ANALYSIS OF DYNAMIC STRUCTURE, GRANGER CAUSALITY AND FORECASTING WITH VECTOR AUTOREGRESSION (VAR) MODELS ON CREDIT RISK DATA

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ABSTRACT: *This research discusses the dynamic structure, causality relationship, and forecasting using Vector Autoregressive (VAR) model approach. The dynamic structure is in the form of Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). The causality analysis is conducted by using granger causality approach. Then the influence of a variable to predict other variables will be directedbyforecasting evaluation on the VAR model. This model is applied to see the relationship on Non-Performing Loan (NPL), Loan Interest Rate (LIR), Inflation (INF), and Rupiah Exchange Rate (EXR). The dynamic structure of the IRF results indicates that each variable requires more than 10 periods to reach equilibirium after experiencing shock. Based on the FEVD results the variance of forecasting errors at the beginning of the period is influenced only by the variable itself. The Granger causality test is significant for claiming a bi-directional causality between credit risk (NPLs) and loan interestrate (LIR), and there is indirect causality between inflation (INF) and credit risk (NPL), and direct causality between the rupiah exchange rate (EXR) and credit risk (NPL). The results of the forecasting evaluation indicate that this model is dynamically good enough to do the forecasting.*

Keywords: Vector Autoregressive Model (VAR), Granger Causality, Impulse Response Function, Forecast Error Variance Decomposition, forecast.

1. INTRODUCTION

Vector Autorgressive (VAR) models are widely applied in economics [1] to obtain linear interdependence relationships between variables. This model is a stochastic process model that is an extension of the Autoregressive (AR) model where the VAR model allows using more than one variable.

There are four core things that can be investigated with the VAR model: (1) Impulse Response Function (IRF) analysis that explains the dynamic impact of change on one variable to another variable, (2) Forecast Error Variance Decomposition (FEVD) that describes huge variance on any variables that can cause changes in other variables, (3) Granger Causality to obtain causal effects between variables, and (4) Forecasting to know whether the value of a current variable is explained by the value of other variables present in the model in the past. Because it is related to the dynamic impact of IRF and FEVD analysis can be summarized as a dynamic structure analysis.

This research uses VAR approach to obtain interaction and relation on credit risk data. The IRF, FEVD, Granger Causality, and Forecasting analyzes will be conducted using credit risk (NPL) and Loan Interest (LIR), Inflation (INF) and Exchange Rate (EXR) data.

The data used is obtained from the monthly report of commercial banks at the Representative Office (KPw) of Bank Indonesia in Lampung Province and the Central Bureau of Statistics in Lampung Province. The data period is from March 2006 to December 2014.

1.1 Definition of Credit Risk

In the package of deregulation policy in May 1993, Bank Indonesia (BI) defines non performing loans are credits classified in underserved, doubtful, and loss collectibility.

In accordance with Bank Indonesia Circular Letter No.3 / 30 / DPNP dated December 14, 2001[2], loans experiencing congestion (non-performing loans) are measured by the percentage of Non Perfoming Loan (NPL). NPL is measured from the ratio of comparison of non-performing loans to total loans.

$$\mathrm{NPL} = \frac{(\mathrm{KL} + \mathrm{DR} + \mathrm{M})}{\mathrm{TK}} \times 100\%$$

with:

KL : Amount of credit included in the substandard collectibility.
DR : Amount of credit included in the doubtful collectibility.
M : Number of credits included in the jammed collectibility.
TK : Total Credit.

The collectibility is the criterion of the ability to pay the debtor. Based on Bank Indonesia Circular Letter no. 7/3/DPNP dated January 31, 2005 [3] the criteria for repayment are as follows:

a) Current credits are credits with timely payment, good account development, and no arrears and in accordance with credit terms.
b) Special interest credits are credits with arrears of principal and / or interest payments of up to 90 days.
c) Non-current credits are credits with arrears of principal and/or interest payments exceeding 90 days up to 180 days.
d) Doubtful credits are credits with arrears of principal and / or interest payments exceeding 120 days up to 180 days.
e) Bad credits are credits with delinquent principal and / or interest payments exceeding 180 days.
f)

1.2 Definition of Loan interest rate

Loan interest rate in this analysis is obtained from Monthly General Report of Commercial Bank of Bank Indonesia which is the Basic Loan Interest Rate (BLIR). Based on Bank Indonesia Circular Letter no. 15/1/DPNP dated January 15, 2013[4], BLIR is the lowest interest rate that reflects the fairness of the cost incurred by the Bank including the expected profit to be gained. Furthermore, BLIR becomes the basis for Banks in determining loan interest rate to be imposed to the customer. CBIR does not yet take into account the risk premium estimation component which the amount is depending on the Bank's assessment of the risk of each debtor or group of debtors.

The calculation of basic loan interest rate is based on 3 (three) components, namely:

a) Primary Cost of Funds for Credit (PCFC) arising from fund raising activities;
b) Overhead costs incurred by the Bank in the form of non-interest operating expenses incurred for fund raising activities and disbursement of liabilities including tax costs to be paid; and
c) Profit margin set by the Bank in the activity of credit lending.

1.3 Definition of Inflation

Inflation is a change from the Consumer Price Index (CPI) from a time (n) to the previous time (n-1). CPI is an indicator to know the development of price level of goods/services need of society on average (aggregate).

In general, the occurrence of inflation indicates an increase of goods/services prices for daily needs of the community. High increase of goods and services prices can result in decreased public ability/power of purchasing to get these goods/services (the real value of the currency declines).

Calculation Method of CPI:

$$I_n = \frac{\sum_{i=1}^{k} \frac{P_{ni}}{P_{(n-1)i}} \times P_{(n-1)i}.Q_{0i}}{\sum_{i=1}^{k} P_{oi}.Q_{oi}}$$

Where

I_n : Index of month n
P_{ni} : Price of item i, in month n
$P_{(n-1)i}$: Price of item i, in month $n-1$
$P_{(n-1)i}Q_{oi}$: Consumption value of goods i, month $n-1$
$P_{oi}.Q_{oi}$: Consumption value of goods i, in base year
K : The number of items of commodity packets

Monthly Inflation Rate

$$LI_n = \frac{I_n - I_{(n-1)}}{I_{(n-1)}} \times 100\%$$

With,

LI_n : Inflation rate month -n
I_n : Index of month n
$I_{(n-1)}$: Index of month $n-1$ [5]

1.4 Definition of Exchange Rates

The exchange rate of a currency or so-called exchange rate is the price of a unit of foreign currency in a domestic currency or it can also be the price of a unit of domestic currency in a foreign currency. The exchange rate (EXR) of Rupiah in one US dollar (USD) is the price of one US dollar (USD) in Rupiah (Rp) or, otherwise, it can also be interpreted as the price of one Rupiah in USD.

