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REALIZED VOLATILITY MODEL FOR MARKET RISKMEASUREMENT IN INDONESIA STOCK EXCHANGE

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ABSTRACT

This paper discussed the testing of Realized Volatility (RV) model.The model was formulated based on intraday stock price data and interday stock price on the Indonesian Stock Exchange. At first, the idea of this research came when researcher looked back at the gambling factor in Indonesia Stock Market.The stocks price moved up and down with highly volatility and not in a normal pattern. Reflection of heteroskedasticity is in stocks price movement. For the investors in stock market it is the risk when the trend of market cannot be predicted, accurately and effectively. Of course investors will need tools to minimize market risk, optimally. In the first observation, found a signal that the behavioral finance of investor influenced the stock price trend, from morning session until the market closed in the afternoon. However, the available tools to measure the price volatility of the shares was originally known ARCH (autoregressive conditionally heteroskedasticity) model, the model by using the closing price of stocks. Based on the ARCH structure, it cannot be used to have the optimal results of lower risk in highly frequency data. To solve that problem, need to formulate the new approach by combining the intraday risk measurement with interday risk measurement which ARCH Model cannot provide it. The proposed model is Realized Volatility. Realize Volatility model is the model with combination between intraday volatility and interday volatility. This mathematical combination must use high frequency data, then the available tools cannot be used. In the process of research, not only the ARCH model, but also the ARIMA (Autoregressive Integrated Moving Average) as the tools to test the model also cannot be used because the data is high frequency data. In this research used ARFIMA (Autoregressive Fragtionally Integrated Moving Average) to test the accuracy of the models, to replace the ARIMA. The result of this research is that RV model provided more accurate measurement than ARCH model. RV model will be helpful for investors who want to select the stocks with lower market risk. RV model also can help a treasury manager in banking sector to assess and minimize market risk of foreign exchange, as well as can help fund manager select lower risk stocks and lower risk mutual fund.

Keywords: *1) Realized Volatility, 2) ARCH, 3) ARFIMA, 4) ARIMA.*

1. Introduction

Fundamental consideration for investors in determining the investment option is the risk and expected return. In investing, of course investors want to have maximum profit even though the risks inherent in an investment instrument is large, this is the case particularly in countries classified as emerging market like Indonesia or other country in Asia or Africa in which the structure of capital markets has not been efficient. Contrary to the countries that have efficient capital markets no longer provide abnormal returns. Like the Indonesia Stock Exchange (BEI) in Indonesia, since 1997 in which the economic crisis began to have recovery in 2010 illustrates that returns of stocks were very high. But in period of time 2000 and 2001 declined again, significantly. In 2000 the stocks index was down by 40.54% over one year despite Gross Domestic Product (GDP) increased by 4.8% (year on year) and in 2001 fell by 4.43% even though Gross Domestic Product grew by 3.3%. But in 2010, growth stock returns in the Indonesian Stock Exchange reached 46.132%, where the economy grew by 5.3% (Indonesian Composite Index (ICI) December 30, 2010 = 3703.51, ICI December 30, 2009 = 2534.36).Up and down are the key words in this observation, it means market risk.

Related to the condition of the market in Indonesia, one of the investment type in Indonesia, Islamic Investment, is very concern on this matter. This investment model manages the fund focus on market risk. It is the reason to use the component of Islamic Stock Index as a sample in this research. Indonesia has had Islamic Stock Index, called Jakarta Islamic Index (JII). This index has been used by investors from Middle East when they came to Indonesia Stock Exchange to invest in the capital market. But in my observations, stock return fluctuations occured also in Jakarta Islamic Index, it means that Jakarta Islamic Index also must concern about selection models to have the lower fluctuation stocks in the index because fund managers of Islamic Mutual Fund will invest its fund into stock market.

To invest in capital market, fund manager of Islamic Mutual Fund should refer to the principles of Islamic sharia as follows:

1. Instruments or securities are bought and sold must be in line with Islamic Sharia principles, such as stocks on the index sharia and sukuk (Islamic bonds), which is free from the element of interest and uncertainty. The company issuing Islamic securities, either stocks or sukuk must reflect all the rules of sharia.

2. Goods and services must be consistent with the ethical of Islam. All effects must be based on the property (asset based) or the real transaction, not to profit from the debt contract.

3. All transactions do not contain excessive uncertainty or element of speculation.

4. Comply with all rules relating to Islamic debts, such as not justified by the sale and purchase of debt with discount, and the company may not issue securities to repay the debt.

