MEASUREMENT OF INTERNAL MODEL OF VALUE AT RISK IN INDONESIAN BANK INDUSTRY UNDER BASEL III

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Abstract

It is well known that in investment the existence of the relationship between risk and return is very strong. Bank as a financial institution that serves to collect funds from the public in the form of demand deposits, time deposits, and other deposits and channeled back in the form of credit, also has to consider the risks very well, especially the credit risks. The global financial crisis in 2008 brought a significant influence on credit risk and also credit valuation adjustment (CVA) risk framework. Since then The Basel II was improved by The Basel III which was first published in December 2009. Introducing new adjustment for capital adequate ratio (CAR) and model of capital cost risk against the volatility model for CVA, as for the improvement of The Basel II risk framework.

The purpose of this study was to measure how well the risk model that has been used by the government bank in Indonesia compare to the new CVA Internal Model based on The Basel III. In this study VaR as the measurement tool for risk framework can be applied into the new regulation of The Basel III. This study is using the purposive sampling technique, and using the data of the banks that go public on the Indonesian Stock Exchange in 2013-2015. To make the calculation of risk volatility more precisely, ARMA and GARCH model will be applied into the Internal Model based on The Basel III.

Keywords: *Bank;Risk; BASEL III; VaR; Internal Model.*

1. Introduction

Risk can be determined as a volatility of unexpected outcomes represents value of assets, equity of earnings (Jorion, 2007). The need to manage the risk and to hedge against these risks has led to the exponential growth of derivatives market (Jorion, 2007). Investors should consider the risks that could affect the level of profits and losses. Risk is also the variability of the actual and expected return. To minimize the risk it takes a statistical approach known as the method of Value at Risk (VaR).

Value at Risk (VaR) is quantitative risk management measurement tools to evaluate the exposure of market risk. VaR has been considered by regulatory authorities and financial institutions as the most important market risk measurement (Angelidis & Benos, 2008, 67). Market risk is dealing with changes in financial instrument prices, which will lead changes in portfolio value and later will affect the profit and loss. Beside to quantify market risk, VaR is widely used to set capital adequacy ratio (CAR) for accommodating market risk and to set the trading limit. This appliances were used widely in banking industry. VaR is also can be used as vehicle for corporate insurance as it calculated the worst possible loss due to market movement. Thus,VaR can be seen as risk control for position limit and margin requirement. VaR can provide accurate asset return and volatility estimation. VaR itself is the quantile function measured the tail of Profit and Loss distribution of portfolio.

VaR can be obtained through conditional mean model i.e Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA) or and volatility modeling i.e GARCH (Standardized and modified). In the research of [Danielson 1997] found that classical GARCH has inadequate estimation for calculating tail quantile. Thus further model modification is needed to represent the actual time series. [Engle&Ng 1993] had Asymmetric GARCH to predict volatility. While [Nelson, Glosten, Jaganathan&Runkle1993] proposed asymmetric GARCH i.e. Exponential GARCH (EGARCH) and Treshold ARCH (TARCH). [Nelson 1990] modified standard GARCH and found negative correlation between stock return and volatility, while increasing volatility as impact of bad news and vice versa. [Thupayagale2010] had evaluated 8 volatility prediction models in emerging market and found that different model fitted different market behavior so that the result can give more accurate prediction.

In this paper, we will see the risk that will face by the Indonesian government banking which in this case we will choose for Mandiri, BNI, BRI and BTN. As a reference to set the limit of risk, Bank for International Settlement has recommend banks throughout the world to use the requirements from Basel Acord, in which VaR can be used as the measurement for the bank risk internally. VaR will be used for calculating banking industrial capital adequacy for accommodating market risk. According to Basel 1998, safety margins for risk capital can be accommodating by multiplying historical VaR with at least 3 as the fudge factor., while in the latest Basel Acord (Basel III) the fudge factor or the stress factor are limited between k=3 and k =7. Therefore to enrich this study, we will use the lates Basel III as the reference for the risk.

2. Background Theory

2.1 Value at Risk

Jorion (2007: 17) argues that "VaR summarizes the worst loss over a horizon targets that will not be exceeded with a given level of confidence". In the process of calculation of VaR, which is the object of the calculation is the distribution simulation of the daily return. The formula for calculating VaR are as follows (Jorion, 2007: 107)

$$VaR = W * \sigma * \alpha * \sqrt{t} \qquad (1)$$

Where

W = eksposure

σ = volatility

α = confidence level

t = *holding period*

2.2 GARCH

Generalised Autoregressive Conditional Heteroscedasticity (GARCH) described in the equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2, \ \alpha_1 + \beta_1 < 1 \qquad (2)$$

2.3 Framework

Value at Risk (VaR) is a risk measurement technique that is very popular discussed and implemented in measuring risk. Moreover, after the Bank for International Settlement recommend banks throughout the world for use in measuring the VaR market risk internally (Internal models Approach) (Basel III Accord).

3. Research Methods

A. Choosing Conditional Mean Model (ARMA)

The first stage, entrance to conduct VaR calculation is to test whether the time series data will behave as stationery process. The null hypothesis in Augmented Dickey Fuller Test specified as below;

H_0; $\theta = 0$; (the data needs to be differenced to make it stationary)

H_1; $\theta < 0$; (the data is stationary and doesn’t need to be differenced)

which gives the result h =1, thus the null hypothesis is rejected and means the time series data is stationary

Second stage, is to identify the ARMA Process. We should observe the Autocorrelation Correlation Function (ACF) and Partial Autocorrelation Correlation Function (ACF) in order to examine the lags which violated the Bartlett’s line. From visually results of lags that violate the Bartlett’s line, the those lags should be analyzed to construct ARMA process.

The goodness of fit should be checked in the chosen model ARMA. The residual for each model together with Normality examination in QuantileToQuantile plot (QQPlot) are plotted in The likelihood value from Akaike/Bayesian Index Criteria (AIC/BIC) which represent as error of the model is calculated for each model and later be compared. The smallest is to be chosen as best ARMA model.

Third,Residual autocorrelation can be checked by conducting Portmanteau/Ljung-Box Q test. The results must show that there is no autocorrelation in the chosen model.

Last, the ARCH Effect is conducted to check if the model's residual is following Strictly White Noise (SWN) and has no heteroskedacity effect. If yes, no necessary extended of volatility model required. If residual behave like White Noise but not SWN, then volatility model is required. Under the null hypothesis that a time series is a random sequence of Gaussian disturbances, this test assumed that no ARCH effects existed. And result of this test was rejection of null hypothesis (h=1) with p-Value under 5%. This test statistic is asymptotically Chi-Square distributed.

B. **Choosing Volatility Model (GARCH)**
From the chosen model of ARMA , the volatility model of GARCH will be found.

C. Calculate Value at Risk from the chosen model of ARCH and GARCH
Value-at-Risk can be obtained from the best suited model of conditional mean ARMA and volatility model of GARCH.

D. Calculating Internal Model
Internal Model will transform calculated VaRto regulatory capital by calculating its Market Risk (MR) with the following risk-capital formula results:

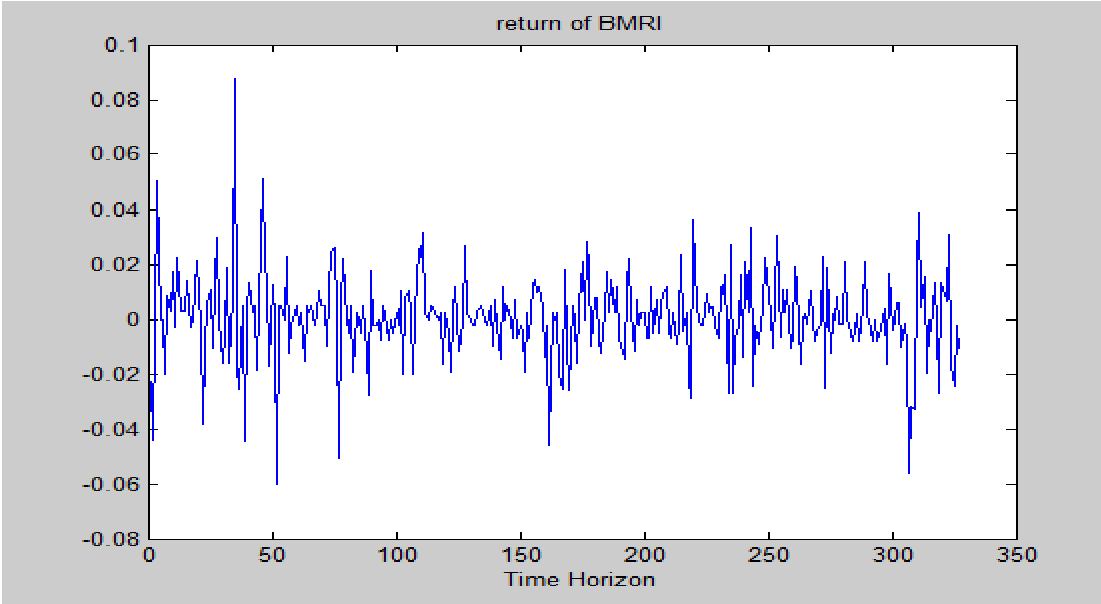
$$RC_{IM}^{t}(MR) = \max\left[VaR_{0.99}^{t,10}, \frac{k}{60}\sum_{i=1}^{60} VaR_{0.99}^{t-i+1,10}\right] + C_{SR} \tag{3}$$

Where VaR*j*,10 0.99 is a 10-day VaR with the 99% confidence level, calculated on day *j* and *t* represents today. The *stress factor* 3<= *k* <= 7 is determined as a function of the overall quality of the bank's internal model. Selecting k = 3.5 and C_{SR} as specific risk assumed to be 0.5.