If the exchange rate is defined as the value of the Rupiah in foreign currency, the following conditions may be formulated:

$NT_{IDR/USD}$= Rupiah needed to buy 1 US dollar (USD);

Or if the exchange rate is defined as the value of foreign currency in Rupiah:

$NT_{USD/IDR}$= US dollar required to buy one Rupiah [6]

1.5 Analysis on Credit Risk Data

Credit Risk needs to get important and serious attention. The number of non-performing loans can cause bad turnover in the Bank and ultimately affect economic growth. This is because credit problems can lead to bankruptcy in Banks affecting a country or regional economy. In general, macroeconomic changes may lead to an increase in the value of NPL [7]. The same thing is also happen with the Cox intensity fit model that general macroeconomic conditions may affect credit risk [8].

The studies on the relationship of credit risk and macroeconomic variables have also been conducted in several countries such as Malaysia [9], Italy, Greece, and Spain [10], and Pakistan [11]. Some macroeconomic variables such as loan interest rate, inflation, and exchange rates are used to find its relationship with credit risk using the VAR model in the Gulf Cooperative Council (GCC) countries [12].

2. THEORETICAL FRAMEWORK

2.1 Stationarity

Suppose the vector time series$Y_t = (y_{1t}, y_{2t}, \ldots, y_{mt})$contains munivariate time series. Then $Y_t$with the first moment and the second finite moment areweakly stationary if:

(i) $E(Y_t)=E(Y_{t+s})=\boldsymbol{\mu}$; constant for all s
(ii) $Cov(Y_t)= E[(Y_t - \boldsymbol{\mu})(Y_t - \boldsymbol{\mu})']=\boldsymbol{\Gamma}(0)$
(iii) $Cov(Y_t, Y_{t+s})=\Gamma(s)$; depends only on s

[13].

Augmented Dickey Fuller (ADF) Test:

ADF test here consists of estimating the following regression:

$$\Delta Y_t = A_1 + A_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t.$$

Where ε_t is a pure white noise error term and where:
$\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$,ect.

Null hypothesis
$H_0: \delta = 0$ (there is unit root, then Y_t nonstationary)
$H_1: \delta > 0$ (there is no unit root, then Y_t stationary)
Null Hypothesis that $\delta = 0$ follow τ (tau) statistics [14].

2.2 Vector Autoregression (VAR)

Suppose the stochastic $\{y_t\}$ is a VAR process of order p (VAR (p)) of the form

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \qquad (2.1)$$

Where A_i $(i = 1, \ldots, p)$ is$k \times k$ parameter matrices and the error process $u_t = (u_{1t}, \ldots, u_{kt})'$ is a k-dimensional zero mean white noise process with covariance matrix $E(u_t u_t') = \Sigma_u$, that is, $u_t \sim (0, \Sigma_u)$. Using the lag operator and defining the matrix polynomial in the lag operator A(L) as $A(L) = I_k - A_1 L - \ldots - A_p L^p$, the process (2.1) can be written as [15, 16]:

$A(L)Y_t = u_t.$ (2.2)

VAR Stable Process:

The VAR process (2.1) or (2.2) is stable if

$$\det A(z) = \det(I_k - A_1 z - \ldots - A_p z^p) \neq 0$$
$$z \in \mathbb{C}, |z| \leq 1. \quad (2.3)$$

In other words, y_t is stable if the determinantal polynomial is outside the complex unit circle, or equivalently determinantal polynomial is inside the inverse complex unit circle [15,16].

VAR Order Selection Criteria:

For selecting optimal lag, several information criteria are used to get optimum lag length. VAR(p) model and $\tilde{\Sigma}_u(p)$ is the ML estimator of Σ_u (white noise variance covariance matrix of VAR model) obtained by vitting a VAR (p) model. T is the sampel size and K is the dimension of the time series. The information criteria to select lag length are :

(i) Final Prediction Error (FPE)

$$FPE(p) = \left[\frac{T+Kp+1}{T-Kp-1}\right]^K \det \tilde{\Sigma}_u(p)$$

(ii) Akaike's Information Criterion (AIC)

$$AIC(p) = \ln\left|\tilde{\Sigma}_u(p)\right| + \frac{2pK^2}{T}$$

(iii) Hannan-Quinn (HQ) Criterion

$$HQ(p) = \ln\left|\tilde{\Sigma}_u(p)\right| + \frac{2\ln\ln T}{T} pK^2$$

(iv) Bayesian arguments Schwarz (SC)

$$SC(p) = \ln\left|\tilde{\Sigma}_u(p)\right| + \frac{\ln T}{T} pK^2$$

[16].

Estimating VAR Model:

Under general assumption a stable process y_t has time invariant means, variance, and covariance structure and, therefore, stationary. In the matrix representation, VAR (p) model can be written as

$\mathbf{Y} = \mathbf{X\beta} + \mathbf{U},$ (2.4)

where $\mathbf{Z}$is a $(T-p) \times k$ matrix with i-th row being z'_{p+i}, $\mathbf{X}$is a $(T-p) \times kp$ design matrix with i-th row being x'_{p+i}, $\boldsymbol{\beta}' = (A_1, \ldots, A_p)$ is a $k \times kp$ matrix, and $\mathbf{U}$is a $(T-p) \times k$ with i-th row being u'_{p+i}.

Ordinary Least-Square estimate for VAR (p) model in Equation (2.4) is

$\widehat{\boldsymbol{\beta}}_{\mathbf{OLS}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}.$ (2.5)

[17].

