Can the islamic banks' credit risk be explained by macroeconomic shocks? evidence from Malaysia

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Can the islamic banks' credit risk be explained by macroeconomic shocks? evidence from Malaysia

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Abstract

Credit risk analysis is a key to a better financial risk management. This issue has been the primary focus of financial and banking industry since loans are the largest and most prominent source of credit risk. Unlike the conventional banking, there is a lack of empirical study on credit risk about Islamic banking. As such, further research regarding the vulnerability of the Islamic banking industry has become vital. Accordingly, this paper is aimed at determining and assessing the long run vulnerabilities of Malaysian Islamic banks proxied by non-performing loan ratio (NPLR) in term of its response to the macroeconomic variables that include Consumer Price Index (CPI), Production Price Index (PPI), Real Interest Rate (INT), Exchange Rate (EXCH) and Money Supply. The study is conducted on monthly data covering eleven years starting from January 2007. Malaysia is used as a case study. The techniques employed in this study are based on Vector Error Correction Modeling (VECM) and Variance Decompositions (VDC). In this study we found that the non-performing loan ratio, interest rate and money supply were relatively exogenous variables. In particular, the non-performing loan ratio being the most exogenous can't be explained by any macroeconomic shocks. The results have strong policy implications.

Keywords: Islamic banks, Non-performing loans, VECM, VDC, Malaysia

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1. Introduction: the issue motivating the paper

The rapid and dynamic changes in the global financial landscape pose various risks to banking institutions such as credit, liquidity, operational and market risks. The survival and success of financial organization depends critically on the efficiency of managing these risks (Khan and Ahmed, 2001). Credit risk management can be treated as the heart of any banks whether for Islamic or Conventional banks since if there is any loophole in the credit risk practices, and then there will be a great challenge for banks to recover the provided loans and advances.

The financial crisis has highlighted the importance of having a prudential credit risk management system, especially in the banking sector. Malaysia is one of the countries where the banking system was affected by the financial crisis of 1997. The extend damages in the financial sector had proved that macroeconomic instability tremendously could lead to crisis in banking sector that would incur considerable costs to real economy and financial institutions. This is due to fact that the banking system reflects the condition of the country's whole economy as whole.

Islamic banks, like their counterparts in conventional banking, get their profit through providing facilities to their customers. But, unlike conventional banks, they cannot lend money to earn interest as interest is prohibited in Islam based on Quranic injunctions. It may seem that Islamic banks face more risk since Islamic banks cannot charge a fixed return unrelated with their client's operation compared with conventional banks. So, Islamic banks will have more volatile return on their assets before they sell or lease it to their client and take on subject matter risk which conventional bank do not take.

Although Islamic banks uses many tools in earning profit such as, Murabahah, Musharakah, Mudarabah and so forth, but in the course of life of each contract underlying these tools, Islamic banks take many risks, especially the major one is Credit risk. Credit risk is one of the main risks that seriously affects bank's viability and performance. Credit risk in banking is defined as the probability of a counterparty to meet its obligations with agreed terms and conditions in loan commitments.

2. Literature Review

The establishment of close relationship between economic conditions and the operations of banks are due to the development of financial markets, economic globalization and expansion of banking activities. The negative effects of financial crises on banking sector make it necessary to examine the vulnerability of macroeconomic shocks towards banks' credit risk. Credit risk is an essential factor that needs to be managed by banks or financial institutions since the performance of a bank depends on how well it manages the risks. This is because the weak credit risk management practiced and poor credit quality continue to be a dominant cause of bank failures and banking crises worldwide (Mohd Ariffin et al, 2007).

Normally, a bank fails when its cash inflows from repayments of credits, sale of assets in place and mobilization of additional funds fall short of its mandatory cash outflows, deposit withdrawals, operating expenses and meeting its debt obligations (Khan and Ahmad, 2001). According to Elgari (2003), conventional banks face credit risk in almost all of their operations, because the relationship between the banks and those who transact with them is that of a debtor with a creditor in all cases. Islamic banks also face this form of risk in most of the modes of financing that they use such as *murabahah*, where the fundamental form of risk in all these contracts is credit risk (Elgari, 2003).

