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A GARCH Approach to VaR Calculation in Financial Market

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Abstract

Value at Risk (VaR) has already becomes a standard measurement that must be carried out by financial institution for both internal interest and regulatory. VaR is defined as the value that portfolio will loss with a certain probability value and over a certain time horizon (usually one or ten days). In this paper we examine of VaR calculation when the volatility is not constant using generalized autoregressive conditional heteroscedastic (GARCH) model. We illustrate the method to real data from Indonesian financial market that is the stock of PT. Indosat Tbk.

Keywords: Value at Risk, Risk Management, GARCH model, skewness, kurtosis, Quantile

1. Introduction

There are some types of financial market risk, i.e. credit risk, operational risk and market risk. Value at Risk (VaR) is mainly concerned with market risk; however the concept can be use for difference type of risks. VaR is single estimator of an institution position quantity decline of profit risk category on the market in the share period. This measure might be applied by the institution for estimating the risk and regulatory committee in this case for analyzing the investment opportunity (Jorion, 2004; Alexader, 1999).

VaR in term of the financial institution is defined as a maximum lost on period of financial position with a certain probability. VaR is considered as a lost measurement related to an extraordinary event under the standard market condition. For the regulatory committee, VaR is defined as a minimum lost under an extraordinary market condition. These two definitions has a similar based on VaR measurement, however the concept seems different (Tsay, 2005; Dowd,

2002).

In general, VaR calculation usually uses econometrics time series models. In this paper, GARCH model is used for the volatility estimating and the VaR calculation worked base on quantile. In seeking the performance of the models, we'll discuss them through the skewness and kurtosis coefficient values.

2. Mathematical Models

2.1 Value at Risk

Assume that at the time index t we are concerned in the risk of a financial position for the next l periods. Let $\Delta V(l)$ be the change in value of the asset in financial position from time t to $t + l$. This quantity is measured in rupiah curenry and is a random variable at the time index t . Represent the cumulative distribution function (CDF) of $\Delta V(l)$ with $F_l(x)$. Dified the VaR of a long position over the time horizon l with probability p as

$$p = \Pr[\Delta V(l) \leq \text{VaR}] = F_l(\text{VaR}) \tag{1}$$

Because the holder of a long financial position suffers a loss when $\Delta V(l) < 0$, the VaR defined in (1) naturally assumes a negative value when p is small. The negative sign signifies a loss. From the definition, the probability that the holder would run into a loss greater than or equal to VaR over the time horizon l is p . Alternatively, VaR can be interpreted as follow. With probability $(1 - p)$, the potential loss encountered by the holder of the financial position over the time horizon l is less than or equal to VaR.

The holder of a short position suffers a loss when the value of the asset increases $\Delta V(l) > 0$. The VaR is then defined as

$$p = \Pr[\Delta V(l) \geq \text{VaR}] = 1 - \Pr[\Delta V(l) \leq \text{VaR}] = 1 - F_l(\text{VaR}) \tag{2}$$

For a small p , the VaR of a short position naturally assumes a positive value. The positive sign signifies a loss. The previous definitions show that VaR is concerned with *tail* behavior of the CDF $F_l(x)$. For a long position, the left tail of $F_l(x)$ is important. Nevertheless a short position focuses on the right tail of $F_l(x)$. The definition of VaR in (1) continues to apply to a short position if one uses the distribution of $-\Delta V(l)$. Therefore, it suffices to discuss method of VaR calculation using a long position (Tsay, 2005; Khindanova).

For any univariate CDF $F_l(x)$ and probability p , such that $0 < p < 1$, the quantity

$$x_p = \inf\{x \mid F_l(x) \geq p\} \tag{3}$$

Is called the p th quantile of $F_l(x)$, where \inf denotes the smallest real number satisfying $F_l(x) \geq p$. If the CDF $F_l(x)$ of (1) is known, then $\text{VaR} = x_p$. However usually the CDF is

unknown in practice, then the studies of VaR are essentially concerned with estimation of the CDF and or its quantile, especially the tail behavior of the CDF.