2.3 Impulse Response Function (IRF)

Reduce form VAR model

$$y_t = v_0 + v_1 t + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \quad (2.6)$$

Where $v_0 = \left(I_k - \sum_{j=1}^{p} A_j\right)\mu_0 + \left(\sum_{j=1}^{p} jA_j\right)\mu_1$ and $v_1 = \left(I_k - \sum_{j=1}^{p} A_j\right)\mu_1$. Since reduced form VAR model represents the conditional mean of a stochastic process. If y_t is generated by a VAR (p) process (2.6), the conditional expectation of y_{T+h} given y_t, $t \leq T$, is

$y_{T+h|T} = E(y_{T+h}|y_T, y_{T-1}, \ldots) = v_0 + v_1(T+h) + A_1 y_{T+h-1|T} + \ldots + A_p y_{T+h-p|T},$ (2.7)

where $y_{T+j|T} = y_{T+j}$ for$j \leq 0$. The forecast error associated with an h-step forecast is

$$y_{T+h} - y_{T+h|T} = u_{T+h} + \Phi_1 u_{T+h-1} + \ldots + \Phi_{h-1} u_{T+1}, \quad (2.8)$$

where the Φ_i matrices may be obtained recursively as

$\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j$, $i = 1,2, \ldots$ (2.9)

In VAR models, changes in the variables are induced by nonzero residual, that is, by shocks which may have a structural interpretation if identifying structural restrictions have been placed accordingly. Hence, to study the relations between variables, the effects of nonzero residuals or shocks are traced through the system. This kind of analysis is known as impulse response analysis [15].

2.4 Forecast Error Variance Decomposition (FEVD)

Related tools are forecast error variance decompositions. In the reduced form VAR model (2.6) impulses, innovations or shocks enter through the residual vector $u_t = (u_{1t}, \ldots, u_{kt})'$. We have to ignore deterministic terms because they are not important for impulse respon analysis given

$y_t = A(L)^{-1} u_t = \Phi(L) u_t = \sum_{j=0}^{\infty} \Phi_j u_{t-j},$ (2.10)

where $\Phi(L) = \sum_{j=0}^{\infty} \Phi_j L^j = A(L)^{-1}$. As mentioned earlier, forecast error variance decompositions are another tool for investigating the impacts of schocks in VAR models. In terms of the structural residuals the h-step forecast error (2.8) can be represented as

$$y_{T+h} - y_{T+h|T} = \Psi_0 v_{T+h} \Psi_1 v_{T+h-1} + \ldots + \Psi_{h-1} v_{T+1}.$$

Using $\Sigma_v = I_k$, the forecast error variance of the k-th component of y_{T+h} can be shown to be

$$\sigma_k^2(h) = \sum_{j=0}^{h-1} (\psi_{k1,j}^2 + \ldots + \psi_{kK,j}^2) = \sum_{j=1}^{K} (\psi_{kj,0}^2 + \ldots + \psi_{kj,h-1}^2),$$

where $\psi_{nm,j}$ denotes the (n,m)th element of Ψ_j [15].

2.5 Granger Causality

Consider the following bivariate VAR model for two variabels (X_t, Y_t) :

$$X_t = A_0 + \sum_{i=1}^{p} A_i X_{t-i} + \sum_{i=1}^{p} B_i Y_{t-i} + \varepsilon_{1t},$$

$$Y_t = B_0 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \varepsilon_{2t}.$$

Granger Causality for linear model, X_t Granger causes Y_t if the behavior of past X_t can better predict the behavior of Y_t than Y_t past alone.

Hypotesis of Granger causality test is as follows :

H_0: **Granger noncausality** x_t does not predict y_t if $\beta_i = 0$, for some $i = 1,2, \ldots, p$

H_1: **Granger causality** x_t does predict Y_t if $\beta_i \neq 0$ for some $i = i = 1,2, \ldots, p$

The null hypothesis is tested under χ~Wald statistics [18].

2.6 Forecasting

There are several measures to know the accuracy of forecast value. Suppose that there are n observations for which forecasts have been made and n one-step-ahead forecast error, $e_t(1)$, $t = 1,2, \ldots, n$. With

$e_t(1) = y_t - \hat{y}_t(t-1)$; and

relative forecast error is defined as:

$$re_t(1) = \left(\frac{y_t - \hat{y}_t(t-1)}{y_t}\right) 100 = \left(\frac{e_t(1)}{y_t}\right) 100$$

(i) Mean Absolut Error (MAE)

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |e_t(1)|$$

(ii) Mean Absoluter Percent Forecast Error (MAPE)

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} |re_t(1)|$$

(iii) Root Mean Square Error

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} [e_t(1)]^2}$$

3. METHODOLOGY

Steps for Specification and Analysis with VAR Model are as follows:

Step 1: Test the stationarity of the data

In this section the stationarity of the data will be examined. Identification plot of time series data will be done to check whether the data contain constants and trends or not. Then if there is non-stationary data, a log transformation will generally be performed to handle the uniformity in variance and differentiation to handle the non-stationary in the mean. The stationarity test / unit root test used is the ADF test.

Step 2: Determine the length of optimum lag

Before Displaying Information Criteria we need to look for maximum order from VAR. The maximum order is an order in which the VAR process is still stable. Maximum order is obtained by trying the VAR model on different lags until an unstable process is found. After that optimum lag is selected by using Information Criteria.

Step 3: Specification and Estimation of VAR Model

The optimized VAR order obtained is used as a model specification. When p is optimum then the VAR model specification is VAR (p). Estimated VAR models will use Ordinary Least Square (OLS).

Step 4: Granger Causality Test

The estimation result on the VAR model is used to test each equation in the model whether there is a causality relationship or not. The test uses$\chi^2 \sim$Wald.

Step 5: IRF Analysis

Through IRF chart dynamic response can be shown from each variable to other variables after some periods experiencing shocks of 1 standard deviation. Because the VAR model only sees short-term dynamics, in this section it will be seen for 10 periods after experiencing shocks.

Step 6: Decomposition of variance error forecasting .

The decomposition of variance error forecasting is shown by the FEVD graph. This graph can explain the magnitude of the contribution of each variable that causes changes to other variables.

Step 7: Forecasting

The goal is to see the accuracy of the past value of another variable in predicting the current value of a variable. Evaluation of forecasting will be used as a measure of the accuracy of forecasting.

