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GLOSTEN JAGANNATHAN RUNKLE-GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICS *(GJR-GARCH)* METHODE FOR VALUE AT RISK (VaR) FORECASTING

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ABSTRACT

A stock returns data are one of type time series data who has a high volatility and different variance in every point of time. Such data are volatile, seting up a pattern of asymmetrical, having a nonstationary model, and that does not have a constant residual variance (heteroscedasticity). A time series ARCH and GARCH model can explain the heterocedasticity of data, but they are not always able to fully capture the asymmetric property of high frequency. Glosten Jaganathan Runkle-Generalized Autoregresive Heteroskedascticity (GJR-GARCH) model overcome GARCH weaknesses in capturing asymmetry good news and bad news taking into the leverage effect. Furthermore GJR-GARCH models were used to estimate the value of VaR as the maximum loss that will be obtained during a certain period at a certain confidence level. The aim of this study was to determine the best forecasting model of Jakarta Composite Index (JSI). The model had used in this study are ARCH, GARCH, and GJR-GARCH.

Keywords: *Forecasting, Volatility, GJR-GARCH, VaR*

INTRODUCTION

Investments related to the placement of funds in the form of other assets during a certain period with a certain expectation.By the object of lnvestment, asset is generally divided into two, real assets and financial assets. Real assets associated with infrastructure that can provide a direct impact on the productive capacity of an investment object. While financial assets have contributed indirectly to the productive capacity of an economy form, because it separates the ownership with management in a company and facilitate the transfer of funds with attractive investment opportunities (Bodie,2006).

Mehmet (2008) who investigate on stock returns says that the financial returns have three characteristics. The first grouping of volatility, which means that very large changes can occur in a specific time period and small changes in other periods. Both are fat tailedness (excess kurtosis), which means financial returns often to show the tail is greater than the standard normal distribution. The third is the leverage effect, is a state where bad news and good news condition gives non symmetrical effect in their volatility.

Generalized autoregressive conditional heteroskedasticity (GARCH) model caught three main characteristics of the financial return. The development of GARCH type started bu Engle (1982) that introduces heteroscedasticity model ARCH by looking at the relations conditional variance of a linear combination of squares in the past. Subsequently Bollersev (1986) introduced a model Generalized Conditional Autoregresive Heteroskedasticity (GARCH) as improvement of ARCH model. GARCH is a simple model with many parameters that are less than a high degree of ARCH models.

ARCH and GARCH is a model that can explain the time series heteroscedasticity in the data. However, ARCH-GARCH models can not always fully capture their heavy-tail property with high frequency, so it is very difficult to give an offender the decision when the stock will position itself as a buyer or seller. In addition ARCH and GARCH models do not consider the leverage effect in depth. The definition of the leverage effect which is a state of bad news and good news that gives effect to the asymmetric volatility. Data is said to be bad news when volatility has decreased while the state is said to be good news when volatility increased periodically.

GJR-GARCH models introduced independently by Glosten, Jaganathan and Runkle (1993) to take into account the leverage effect. The model is similar to the GJR GARCH model, but there is no previous innovation shadow variable (a dummy variable i_{t-j}), so GARCH had additional expansion variables that are added as a sign for a possible asymmetric.

Risk Metrics (1996) introduce method of Value at Risk (VaR) in the measurement of risk. In the next period of very broad use of this method for measuring various types of risk because in addition to measuring the risk of a single asset can also be used to measure the risk of the assets in a portfolio. Methods Value at Risk (VaR) (Best,1998) is a method of measuring risk that is statistically estimate the maximum loss that may occur on a portfolio level of confidence (confidence level) specific.

METHODS

Stationarity

Statinarity holds a central part in time series analysis. This is an assumption underlying many statistical procedures used in time series analysis. Using stationarized series is relatively easy to bulit a forecasting stuff.