Related to the stocks selection process with the Islamic sharia is one of the main objectives of this study is to measure the level of volatility to see a factor of gambling and speculation in the stock price. Usually the measurement tools that are understood and used in Indonesia is ARCH model, as was first popularized by Engle (1982). But the stock market, in this research, is Indonesia Stock Exchange which has the data, interday and intraday (high frequency data) which could explain the presence of speculation that occurred in a single second during the trading days, from the open market until closing in the afternoon in several years. Then, ARCH model becomes inadequate considering its use is for the short term period of data. In this case, there should be available a model that can accurately calculate the volatility of long memory nature of a large number of data derived from high frequency data. In this research tested the use of Realized Volatility model as a comparison of ARCH model. The model with the most accurate results and lowest Mean Square Error (MSE), as in accordance with Islamic principles can be considered. In previous studies Realized Volatility has been tested and applied with a different formulation of the volatility by Ebens (2000). Kayahan, Stengos, Saltoglu (2000), in their research also evaluated the implementation of realized volatility in emerging markets.

2. Volatility Models

A. ARCH Model and ARIMA

Volatility model that has been known and most frequently applied is the model by using a 2 (two) elements of ARCH model with volatility estimation using ARIMA as applied by Goudarzi and Ramanarayanan (2010). ARCH model approach starts with the behavior of time series data which is very volatile, the opposite of time series principle, homoscedasticity. By Engle (1982) as the inventor of ARCH models, it is stated that the residual variance change occurs because the residual variance is not only a function of the independent variable but depends on how large residuals in the past.

ARCH models can be defined as a tool to measure the fluctuations of a time series data by using the residual as the data is processed to obtain volatility rates as the following formula:

$Y_t = \beta_0 + \beta_1 X_1 + e_t$,
Y_t = independent variable
X_t = dependent variable
e_t = residual

The fact in the stock market, the price movements with high volatility followed by a residual which is also high and low volatility, is also followed by a low residual thus concluded that the residual variance is also influenced by the residual in the past. So the residual variance can be formulated as follows:

$\sigma^2 = \alpha_0 + \alpha_1 e^2{}_{t-1}$,
σ^2 = variant residual
α = coefficient
e = residual

If the residual variance depends on the volatility of the residual square one then the formula is the equation above, but the time series data with very large in number, it can be formulated as follows:

$$Y_t = \beta_0 + \beta_1 X_{1t} + e_t$$

$$\sigma^2 = \alpha_0 + \alpha_1 e^2{}_{t-1} + \alpha_2 e^2{}_{t-2} + \cdots + \alpha_n e^2{}_{t-n}$$

The estimation process that uses ARIMA was first launched by the Box-Jenkins. ARIMA is a model to make a constant variance of time series data using differentiation process. The underlying ARIMA modeling is the theory of auto-regressive moving average (ARMA) which states predictions would be good if the time series data are stationary means that variants are homoscedasticity. Differentiation process is in ARIMA using the distinguishing number'd' which tested into the model equations to achieve a constant variance. Variants are found by applying constant correlogram method or identifying data to the model by using the χ^2 (chi square) in the Q Statistic. ARIMA process is done by inserting the numbers d = 1 or d = 2 into the equation and analyzed by observing Autocorelation (AC) and Partial Autocorrelation (PAC). In fact the model formed is not accurate because the process of experimenting 'd' into the model are integer numbers, whereas the numbers 'd' can be between 0 and 0.5 (0 <d <0.5) and the form of fractions. Given the inaccuracies by using ARIMA estimation as a tool, in this study that need to be refined using a method that can measure the differentiating factor'd' directly, in order to obtain stationary time series data.

In the last decade the study used a combination between the ARCH model with ARIMA. But in this research is compared by using a combination between the model Realized Volatility model and ARFIMA (autoregressive fractionally integrated moving average) with the purpose of obtaining a more accurate model to be used in Islamic stock selection process.

B. Realized Volatility Model and ARFIMA

Realized Volatility models in this study is a model formed by the combination between the variants of intraday and interday variants derived from stock price data in the Indonesia Stock Exchange. The formulation of Realized Volatility as defined in this study are as follows :