In practical applications, calculation of VaR involves several factors:

1. The probability of interest p , such as $p = 0.01$ or $p = 0.05$.
2. The time horizon l . It might be set by a regulatory committee, such as 1 day or 10 days.
3. The frequency of the data, which might not be the same as the time horizon l . Daily observations are often used.
4. The CDF $F_l(x)$ or its quantiles.
5. The amount of the financial position or the mark-to-market value of the portfolio.

Among these factors, the CDF $F_l(x)$ is the focus of econometric modeling.

2.2 The GARCH Approach

For a log return series, the time series models can be used to model the mean equation, and conditional heteroscedastic models are used to handle the volatility. In this paper, we will use GARCH models to the approach as an *econometric approach* to VaR calculation (Tsay, 2005; Engle & Manganelli, 2002).

Consider the log return r_t of an asset. A general time series model for r_t can be written as

$$r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} + a_t - \sum_{j=1}^q \theta_j a_{t-j} \quad (4)$$

$$a_t = \sigma_t \varepsilon_t,$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^u \alpha_i a_{t-i}^2 + \sum_{j=1}^v \beta_j \sigma_{t-j}^2 \quad (5)$$

If one further assumes that ε_t is Gaussian, then the conditional distribution of r_{t+1} given the information available at time t is $N[\hat{r}_t(1), \hat{\sigma}_t^2(1)]$. Quantiles of this conditional distribution can easily be obtained for VaR calculation. For example, the 5% quantile is $\hat{r}_t(1) - 1.65\hat{\sigma}_t(1)$. If one assumes that ε_t is a standardized Student- t distribution with ν degrees of freedom, then the quantile is $\hat{r}_t(1) - t_\nu^*(p)\hat{\sigma}_t(1)$, where $t_\nu^*(p)$ is the p th quantile of standardized student- t distribution with ν degrees of freedom.

The relationship between quantiles of a Student- t distribution with ν degrees of freedom, denoted by t_ν , and those of its standardized distribution, denoted by t_ν^* , is

$$p = \Pr(t_\nu \leq q) = \Pr\left(\frac{t_\nu}{\sqrt{\nu/(\nu-2)}} \leq \frac{q}{\sqrt{\nu/(\nu-2)}}\right) = \Pr\left(t_\nu^* \leq \frac{q}{\sqrt{\nu/(\nu-2)}}\right) \quad (6)$$

where $\nu > 2$. That is, if q is p th quantile of a Student- t distribution with ν degrees of freedom,

then $q / \sqrt{v/(v-2)}$ is the p th quantile of a standardized Student- t distribution with v degrees of freedom. Therefore, if ε_t of the GARCH model (5) is a standardized Student- t distribution with v degrees of freedom and the probability is p , then the quantile used to calculate the 1-period horizon VaR at time index t is

$$\hat{r}_t(1) + \frac{t_v(p)\hat{\sigma}_t(1)}{\sqrt{v/(v-2)}} \tag{7}$$

Where, $t_v(p)$ is the p th quantile of a Student- t distribution with v degrees of freedom and assumes a negative value for a small p .

2.2.1 The Model Parameter Estimation

Let $L(r; \theta)$ is denote the conditional likelihood function concerned with r_t . The likelihood function of r_1, \dots, r_T conditional on r_0 is

$$L(r; \theta) = \prod_{i=1}^T L_i(r; \theta) \tag{8}$$

Therefore the estimator is a solution for maximize the problem

$$\max_{\theta} \log L(r; \theta) \tag{9}$$

This estimator denoted by $\hat{\theta}_T$ and is called pseudo maximum likelihood estimator (PMLE), and the likelihood function is constructed by the assume that a normally distribution. When the distribution assumption is not true, this estimator is a normal asymptotically with the covariance matrix is

$$V_{as}[\sqrt{T}(\hat{\theta}_T - \theta)] = \mathbf{J}^{-1} \mathbf{I} \mathbf{J}^{-1} \tag{10}$$

$$\mathbf{J} = E_0 \left[- \frac{\partial^2 \log L_i(r; \theta)}{\partial \theta \partial \theta'} \right] \tag{11}$$

$$\mathbf{I} = E_0 \left[\frac{\partial \log L_i(r; \theta)}{\partial \theta} \frac{\partial \log L_i(r; \theta)}{\partial \theta'} \right] \tag{12}$$

where E_0 showed that the expectation taken to the true distribution (Gourieoux, 2002).