Definition 1.1 Let $\mathcal{T}$ denote the set of all vector $\{t = (t_1, t_2, \dots, t_n)' \in T^n : t_1 < t_2 < \dots < t_n, n =$ 1, 2, ..., joint distribution/cumulative distribution function of $\{X_t, t \in T\}$ is a function $\{F_t(°), t \in \mathcal{T}\}$ defined at $t = (t_1, t_2, \dots, t_n)', x = (x_1, x_2, \dots, x_n) \in \mathbb{R}$ n by

$$\begin{aligned} Fx(x,t) = Ft(x) &= F_{X_{t_1},X_{t_2},\dots,X_{t_n}}(x_1,x_2,\dots,x_n{:}t_1,t_2,\dots,t_n) \\ &= P(X_{t_1} \le x_1, X_{t_2} \le x_2, \dots, X_{t_n} \le x_n,) \\ &= \sum_{i=1}^{T} P_x(x_i) \\ &= P_x(x_1) + P_x(x_2) + \dots + P_x(x_t) \end{aligned}$$

for discrete data,and following for continue data

$$\begin{aligned} Fx(x,t) = Ft(x) &= F_{X_{t_1},X_{t_2},\dots,X_{t_n}}(x_1,x_2,\dots,x_n{:}t_1,t_2,\dots,t_n) \\ &= P(X_{t_1} \le x_1, X_{t_2} \le x_2, \dots, X_{t_n} \le x_n,) \\ &= \prod_{i=1}^{T} f_x(x_i) \\ &= \int f_x(x_1)dx + \int f_x(x_2)dx + \dots + \int f_x(x_t)dx \end{aligned}$$

Definition 1.2 A time series process called strictly stationary if the joint distribution function (CDF) of $X_1, X_2, \dots, X_k$ equal with joint distribution function of $X_{t+1}, X_{t+2}, \dots, X_{t+k}$

$$F_{X_1,X_2,\dots,X_k}(x_1,x_2,\dots,x_k) = F_{X_{t+1},X_{t+2},\dots,X_{t+k}}(x_{t+1},x_{t+2},\dots,x_{t+k})$$

In other words, the entire statistical properties of the strictly stationary process unchanged for the time shift.

Definition 1.3 A time series process $\{X_t, t \in T\}$ with $T = \mathbb{Z} = \{0, \pm 1, \pm 2, \dots\}$ called Wide – Sense Stationary process if comply following properties

$E(|X_t|^2) < \infty, \forall t \in \mathbb{Z}$
$E(X_t) = \mu$, independent with t, $\forall t \in \mathbb{Z}$
$Cov(X_t, X_{t+k}) = Cov(X_{t+1}, X_{t+1+k}) = \dots = Cov(X_{t+p}, X_{t+p+k})$

The other term of "Wide – Sense Stationary" is "weakly stationary", "covariance stationary", or "second order stationary".

Theorema 1.4 If $\{X_t\}$ are stationer, then $Cov(X_t, X_{t+k}) = Cov(X_{t-k}, 0)$a some covariance function depend only on a time (t – k) and independent with t and k.

Autoregressive Conditional Heterocedastic (ARCH) Model

These three common models of time series AR (p), MA (q) and ARMA (p, q) assumes that the variance is homokedastik. In fact, for the majority of the data in the financial sector are heteroscedastic variance.

In ARCH(a) models, obtained the conditional variance of rt on past information as

$V \quad (r_t|\mathcal{F}_{t-1}) = E(\varepsilon_t^2|\mathcal{F}_{t-1}) = \sigma_t^2$ Described by the equation

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \dots + \alpha_m\varepsilon_{t-m}^2 = \alpha_0 + \sum_{i=1}^{a} \alpha_i\varepsilon_{t-i}^2$$

with $\alpha_0 > 0, \alpha_i \ge 0, i = 1, 2, \dots, a$. $\alpha_i \ge 0$ conditions are necessary for non negativ volatility equation. If $\alpha_i = 0, \forall i$, then conditional variance σ_t^2 will be constant α_0. For ARCH (1) model cajn be written:

$$\varepsilon_t = \sigma_t v_t, \sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2, \alpha_0 > 0, \alpha_1 \ge 0, v_t \sim N \quad (0,1)$$

These results suggest that this tail distribution form ε_t, i.e $P(\varepsilon_t > x)$ always thicker than the normal distribution. In other words, the shock function of ε_t of conditional Gaussian models ARCH (1) will generate more extremely events than the usual white noise Gaussian distributed.