In recent years, several studies had been carried in order to examine the influencing of macroeconomic variables towards banks' credit risk. Wilson, T. (1997) constructed a model that include the macroeconomic variables such as GDP, interest rate, government expenditure and, housing price index and etc. that could influence a firm's probability default where he used a pooled of logit regression and he confirmed the relationship between macroeconomics factors and probability of default.

After this study, there were many studies had been done using macroeconomic variables in order to determine the behavior of banking system towards macroeconomic shocks. Gunsel (2008), examined the bank fragility in North Cyprus by using some bank specific variables (CAMELS criteria), macroeconomic variables, financial variables and external conditions. Their study showed that the bank fragility in North Cyprus was mainly influenced by micro and macro factors even though they failed to elaborate on their model regarding how transmission of monetary policy indicator.

In 2005, Baboucek and Jancar empirically investigated the transmission of macroeconomic variables as early warning signal of the banks' loan quality in Czech by using VAR model. In this study, both of the researchers examined the relationship between macroeconomic variables and the NPL ratio where the result suggested that the loan portfolio on an aggregate level has been able to absorb macroeconomic shocks without endangering the banking sector's capital base.

Next, in order to determining the factors for the NPF in Malaysia, Adebola (2011) has explored some macroeconomic variables such as industrial production index, interest rate, and producer price by using ARDL approach. The findings indicated that, interest rate has significant positive long run impact on NPF of Islamic banking. It is believed that, Islamic banking system in Malaysia employ less of profit and loss mechanism since the interest rate has been found to be relatively stronger to productivity.

3. The Objective of the Study

The primary objective of this study is to examine the vulnerability of macroeconomic shocks towards the credit risk in Islamic Banks in Malaysia that is proxied by non-performing loan ratio. Both long- and short-run relationships between the variables are measured by using VECM and VDC approaches.

4. The Methodology Used

This study employs a time series technique, in particular, cointegration, error correction modelling and variance decomposition, in order to find empirical evidence of the nature of relations between macroeconomic shocks and Islamic banks' credit risk as alluded to in the introductory paragraphs.

To test whether the macroeconomic factors affect credit risk of Islamic banks in Malaysia, the following variables are being used in this study:

1. Non-performing loan ratio (NPLR)
2. Consumer Price Index (CPI)
3. Producer Price Index (PPI)
4. Real Interest Rate (INT) and
5. Real Exchange Rate EXCH)

6. Money Supply (M2)

This study uses monthly time series data dated from January 2007 – Jan 2017 with the total number of 121 observations. All data are available via Bank Negara Malaysia's (BNM) monthly statistically bulletin (Bank Negara Malaysia, BNM, 2016).

5. Empirical Results and Discussions

5.1 Stationary Test

In time series analysis, to avoid a spurious regression in the model, the stationarity of the variables are necessary. The data is stationary when there is a constant pattern over time or inclination fluctuating around the average value (Gujarati, 2003). Therefore, we begin our empirical testing by determining the stationarity of the variables used. Ideally, in order to proceed with the testing of cointegration later, our variables should be in I(1) that is in their original level form, they are non-stationary meanwhile in their first differenced form, they are stationary. The differenced form for each variable used is created by taking the difference of their log forms. For example, $DNPLR = LNPLR - LNPLR_{t-1}$.

In this study, we performed two types of unit root tests which are Augmented Dickey-Fuller (ADF) tests (1979) and Philip-Perron (PP) test. The results of ADF and PP are tabularized in below tables. Both tests confirmed all six variables are I(1) at the 5% significance level. Since both the ADF and PP tests confirm the variables' I(1) status, we proceed with the cointegration test, pending the VAR (lag) order.