Two matrix \mathbf{I} and \mathbf{J} is usually different. But \mathbf{I} and \mathbf{J} is equal if its distribution is true and appropriate with the likelihood function, that is in this case a conditional normal distribution. When the matrix $\mathbf{I} = \mathbf{J}$, the asymptotic patern becomes simple, that is

$$V_{as}[\sqrt{T}(\hat{\theta}_T - \theta)] = \mathbf{J}^{-1} = \mathbf{I}^{-1} \tag{13}$$

On the GARCH model, notified that the MLE of ARMA model usually solved by using the backward forecast algorithm or Kalman filter. The similar case when the ARCH specification is replaced by GARCH. Let given a GARCH(p, q) model conditionally Gaussian

$$r_t | r_{t-1} \sim N[0, \sigma_t^2] \tag{14}$$

where σ_t^2 given in (5).

The conditional variance pattern in the parameter terms and the variable observed is

$$\sigma_t^2 = \frac{1}{1 - \sum_{j=1}^q \beta_j L^j} \left(c + \sum_{i=1}^p \alpha_i r_{t-i}^2 \right) \quad (15)$$

where L represent the operator-lag. Hence, $\sigma_t^2(\theta)$ depend on the all previous values of r_t process.

Since the time period of observation is limited, that is $t = 1, \dots, T$, here need to replace $\sigma_t^2(\theta)$ with truncated approximation, where r_t^2 is values that concerned with negative sign that defined equal to zero. It is equivalent with the recursive equation

$$\hat{\sigma}_t^2 = c + \sum_{i=1}^p \alpha_i \bar{r}_{t-i}^2 + \sum_{j=1}^q \beta_j \hat{\sigma}_{t-j}^2 \quad (16)$$

with

$$\bar{r}_t = 0, \text{ if } t \leq 0; \bar{r}_t = r_t, \text{ if } t \geq 1; \text{ and } \hat{\sigma}_t^2 = 0, \text{ if } t \leq 0.$$

The initially log-likelihood function replaced with truncated version:

$$\log \tilde{L} = -\frac{T}{2} \log 2\pi - \frac{1}{2} \sum_{t=1}^T \log \tilde{\sigma}_t^2(\theta) - \frac{1}{2} \sum_{t=1}^T \frac{r_t^2}{\tilde{\sigma}_t^2(\theta)} \quad (17)$$

Continuously, the optimization is worked with numerical procedure and for the value of θ_1 from θ that given, the conditional variance respectively calculated by using

$$\tilde{\sigma}_t^2(\theta_1) = c_1 + \sum_{i=1}^p \alpha_{i1} \tilde{r}_{t-i}^2 + \sum_{j=1}^q \beta_{j1} \tilde{\sigma}_{t-j}^2(\theta_1) \quad (18)$$

2.2.2 Diagnostic Check for ARCH Effect

Remembering that the ARCH model is $a_t = \sigma_t v_t$, $v_t \sim iidN(0,1)$ or standardized Student- t distribution. By using the "Standardize-Shock" $\hat{v}_t = \hat{a}_t / \hat{\sigma}_t$ where $\hat{\sigma}_t$ is calculated by ARCH model that estimated. When the ARCH model used is good adequate \hat{v}_t is being equivalent with v_t . It can be done by several ways: (1) Plot of the ACF and PACF for \hat{v}_t ; (2) Determine Potmanteu statistic for \hat{v}_t , if the ARC/GARCH model is appropriate, then Potmanteu statistic is not rejected; and observation can be done one is using the kurtosis toward $\{\hat{v}_t\}$ for seeing appropriation of the chosen assumption (Shi, 2004).