Generalized Autoregressive Conditional Heterocedastic (GARCH) Model

GARCH model had developed [2]) in order to streamline the large order that probably occurred on the ARCH models. Define $\varepsilon_t = r_t - \mu_t$ i.e *mean corrected log return*, ε_t said to follow GARCH (a, b) model by

$$\varepsilon_t = \sigma_t v_t \text{ dan}$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{b} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{a} \beta_j \sigma_{t-j}^2$$

with v_t IID (independent identically distributed) N(0,1), $\alpha_0 > 0, \alpha_i \geq 0, i = 1, 2, \ldots, a$, $\beta_j \geq 0, i = 1, 2, \ldots, b$, $\sum_{i=1}^{m} {}^{(m,s)}(\alpha_i + \beta_j) < 1$. Assume $E(\varepsilon_t|\mathcal{F}_{t-1}) = 0$ dan $V \quad (\varepsilon_t|\mathcal{F}_{t-1}) = E({\varepsilon_t}^2|\mathcal{F}_{t-1}) = \sigma_t^2$.

From the existing model, implied a limitation of GARCH is non-negative condition may be violated by this estimation method by the coefficients of the model to be negative. Another thing is the nature of the GARCH model is [7]

1. GARCH model on the volatility forecasting having bad accuration
2. In many case, stock returns have an asymmetric effect that is not detected by GARCH

Glosten,Jagannathan, and Runkle (GJR)-GARCH Model

The following development of GARCH model which further accommodate the symmetrical response volatility. Their different impact for the volatility of the stock that is influenced by good shock (positive issues) and bad shock (negative issues).GJR is Proposed by Glosten Jagannathan, and Runkle in 1993. The model is similar to the GJR GARCH model, but there is no previous innovation shadow variable (a dummy variable i_{t-j}) so GARCH get an additional expansion variables that are added as a sign for the possibility of asymmetric. For asymmetric effect can be seen by the parameter γ>0. In general, GJR models can be defined as follows:

$$Y_t|F_{t-1} \sim N(0, \sigma_t^2) \text{dengan } t = 1,2,\cdots,n \quad \text{with}$$

$$Y_t = \gamma_0 + \gamma_1 + \gamma_2 Y_{t-1} + \beta_0 + \beta_1 Y_{t-1} + \alpha_1 \sigma_t^2 + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_i \sigma_{t-i}^2 + \cdots + \alpha_i \sigma_{t-i}^2 + \beta_j \varepsilon_{t-j}^2 + \cdots + \beta_j \varepsilon_{t-j}^2 + \gamma_j i_{t-j} \varepsilon_{t-j}^2 + \cdots + \gamma_j i_{t-j} \varepsilon_{t-j}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{P} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{Q} \beta_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} \gamma_j i_{t-j} \varepsilon_{t-j}^2$$

For i_{t-j} is a dummy variable value of i_{t-j} equal to ε_{t-j} negatif. equal to zero jika positif. are parameters required for estimation. Variance is positive if $\alpha_0 > 0$, dan $\alpha_i, \beta_j \geq 0$ for each $i = 1,2,\cdots,P$ dan $j = 1,2,\cdots,Q$, so that the model can be accepted.. Although $\gamma < 0$ provided by $\beta_j + \gamma_j \geq 0$ for each $j = 1,2,\cdots,Q$ and the model is said to be stationary $\sum_{i=1}^{P} \alpha_i + \sum_{i=1}^{Q} \beta_j + \sum_{i=1}^{Q} \gamma_j < 1$.