Table 1: Stationarity Test (Level/Log Form) - ADF

Variable	T-Stat	C.V	Result
LNPF	-1.2513	3.4486	Non Stationary
LCPI	-4.0660	-3.4351	Stationary
LINT	-1.8917	-3.4327	Non Stationary
LPPI	-2.9155	-3.4486	Non Stationary
LEXC	-1.1187	-3.4351	Non Stationary
LM2	-0.69984	-3.4327	Non Stationary

Table 2: Stationarity Test (Differenced Form) - ADF

Variable	T-Stat	C.V	Result
DLNPF	-10.5670	-3.3712	Stationary
DLCPI	-6.6222	-3.3712	Stationary
DLINT	-9.6079	-3.3786	Stationary
DLPPI	-3.994	-3.3712	Stationary
DLEXC	-7.5475	-3.3786	Stationary
DLM2	-10.7204	-3.3786	Stationary

Table 3: Stationarity Test (Level/Log Form) - PP

Variable	T-Stat	C.V	Result
LNPF	-2.0579	-3.4523	Non Stationary
LCPI	-1.9813	-3.4523	Non Stationary
LINT	-1.3766	-3.4523	Non Stationary
LPPI	-2.1339	-3.4523	Non Stationary
LEXC	-0.36234	-3.4523	Non Stationary
LM2	-0.22534	-3.4523	Non Stationary

Table 4: Stationarity Test (Differenced Form) - PP

Variable	T-Stat	C.V	Result
LNPF	-12.9339	-3.4273	Stationary
LCPI	-6.1798	-3.4273	Stationary
LINT	-9.9836	-3.4273	Stationary
LPPI	-6.0933	-3.4273	Stationary
LEXC	-7.2951	-3.4273	Stationary
LM2	-11.0576	-3.4273	Stationary

5.2 Determination of Order of The VAR Model

Before proceeding with test of cointegration, we need to first determine the order of the vector auto regression (VAR), that is, the number of lags to be used. As per the table below, results show that AIC recommends order of 1 whereas SBC favours zero.

Table 5: Optimal Lag

Order	AIC	SBC	Adjusted LR Test [Prob]
6	1936.2	1632.5	-
5	1940.7	1686.2	42.6284[.207]
4	1944.0	1738.8	86.7267[.114]
3	1948.6	1792.7	129.1336[.081]
2	1963.1	1856.4	158.1742[.198]
1	1966.8	1909.4	201.8003[.127]
0	1951.1	1942.9	271.7034[.006]

Since there is apparent conflict between recommendation of AIC and SBC, we checked for serial correlation for each variable and obtained the following results.

Table 6: Results for Serial Correlation

Variables	Chi square p-value	Implications (at 10%)
DNPLR	0.103	There is no serial correlation
DCPI	0.815	There is no serial correlation
DPPI	0.363	There is no serial correlation
DINT	0.427	There is no serial correlation
DEXCH	0.343	There is no serial correlation
DM2	0.000	There is serial correlation

There is autocorrelation one of variable out of the six variables. Thus, if we adopted a lower order, we may encounter the effects of serial correlation. However, the disadvantage of taking a higher order is that we risk over-parameterization. Therefore, we decided to ***choose the higher VAR order of 1***.

5.3 Testing Cointegration

In order to test the cointegration, we used two types of tests that are Eagle-Granger and Johanssen cointegration test. The results are showed in below tables.

Table 7: Eagle Granger Cointegration Test

	Test Statistic	LL	AIC	SBC	HQC
DF	-3.1845	177.6521	176.6521	175.2796	176.0950
ADF(1)	-2.7790	178.1485	176.1485	173.4036	175.0343
ADF(2)	-2.2675	179.7782	176.7782	172.6608	175.1070
ADF(3)	-2.2547	179.7954	175.7954	170.3055	173.5671
ADF(4)	-2.4100	180.3659	175.3659	168.5036	172.5805
ADF(5)	-2.0818	181.2532	175.2532	167.0184	171.9107

95% critical value for the Dickey-Fuller statistic = -4.8545

As the absolute value of the T-statistic (2.2675)of the ADF test for the highest AIC and SBC values is less than the 95% critical value (4.8545) the null hypothesis of non-stationarity of the error correction term cannot be rejected. This indicates no cointegration among the variables.

