the estimated margin on robusta coffee futures at JFX using Value at Risk (VaR). The analysis used symmetrical and asymmetric GARCH (Exponential-GARCH, Threshold-GARCH, and GJR-GARCH). It used data of robusta coffee price, covering spot prices, March contract prices, and September contract prices for the 2016-2019 period. The result of the study indicates that the GARCH (1,1) is the most suitable model for the three robusta coffee prices. Based on the VaR value, the investment risk in the robusta spot is higher than the robusta contract. The margin value interval that may be applied to JFX robusta coffee based on spot price analysis, March contracts, and September contracts reach 2.39% - 2.91%.

1. Introduction
Futures trading develops rapidly in various countries and has become one of the supports for economic growth. A futures exchange is a marketplace for the sale and purchase of futures contracts for some agricultural and plantation commodities, mining products, and others at a certain price in which the delivery is agreed for a future date. Trading that occurs in the futures market is based on a standardized contract or a futures contract. The futures exchange covers three important roles, namely hedgers, speculators, and brokers. [1] The hedger group is a party that takes advantage of the existence of a futures exchange to manage risks due to price changes of the handled commodities. Meanwhile, the speculator group is a party that takes advantage of commodity price changes that occur on the stock exchange for profit. Speculation in this futures market can result either in profit or loss. The potential profit of this speculation is proportional to the risks that must be faced depending on the skill of the speculator in predicting price changes. In the futures exchange transaction, investors cannot make a direct transaction. They have to go through an intermediary called a broker. In this case, the investor has to hand over a certain amount of margin or guarantee for the transaction. The determination of the margin value is also important. When an investor's investment experiences a loss, the margin will be reduced or even increased to cover the loss. Therefore, it requires skills in predicting the risks that might occur. The predictable risk becomes the investor’s consideration in making decisions and can be the range in determining the amount of margin.
One of the methods to measure risks is Value at Risk (VaR). VaR can be defined as a prediction of the maximum potential loss in a certain period with a certain level of confidence. Besides precise risk measurement, it should also be noted that financial market data are fluctuating. There are time series in the financial sector with high volatility and diversity which differ at each point in time. Time-series data with non-constant variance are called heteroscedastic. It can be solved using the Autoregressive Conditional Heteroscedasticity (ARCH) model. The ARCH model was introduced by Engle (1982) and then it was later developed by Bollerslev (1986) called GARCH. [2]

Several studies on economic data indicate that returns have asymmetric volatility, that is, there are differences in volatility movements towards an increase or decrease in asset prices. Research conducted by Arifin et al on data on three stock assets in Indonesia with GARCH and GARCH asymmetric models showed that the GARCH asymmetric model is better [3]. Another study by Julia et al provides an overview of the comparison of the GARCH model and some GARCH asymmetric models, namely EGARCH and TGARCH in modeling the Composite Stock Price Index (IHSG) return. It revealed that the asymmetric GARCH model is better than GARCH. [4] Therefore, the researcher is interested in applying the asymmetric GARCH model to the futures exchange cases in Indonesia. Jakarta Futures Exchange (JFX) is the first futures exchange in Indonesia. One of the current dominating commodity transactions at JFX is robusta coffee. Indonesia is the 4th largest coffee producer in the world after Brazil, Vietnam, and Colombia. Moreover, the increasing popularity of the coffee business, coffee trade between farmers and traders, or coffee entrepreneurs will increase so that investors will be interested in investing. Therefore, researchers are interested in using the price data of robusta coffee commodities at JFX.