4. RESULTS AND DISCUSSION

4.1 Data Stationarity Test

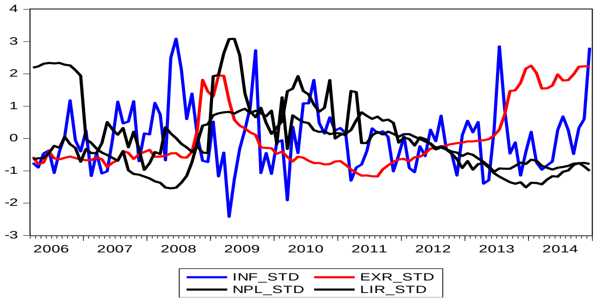

Fig. 1. Graph of Standardized Data

tested by using Augmented Dicky Fuller (ADF) test. Before performing Specification and Estimation model to perform analysis with VAR model, the identification is done to see whether the data is stationary or not. Figure 1 presents graph analysis for stationarity for NPL, LIR, EXR, and INF variables. Judging from the time-to-time movement it is suspected that EXR, NPL, and LIR are not stationary in either mean or variance. Meanwhile, inflation is stationary at the level. To deal with uniformity in variance, justification is used for transforming log transformations. The result of log transformation is LNPL, LLIR, and LEXR. Then the roots of the units on all four variables are

Table 1. Result of ADF unit root test in level

Variable	,Critical Value, t-statistik value, dan P-Value		
	C-Value 5%	t-Statistik	P-Value
LLIR	-2.889474	-2.328469	0.1651
LNPL	-2.889200	-1.911714	0.3259
LEXR	-3.453601	-1.706942	0.7414
INF	-2.889200	-6.229594	0.0000

Table 1 shows the results of unit root test at the data level. With the hypothesis :

$H_0: \delta = 0$ (data is not stationary at the level)

$H_1: \delta < 0$ (data is stationary at the level)

With $\alpha = 0.05$, then the LLIR, LNPL, and LEXR variables in the data level do not reject the null hypothesis that the time series have unit roots or not stationary at the level. As for INF, the null hypothesis that INF has the root of the unit is rejected. So, the INF is stationary at the level.Then the root of the unit is tested with all the data on the first difference to see whether the data satisfies the stationary conditions on the first difference. The results of the ADF test on the first difference are shown in Table 3.

Table 2. Result of ADF unit root test on the 1st difference

Variable	ADF Test	C-Value	P-Value
LLIR	-13.27344	-3.494378	0.0000
LNPL	-10.81319	-3.494378	0.0000
LEXR	-7.679185	-4.048682	0.0000

Using the same hypothesis, the LLIR, LNPL, and LEXR on the first difference reject the null hypothesis that time series have unit roots. So LLIR, LNPL, and LEXR are stationary on the first difference.

Since the purpose of this model is to see the short term of dynamic structure, there is no need to test cointegration relationships [18]. This is because if the goal is only to see a causal relationship and a short-term dynamic relationship, then the effective VAR approach is used.

In this research we will use the VAR system on the first difference data, known as VAR in difference. So all the data used are NPL, LIR, INF, and EXR into the VAR equation on the first difference. The occurrence of over differencing in INF data that is stationary at the level is not a problem [19].

4.2 Determining the Length of Optimum Lag

To determine the optimum lag length, it is necessary to search first the maximum lag length of the VAR model. The maximum lag length is the length of the lag where the VAR process is still stable. That is, until the length of the lag, the VAR process is still stable. This is done by trial and error to find the maximum lag length.

The VAR process is said to be stable if all the roots of the unit are within the circle of the complex unit or $|z| < 1$. Based on the inverse graph the unit roots of the polynomial characteristics of AR show that in lag 17 all the roots of the unit are within the circle of the complex unit or the whole modulus is less than 1. While in the VAR model with lag 18, there are 2 roots units that are outside the circle complex with a modulus of more than 1 i.e. $|z| > 1$. Thus, the maximum lag on the VAR model is 17.

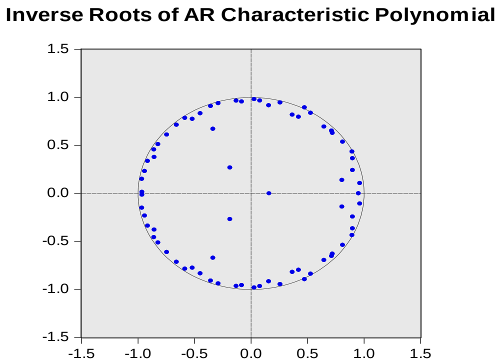

Fig.2.The inverse graph of the unit roots of the polynomial characteristics of AR for lag equals to 17.

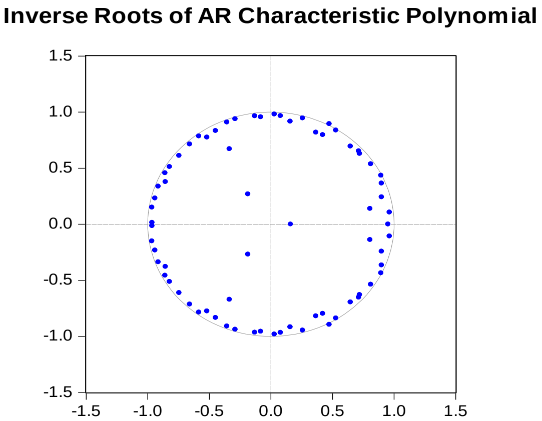

Fig.3. The inverse graph of the unit roots of the polynomial characteristics of AR for lag equals to18.

To obtain optimum lag then the order selection criteria shown in Table 3 below is used.

Table 3. Information Criteria for Selected Lag

VAR Lag Order Selection Criteria					
Lag	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	NA	4.09e-09	-7.9634	-7.8508*	-7.9180*
6	27.884*	3.20e-09	-8.2713	-5.4562	-7.1371
16	23.932	3.08e-09*	-9.9161	-2.5967	-6.9673
17	12.310	3.84e-09	-10.200*	-2.4305	-7.0701

Table 4. Goodness of fit for VAR model on selected lag.

lag	Model Criteria	Endogen Variables			
		D_INF	**D_LEXR**	**D_LNPL**	**D_LLIR**
6	R-squared	0.439658	0.370705	0.471685	0.22283
	Adj. R-squared	0.257925	0.166610	0.300340	-0.02921
16	R-squared	0.801968	0.765074	0.862508	0.83505
	Adj. R-squared	0.273882	0.138604	0.495861	0.39521
17	R-squared	0.825908	0.808534	0.914075	0.86518
	Adj. R-squared	0.202842	0.123289	0.606552	0.38268

Table 3 contains the selected order which has a minimum value for each information criterion marked with * in each model. The optimum lag selected is 0 based on SC and HQ, 6 based on LR, 16 based on FPE and 17 based on AIC. To select the lag used it is necessary to consider the goodness of fit of each model with the lag.