According to the Basel III regulatory capital and market risk of the final rule, the specific risk in an internal model should include risk weight, to participate in various assets: sovereign debt, debt position multilateral development banks, government debt, foreign bank, credit union, bank public, corporate debt and securitization position (Basel III in www.pweregulatory.com). This factor should be adjusted in a state of debt and the bank's internal rating at this time. The highest factor is stressed in VaR.

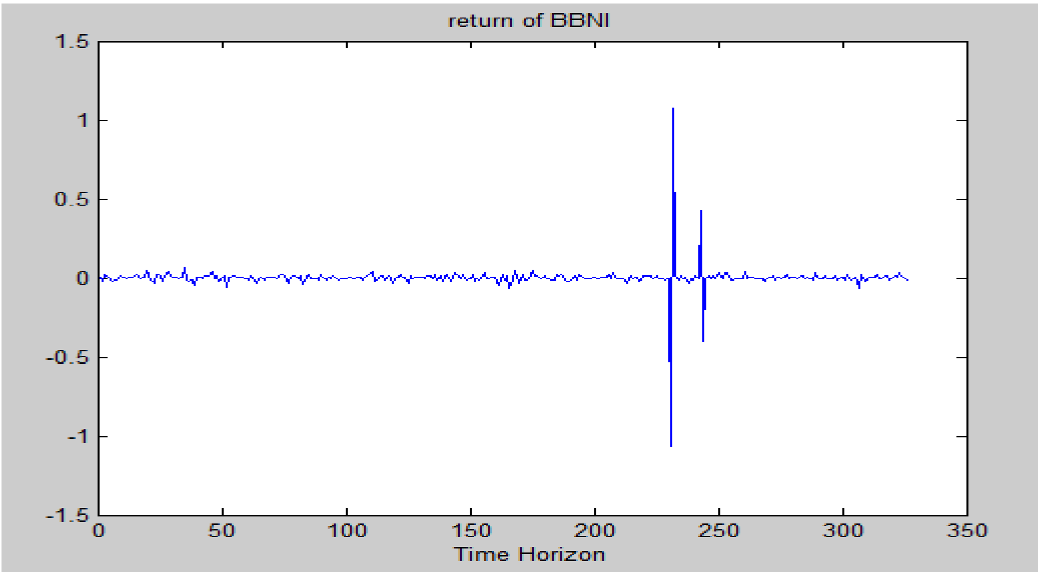
4. Results Analysis

Before long way to obtain VaR, we take snapshot of return data of Mandiri, BNI, BRI and BTN. The data are taken from [1-Jan-2013] to [31 Mei 2015] , the return will be depicted in figure (1) to (4) respectively:



Source : Data Processing

Figure 1 Return price stock of Mandiri (October 2013 – Mei 2015)



Source : Data Processing

Figure 2. Return price stock of BNI (October 2013 – Mei 2015)

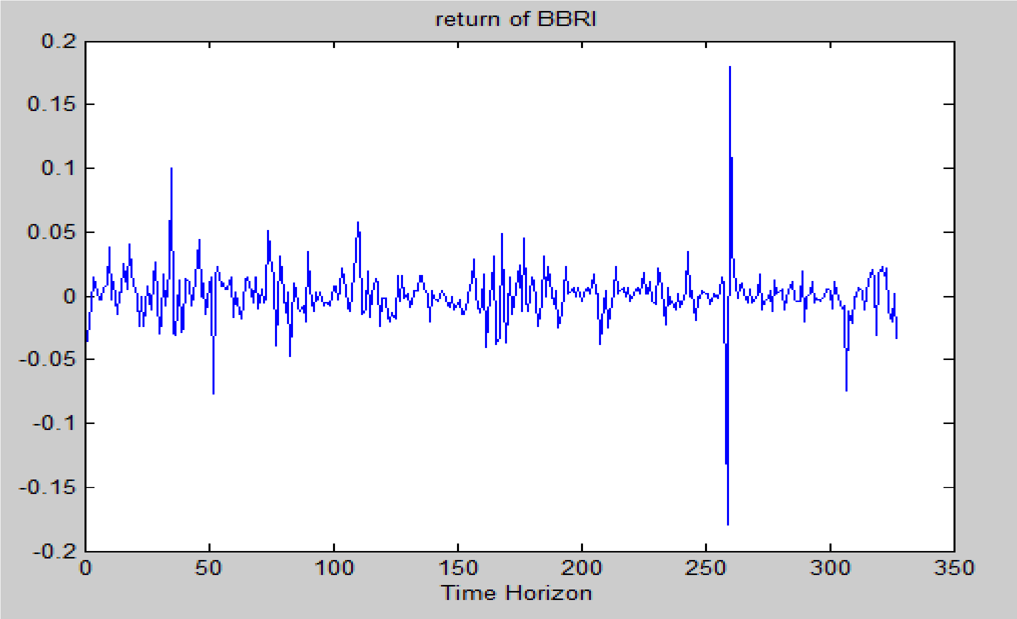


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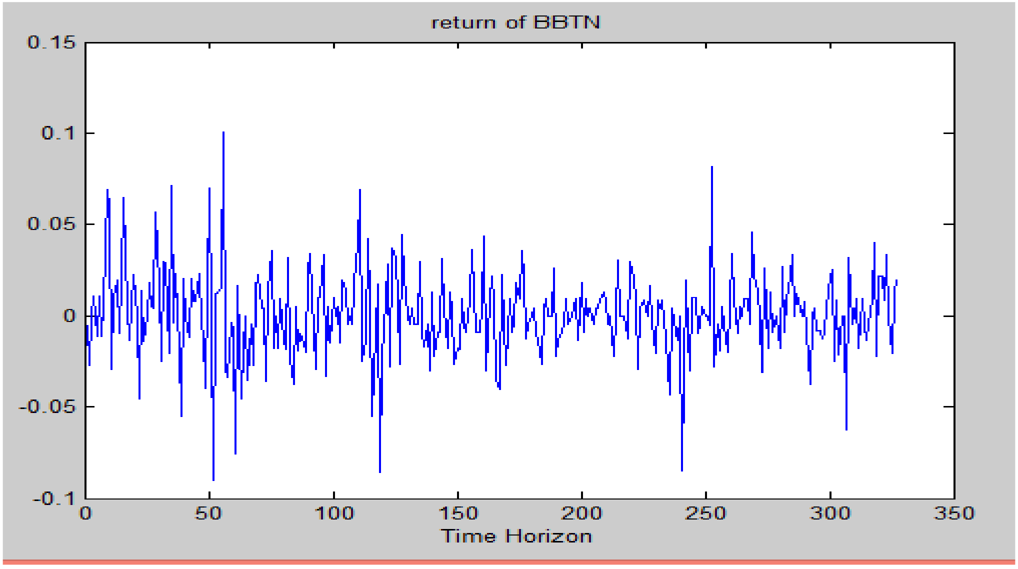
Figure 3 Return price stock of BRI (October 2013 – Mei 2015)



Source : Data Processing

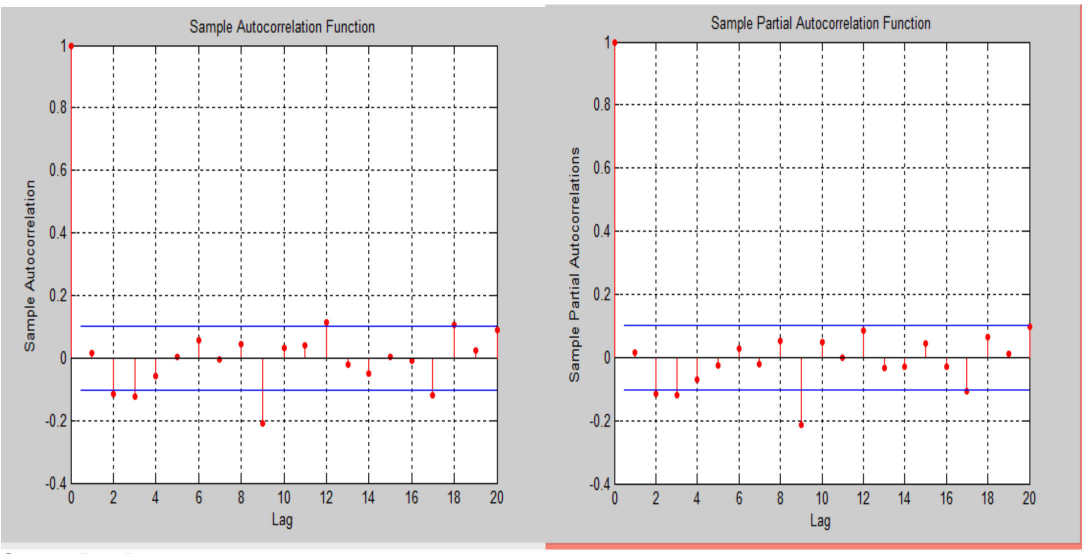
Figure 4 Return Price Stock of BTN (October 2013 – Mei 2015)

Below is the explanation for each ARMA model of all banks.