At first the data available for time series in the Indonesia Stock Exchange is the daily closing price data so that the variance is calculated by a simple formula, as follows :

$$S_{\bar{x}}^2 = \frac{1}{k-1}\sum(\overline{x_i} - \bar{x})^2$$

But current time, the data available in the Indonesia Stock Exchange is the high frequency data from the open market until the close market in the afternoon so that the variance formula involves changing the data in a single day of the exchange as follows:

$$\overline{S^2} = \frac{1}{k(n-1)}\sum_i\sum_j(x_{ij} - \overline{x_j})^2$$

or simplified as follows :

$$= \frac{1}{k}\left\{\frac{1}{n-1}\sum_i\sum_j\left(x_{ij} - \overline{x_j}\right)^2\right\}$$

k = population
n = sample
j = interday data
i = intraday data

Given the availability of intraday data and interday data then the two formulas above are combined to produce a formula as follows:

$$\sum_i^n\sum_j^k\left(x_{ij} - \bar{x}\right)^2 = \sum_i^n\sum_j^k\left(x_{ij} - \overline{x_j} + \overline{x_j} - \bar{x}\right)^2$$

$$= \sum_i^n\sum_j^k\left[\left(x_{ij} - \overline{x_j}\right) - \left(\bar{x} - \overline{x_j}\right)\right]^2$$

$$= \sum_i^n\sum_j^k\left[\left(x_{ij} - \overline{x_j}\right)^2 - 2\left(x_{ij} - \overline{x_j}\right)\left(\bar{x} - \overline{x_j}\right) + \left(\bar{x} - \overline{x_j}\right)^2\right]$$

but :

$$\overline{x_j} = \frac{1}{n}\sum_j^n x_{ij}$$

$$\sum_{i=1}^n x_{ij} = n\overline{x_j}$$

Then, realized volatility formulated as follows :

$$\underbrace{\sum_i^n\sum_j^k\left(x_{ij} - \overline{x_j}\right)^2}_{\text{Total sum square}} = \underbrace{\sum_i^n\sum_j^k\left(x_{ij} - \overline{x_j}\right)^2}_{\text{sum square interday}} + \underbrace{n\sum_j^k\left(\overline{x_j} - \bar{x}\right)^2}_{\text{sum square intraday}}$$

The formulation of the Realized Volatility model above is used as a comparison to find which of the two approaches are more accurate and better. Surely ARCH model will be integrated by using ARFIMA as well, so the comparison is more reasonable and fair. But in this study, researcher performed also a comparison between ARIMA and ARFIMA.

ARFIMA modeling was first developed by Granger and Joyeux (1980) which is an alternative to ARIMA models. What distinguishes them is the variable d is the fraction that is more certain and do not need to take action to try as done in the ARIMA and long-memory data must be determined by using the formula of Hurst (1951) by H indicator.

The formulation of ARFIMA developed by Granger dan Joyeux (1980) as follows:

$\Phi(B)\,(1-B)^d\,(Z1-\mu) = \theta(B)$

t = observation index
d = difference parameter
μ = the average of observation
Φ(B) = polynomial AR (p)
θ (B) = polynomial MA (q)
$(1-B)^d$ = difference operator

The number d in ARFIMA obtained by using the formula:

$$(1-L)^d = 1 + \sum_{j=1}^{\infty} \frac{\Gamma(d+1)}{\Gamma(d-j+1)\,\Gamma(j+1)} (-L)^j$$

$\Gamma = 1/4\pi \int [\Delta \lg f(\lambda)\, \Delta \lg f(\lambda)'] \, d\lambda$
(*distribution convergence*)
d = difference variable
L = regressor function

Before using the ARFIMA model, the first step in the process is checked whether the data is the long persistence time series to describe the long memory. Checks carried out by long persistence perform calculations by the method of Hurst (1951) in addition to calculating differentiantion variable "d". The Hurst method using the formula R/S (rescaled range analysis) as follows:

$$\frac{Max\sum_{t=1}^{k}(X_t-\bar{X}_n) - Min\sum_{t=1}^{k}(X_t-\bar{X}_n)}{S(n)},$$

where $0 \le k \le n$.

If the calculation is obtained 0 <H <1 then indicated that time series data are a long memory so it can use the ARFIMA model. But also can be seen in the amount of numbers in which its d differentiator standard is -1<d <0.5 where d≥0.5 (away from 0.5) is the long persistence but non stationary and ≤-1 short persistence and also non stationary.

In the ARFIMA estimation tool distinguishing variable calculation is not done with the test differentiation by using autocorrelation (AC) or partial autocorrelation (PAC) in correlogram because:

1. The process of generating AC and PAC used integer number between 0 to 2, while the number of variables distinguishing the desired d is the more accurate the fractional number between 0 and 0.5.
2. Determination of lag on the AC and PAC is to examine the first significant spike in the AC or the PAC to determine autoregression and moving average, so it will be a fundamental deviation.