For that each R-Square and Adjusted R-Square is shown for each model with different lag. Lag with the highest R-Square and Adj-R-Square values are selected as the optimum lag on the VAR model. Based on the results in Table 4, the optimum lag selected is lag 17.

4.3 Specification and Estimation of VAR Model

The initial specification of the VAR model equation system requires the length of the lag p. From the previous result, the optimum lag value on the VAR model equation system is 17. So the model that will be estimated is the VAR model (17). The system specification describes the estimation method for the VAR model. In this case, the OLS (Ordinary Least Square) estimation method is used.

Table 5. Goodness of Fit Estimation Result on OLS VAR(17)

Variabel	D_INF	D_EXR	D_LNPL	D_LLIR
R-squared	0.82590	0.80853	0.91408	0.86518
Adj. R-squared	0.20284	0.12328	0.60655	0.38268
Sum sq. resids	11.1005	0.01248	0.10408	0.00653
S.E. equation	0.76435	0.02563	0.07401	0.01855
F-statistic	1.32555	1.17991	2.97238	1.79313
Log likelihood	-33.7714	265.007	171.689	293.469
Akaike AIC	2.33571	-4.45472	-2.33386	-5.10157
Schwarz SC	4.27817	-2.51226	-0.39140	-3.15912
Mean dependent	0.02023	0.00297	-0.00519	-0.00029
S.D. dependent	0.85609	0.02737	0.11799	0.02360

Table 5 shows the goodness of fit, F-Statistic, and mean and standard deviation of each equation obtained from the estimation of each equation in the VAR model. R-Square in each equation of INF, EXR, NPL, and LIR is equal to 0.83, 0.81, 0.91, and 0.87.

4.4 Granger Causality Test

Granger causality can only be interpreted as the correlation between the current value of a variable with the past value of the other variables [20]. Below is considered Granger's causality test of the estimated model. All equations in the VAR model were tested with the Wald-Chi-Square distribution $\chi^2 \sim$Wald [21]. The probability value of each equation is shown in Table 6-9.

Table 6. Result of Granger-Causality test for INF

Dependent variable: D_INF			
Excluded	Chi-sq	Df	Prob.
D_EXR	12.23841	17	0.7855
D_LNPL	6.965945	17	0.9840
D_LLIR	14.96761	17	0.5978
All	54.17431	51	0.3543

Table 7. Result of Granger-Causality test for EXR

Dependent variable: D_LEXR			
Excluded	Chi-sq	Df	Prob.
D_INF	17.60699	17	0.4140
D_LNPL	15.81238	17	0.5372
D_LIR	12.24876	17	0.7848
All	46.21379	51	0.6639

Table 8. Result of Granger-Causality test for NPL

Dependent variable: D_LNPL			
Excluded	Chi-sq	Df	Prob.
D_INF	26.43711	17	0.0669
D_LEXR	53.02162	17	0.0000
D_LLIR	38.58909	17	0.0020
All	148.4883	51	0.0000

Table 9. Result of Granger-Causality test for LIR

Dependent variable: D_LLIR			
Excluded	Chi-sq	Df	Prob.
D_INF	31.97816	17	0.0151
D_LEXR	23.70015	17	0.1278
D_LNPL	32.10658	17	0.0146
All	93.43608	51	0.0003

Testing hypothesis:

H_0: Granger nonCausality (there is no causality relationship between $x_t$andy_t)

H_1: Granger Causality (there is a causal relationship between x_t and y_t)

Based on the results in Table 6, at $\alpha = 0.05$ the granger causality test on the EXR, NPL, and LIR variables does not reject the null hypothesis that there is no causality relationship. This means that the past values of EXR, NPL, and LIR in the equation system cannot predict INF or in other words there is no causal relationship between INF with EXR, NPL, and LIR. Similarly in the causality test for the EXR variable. The results in Table 7 show that the null hypothesis is not rejected. This means that there is no causal relationship between EXR with INF, NPL, and LIR.

For the causality test of the NPL variable, there are two significant variables, namely EXR granger causes NPL and LIR granger causes NPL. It is obtained from Table 8 where the null hypothesis of no causality relation is rejected. The granger causality test on the LIR variable presented in Table 9 also has two significant variables, the INF granger causes LIR and the NPL granger causes LIR.

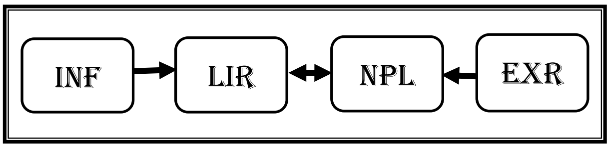

Fig. 4. Diagram of Granger Causality Test Result

Figure 4 summarizes the results of the Granger Causality Test. The causality diagram shows that there is bi-directional causality between NPL and LIR. There is also an undirectional causality from INF to NPL through LIR and EXR to LIR through NPL. Directional causality occurs from EXR to NPL and INF to LIR. EXR and INF variables are strongly exogenous in equations to LIR and NPL due to INF Granger causes LIR and EXR Granger causes NPL, but not vice versa. This indicates a direct causality relationship on the credit risk data either two-way or one-way and the relationship of indirect causality.

4.5 Analisis Impulse Respon Function (IRF)

In this section we will discuss the results of IRF on the predicted VAR model. Figure 5 is the IRF graph which is the response of a variable over other variables as well as overitself. The information is measured at one standard deviation. The IRF graph follows the confidence interval ± 2 Standard Error (S.E.). The main purpose of this analysis is to determine the positive or negative response of a variable to other variables. The short-term response is usually very significant and fluid. IRF gives an idea of how to respond to a variable in the future if there is intervention on other variables.