4.1 Choosing Conditional Mean Model ARMA

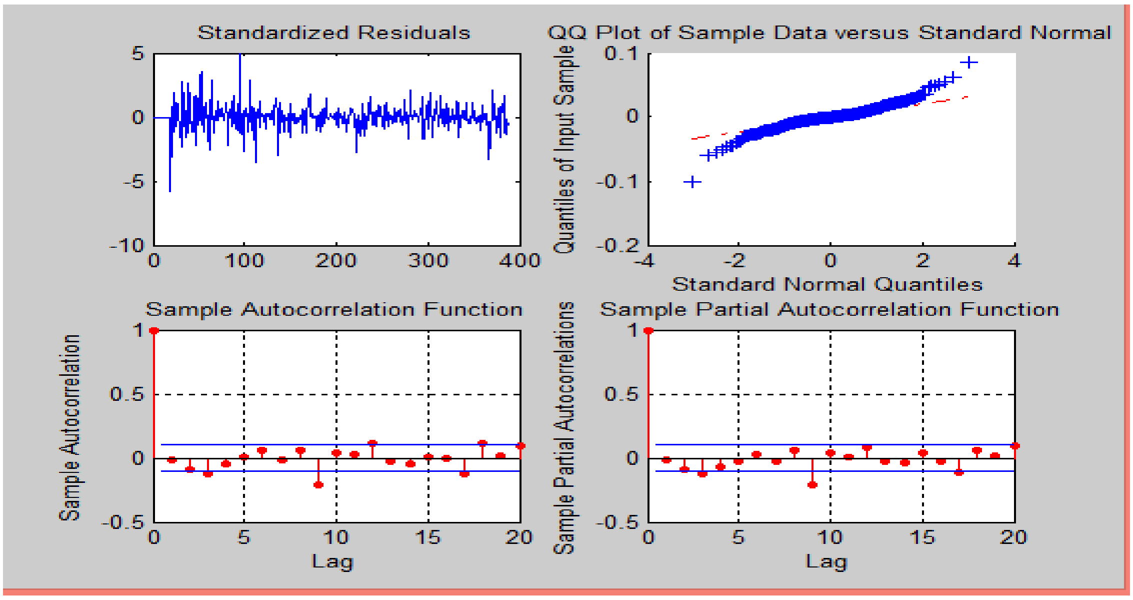
A. ACF and PACF Bank Mandiri

We define the Portmanteau / Ljung-Box Q test to begin with. From Ljung-Box Q test we have to pay attention to lag out the Bartlett's line



Source : Data Processing

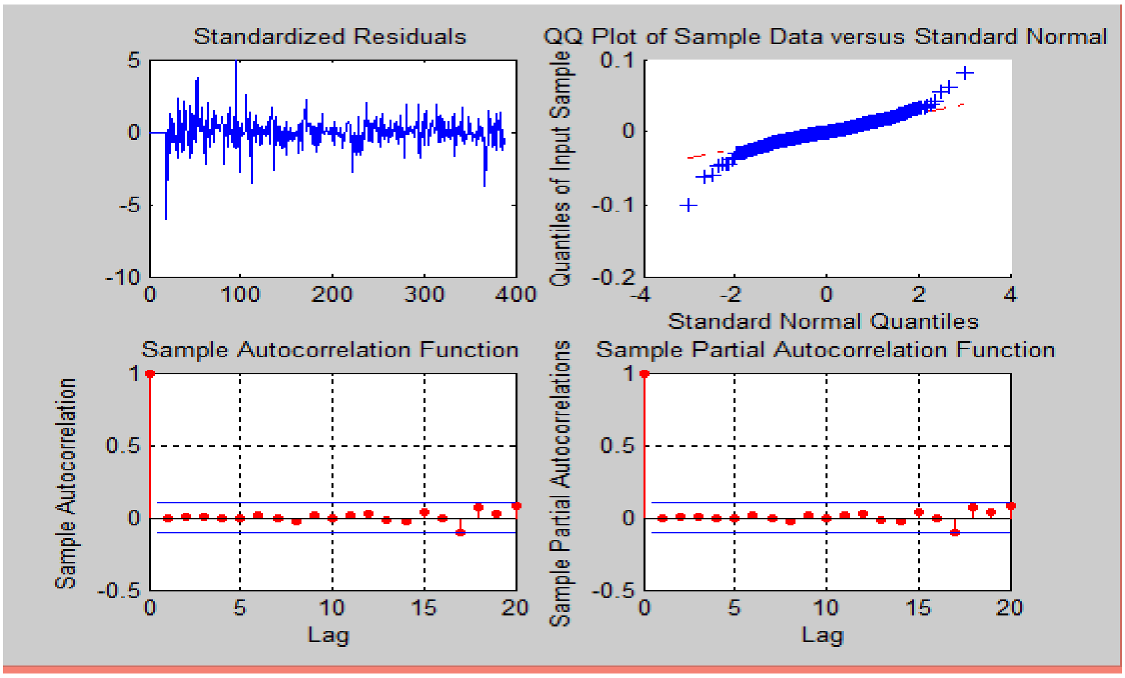
Figure 5 ACF and PACF *time series data*



Source : Data Processing

Figure 6 ARMA (1,1)

ARCH effects can also be visually inspected to check the ACF and PACF of residual current ARMA (1,1) model in Figure 6, and thus can be seen breaking the line of Bartlett. We have conducted several test of ARMA where here we have ARMA (1,1), (3,9) and (9,3). ARMA (1,1) gives the fit model, so it can be concluded that the model ARMA (1,1) has the effect of ARCH.



Source : Data Processing

Figure 7 ARMA (3,9)

B. ACF and PACF of Bank BNI

ARMA process for Bank BNI has been done by observation autocorrelation function (ACF) and partial autocorrelation function (PACF) to check lags that violates the Bartlett's line. Results are shown in Figure 9 the lag of 1, 2, 3, 4, 5, 6, 11 and 12 need to be analyzed to build an ARMA process, since they violates the line of Bartlett.

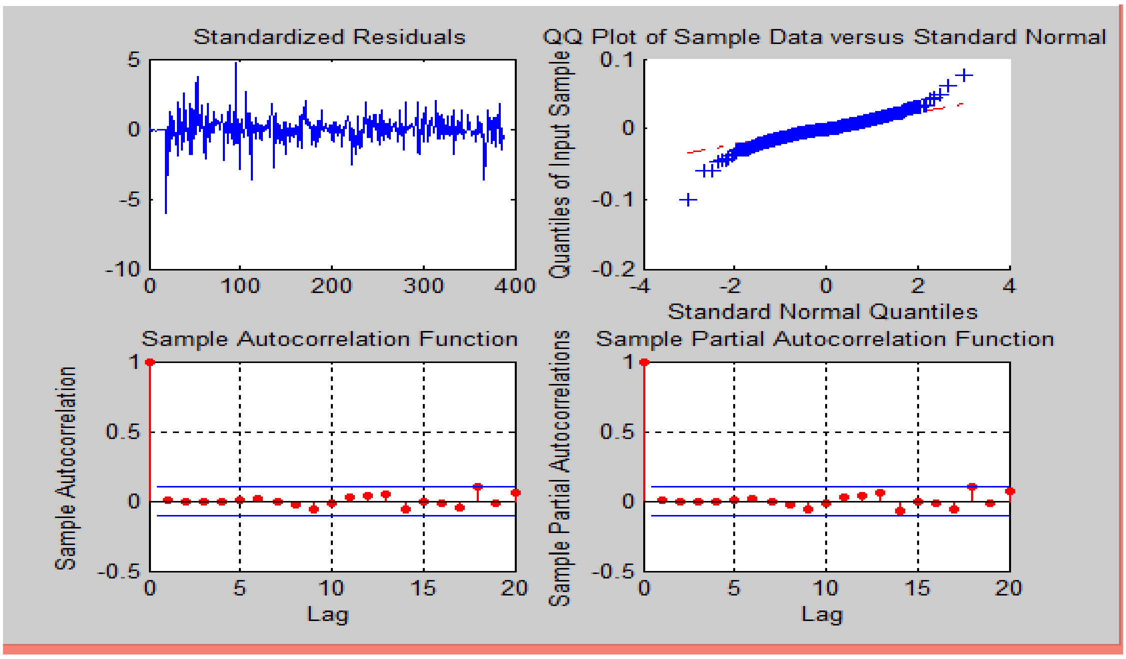


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Figure 8 ARMA (9,3)