2. Literature Review

This study was conducted to generate most accurate model for measuring volatility in stock prices in Indonesia where the model will be very useful in selecting stocks for the Jakarta Islamic Index or other Sharia Index in Indonesia and another stock market in the world. Impressed nothing to do with the volatility of Islamic sharia but actually there, as evidenced by the presence of Islamic principles do not justify the speculation in the investment instruments selection process. Islamic principles will give priority to investing in stocks that have a constant variance (homoscedasticity). But because the nature of the stock is volatile, especially in emerging countries, markets are not efficient then selected stocks must have the prices with the smallest heteroskedasticity. To have the most accurate measurement, heteroskedasticity would require an accurate model as well. Beside for islamic investment model, this Realized Volatility model also can be used in measuring market risk for conventional mutual fund, even for other financial intermediaries such as banks, insurance companies and pension fund institutions.

For the first time, volatility is measured by the ARCH model proposed by Engle (1982). ARCH model was further developed by some researchers to be generalized ARCH (GARCH), ARCH in mean (ARCH-M), Threshold ARCH (TARCH) and Exponential GARCH (EGARCH). ARCH model was developed by Bollerslev (1986), generalized ARCH become GARCH in which the residual variance depends not only on the last period but also the residual variance and residual periods. In his research, since Bollerslev (1986) found that GARCH models could not be estimated by ordinary least square but by using the method of maximum likelihood, the study did not discuss any more about the other ARCH family.

Realized volatility was developed by Andersen, Bollerslev, Diebold and Labys (1999) using a 5 minute returns data in the measurement of daily exchange rate volatility. The exchange rate was considered as the instrument with a very dynamic movement. To analyze the volatility of that instrument, needs a new approach or models by using higher frequency data. The researchers used the realized volatility models. The realized volatility was also used to analyze the volatility of the 30 types of stocks in the Dow Jones Industrial Average. In their findings, Andersen, Bollerslev, Diebold and Labys (1999) showed that the price changed from day to day with highly fluctuation in single second. Later can be seen that by using the Realized Volatility, in the first variant of the data was skewed cleary, then having made a standard deviation moved in the normal direction and created after the log variance showed a normal distribution. In the present study also found that the realized correlation was almost always positive in which the realized correlation have a strong correlation with realized volatility. Andersen, Bollerslev, Diebold and Labys (1999) later termed this as the volatility effect in correlation.

Ebens (2000) did a realized volatility research focusing on measuring, modeling and forecasting volatility. In his study, the estimation by using an economic model was not valid. Furthermore Ebens (2000) showed that direct indicators such as daily squared return volatility is a fundamental error. In his research Ebens (2000) choosed square intraday return volatility as measuring instruments and the variance is log normally distributed and long persistence. Research results also indicated that the volatility with the realized volatility was correlated with lagged negative returns than positive returns lagged. By comparing the ARCH model with realized volatility was also found that realized volatility is more accurate in calculating the volatility in the Dow Jones Industrial Average's (DJIA).

Kayahan, Stengos and Saltoglu (2002) conducted a study of Realized Volatility by comparing with GARCH in the Istanbul Stock Exchange by using a 5 minute returns data. They concluded that standardization by using GARCH variance is insufficient to eliminate the excess kurtosis, where as standardization with the variance using Realized Volatility was able to accomplish the elimination process of the excess kurtosis. The research of Kayahan, Stengos and Saltoglu (2002) is represented emerging markets such as stock exchange in Turkey.

In Asia, research on the Realized Volatility performed by Nor, Isa and Wen (2007) to produce the findings in the Malaysia capital market, risk premium was not found, but there is a significant relationship between the news stories that indicated by the lagged return volatility. It means that there are the impacts of good news and bad news on volatility. The data in the capital market in Malaysia is long persistence. In their study in Malaysia, Nor, Isa and Wen (2007) used Autoregressive Fractionally Integrated Moving Average (ARFIMA) as a tool for estimation.

ARFIMA as a model for estimating, was introduced by Granger and Joyeux (1980). The idea of fractionally differencing is introduced in terms of the infinite filter that corresponds to the expansion of the service differentiator $(1 - B)^d$. When the filter is applied to white noise, a class of time series is generated with distinctive properties, particularly in the very low frequencies and provides potentially useful forecasting long memory properties. Granger and Joyeux argued that for data analysis in time series of the most important was to ensure that the data was stationary. Basic ARFIMA is autoregressive moving average (ARMA). ARFIMA is the process by finding stationary differentiating factor which produces a number d, p (AR) and q (MA). Initially used by the Box Jenkins, ARMA, was implemented by applying autoregressive integrated moving average (ARIMA) to search for differentiating factor dusing the correlogram to determine p (AR) and q (MA). The ARIMA process is to use direct observation of the AC and PAC. In this process often inaccurate because the numbers obtained differentiator d are integers. And of course it would not be effective for data very much and in the long term. Granger and Joyeux argued that the ARFIMA process could be implemented only for the long memory data and thus required special calculations.