Value at Risk (VaR)

One of instrument to measure risk is VaR (Value at Risk). VaR can be defined as an estimate of the maximum potential loss at a certain period with a certain level of confidence in the condition of the circumstances (market) is normal. VaR always accompanied by the probability that indicates how likely the losses incurred would be less than the VaR value. The advantages of VaR is that these methods focus on downside risk, does not depend on the assumption of the distribution of returns, and the VaR measurement can be applied to all financial products and derivatives trading. Application of various types of approaches ARCH / GARCH them to the circumstances in which the data dissemination return volatility is a major issue. Many banks and other financial institutions use VaR concept as a way to measure the risks faced by the portfolio. VaR 1% means that the amount of money which has a 99% certainty to exceed any loss on the next day. The statisticians call it a 1 percent quantile, because deciphering 1% of poor results and 99% better results. VaR with a confidence level (1-α) has the following formula.

$$V \quad _{(1-\alpha)} = -W_0 R^*$$

with $R^* = \mu - Z_\alpha \sigma_t$ is quantile of the distribution of returns on t.

RESULT AND DISCUSSION

This study takes a case on the movement of the stock price index (JCI) with the daily data for the period June 30th, 2010 until July 1st, 2015 [9]. The JCI analyzed consist of 1222 data in the form of time series. The plot of the closing prices of JCI seen in the following fig 1.

Visually it appears that the data contains closing value JCI trend. In this study analyzed data instead of the raw data, but the data returns (return), in which case the return value of the continuously compound, namely

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

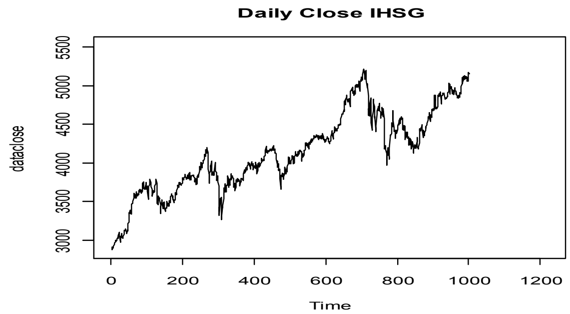

Figure 1. Closing Price JCI on Juni,30th 2010 until Juli, 1st 2015 Period

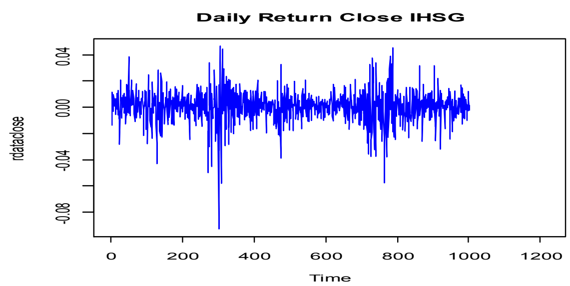

Figure 2. Return of JCI on Juni, 30th 2010 until Juli, 1st 2015 Period

With p_t is the value of the stock index at the time t, and p_{t-1} is the value of the stock index at time to t-1. The following Fig 2 plots the returns JCI data.

The plot on Fig 2 shows the clustering on the return data. By using the R software obtained kurtosis value 6.572254. From the positively excess kurtosis value indices the data is not normal, it will be more obviously when looking visually from the histogram data.

The phenomenon of not normally distributed present the assumptions of normality are necessary. One thing that can overcome these problems is to perform data transformations. Transformation that taken in this research is differencing, then take the absolute value of the data, and continued with the Box-Cox transformation.. supported with R software retrieve optimal estimation ordo λ value is 0,3079685. The result of the transformation has shaped normal distribution, indicated by the p-value = 0.4179> 5%.

Parameter Estimation

Stationarity assumptions in the analysis of time series data is a very important thing. Augmented Dickey Fuller Test is one of the most frequently used in stationary testing data. Due R program of ADF test showed that p-value= 0,01 <5% means that the null hypothesis is rejected indicating the absence of unit roots in the data means that the data is stationary.

Furthermore, the model identified Autoregressive Moving Average (ARMA) is appropriate to describe the data of distinction. Based on the plot can be seen that the function ACF / PACF lag significantly on the 1st and decays to zero for the next lag. Furthermore, the estimate of several alternatives the following models. It is understandable that the model is impossible to describe the data according to the principles of simplicity modeling, selected from several alternative models: (ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (1,1,1), ARIMA (0,1,1), ARIMA (0,1,2), ARIMA (2,1,1), ARIMA (1,1,2), and ARIMA (5,1,0). From the ACF plot shows that the residuals had a white noise process, marked by the absence of lag (≥1) is out interval boundary lines.