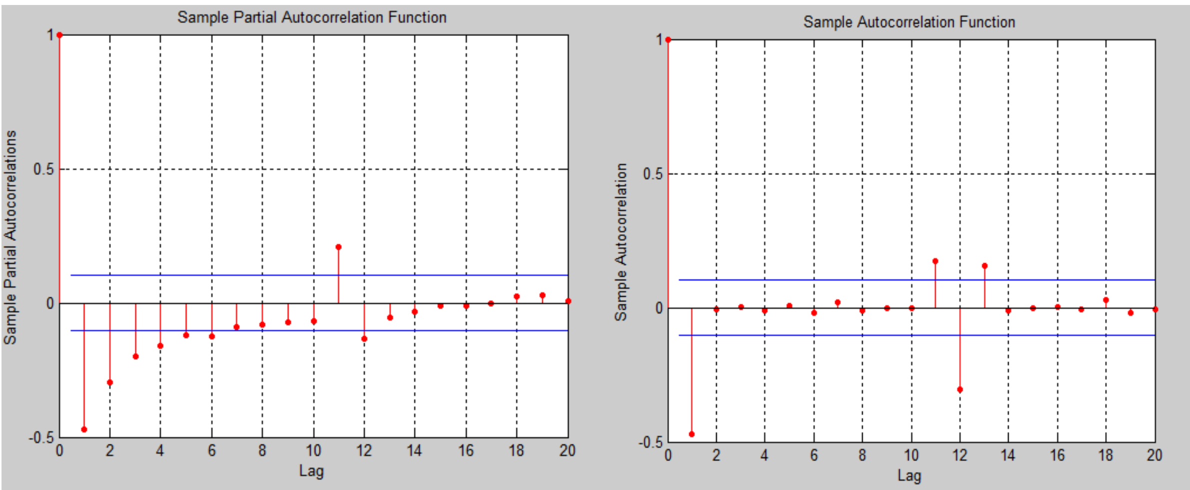

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Figure 9 ACF dan PACF *time series data*

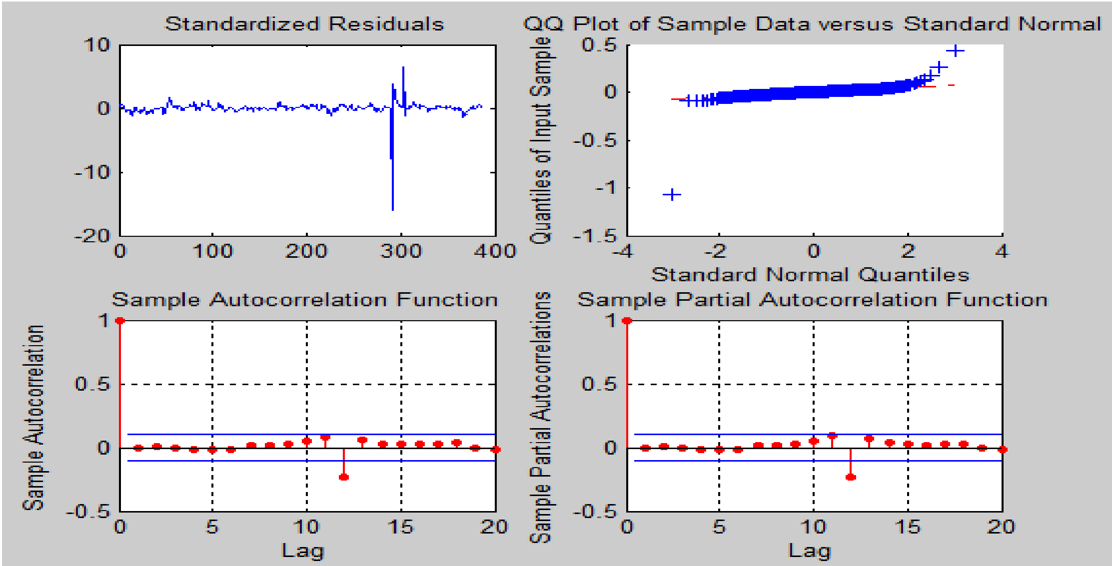

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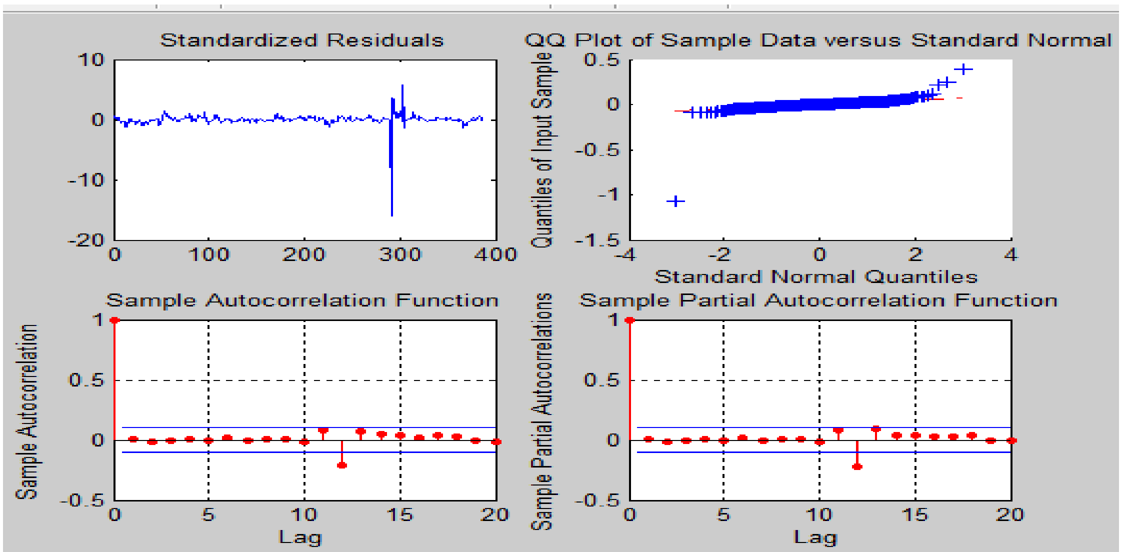
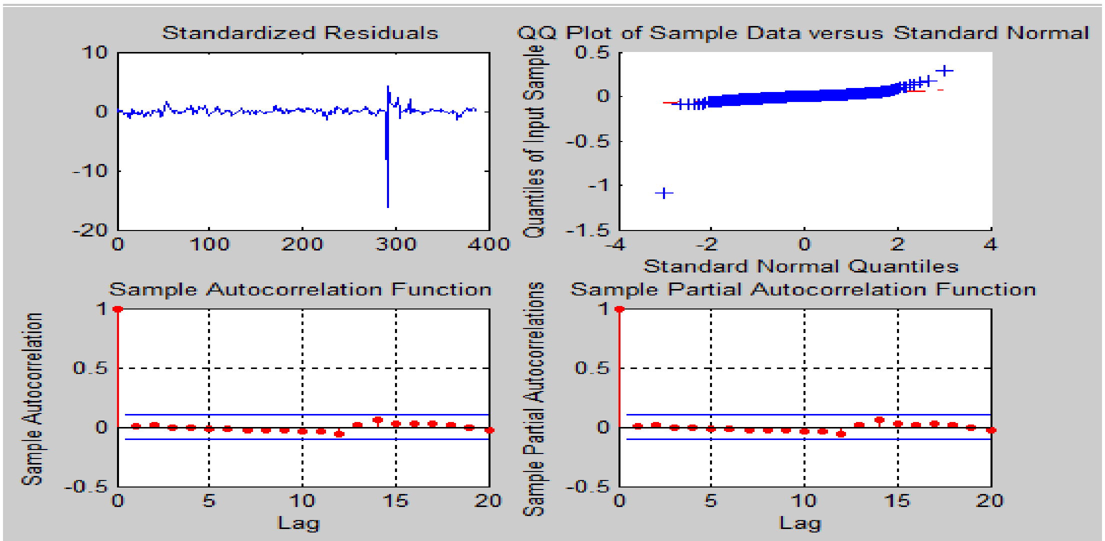
Figure 10 ARMA (1,1)



Source : Data Processing

Figure 11 ARMA (1,11)



Source : Data Processing

Figure 12 ARMA (11,1)

From figure 10 to figure 12, it can be seen that ARMA (11,1) gives a good fit test. The lines does not lag out from the Bartlett's line. Therefore for the case of BNI we choose ARMA (11,1) model.