2. Materials and Methods

2.1 Return

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

\[
R_t = \ln \frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1}
\]

\( P_{t-1} \) shows the asset price at the end of the period \( t - 1 \). [5]

2.2 Stationary Test

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

\[
\Delta Y_t = aY_{t-1} + \varnothing_1\Delta Y_{t-1} + \cdots + \varnothing_k\Delta Y_{t-p+1} + \varepsilon_t
\]

\( Y_t \) 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

\[
\tau^* = \frac{\hat{a}}{\text{se}(\hat{a})}
\]

If the value of \( |\tau^*| \) is higher than the critical value of \( \tau \) Dickey-Fuller with the degree of freedom (n) and significance level (\( \alpha \)), 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)
\[ Y_t = \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q} \]

b. ARIMA Model (p,0,0) or AR(p)
\[ Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t \]

c. ARIMA Model (p,0,q) or ARMA(p, q)
\[ Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q} \]

where:
\( \phi \) = autoregressive parameter
\( \theta \) = moving average parameter
\( p \) = autoregressive level
\( q \) = moving level
\( \epsilon_t \) = residual

2.4 Ljung-Box Test
The Ljung-Box test is an error autocorrelation test of the ARIMA 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 \( k = 1, 2, \ldots, k \) (there is autocorrelation)

Statistic Test
\[ Q = n(n + 2) \sum_{k=1}^{K} \frac{r_k^2}{n - k} \]

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 \( \alpha \) or the \( p \)-value of the Q test statistic is higher than the \( \alpha \) 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 \( \epsilon_t \). 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. [6] The AutoRegressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test is to determine the presence of heteroscedasticity effects on data.
\[ LM = TR^2 \]

\( T \) represents the number of observations and \( R^2 \) is determination coefisient. The hypothesis of the LM test is as follows:
\( H_0 : \alpha_0 = \alpha_1 = \cdots = \alpha_p = 0 \) (no ARCH effect)
\( H_1 : \) at least one \( \alpha_k \neq 0, k = 0, 1, 2, \ldots, p \)(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. [7] This model was then developed into Generalized Autoregressive Conditional Heteroscedasticity (GARCH). The GARCH model \((p, q)\) can be seen below.
\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 \]
\( \sigma_t^2 \) is conditional variance, \( \alpha_l \) and \( \varepsilon_{t-j}^2 \) are components of ARCH, \( \beta_i \) and \( \sigma_{t-i}^2 \) are components of GARCH. In the GARCH model (p,q), \( \varepsilon_t \) is generated by the process of \( \varepsilon_t = z_t\sigma_t \) where \( \sigma_t \) the positive root of \( \sigma_t^2 \) and \( z_t \) is the iid process (independent and identically distributed). [8]

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 al. in 1993 as cited by:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \gamma_j S_{t-j} \varepsilon_{t-j}^2
\]

where \( S_{t-j} \) is a dummy variable which has a value of 1 if \( \varepsilon_{t-j} \) is negative and 0 if \( \varepsilon_{t-j} \) is positive. Then, the Threshold GARCH (TGARCH) is quite similar with the GJR in the use of the dummy variable but the TGARCH model proposed by Zakoian in 1994 using standard deviation.

\[
\sigma_t = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i} + \sum_{j=1}^{q} \alpha_j |\varepsilon_{t-j}| + \gamma_j I_{\varepsilon_{t-j}<0} \varepsilon_{t-j}^2
\]

The asymmetric effect can be detected by looking at the coefficient \( \gamma \) on the asymmetric GARCH model. The resulting coefficient \( \gamma \neq 0 \) showed a significant asymmetric effect. [9]

2.8 Value at Risk (VaR)

VaR is defined as the maximum potential loss that investors will experience at a certain period with a certain level of confidence [10]. Technically, VaR with the confidence level \( 1-\alpha \) is expressed as the quantile of the return distribution. If the initial investment of the investor is denoted by \( W_0 \) and the quantile value of the return distribution is \( R^* \), then the VaR at the confidence level of \( 1-\alpha \) in t-period is as follows:

\[
\text{VaR} = W_0 R^*/\sqrt{t}
\]

The simulation approach is one of the method to predict VaR. [11]

1. Generating the standard error (\( z_t \)) from the best distribution function
2. The standard error (\( z_t \)) of the generation is multiplied by \( \sigma_t \) to find the error (\( \varepsilon_t \))
3. The R-value is gained by adding \( \varepsilon_t \) error with the \( \mu \) parameter of the best ARIMA-GARCH model
4. Sorts R values from low to high
5. If \( R_1 < R_2 < \cdots < R_n \) is the return sequence, \( \alpha \) is significance level, \( k = [\alpha.n] + 1 \) with [.] of the largest integer function, then the VaR value is determined by \( \forall R_\alpha = R_k \)
6. Repeating steps 1 - 5 for 1000 times, so that they reflect several possible VaRs, namely \( \forall R_\alpha = R_k \)
7. Counting the average results of step 6 to stabilize the VaR value.