Alana and Toro (2002) used the ARFIMA to perform analysis on the real exchange rate that is performed on the model hypothesis of the Purchasing Power Parity (PPP). ARFIMA approach is allowed to capture the low frequency dynamics relevant for examination of the long run parity. In the process of this analysis they focused on the estimation of d in order to validate or reject some theories, depend on the stationary or on the mean reversion of the process. On their paper, that theory is investigated by using fractionally integrated models, putting emphasis on the modeling aspects of analysis. This suggests that the high frequency data such as the exchange rate is the ARFIMA absolutely necessary.

Erfani and Samimi (2009) investigated whether the stock price index in Iran is long memory or not by using the ARFIMA model. In the process of analysis, Erfani and Samimi (2009) computed long memory by using a method of Hurst (1951) with rescaling range analysis (R/S) where if $0 < H < 1$ then the data is both long memory.

3. Methelodogy

Research in this paper used the data as much as 65,520 data, per 5 minute data, from January 2, 2006 to June 30, 2010 which is processed into the volatility of daily data as many as 1086 observations. The data used in this study is from one of the stock which have price data available on the Jakarta Islamic Index. It is Astra Agro Lestari (AALI). Stock was selected from several stocks because the volatility of the AALI price provided a requirement for processed using ARFIMA, stationary and long memory. AALI stock volatility with the variance had a long memory properties with the number H of 0.7241 and d of 0.4166. AALI volatility with the standard deviation had H of 0.7103 and d of 0.4087. AALI volatility with log variance had a rate H of 0.6866 with d figure of 0.4491.

With d figures for the above was found that the data was stationary. AALI volatility can also be proved by comparison of the numbers χ^2 smaller than the figure calculated χ^2 with $\alpha = 5\%$ for various levels of degree of freedom (df). In the research, I used the df 1, 6 and 8. Then later in the process accounted for the comparison between ARFIMA and ARIMA for data volatility AALI to produce the most accurate estimation tools used in estimating the ARCH model of volatility and volatility model Realized Volatility.

4. Findings

The first analysis performed to compare between ARFIMA and ARIMA then obtained is that the ARFIMA have numbers of Mean Square Error (MSE) is smaller than the MSE by using ARIMA. The conclusions drawn as a tool to use ARFIMA estimation of ARCH models and realized volatility as in the table 1 and table 2, as follows:

Table 1: Analysis of ARFIMA

	VAR	LOG VAR	STD	Q Stat (table)
ARFIMA				
MSE	1.6983×10^{-11}	0.5887	4.8963×10^{-7}	
x^2df1/p – value	0.0002×10^{-1}/0.9901	0.0236/0.8780	0.0002×10^{-1}/0.9900	3.8415
x^2df6/p – value	7.1059/0.3112	3.8726/0.6939	3.0783/0.7990	12.5926
x^2df8/p – value	15.6160/0.4822×10^{-1}	4.4760/0.8118	4.2170/0.8319	21.0261

Table 2: Analysis of ARIMA

	VAR	LOG VAR	STD	Q Stat (table)
ARIMA				
MSE	2.6277×10^{-11}	152.3590	7.0725×10^{-7}	
x^2df1/p – value	0.0120/0.9128	0.0120/0.9128	0.0129/0.9097	3.8415
x^2df6/p – value	1.1747/0.9781	1.9857/0.9781	12.5916/0.9210	12.5916
x^2df8/p – value	12.5179/0.1295	12.5179/0.1295	3.4670/0.9017	21.0261

The second analysis showed that from a normal distribution curve of the actual data during the last 10 days of research with the number estimated last 10 days of the study is that the numbers 10 days after estimation using realized volatility for the variance and standard deviation shows a negative skewness which has a long tail to the left with a sense of the median is greater than the mean and still be around 0. Tentative conclusion of the third instrument is the volatility of realized volatility tend to be normally distributed. Kurtosis of each normal curve the last 10 days and 10 days of the actual number estimates showed that the log variance is a number that is platykurtic kurtosis below the 3 but still close to the number 3, because the data are normally distributed with kurtosis 3 while the other volatility tool showed a leptokurtic (K> 3). In the test for normality there is no principle that absolutely must be based on the Jarque Berra (JB), but the relative numbers that must be seen also from figures kurtosis and skewness. Calculations using the ARCH model with ARFIMA also showed a tendency normally distributed with a number JB 1.63 and 1.45 for the actual data to estimate data where skewness of 0.99 and 0.92 on the actual figures on the number of estimates and 2.94 for kurtosis in actual numbers and 2.65 for estimates. From the results of both approaches normality test estimates both realized volatility and ARCH using the ARFIMA model can be interpreted that both acts generate data with high heteroskedasticity properties (tend to have non constant variance). The results of analytical calculation of normality can be seen in the table 3, as follows:

Table 3: Volatility – Normal Distribution

	Jarque Berra								
	JB	PR(%)	Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis
Var 10 days	3.77	15.16	0.53×10^{-7}	0.36×10^{-7}	0.14×10^{-7}	0.23×10^{-7}	0.37×10^{-7}	1.41	4.03
Var estimation	5.06	7.97	0.73×10^{-7}	0.75×10^{-7}	0.78×10^{-7}	0.55×10^{-7}	0.07×10^{-7}	(1.58)	4.45
Log Var 10 days	1.03	59.80	(12.33)	(12.53)	(11.18)	(12.97)	0.60	0.68	2.22
Log Var estimation	0.87	64.68	(12.36)	(12.25)	(11.74)	(13.18)	0.51	(0.43)	1.84
Std 10 days	1.78	41.15	0.22×10^{-2}	0.19×10^{-2}	0.37×10^{-2}	0.15×10^{-2}	0.72×10^{-3}	1.03	3.00
Std estimation	11.05	0.39	0.23×10^{-2}	0.24×10^{-2}	0.24×10^{-2}	0.19×10^{-2}	0.13×10^{-3}	(2.08)	6.03
ARCH 10 days	1.63	44.23	(0.95×10^{-3})	(0.12×10^{-2})	0.50×10^{-3}	(0.16×10^{-3})	0.69×10^{-3}	0.99	2.94
ARCH estimation	1.45	48.50	0.65×10^{-3}	0.61×10^{-3}	0.92×10^{-3}	0.51×10^{-3}	0.14×10^{-3}	0.92	2.65

The analysis shows that the results of the comparison between the ARCH model with realized volatility models, by using Realized Volatility model with ARFIMA is better and more accurate than the ARCH model, considering some of the test results: MSE model of realized volatility, especially variance and standard deviation is smaller than MSE ARCH models. Figures d in ARFIMA realized volatility is equal to 0.4449 for the log variance, 0.4166 for variance and 0.4087 for standard deviation, than ARCH has a rate d of 0.4077.

The results of the comparison between the realized volatility and ARCH models can be seen in the table 4, as follows:

Table 4: Realized Volatility model versus ARCH model

	VAR Realized Volatility	LOG VAR Realized Volatility	STD Realized Volatility	ARCH
ARFIMA				
d/MSE	0.4166/ 1.6983 x 10^{-11}	0.4491/0.5887	0.4087/ 4.8960 x 10^{-7}	0.4077/ 0.0003x10^{-3}
x^2df1/p – value	0.0002 x 10^{-1}/ 0.9901	0.0236/0.8780	0.0002 x 10^{-1}/ 0.9900	0.0009 x 10^{-1} / 0.9763
x^2df6/p – value	7.1059/0.3112	3.8726/0.6939	3.0783/0.7990	2.7640/0.8378
x^2df8/p – value	15.6160/0.0482	4.4760/0.8118	4.2170/0.8319	3.2874/0.9150

Based on the calculation of several measurements, concluded that the Realized Volatility model by using ARFIMA model is the best and the most accurate estimates for the calculation of the volatility of stocks in Indonesia Stock Exchange. It means that the analysis of intraday data is commonly used ARCH models considered to change, although the differences is small MSE. This conclusion relates to the results and the previous analysis which shows that good results with Realized Volatility model and ARCH model using ARFIMA models had the same tendency is normally distributed (having small heteroskedasticity). Realized Volatility model determining factor is better than ARCH model as distinguishing number 'd' on Realized Volatility Model larger than the ARCH model.

5. Conclusion

This study shows that the volatility of stock price data of AALI on the Indonesia Stock Exchange for the period January 2, 2006 until June 30, 2010 to 65520 number of observations is processed into a daily volatility of the 1086 data, the most accurate result is computed by Realized Volatility model. Thus this Realized Volatility model is strongly recommended to measure the volatility of stocks listed in the Indonesia Stock Exchange. Realized Volatility model also can be considered by market analysts for any financial market in the world to measure the volatility. For the same character, heteroskedasticity, Realized Volatility model also can be used to measure the market risk profile of stocks, mutual funds, foreign exchange in banking industry, insurance companies, investment management company, pension fund company and investors over all because volatility is the reflection of market risk.