C. ACF and PACF of Bank BRI

In identifying ARMA Process for BRI there is no lag that violate the Bartlett's line. Autocorrelation function (ACF) and partial autocorrelation function (PACF) to check the lag which violates the Bartlett's line. Results are shown can be seen in Figure 13. Since there is no lag out in ARMA the ACF and PACF, therefore we choose the default model of ARMA (1,1). It can be seen from figure (14) that this model gives a clean lags. We also try to test ARMA model (1,2) and (2,1), figure (15) and (16) respectively. They also give no lag out that violate the Bartlett's line

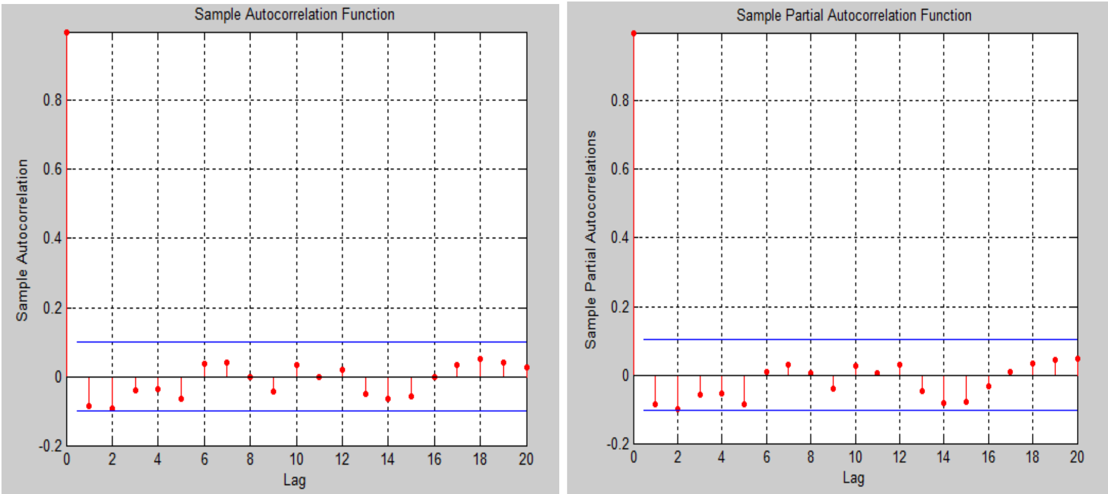


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Figure 13 ACF dan PACF *time series data*

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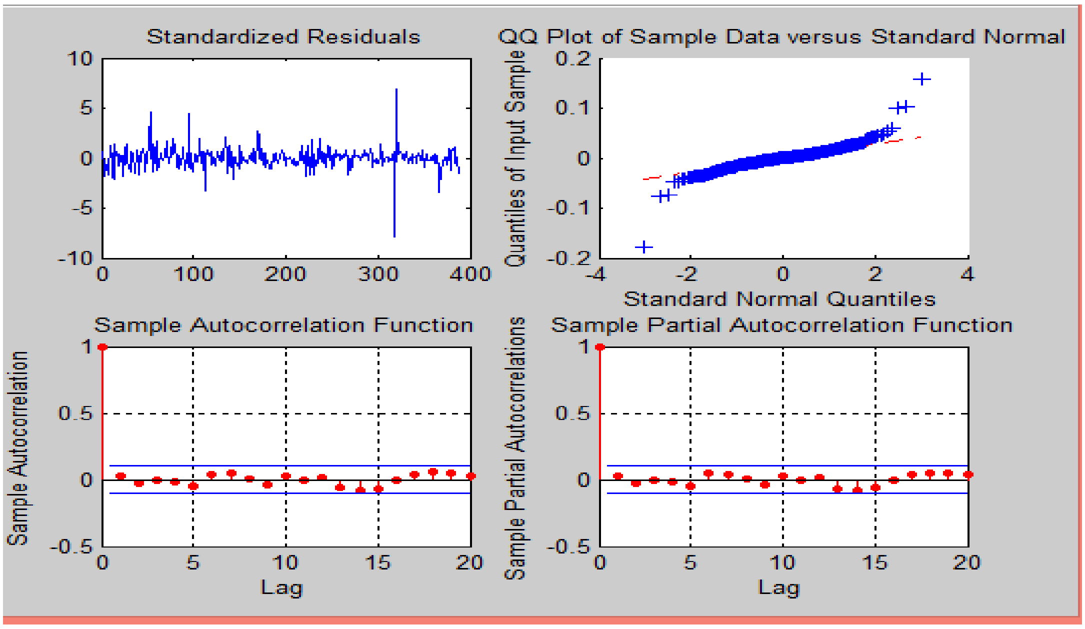

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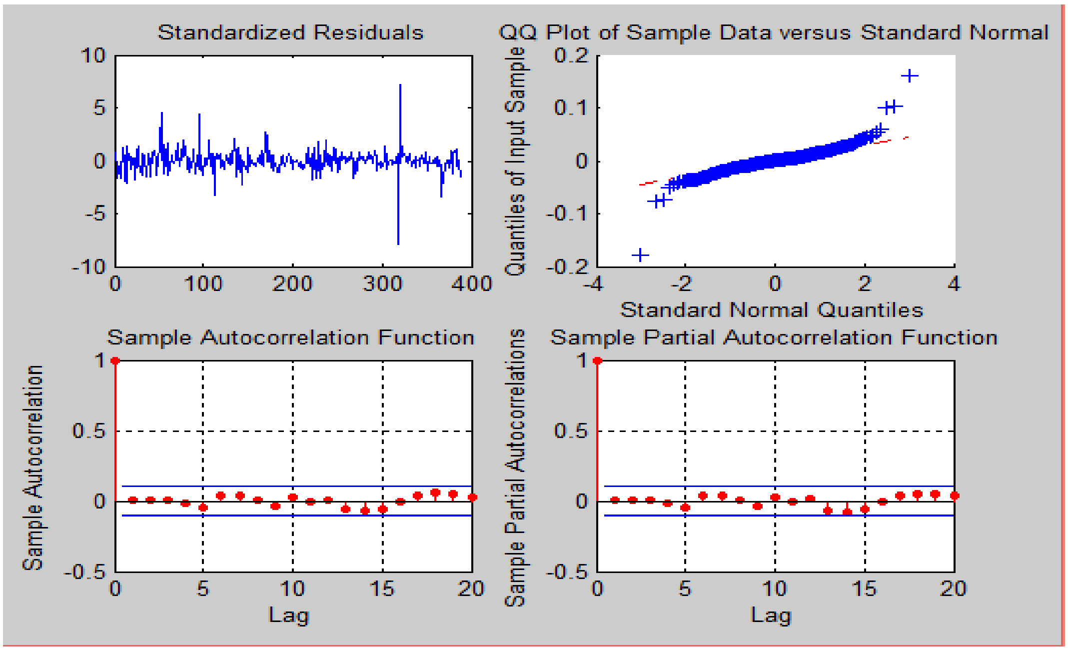
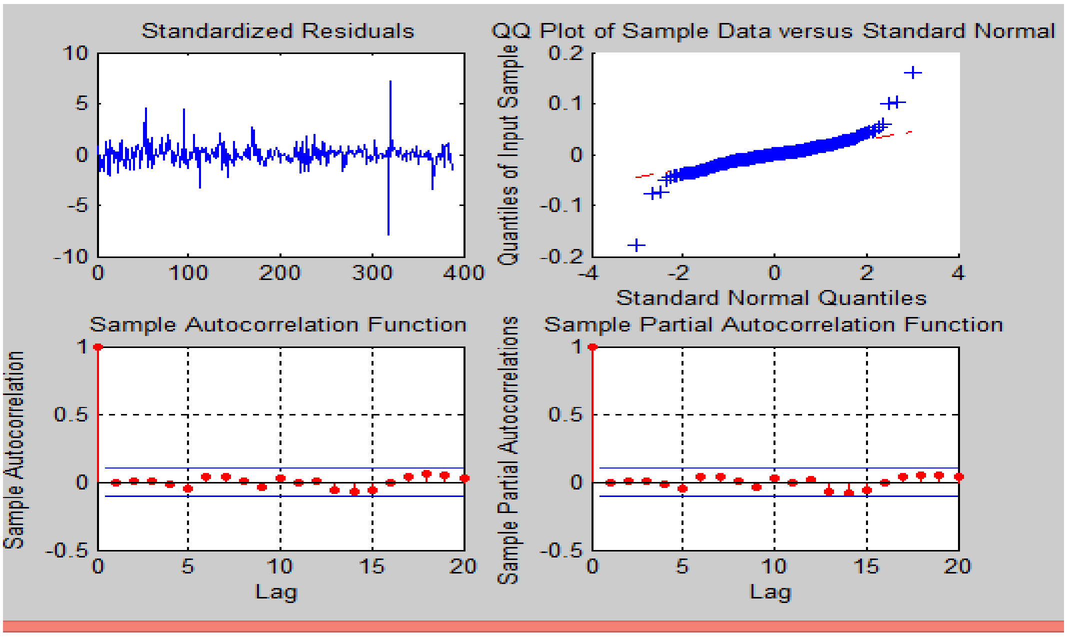
Figure 14 ARMA (1,1)



Source : Data Processing

Figure 15 ARMA (1,2)

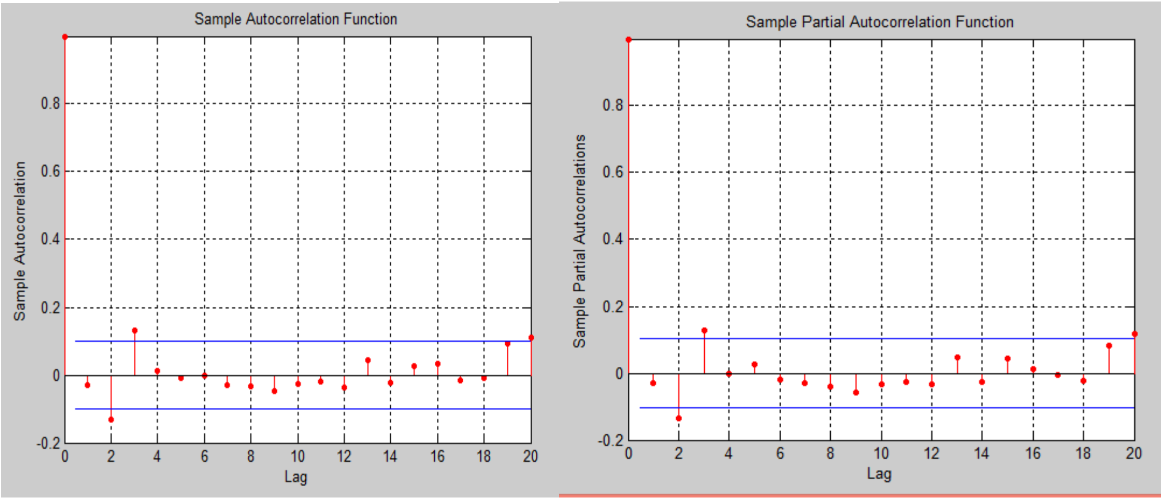


Source : Data Processing

Figure 16 ARMA (2,1)

D. ACF and PACF of Bank BRI

For ARMA process of bank BTN by observation of autocorrelation function (ACF) and partial autocorrelation function (PACF) we can check the lags that violates the Bartlett's lineare the lag of 2, 3 and 20. From this starting poing we can build the ARMA process from this lines.