2.9 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 Akaikie 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)
   \[ AIC = -2 \ln(l) + 2k \]
dengan
   \[ l = -\frac{R}{2} \left[ 1 + \log(2\pi) + \log\left(\frac{\epsilon'}{R}\right) \right] \]
2. Mean Absolute Deviation
   \[ \text{MAD} = \frac{1}{T} \sum_{t=1}^{T} |Y_t - \hat{Y}_t| \]
3. Mean Square Error
   \[ \text{MSE} = \frac{1}{T} \sum_{t=1}^{T} (Y_t - \hat{Y}_t)^2 \]
4. Root Mean Square Error
   \[ \text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (Y_t - \hat{Y}_t)^2} \]

where \( T \) = number of data, \( Y_t \) = actual data, \( \hat{Y}_t \) = 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, to January 19, 2020. 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 - January 19, 2020, were for model validation.

3. 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](image)

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*     |

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%. It means that the two returns are not normally distributed at the significance level of 5%.

![Figure 2 Plot Return of Robusta Coffee](image)

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**

| Robusta      | p-value |
|--------------|---------|
| Spot         | 0.01    |
| March        | 0.01    |
| September    | 0.01    |

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 ARIMA modeling.
3.2 ARIMA Model
The initial model used for this study was the ARIMA 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:

| Robusta | Model | Parameter | Estimation | p-value |
|---------|-------|-----------|------------|---------|
| Spot   | ARIMA (2,0,4) | AR(1) | -0.99028 | 0.000 |
|         |       | 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 (0,0,3) | MA(1) | 0.089001 | 0.000 |
|         |       | 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 (2,0,4). While the best model for March and September were ARIMA (0,0,3) and ARIMA (2,0,1) 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.

| 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) |
| \(\omega\) | 0.000066 (0.000) | 0.000064 (0.000) | 0.000068 (0.000) |
| \(\alpha_1\) | 0.387601 (0.000) | 0.408370 (0.000) | 0.485760 (0.000) |
| \(\beta_1\) | 0.255707 (0.000) | 0.129625 (0.009) | 0.107781 (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, TGARCH, 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 | March | September |
|-----------|------|-------|-----------|
|           | GJR-GARCH(1,1) | EGARCH(1,1) | EGARCH(1,1) |
| \(\omega\) | 0.00007 (0.000) | -5.959710 (0.000) | -5.759374 (0.000) |
| \(\alpha_1\) | 0.47627 (0.000) | 0.009153 (0.815) | -0.018357 (0.616) |
| \(\beta_1\) | 0.164695 (0.000) | 0.340790 (0.815) | 0.357774 (0.616) |
| \(\gamma\) | 0.012616 (0.9131) | 0.712626 (0.000) | 0.0847718 (0.000) |
| AIC | -6.0494 | -6.2723 | -6.2348 |

Table 6 shows the most appropriate estimation result of the asymmetric model. The coefficient \(\gamma\) 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, AIC from the asymmetric GARCH model presents a better model than the symmetric GARCH model. But, the symmetric GARCH model presents a better model than the asymmetric GARCH model 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 January 19, 2020. 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)      | 0.0214 | 0.00136  | 0.0368|
|               | GJR-GARCH(1,1)  | 0.0218 | 0.00139  | 0.0373|
| March         | GARCH(1,1)      | 0.0155 | 0.00055  | 0.0236|
|               | EGARCH(1,1)     | 0.0156 | 0.00057  | 0.0239|
| September     | GARCH(1,1)      | 0.0197 | 0.0079   | 0.0280|
|               | EGARCH(1,1)     | 0.0198 | 0.0080   | 0.0284|

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). Similar to the March and September contracts, the MAD, MSE, and RMSE value of the GARCH (1,1) is smaller than EGARCH. Therefore, the best model based on validation in forecasting for robusta spot, March contracts, and September contracts is the GARCH (1,1).