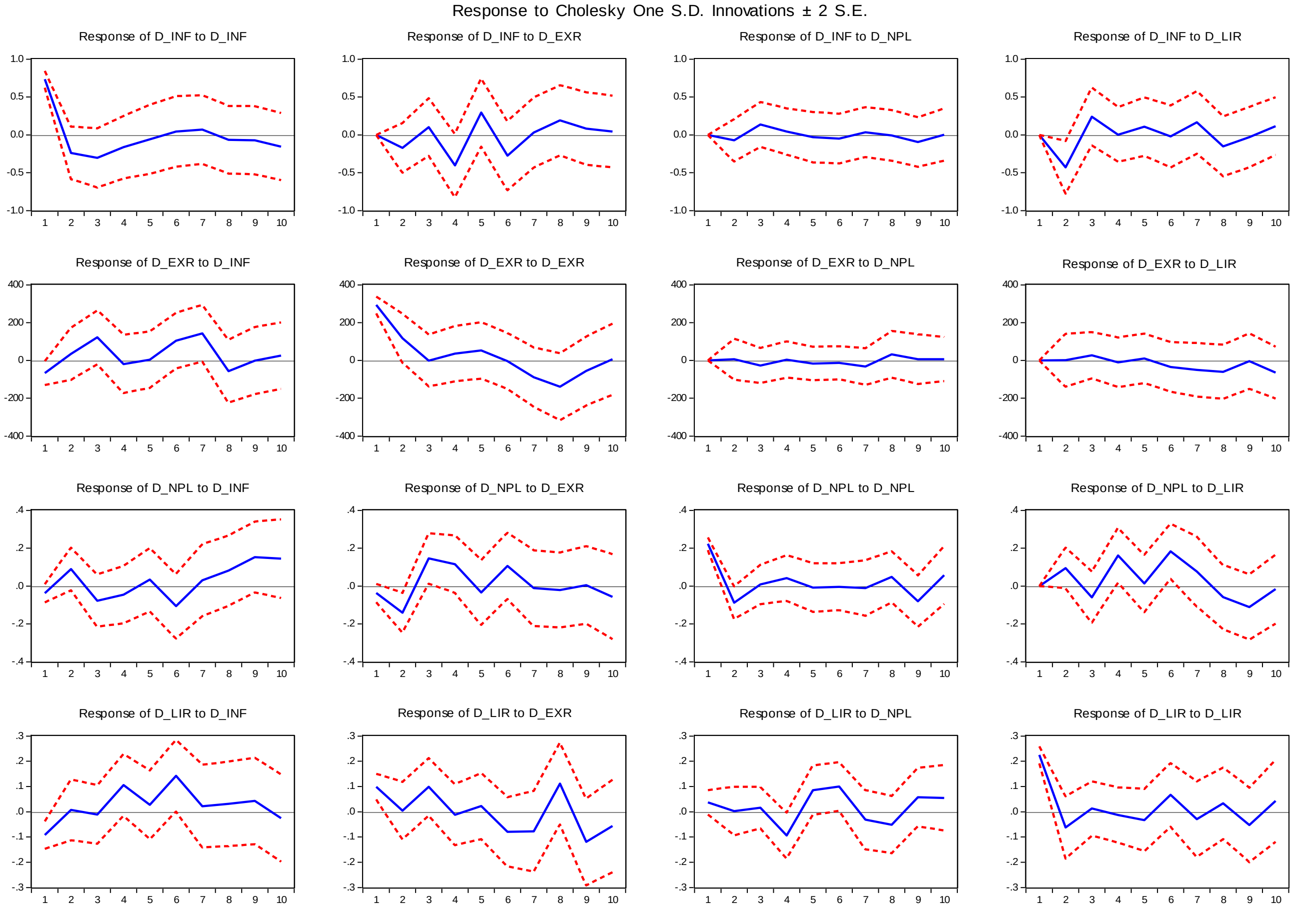

Fig. 5. Impulse Response Function (IRF) Cholesky One S.D. Innovation ±2 S.E.

Figure 5 is an IRF graph for the response given to each variable over another variable or the variable itself for 10 periods after the occurrence of a shock. Horizontal axis is the period (time) within months after the occurrence of change/shock, and vertical axis is the value of the given response.

INF gives a positive response in the first period after the shock of a standard deviation on itself. Then it fluctuates from the second to the fifth period and tends to reach equilibrium in the sixth to the tenth period. Changes in the exchange rate cause the INF to fluctuate (positive and negative responses interchangeably) with a fairly high gap up to the 10th period. This is possible because changes in the exchange rate will lead to changes in food prices and basic materials that cause inflation to be difficult to achieve stability. Inflation moves around the equilibrium line when responding to changes that occur in the NPL. Similarly, when responding to changes in loan interest rates, INF fluctuates around the equilibrium line. This means when there is a change in the variable LIR, EXR, and NPL then there is a large INF fluctuation when there is a change in the EXR.

The EXR response to INF changes tends to fluctuate while the EXR responds with equilibrium (fixed on equilibrium) to NPL and LIR changes. EXR changes to itself are in positive responses up to the sixth and negative in periods of the sixth to the tenth.

NPL is very sensitive to changes both from EXR, INF, LIR, and itself. This is shown from the highly fluctuating IRF graph. This is indicated by the NPL that has not reached equilibrium after ten periods of shock occured. That is, it may take more than ten periods for NPL to achieve equilibrium after the changes to EXR, INF, LIR, and NPL itself. This can be of particular concern to the government to see if the impact of these variables changes could lead to high credit risk and eventually many banks will go bankrupt.

The fluctuations that occur in the LIR tend to be on the equilibrium line. The LIR responds positively and negatively alternately from the first to the tenth period after the shock.

4.6 Forecast Error Variance Decomposition (FEVD)

The decomposition of variance error forecasting (Innovation Accounting) is a method other than IRF that is used to interpret the relationship of dynamic changes to the VAR model. FEVD is used to construct a variance of forecasting errors of a variable, namely how the difference between the range before and after the change in other variables. These differences include shocks coming from other variables as well as the variables themselves. With this, then the relative influence of the observed variables over other variables can be explained.