2.3 Kurtosis of GARCH Models

To assess the variability of an estimated volatility, one must consider the kurtosis of a volatility model. In this section, we will derive the excess kurtosis of a GARCH(1,1) model. The same idea applies to other GARCH models. The model considered is

$$a_t = \sigma_t \varepsilon_t, \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{19}$$

where $\alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0, \alpha_0 > 0$, and $\{\varepsilon_t\}$ is an iid sequence satisfying

$$E(\varepsilon_t) = 0, \text{Var}(\varepsilon_t) = 1, E(\varepsilon_t^4) = K_\varepsilon + 3 \tag{20}$$

Where K_ε is the excess kurtosis of the innovation ε_t . Based on the assumption, obtained the following:

- $\text{Var}(a_t) = E(\sigma_t^2) = \frac{\alpha_0}{1 - (\alpha_1 + \beta_1)}$
- $E(a_t^4) = (K_\varepsilon + 3)E(a_t^2)^2$ provided that $E(a_t^4)$ exists.

Taking the square of the volatility model (5) for $i = 1$, obtained

$$\sigma_t^4 = \alpha_0^2 + \alpha_1^2 a_{t-1}^4 + \beta_1^2 \sigma_{t-1}^4 + 2\alpha_0 \alpha_1 a_{t-1}^2 + 2\alpha_0 \beta_1 \sigma_{t-1}^2 + 2\alpha_1 \beta_1 \sigma_{t-1}^2 a_{t-1}^2 \tag{21}$$

Taking expectation of the equation (21) and using the two properties mentioned earlier, obtained

$$E(\sigma_t^4) = \frac{\alpha_0^2 (1 + \alpha_1 + \beta_1)}{[1 - (\alpha_1 + \beta_1)][1 - \alpha_1^2 (K_\varepsilon + 2) - (\alpha_1 + \beta_1)^2]} \tag{22}$$

Provided that $0 \leq \alpha_1 + \beta_1 < 1$ and $1 - \alpha_1^2 (K_\varepsilon + 2) - (\alpha_1 + \beta_1)^2 > 0$. Excess kurtosis of a_t , if exists, is

$$K_a = \frac{E(a_t^4)}{[E(a_t^2)]^2} - 3 = \frac{(K_\varepsilon + 3)[1 - (\alpha_1 + \beta_1)^2]}{1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 - K_\varepsilon \alpha_1^2} - 3 \tag{23}$$

This excess kurtosis can be written in an informative expression. First, consider the case that ε_t is normally distributed. In this case, $K_\varepsilon = 0$, and some algebra shows that

$$K_a^{(g)} = \frac{6\alpha_1^2}{1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2}, \tag{24}$$

Where, the superscript (g) is used to denote Gaussian distribution. This result has two important implications: (a) the kurtosis a_t exists if $1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 > 0$, and (b) if $\alpha_0 = 0$, then $K_a^{(g)} = 0$, denotation that the corresponding GARCH(1,1) model does not have heavy tails.

Second, consider the case that ε_t is not Gaussian. Using the previous result, obtained

$$K_a = \frac{K_\varepsilon - K_\varepsilon (\alpha_1 + \beta_1) + 6\alpha_1^2 + 3K_\varepsilon \alpha_1^2}{1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 - K_\varepsilon \alpha_1^2}$$

$$\begin{aligned}
&= \frac{K_\varepsilon [1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2] + 6\alpha_1^2 + 5K_\varepsilon \alpha_1^2}{1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 - K_\varepsilon \alpha_1^2} \\
&= \frac{K_\varepsilon + K_a^{(g)} + \frac{5}{6} K_\varepsilon K_a^{(g)}}{1 - \frac{1}{6} K_\varepsilon K_a^{(g)}} \tag{25}
\end{aligned}$$