### 3.6 Calculation of Value at Risk

After obtaining the ARIMA-GARCH model, then the next step is to find the correct distribution for the standard error of each model by plotting the empirical distribution and estimating the distribution which is close to the empirical distribution of the standard error ($\hat{z}_t$).

![Figure 3. Comparison of empirical $\hat{z}_t$ (spot, March and September contracts), t-student, and normal distribution](image)

It can be seen from the figure for each robusta, t-student is closer to the form of empirical. Then, the obtained distribution was to generate data as much as the number of initial observations based on the obtained parameter and the best ARIMA-GARCH model to calculate the Value at Risk.

### Table 8. Result of Value at Risk Calculation

| Robusta   | Value at Risk |
|-----------|---------------|
| Spot      | 2.91%         |
| March     | 2.39%         |
| September | 2.77%         |
Table 8 shows the result of the VaR calculation. It can be seen that at the confidence level of 95%, the value at risk of robusta spot reaches 2.91%, while March and September contracts are 2.39% and 2.77% respectively. The estimation of the value at risk is not only required by investors but also by a broker of the futures exchange. In the transaction in the futures exchange, investors are required to deposit margin. Thus, the determination of the right amount of margin helps the broker in managing the potential financial risk. Therefore, the Value at Risk calculation can be a consideration in determining the margin value. The result of VaR calculations for spot prices, march and september contracts of 2.39% - 2.91% can be used as an interval in determining the robusta margin in the Jakarta Futures Exchange.

4. RESULT

The estimated value of VaR for robusta spot reaches 2.91%, while for March and September contracts are 2.39% and 2.77% respectively. Based on the VaR, it can be calculated that the investment risk for the robusta spot is higher than that of March and September contracts. Based on the VaR, the interval of the margin of 2.39% - 2.91% can be used as an estimation.

References

[1] Siregar A, Nasution B, Syahrin A, Nasution S 2012 Analisis Yuridis Kontrak Olein pada Perdagangan Bursa Berjangka Jakarta USU Law Journal 4(4): 124-131
[2] Bollerslev, T 1986 Generalized Autoregressive Conditional Heterokedasticity Journal of Econometrics 31:307-327
[3] Arifin M, Tarno, Budi W 2017 Pemodelan Return Portofolio Saham Menggunakan Metode Garch Asimetris Jurnal Gaussian 6:51-60
[4] Julia, Wahyuningsih S, Hayati 2018 Analisis Model Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) dan Model Exponential Generalized AutoregressiveConditional Heteroskedasticity (EGARCH) Jurnal Eksponenial 9(2):127-136
[5] Tsay RS 2010 Analysis of Financial Time Series Dalam R S Tsay Analysis of Financial Time Series New Jersey: John Wiley & Sons, Inc
[6] Xu R, Li X 2017 Study About the Minimum Value at Risk of Stock Index Futures Hedging Applying Exponential Weight Moving Average- Generalized Autoregressive Conditional Heteroskedasticity Model International Journal of Economics and Financial Issues7(6): 104-110
[7] Engle R 1982 Autoregressive Conditional Heteroskedasticity with Estimates of The Variance of United Kingdom inflation Journal of Econometrica 50(4):987-1007
[8] Montgomery DC,Jennings CL,Kulahci M 2007 Introduction to Time Series Analysis and Forecasting Toronto: Wiley
[9] Dutta A 2014 Modelling volatility: symmetric or asymmetric garch models? Journal of Statistics: Advances in Theory and Applications.2:99-108
[10] Cao Z, Harris RDF, Shen J 2009 Hedging and Value at Risk : A Semi-Parametric Approach Journal of Futures Markets 30(8) :780-794
[11] Klugman SA, Panjer HH, Willmot GE 2012 Loss Model from Data to Decisions Ed ke-4 New Jersey (US): J Wiley