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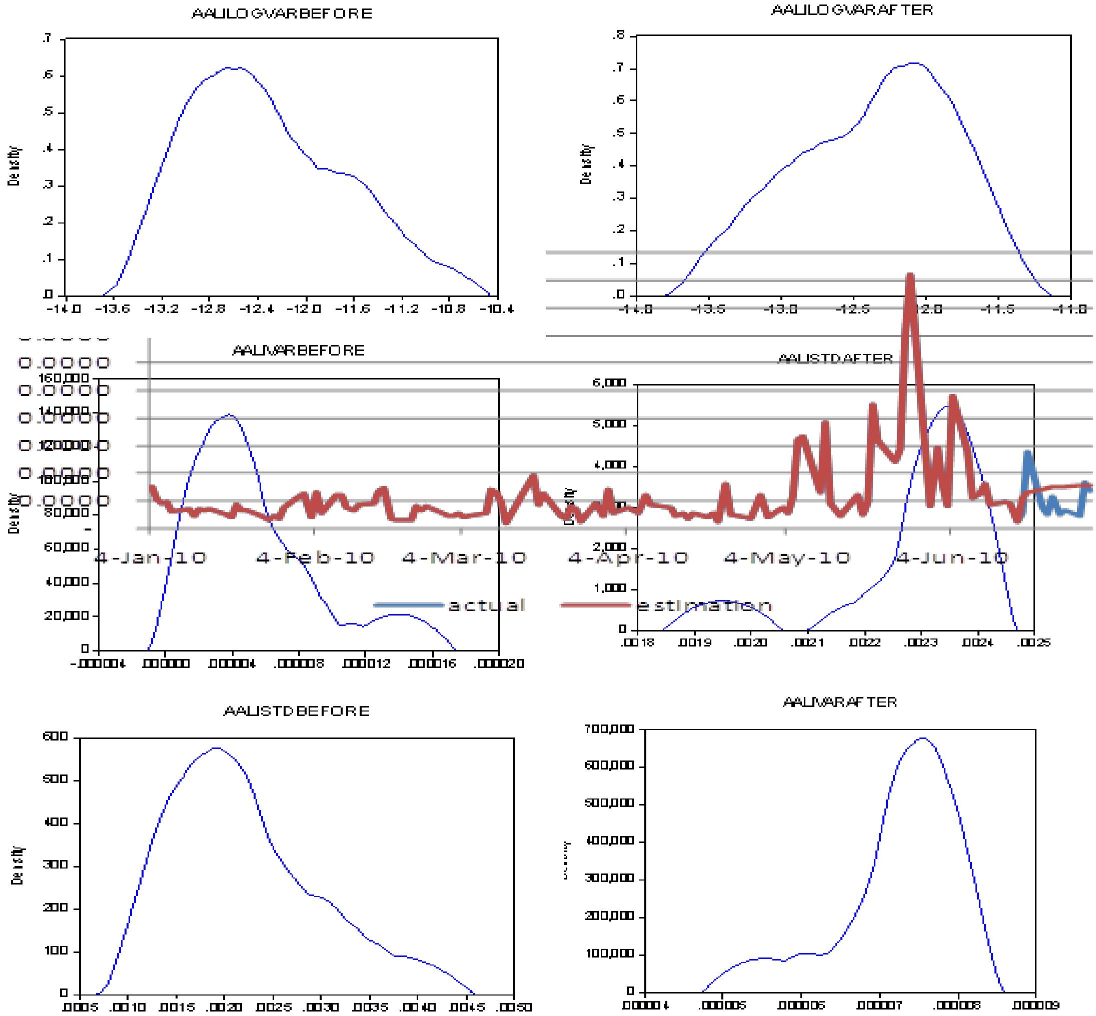