Source : Data Processing

Figure 17 ACF dan PACF *time series data*

From figures 18, 19 and 20, we see that only model of ARMA (1,1) that doesnot lag out from Bartlett's line. Therefore we chose ARMA(1,1) model for Bank BTN.

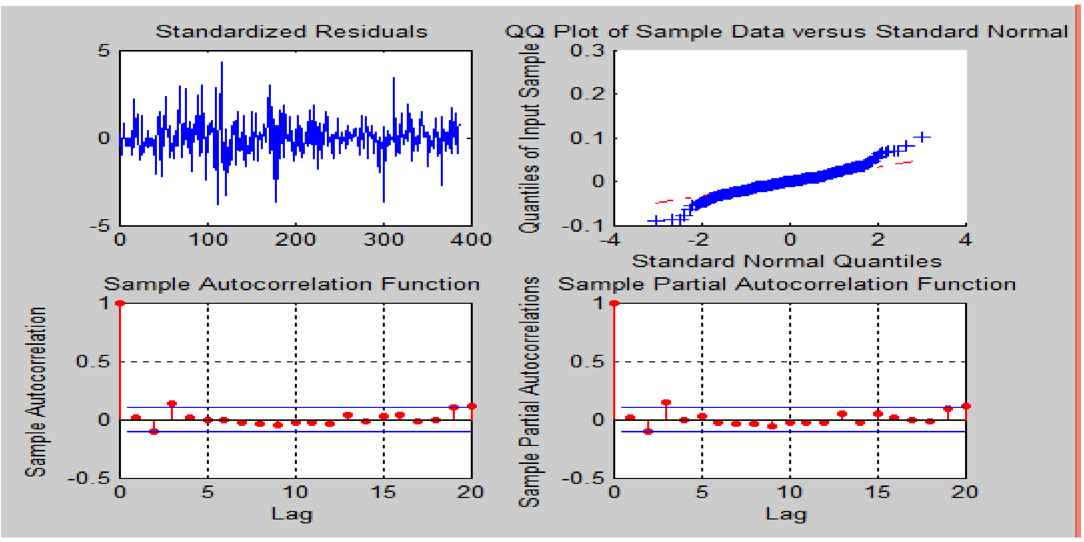


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Figure 18 ARMA (1,1)

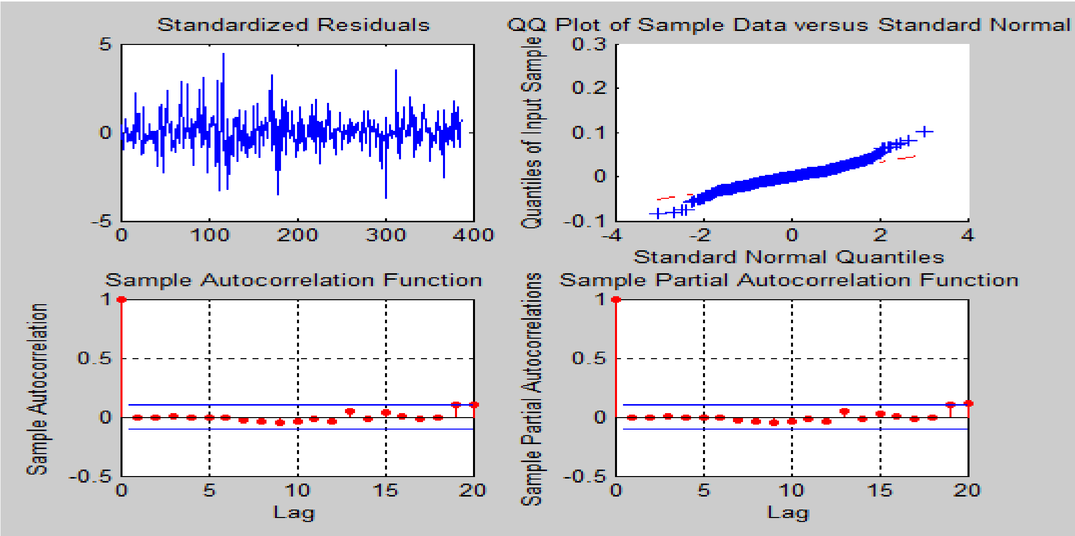

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Figure 19 ARMA (2,3)

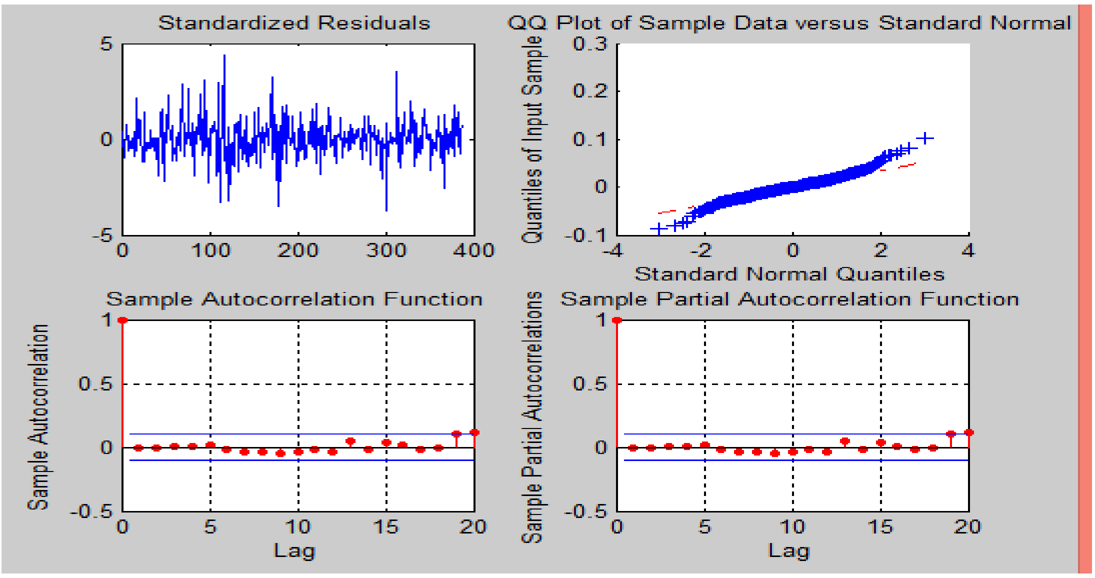

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Figure 20 ARMA (3,2)

4.2 Choosing Volatility Model GARCH

Determining the VaR model based on GARCH volatility. GARCH model has been developed by Bollerslev (1986) .Next we calculate the model of GARCH for each Bank.

A. For Bank Mandiri GARCH (1,1) of ARMA (3.9) represented in equation (4) below;

$$y_t = 0.00000 + \varepsilon_t$$
$$\sigma_t^2 = 1.0748e.10^{-04} + 0.3997\,\sigma_{t-1}^2 + 0.1579\,\varepsilon_{t-1}^2 \quad (4)$$

From this result it can be obtained that the value of GARCH α_1 = 0,3997 and ARCH, β_1 = 0,1579, in which the requirement of $\alpha_1 + \beta_1$ = 0,5576 <1 is achieved. By this the choosing model of GARCH (1,1) of ARMA (3.9) as a model of volatility is acceptable.

B. For Bank BNI GARCH (1,1) of ARMA (11.1) represented in equation (5) below;

$$y_t = 0.00000 + \varepsilon_t$$
$$\sigma_t^2 = 1.5906e.10^{-04} + 0\,\sigma_{t-1}^2 + 0.3705\,\varepsilon_{t-1}^2 \quad 5)$$

From this result it can be obtained that the value of GARCH α_1 = 0 and ARCH β_1 = 0,3705 , in which the requirement of $\alpha_1 + \beta_1$ = 0,3705 <1 is obtained. By this the choosing model of GARCH (1,1) of ARMA (11.1) as a model of volatility is acceptable. Parameter K = 1.5906e.10-04 and C was found to be NaN (much smaller).