It holds for all GARCH models provided that the kurtosis exists. For instance, if $\beta_1 = 0$, then the model reduces to an ARCH(1) model. In this case, it is easy to verify that $K_a^{(g)} = 6\alpha_1^2 / (1 - 3\alpha_1^2)$ provided that $1 > 3\alpha_1^2$ and the excess kurtosis of a_t is

$$\begin{aligned}
K_a &= \frac{(K_\varepsilon + 3)(1 - \alpha_1^2)}{1 - (K_\varepsilon + 3)\alpha_1^2} - 3 = \frac{K_\varepsilon + 2K_\varepsilon \alpha_1^2 + 6\alpha_1^2}{1 - 3\alpha_1^2 - K_\varepsilon \alpha_1^2} \\
&= \frac{K_\varepsilon (1 - 3\alpha_1^2) + 6\alpha_1^2 + 5K_\varepsilon \alpha_1^2}{1 - 3\alpha_1^2 - K_\varepsilon \alpha_1^2} \\
&= \frac{K_\varepsilon + K_a^{(g)} + \frac{5}{6} K_\varepsilon K_a^{(g)}}{1 - \frac{1}{6} K_\varepsilon K_a^{(g)}} \tag{26}
\end{aligned}$$

The previous result shows that for a GARCH(1,1) model the coefficient α_1 plays a critical role in determining the tail behavior of a_t . If $\alpha_1 = 0$, then $K_a^{(g)} = 0$ and $K_a = K_\varepsilon$. In this case, the tail behavior of a_t is similar to that of the standardized noise ε_t . Nevertheless if $\alpha_1 > 0$, then $K_a^{(g)} > 0$ and the a_t process has heavy tails (Tsay, 2005; Shi, 2004).

For a standardized Student- t distribution with ν degrees of freedom, obtained $E(\varepsilon_t^4) = 6/(\nu - 4) + 3$ if $\nu > 4$. Therefore, the excess kurtosis of ε_t is $K_\varepsilon = 6/(\nu - 3)$ for $\nu > 4$. This is part of the reason that used t_5 when the degrees of freedom of a student- t distribution are prespecified. The excess kurtosis of a_t becomes $K_a = [6 + (\nu + 1)K_a^{(g)}] / [\nu - 4 - K_a^{(g)}]$ provided that $1 - 2\alpha_1^2(\nu - 1)/(\nu - 4) - (\alpha_1 + \beta_1)^2 > 0$.

3. Cases Study

The aim of this research is to determine the Value at Risk (VaR) of the real data. As a case study, we use PT. Indosat, Tbk. stock data. In this research, we employ GARCH model to estimate this VaR value. The result of this approach can be used by investors to save their stocks. We implement MATLAB 7.1 and EView 3 for analyzing the data.

The data which will be analyzed are log return data (Continuously Compounded Return) of closing price. We observe the data from July, 4th, 2004 till March, 3rd 2006, or contain 396 observations. Time series plot of the data can be seen at Figure 3.1 as follow:

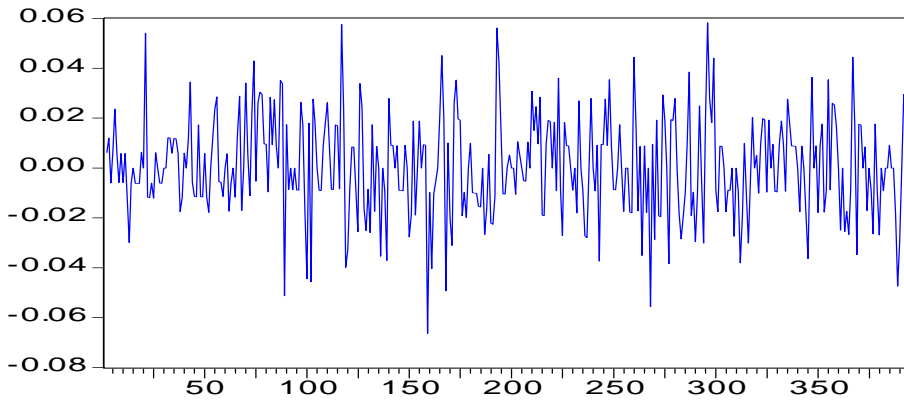


Figure 1: Plot of Log Return the transaction from July 4th, 2004 to March 3rd, 2006

The summary of descriptive statistics for the data is as follows: the minimum is -0.066375, the maximum is 0.058269, mean is 0.000602, variance is 0.000385, and standard deviation is 0.019634.

3.1 Normality Test

We employ MINITAB 13 to do normality test with the hypothesis test as follow

- H_0 : The log return data are normally distributed
- H_1 : The log return data are not normally distributed.