Summary of ARIMA Results and Best Model Selection

The significance of the estimated value of the coefficient, standard error coefficient, and the values of the statistics for diagnostic checks models that were observed are presented in the following Table 1.

Learned that the ARIMA (0,1,2) be the best model with statistic t-test value more than the value of statistical t tables (df = 1221-1 = 1220; α = 2.5%) for the entire coefficient as well as by the minimum value of RMSE, AIC, and BIC that is supported by the parsimony principles of modeling.

ARCH/GARCH Test

ARCH/GARCH plays the key concept on conditional variance, that is the variance conditional on the past. This particular specification is able to capture the main stylized facts characterizing financial series.

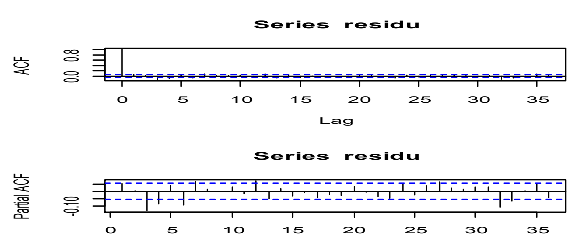

Figure 3. Plot ACF/PACF from Residual Data

Table 2. Summary of ARCH/GARCH Modelling

<table>
<tr><th></th><th>Mu</th><th>ma1</th><th>ma2</th><th>Omega</th><th>alpha1</th><th>alpha2</th><th>alpha3</th><th>beta1</th><th>beta2</th></tr>
<tr><td>ARCH (1)</td><td>0.227012
Pr(>|t|)
=0.0000
***</td><td>0.2618
Pr(>|t|)
0.0000
***</td><td>0.0407
Pr(>|t|)
0.0937</td><td>0.0043
Pr(>|t|)
0.00
***</td><td>0.0612
Pr(>|t|)
=0.017
**</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td colspan="9">$\sigma_t^2 = 0.227012 + 0.261899 \quad \varepsilon_{t-1} + 0.004391 + 0.061231\varepsilon_{t-1}^2$</td></tr>
<tr><td>ARCH(2)</td><td colspan="9">Convergence problem</td></tr>
<tr><td>ARCH (3)</td><td>0.22608
Pr(>|t|
=0.000
***</td><td>0.25802
Pr(>|t|)
=0.00000
***</td><td>0.03975
Pr(>|t|)
=0.1339</td><td>0.0041
Pr(>|t|)
0.00000
***</td><td>0.06056
Pr(>|t|)
0.0412
***</td><td>0.00483
Pr(>|t|)
0.8717</td><td>0.0592
Pr(>|t|)
0.077</td><td></td><td></td></tr>
<tr><td>GARCH (1,1)</td><td>0.2240
Pr(>|t|)
=0.0000
***</td><td>0.2492
Pr(>|t|)
=0.00000
***</td><td>0.0323
Pr(>|t|)
=0.186</td><td>0.0001
Pr(>|t|)
0.0383
*</td><td>0.0306
Pr(>|t|)
0.001
***</td><td></td><td></td><td>0.9352
Pr(>|t|)
=0.000
***</td><td></td></tr>
<tr><td></td><td colspan="9">$\sigma_t^2 = 0.224 + 0.24924 \quad \varepsilon_{t-1} + 0.00016 + 0.0306\varepsilon_{t-1}^2 + 0.9352 \ \sigma_{t-1}^2$</td></tr>
<tr><td>GARCH (1,2)</td><td>0.2239
Pr(>|t|)
=0.000
***</td><td>0.25
Pr(>|t|)
=0.000
***</td><td>0.033
Pr(>|t|)
0.177</td><td>0.0002
Pr(>|t|)
0.0243
**</td><td>0.0527
Pr(>|t|)
0.0002
***</td><td></td><td></td><td>0.0691
Pr(>|t|)
0.344</td><td>0.817
Pr(>|t|)
0.00
***</td></tr>
<tr><td></td><td colspan="9">$\sigma_t^2 = 0.224 + 0.25 \ \varepsilon_{t-1} + +0.0002 + 0.0527\varepsilon_{t-1}^2 + 0.817 \ \sigma_{t-2}^2$</td></tr>
</table>