C. For Bank BRI GARCH (1,1) of ARMA (1.1) represented in equation (6) below;

$$y_t = 0.00000 + \varepsilon_t$$
$$\sigma_t^2 = 1.4332e.10^{-04} + 0.3112\,\sigma_{t-1}^2 + 0.0192\,\varepsilon_{t-1}^2 \quad (6)$$

From this result it can be obtained that the value of GARCH α_1 = 0,3112 and ARCH β_1 = 0,0192, in which the requirement of $\alpha_1 + \beta_1$ = 0,3304 <1 is obtained. By this the choosing model of GARCH (1,1) of ARMA (11.1) as a model of volatility is acceptable. Parameter K = 1.4332e.10-04 and C was found to be NaN (much smaller).

D. For Bank BTN GARCH (1,1) of ARMA (2.3) represented in equation (7) below;

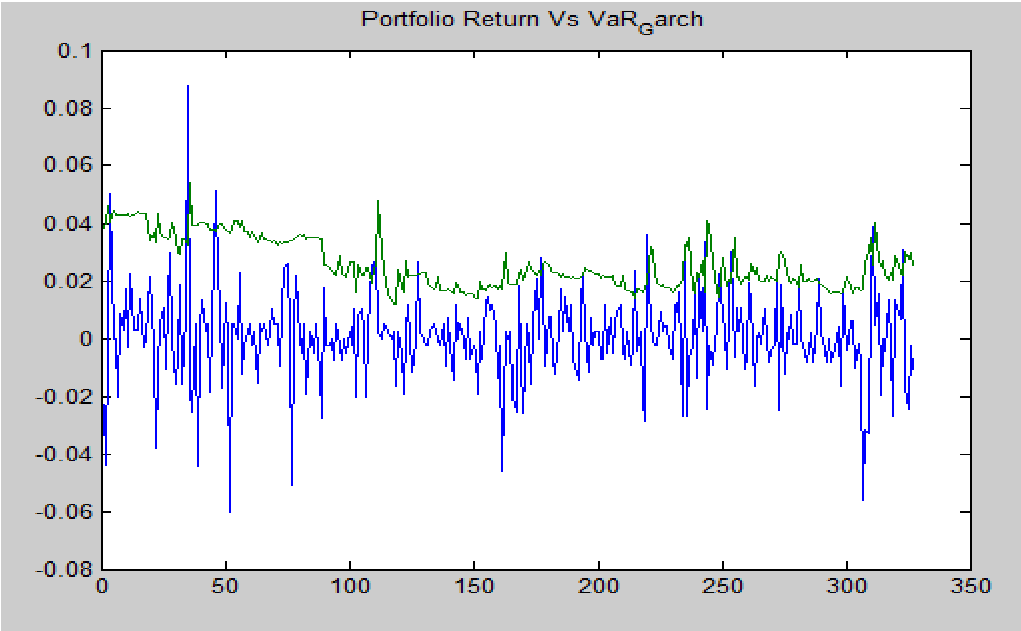
$$y_t = 0.00000 + \varepsilon_t$$
$$\sigma_t^2 = 3.7563e.10^{-04} + 0\,\sigma_{t-1}^2 + 0.0133\,\varepsilon_{t-1}^2 \quad (7)$$

From this result it can be obtained that the value of GARCH α_1 = 0 and ARCH β_1 = 0,0133, in which the requirement of $\alpha_1 + \beta_1$ = 0,0133 <1 is obtained. By this the choosing model of GARCH (1,1) of ARMA (11.1) as a model of volatility is acceptable. Parameter K = 3.7563e.10-04 and C was found to be NaN (much smaller).

4.3 Calculate Value at Risk from the chosen model of ARCH and GARCH

The next figures are showing the comparation between Var prediction from equation (2) with the observed return. The comparation of VaR and return of Bank Mandiri, BNI, BRI and BTN are depicted in figure 21, 22, 23 and 24 respecively.

From those figures, it can be seen that the values of VaR and the return value are still stable for all banks. Only on the trading day to 260 a surge exceeding the VaR value return for BRI and BTN, but that is still in a stable category . Therefore it can be interpreted that the rate of return and the VaR can still be resolved by the bank, where it can be concluded that the VaR model for all banks are good..



Source : Data Processing

Figure 21 The Comparation of return and VaR value for Mandiri

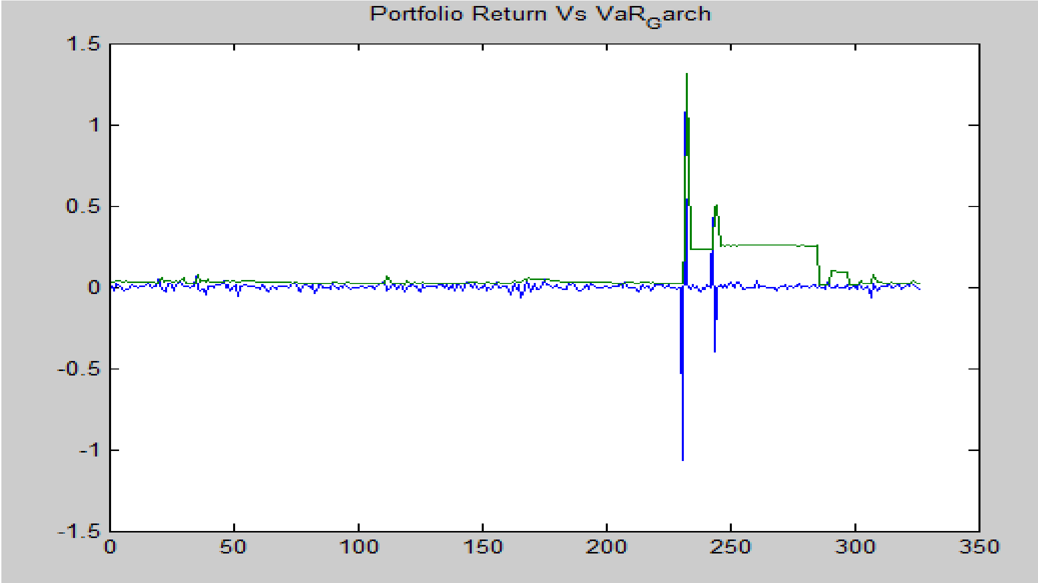


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Figure 22 The Comparation of return and VaR value for BNI

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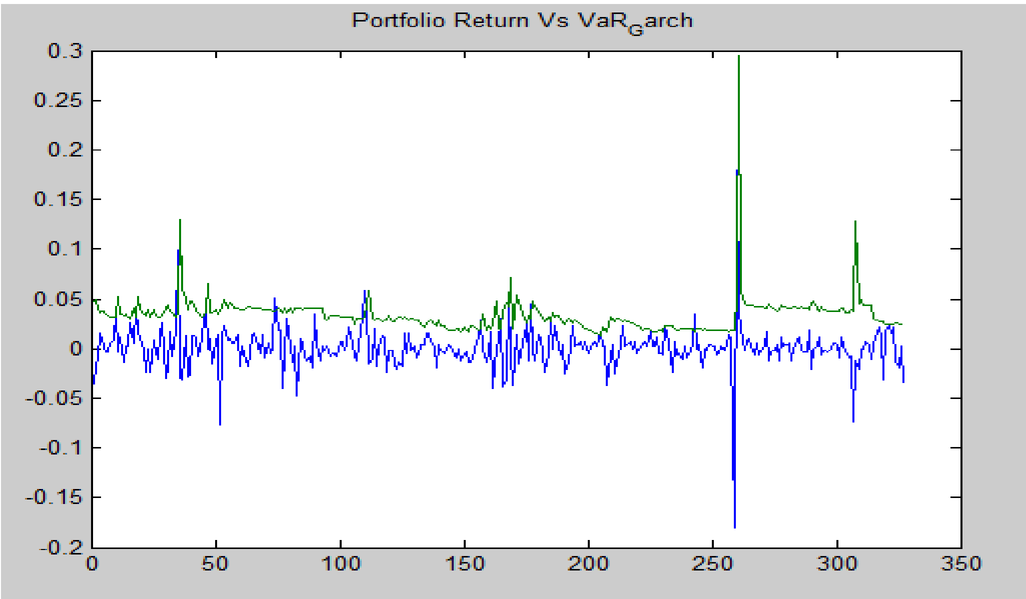

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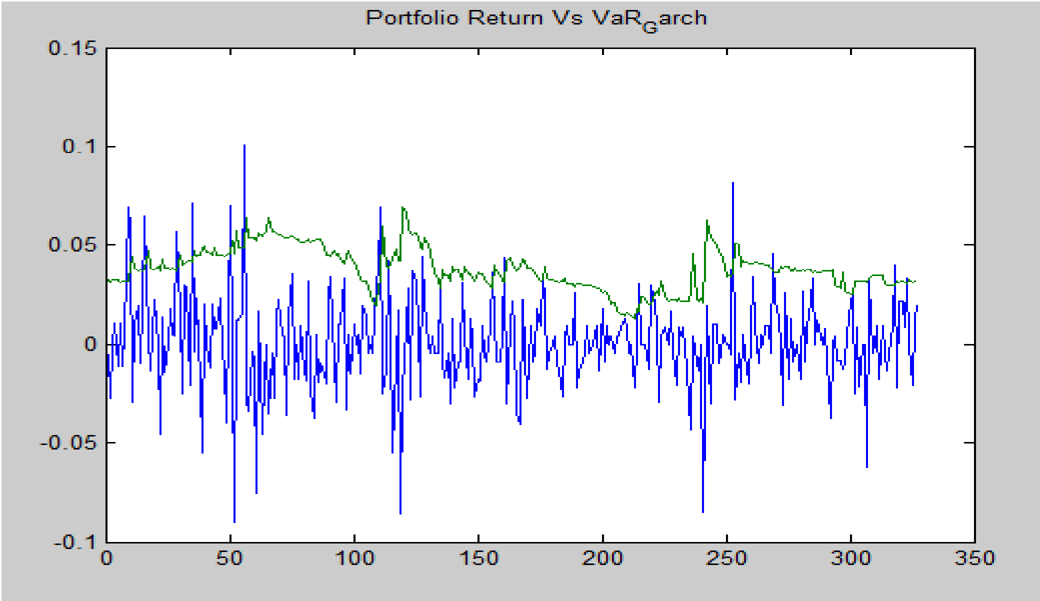
Figure 23 The Comparation of return and VaR value for BRI