The hypothesis null is rejected if p-value of the statistic test less than 0.05 (significance level). In this paper, we use Ryan-Joiner and Shapiro-Wilk Test as statistic tests. The results show that p-value of both tests are the same, i.e. 0.081. It means we fail to reject H_0 and conclude that log return data are normally distributed.

3.2 GARCH Modeling

In this section we will estimate whether the log return data have volatility pattern following GARCH model. Identification step by using time series plot (see Figure 3.1) shows that data satisfy stationery condition in mean. Both of the ACF and PACF indicate only significant at the first lag or cut off after lag 1. Based on this result, we can propose that the appropriate ARIMA models are AR(1) or MA(1). The results of parameter estimation and diagnostic check steps show that MA(1) model is the best appropriate model. The output of MA(1) model is illustrated at Table 3.1 as follow:

Table 1: Moving Average orde 1 modeling parameter estimation

Dependent Variable: LOGRET
Method: Least Squares
Date: 04/20/06 Time: 12:54
Sample(adjusted): 2 396
Included observations: 395 after adjusting endpoints
Convergence achieved after 5 iterations
Backcast: 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.147232	0.049853	2.953349	0.0033
R-squared	0.017677	Mean dependent var		0.000602
Adjusted R-squared	0.017677	S.D. dependent var		0.019634
S.E. of regression	0.019460	Akaike info criterion		-5.038365
Sum squared resid	0.149207	Schwarz criterion		-5.028292
Log likelihood	996.0770	Durbin-Watson stat		2.017408
Inverted MA Roots	-0.15			

Hence, MA(1) model is an appropriate for modeling the mean of log return data of PT. Indosat, Tbk stock. This model can be presented as $\hat{F}(r_t, t-1) = 0.147232a_{t-1}$.

Then, we continue to analyze whether the square of residuals model have heteroscedasticity. In this case, the residuals component are calculated as follows; $\hat{a}_t = r_t - \hat{F}_{t-1}$, with $r_t = \log \text{return}$ of actually price at the t time and \hat{F}_{t-1} = forecast value at the $t-1$ time. We apply ARCH-LM test to evaluate it and the results are illustrated at Table 3.2 as follow:

Table 2: ARCH LM test MA(1)

ARCH Test:

F-statistic	2.398786	Probability	0.036810
Obs*R-squared	11.81238	Probability	0.037451

The results show that residuals model contain ARCH effect or follow heteroscedasticity pattern. The correlogram of residual indicates that lag 1 and 2 are significant. Hence, we propose that ARCH(2) and GARCH(2,2) are appropriate for this data.

Parameter estimation step show that ARCH(2) model is not appropriate for modeling heteroscedasticity pattern at the residuals. It's caused one of parameters model is not statistically significant. Then, we continue to estimate GARCH(2,2) model and the result can be seen at Table 3.3 as follow:

Table 3: MA(1)-GARCH(2,2) models parameter estimation

Dependent Variable: LOGRET
 Method: ML – ARCH
 Date: 04/20/06 Time: 13:00
 Sample(adjusted): 2 396
 Included observations: 395 after adjusting endpoints
 Convergence achieved after 100 iterations
 Backcast: 1

	Coefficient	Std. Error	z-Statistic	Prob.
MA(1)	0.121191	0.036980	3.277216	0.0010
Variance Equation				
C	0.000325	4.53E-05	7.180326	0.0000
ARCH(1)	-0.055797	0.018734	-2.978347	0.0029
ARCH(2)	0.208991	0.052118	4.009946	0.0001
GARCH(1)	0.621212	0.054120	11.47834	0.0000
GARCH(2)	-0.620338	0.105962	-5.854361	0.0000
R-squared	0.017082	Mean dependent var		0.000602
Adjusted R-squared	0.004448	S.D. dependent var		0.019634
S.E. of regression	0.019591	Akaike info criterion		-5.055651
Sum squared resid	0.149298	Schwarz criterion		-4.995212
Log likelihood	1004.491	Durbin-Watson stat		1.968835
Inverted MA Roots	- .12			