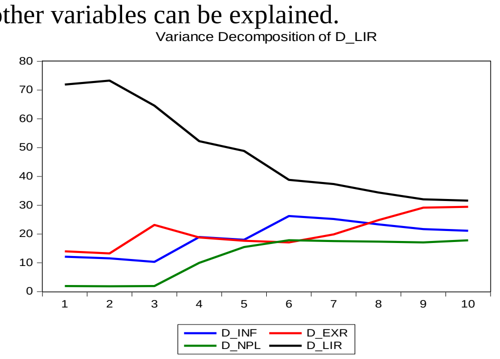

Fig. 6. Variance Decomposition Graphic of LIR

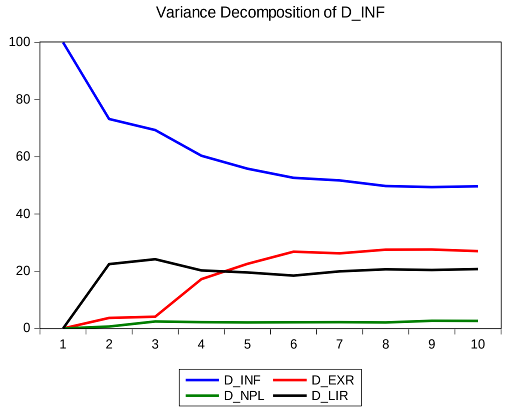

Fig. 7. Variance Decomposition Graphic of INF

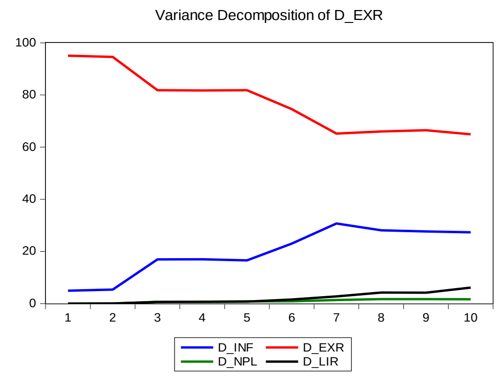

Fig. 8. Variance Decomposition Graphic of EXR

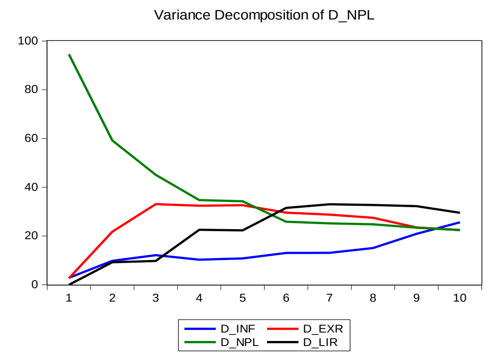

Fig. 9. Variance Decomposition Graphic of NPL

Figure 6-9 is a variable decomposition graph of each variable for 10 periods. This graph is a graph between time periods (lags) or periods and percentages of variance. When the line rises, it indicates the addition of the contribution of variance error forecasting to a variable by other variables. Figure 6 illustrates the variance contributions of LIRs both by the LIR itself and the NPL, INF, and EXR. In the first to sixth period it can be seen that the contribution of the variance of the error is largely influenced by the LIR itself. But in the 10th period, the contribution of variance is almost towards the same point, meaning that in the 10th period other variables contribute to the variance of LIR.

The contribution of variance to the INF from the first to the tenth period tends to be explained by the INF itself. Based on the results in Figure 7, NPL tends to be stagnant for 10 periods, so the possibility of the variance contribution provided by the NPL to INF is very small. In Figure 8, during the ten periods the greatest variance tends to be contributed by EXR itself and by INF. LIR and NPL contributes very little to the variance of EXR forecasting errors.

Different things happen to the NPL. Based on the decomposition of its variance, it can be seen that the four variables tend to contribute the same after the third period. This means that after the third period, the variance of NPL forcasting errors is contributed by INF, EXR, and LIR as well as NPL itself and together with almost the same value in period 10. The magnitude of each variable can be seen in Table 10-13

Table 10. Variance Decomposition of NPL

Variance Decomposition of D_LNPL:				
Period	D_INF	D_LEXR	D_LNPL	D_LLIR
1	7.697	16.022	76.279	0.0000
2	15.432	24.480	55.220	4.8662
3	23.703	29.289	43.220	3.7868
4	21.547	31.232	35.359	11.861
5	21.770	31.731	34.754	11.743
6	20.586	28.966	27.187	23.259
7	20.391	29.420	27.150	23.037
8	20.958	28.800	26.908	23.332
9	24.319	27.031	25.849	22.799
10	25.565	25.999	26.413	22.021

Table 11. Variance Decomposition of LIR

Variance Decomposition of D_LLIR:				
Period	D_INF	D_LEXR	D_LNPL	D_LLIR
1	11.262	10.9029	6.883581	70.95127
2	9.5908	9.32637	8.423313	72.65945
3	8.6503	18.6449	8.283581	64.42116
4	19.647	14.8905	14.29129	51.17049
5	18.656	14.4560	18.88059	48.00644
6	26.305	14.5092	20.17523	39.00991
7	23.386	23.1820	18.59251	34.83899
8	20.484	31.3140	16.05049	32.15136
9	19.616	34.2697	15.06232	31.05164
10	18.266	33.8626	16.35802	31.51232

Table 12. Variance Decomposition of EXR

Variance Decomposition of D_LEXR:				
Period	D_INF	D_LEXR	D_LNPL	D_LLIR
1	3.1505	96.84940	0.000000	0.000000
2	6.0731	92.68740	0.432428	0.807035
3	20.056	77.59827	0.601410	1.743785
4	20.670	76.84733	0.713994	1.767833
5	20.579	76.76342	0.923075	1.734413
6	24.501	72.51725	0.903594	2.078055
7	32.828	64.44414	0.783701	1.943198
8	30.482	65.21513	2.577966	1.724754
9	30.279	65.11437	2.576135	2.029790
10	30.603	63.87228	2.578169	2.945626

Based on Table 10, the contribution of variance from NPLs is contributed by INF, EXR, NPL, and LIR of 25.57%, 25.99%, 26.41% and 22.02%, respectively. This means that after reaching the 10th period each variable has a similar contribution. It means the innovation of the NPL is caused by both the NPL itself and other variables. Table 11 provides an explanation of the contribution to LIR innovation. This result is similar to the NPL that the contribution of LIR forecasting erroris influenced by 18.27%, 33.29%, 16.96%, 31.83% INF, EXR, NPL, and LIR respectively.