Figure 3 shows that there is no strong indication of the existence of serial correlation of the data (except on some major lag over the limit $\frac{Z\frac{\alpha}{2}}{\sqrt{n-1}} = \frac{1,9}{\sqrt{1}} = 0,056$). Based on the statistics QLjung -Box null hypothesis on the absence of correlation until to lag-5 received at test level 5%. It is seen that although the residual data is not correlated, but the variance of the residuals show a correlation. The same is evident from the test results QLjung-Box at a test rate of 5%.

Based on the autocorrelation of the squared residual plot on Fig 3, component containing ARCH / GARCH, the following stuff will try to use several models for the residual. The estimation results of ARCH / GARCH shown in the Table 2.

Diagnostic Test of Post-Analysis ARCH / GARCH Model

Table 2 shows that the model that passes the significance test is ARCH (1), GARCH (1,1) and GARCH (2,1) which reduces to GARCH (1,1). Furthermore, of the chosen model is done post-analysis with diagnostic tests. This test is done to see if there was any remaining ARCH effects in the residuals result estimation model. In ARCH models (1) LM values obtained with p-value <0.05 for all lag so that the null hypothesis is rejected, meaning that there are ARCH effects in the ARCH (1) model, the GARCH (1,1) there is no ARCH effects, the GARCH (2,1) for beta2 coefficient is not significant, then the GARCH (2,1) in this case reduces to GARCH (1,1) and on the model there is no ARCH effects.

Serial Corelation Test for Standarization Residual

Another test that can be done is the test of serial correlation of the residuals squared up to the lag - m with QLjung-Box statistics are compared with quintile of the distributionχ_m^2. From the Table 2, we have

a) The ARCH (1) model, there is no serial correlation in the residuals squared at a significance level of 5%.
b) The GARCH(1,1) model, concluded that the null hypothesis is not rejected it means there is no serial correlation in the residuals squared at a significance level of 5%.
c) GARCH (2,1) which reduces to GARCH (1,1) we can conclude that the null hypothesis is accepted meaning in this model there is no serial correlation in the residuals squared at a significance level of 5%

From the diagnostic test results has been done that the best model is GARCH (1,1).

Table 3. Modelling Summary

Model	Pasca Analisis	Log Likelihood	AIC	BIC	SIC	HQIC
ARCH(1)	MA (2) coefficient is not significant so that the model reduced by MA (1), Passed all post nalysis	1543.949	-2.5229	-2.5019	-2.5229	-2.5150
ARCH(2)	Convergence problem					
ARCH(3)	unsignificance MA(2),α_1, α_2, dan α_3 coefficient	1546.211	-2.5233	-2.4940	-2.5234	-2.5123
GARCH(1,1)	MA (2) coefficient is not significant so that the model reduced by MA (1), Passed all post nalysis	1551.711	-2.5340	-2.5088	-2.5340	-2.5245
GARCH(1,2)	unsignificance MA(2),ω, dan β_1 coefficient	1552.802	-2.5341	-2.5048	-2.5342	-2.5231
GARCH(2,1)	unsignificance MA(2),ω, α_1, dan α_2 coefficient	1551.711	-2.5323	-2.5030	-2.5324	-2.5213
GARCH(2,2)	unsignificance MA(2),$\omega, \alpha_1, \alpha_2$, dan β_1 coefficient	1552.802	-2.5325	-2.4990	-2.5325	-2.5199
GJR-GARCH(1,1)	Passed all post nalysis	3865.773	-6.3275	-6.3024	-6.3275	-6.3180