We can observe that all parameters model are significant. Hence, we can conclude that GARCH(2,2) is the appropriate model for modeling heteroscedasticity pattern at the residuals. This model can be written mathematically as follows $r_t = \theta_1 a_{t-1}$ and $\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \alpha_2 r_{t-2}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2$. Based on the results for mean and volatility models, we get MA(1)-GARCH(2,2) as follows:

$$r_t = 0,121191a_{t-1}$$

$$\sigma_t^2 = 0,000325 - 0,055797r_{t-1}^2 + 0,208991r_{t-2}^2 + 0,621212\sigma_{t-1}^2 - 0,620338\sigma_{t-2}^2$$

Diagnostic Checking to understand what the model is good enough for the data modeling, we used the ARCH LM test and the result can be seen at Table 3.4 as follow:

Table 4: ARCH LM test

ARCH Test:

F-statistic	0.933450	Probability	0.502208
Obs*R-squared	9.375056	Probability	0.496917

The result at diagnostic check step is illustrated at Table 3.4. It shows that MA(1)-GARCH(2,2) model satisfies the adequacy model. Additionally, we also check the normality of the residuals model by using Jarque-Berra test, and the result obtained a probability value is 0.358359 greater than of 5% significance level. It is shows that residuals satisfy normal distribution assumption. Besides that also obtained the coefficient skewness is 0.084146 and the coefficient kurtosis is 3.310456. Hence, we can conclude that MA(1)-GARCH(2,2) is the best model for volatility estimating log return data. The estimated of this model can be seen at Figure 4.8 as follow:

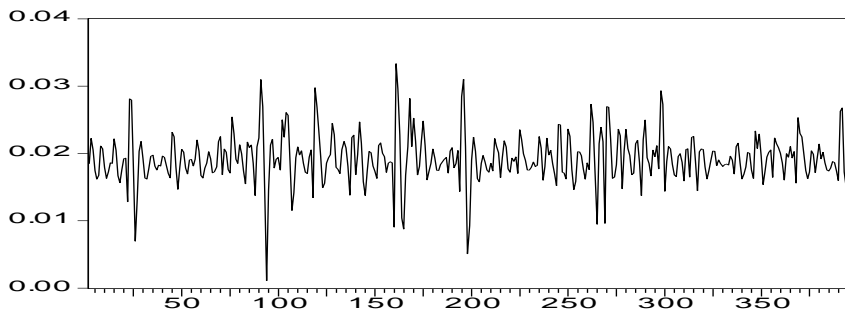


Figure 2: Plot of MA(1)-GARCH(2,2) model volatility

We only need variance model to estimate the volatility. The variance forecast at 397th period by using GARCH(2,2) model is 0.00041. It means the daily volatility is 0.0202.

3.3 Value at Risk Calculation

In this paper, the method for calculating VaR is a variance-covariance approach model. This model has an assumption that return data are normally distributed. From the results at the previous section, we can construct a summary of VaR values at some level confidence interval, i.e.

Table 5: VaR value at several of the volatility estimation method and cl

Volatilitas	Constant Volatility 0,019634			MA(1)-GARCH(2,2) 0,0202		
	90%	95%	99%	90%	95%	99%
<i>VaR</i>	0.0252	0.0323	0.0457	0.0259	0.0332	0.047

This result explained if the investor allocate Rp. 100,000,000,00 and invest to PT. Indosat Tbk. stock by 95% confidence level, then he will be lost Rp. 3.230.000,- (i.e. 0.0323 x Rp. 100,000,000,-) based on the Constant Volatility, or Rp. 3,332,000,- (i.e. 0.0332 x Rp. 100,000,000,-) based on the GARCH model. Hence, the VaR based on the GARCH model is greater than Constant Volatility approach.

4. Conclusion

Based on the results at the previous section, we can conclude that the log return data of daily closing price of PT. Indosat, Tbk. stock follows the normal distribution. We further obtain that the MA(1)-GARCH(2,2) is the appropriate model for estimating the volatility of this log return data. The model yields the daily volatility forecast around 0.0202. In general, the VaR based on the GARCH model is greater than the Constant Volatility approach.

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