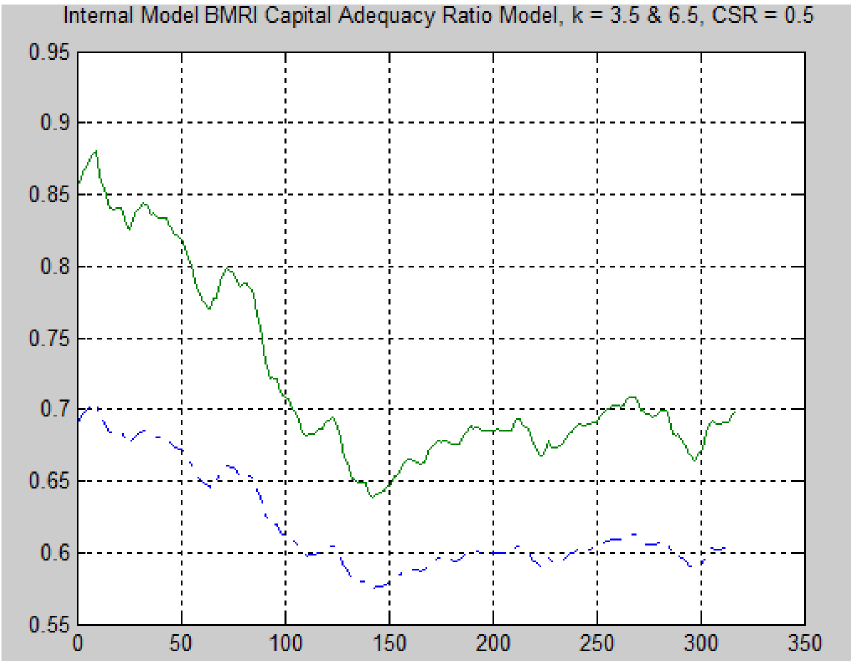
Source : Data Processing

Figure 24 The Comparation of return and VaR value for BTN

4.4. Calculating Internal Model

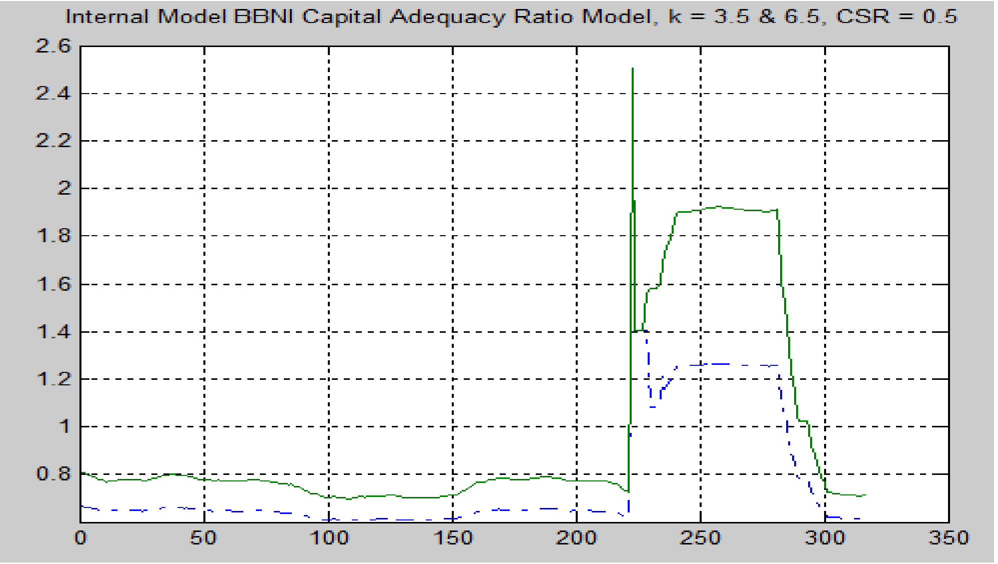
Internal Model will transform calculated VaR to regulatory capital by calculating its Market Risk (MR) with the following risk-capital formula

From the data processing internally generated models as follows:



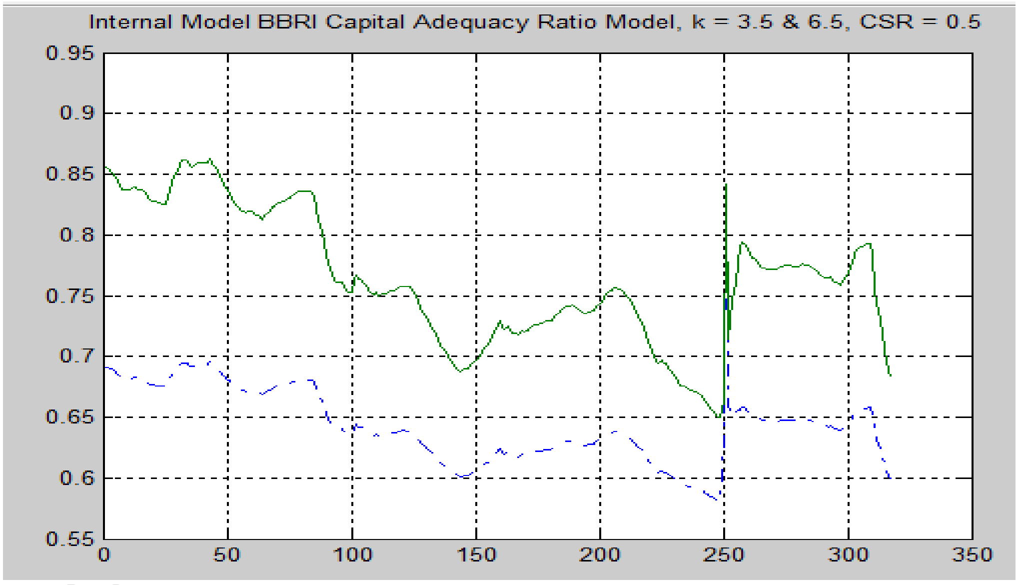
Source : Data Processing

Figure 25 Internal Model of Bank Mandiri



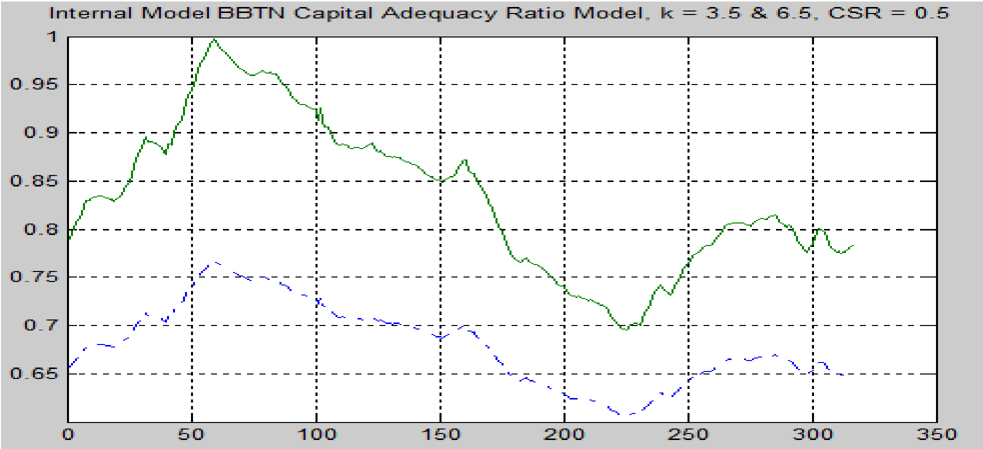
Source : Data Processing

Figure 26 Internal Model of Bank BNI



Source : Data Processing

Figure 27 Internal Model of Bank BRI



Source : Data Processing

Figure 28 Internal Model of Bank BTN

5. Conclusions and Recommendations

Based on the results of data processing, it can be seen each level VaR state banks and the internal value of each model of state-owned banks. Where the Bank VaR is 0.05 and internal models was 0.87 k = 6.5 and k = 3.5 is 0.57. Bank BNI value is 1.3 and the internal VaR models is a 2.5 k = 6.5 and k = 3.5 is 0.7. Bank BRI value was 0.29, and the internal VaR models are 0.86 k = 6.5 and k = 3.5 is 0.58. BTN Bank VaR value is 0.06 and internal models are 0.99 k = 6.5 and k = 3.5 is 0.61. Based on the VaR model each state bank by BASEL III considered good.

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