Table 13. Variance Decomposition of INF

Variance Decomposition of D_LINF:				
Period	D_INF	D_LEXR	D_LNPL	D_LLIR
1	100.00	0.000000	0.000000	0.000000
2	85.659	4.299977	0.203815	9.837109
3	78.802	5.882392	3.058546	12.25703
4	67.092	20.15226	2.507900	10.24747
5	62.295	24.42742	2.485053	10.79251
6	58.130	27.16305	4.077405	10.62895
7	56.605	26.57429	4.345964	12.47401
8	53.151	28.27273	4.705828	13.86957
9	53.185	28.03136	4.960038	13.82309
10	52.443	27.46444	4.881815	15.21011

Table 12 describes the very small variance contribution of NPL and LIR to the variance of EXR forecasting errors. At the beginning of the second period it did not contribute to variance and at the end of the period only 2.58% and 2.95%. The greatest variance was contributed by EXR of 96.85% at the beginning of the period and 63.87% at the end of the period.

From Table 13, we can obtain information that in the first period 100% of the variance of INF was generated by the INF itself. This means that at the beginning of the period other variables do not contribute variance to INF. However, in the 10th period INF contributed 52.44% and 27.46%, 4.88%, and 15.24% of the variance of INF was conceived by the variance of EXR, NPL, and LIR.

4.7 Forecasting

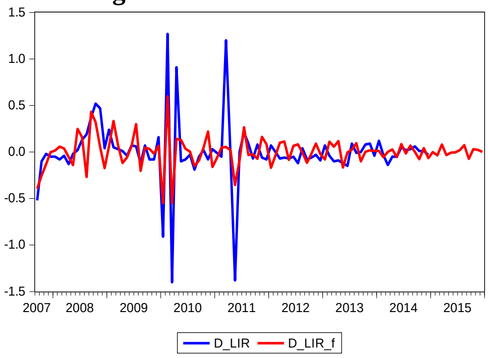

Fig. 10. Graph of forecasting fromLIR

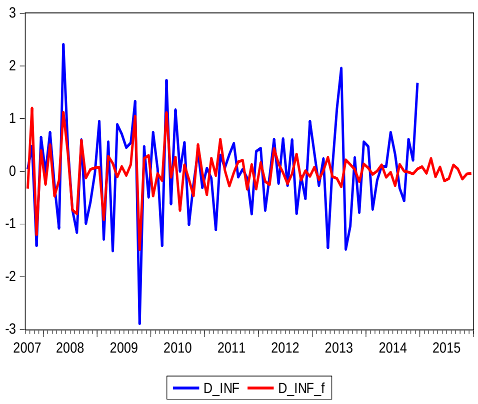

Fig. 11. Graph of forecasting from INF

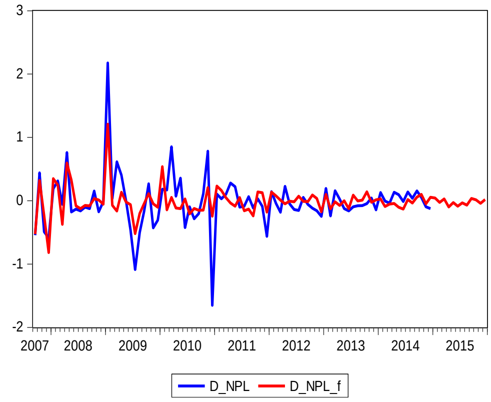

Fig. 12. Graph of forecasting from NPL

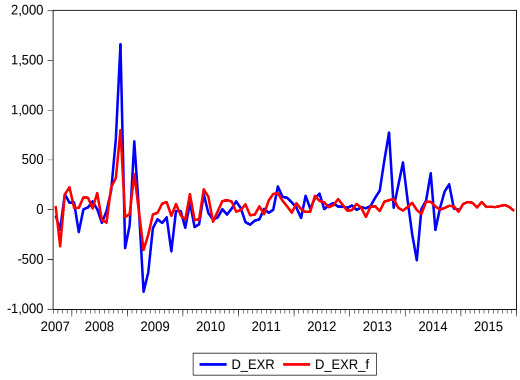

Fig. 13. Graph of forecasting from EXR

Figure 10-12 is a plot of actual data and forecasting value called forecasting graph, the more fit the forecast line against the actual data line, the better the forecasting is. In Figure 10, the LIR variable forecasting graph shows a good result, even when fluctuations occur during the forecast period, the result of the forecast is away from actual data. On the other hand, Figure 11 illustrates that the INF variable result does not fit in its actual data, so the value of other variables in the past are not appropriate to explain or predict the value of current INF.

The NPL forecast graph in Figure 12 shows quite good results. The past values of INF, LIR, and EXR affect the NPL's present value. The forecasting value in Figure 13 indicates that the EXR forecasting results are quite good even though at the end of the period they are not fit on the actual data.

Table 14. Results of Dynamic Forecasting Evaluation

Forecast Evaluating				
Actual:	D_INF	D_LEXR	D_LNPL	D_LLIR
Forecast sample:	2007M09 2015M12	2007M09 2015M12	2007M09 2015M12	2007M09 2015M12
RMSE	0.69982	0.019331	0.08438	0.01882
MAE	0.53893	0.013857	0.06236	0.01206
MAPE	658.444	361.9762	302.583	258.995
TIC	0.53582	0.452924	0.42686	0.52355

A summary of the forecasting evaluation is shown in Table 14 above. The results of forecasting are based on RMSE, MAE, and MAPE. Loaninterest rate has the smallest evaluation result that is equal to 0.019, 0.012, and 258.9. This means that in this model, the best forecasting is the one generated at a equation with the edogenous variable LIR.

5 CONCLUSION

Based on the results and discussion in the previous section it can be concluded that Non-Performing Loan (NPL), Loan Interest Rate (LIR), Exchange Rate (EXR), and Inflation (INF) have the relationship described by dynamic structure (IRF and FEVD), granger causality and forecasting with VAR model. The optimum lag obtained is 17. So the VAR model used to model non-performing loan is VAR (17). From the results obtained on the relationship of granger causality it shows a direct causal relationship on the non-performing loan data either two-way or one-way and the relationship of indirect causality with LIR, EXR, and INF variables. The IRF analysis results show that for 10 periods after the shock NPL and LIR respond with fluctuations (positive and negative responses alternately) that have not achieved stability until the 10th period. This allows NPL and LIR to take more than 10 periods to achieve stability (equilibrium). The result of the variance decomposition explains that after 10 periods variance of forecasting non-performing loan (NPL) is contributed by INF, LIR, and EXR variables with almost the same value that ranges between 22% -26%. The result of the forecast shows that the equation with the best accuracy is in the equation with the exogenous variable of LIR.

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