GJR-GARCH Estimation

Developing from GARCH model which further accommodate the asymmetrical volatility response. The estimation results of GJR-GARCH (1,1) get the equations model

$$\sigma_t^2 = -0.000009 - 0.958869\ \varepsilon_{t-1} + 0.000003 + 0.047653\ \sigma_{t-1}^2 + 0.890029\ \varepsilon_{t-1}^2 + 0.077586\quad i_{t-1}\varepsilon_{t-1}^2.$$

Best Model Selection

Although from the analysis conducted has shown a good models for using of describe the data, to obtain comprehensive results need to compare the value of the log likelihood statistics and information criteria such as AIC (Akaike), BIC (Bayes), SIC (Shibata), and HQIC (Hannan -Quinn). Statistical Summary results of the analysis will be given in the Table 3.

Noting the results of Table 3, reflected some relatively optimal models in modeling the return JCI data. By the analysis shows that the GARCH (1,1) and GJR-GARCH (1,1) model is relatively the most good by looking at the statistical value information and log likelihood criterion. Models are chosen to be the best model to describe the data is a model GJR-GARCH (1,1) is indicated on the condition of all significant coefficients and the value of the log likelihood is greatest with the most minimum information criteria.

Forecasting

Forecasting is done is to find the value of the custom of value estimates and predictions of the mean and variance with the best models that have been obtained. JCI price forecast value with GARCH (1,1) for the next 10 periods shown in the Table 4.

Value at Risk (VaR) Calculation

In calculating VaR, first which need to be done to assume that the funds allocated for investment. In this study assumes the funds used are Rp500,000,000.00. It can be deduced that for a period of one day after the date of July 1st, 2015 can be predicted that the maximum loss that can be tolerated investor with an investment of USD 500,000,000.00 for the 95% confidence level with a GARCH (1,1) is Rp 3,622. 420.50, while the model with GJR-GARCH (1,1) of Rp 23,471,863.80.

CONCLUSIONS

Based on the results of the discussion in the study, the following conclusions can be obtained.

1. From the case studies were carried out, the result of forecasting volatility of stock index by using GARCH (1,1) obtained log likelihood values that 1551,711 to the information criteria AIC = -2.5340; BIC = -2.5088; SIC = -2.5340; and HQIC = -2.5245. As for the model GJR-GARCH (1,1) values obtained log likelihood is 3865.773 value information criteria AIC = -6.3275; BIC = -6.3024; SIC = -6.3275; and HQIC = -6.3180. Models are chosen to be the best model to describe the data is a model GJR-GARCH (1,1) is shown on the value of the log likelihood is greatest with the most minimum value of information criteria.

Table 4. Forecasting Value

Periode	GARCH(1,1)		GJR-GARCH(1,1)	
	Return IHSG	IHSG	Return IHSG	IHSG
1223	0,007455236	4988,97136	-4,52E-04	4898,962
1224	0,007709897	5078,329877	-9,49E-06	4898,855
1225	0,007777308	5170,09134	-9,49E-06	4898,748
1226	0,007777308	5263,510862	-9,49E-06	4898,641
1227	0,007777308	5358,618402	-9,49E-06	4898,534
1228	0,007777308	5455,444461	-9,49E-06	4898,427
1229	0,007777308	5554,020091	-9,49E-06	4898,32
1230	0,007777308	5654,376906	-9,49E-06	4898,213
1231	0,007777308	5756,54709	-9,49E-06	4898,106
1232	0,007777308	5860,563411	-9,49E-06	4897,999

2. Value of VaR movement of the JCI if it becomes greater the investment is Rp.500,000,000.00 with a confidence level of 95% on the date of July 2, 2015 using a model GJR-GARCH (1,1) is USD 23,471,863.80.

The results of the analysis conclude that GJR-GARCH is the best model. But in an effort to resolve the situation of asymmetry in the data, it is necessary that the other models to correct deficiencies GARCH. Another model that can be used to overcome the asymmetry problem of which is the model EGARCH (Exponential GARCH), T-GARCH (Threshold-GARCH), APARCH (Asymmetric Power ARCH), and GARCH Model with Conditional contemporaneous asymmetry.

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