Figure 1: Kernel Density – Log Variance, Variance and Standard Deviation

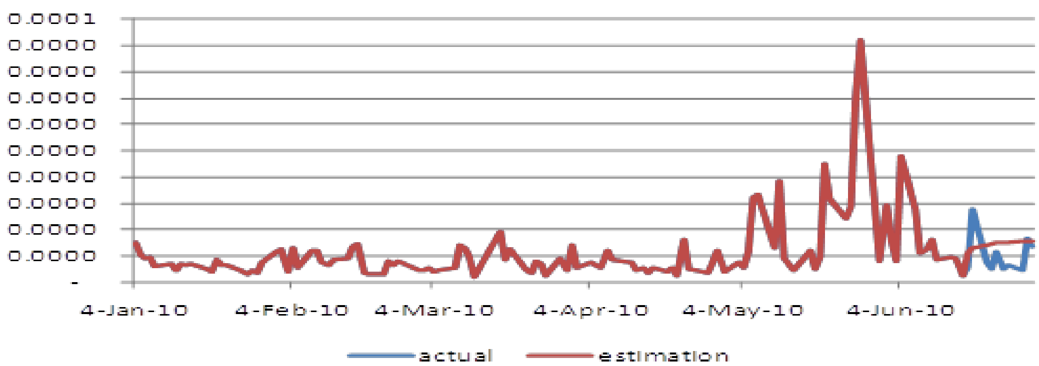

Figure 2: Actual – Estimation Variance AALI

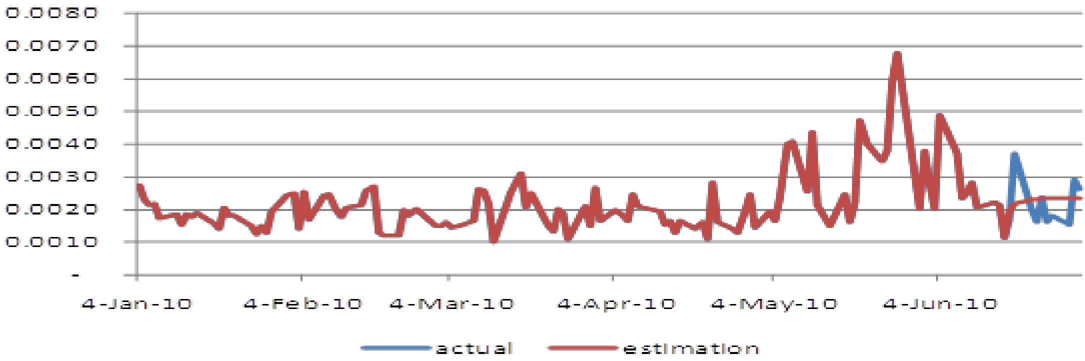

Figure 3: Actual – Estimation Standard Deviation AALI

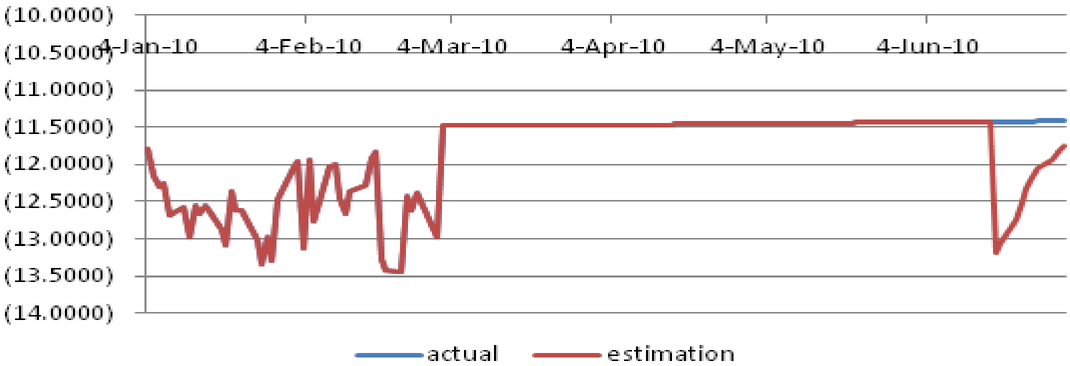

Figure 4: Actual – Estimation Log Variance AALI

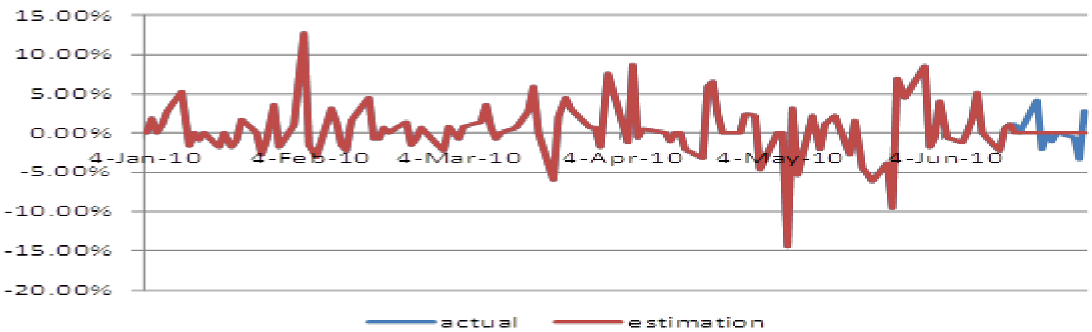

Figure 5: Actual – Estimation ARCH AALI