We thus proceed with the Johansen cointegration test, having determined the variables' I(1) status and a lag order of one. The results show strong evidence of cointegration among the six variables over the long term. That they are cointegrated suggests that there is a theoretical, long-term relationship among them and that each variable contains information for the prediction of other variables. Both the maximal eigenvalue and trace statistics (Table 8) suggest a cointegration vector of 1 at the 5% significance level. This is when the statistic is less than the critical value and thus, the null hypothesis of one or less cointegration vectors cannot be rejected. This means that there is one group of two variables each which tend to move together over the long term.

Table 8: Johansen Cointegration Test

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	74.2341	43.6100	40.7600
r<= 1	r = 2	32.3745	37.8600	35.0400
r<= 2	r = 3	21.4341	31.7900	29.1300
r<= 3	r = 4	18.5824	25.4200	23.1000
r<= 4	r = 5	9.2949	19.2200	17.1800
r<= 5	r = 6	4.9817	12.3900	10.5500

Cointegration with unrestricted intercepts and restricted trends in the VAR Cointegration LR Test Based on Trace of the Stochastic Matrix				
Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r>= 1	160.9017	115.8500	110.6000
r<= 1	r>= 2	86.6676	87.1700	82.8800
r<= 2	r>= 3	54.2931	63.0000	59.1600
r<= 3	r>= 4	32.8590	42.3400	39.3400
r<= 4	r>= 5	14.2766	25.7700	23.0800
r<= 5	r = 6	4.9817	12.3900	10.5500

5.4 Long Run Structural Modeling (LRSM)

Having ascertained that the six variables are cointegrated by one vectors, a long-run structural modeling (LRSM) test was conducted to estimate a theoretically meaningful long- run relationship between the variables. This was done by first imposing some restrictions on the relationships and then testing them.

Table 9 : Exact and Over Identification Result

Variable	Panel A	Panel B
LNPLR	0.0083096	0.00
	(0.014023)	(NONE)
LCPI	1.0000	1.0000
	(NONE)	(NONE)
LPPI	-0.24851*	-0.24757
	(0.039993)	(0.041200)
LINT	0.067300*	0.067429
	(0.023590)	(0.022273)
LEXCH	-0.072992*	-0.075041
	(0.023590)	(0.023942)
LM2	0.21906*	0.19292
	(0.071827)	(0.056587)
TREND	-0.0027950*	-0.0027139
	(0.4179E-3)	(0.4014E-3)
CHI-SQUARE	NONE	0.33267[0.564]

The Table 9 above shows exactly identification (Panel A) and over identification (Panel B) restrictions. The 'Panel A' estimates show that all the variables are significant except LNPLR. Testing over identification shows that the restriction is correct since the p-value is greater than 5% therefore null is accepted (restriction is correct).

5.5 Vector Error Correction Model (VECM)

Table 10: Error Correction Model based on AIC

ecm(-1)	Coefficient	Standard Error	T-Ratio [Prob]	C.V	Result
dNPLR	0.95150	0.51518	1.84691[.067]	5%	Exogenous
dLCPI	-0.17816	0.042939	-4.1490[.000]	5%	Endogenous
dLPPI	-0.70051	0.093450	-7.4961[.000]	5%	Endogenous
dLINT	-0.35063	0.13191	-2.6581[.009]	5%	Endogenous
dLEXCH	0.62773	0.1697	3.6973[.000]	5%	Endogenous
dLM2	-0.22780	0.083359	-2.7328[.007]	5%	Endogenous

From the result table above, all variables are endogenous excepting non-performing loan ratio (NPLR).

Variance Decomposition

Table 11: Variance Decomposition

	Horizon	LNPLR	LCPI	LPPI	LINT	LEXCH	LM2	TOTAL	SELF DEP	RANKING
LNPLR	24	86%	9%	4%	1%	0.29%	0.09%	100%	86.11%	1
LCPI	24	0.12%	21%	42%	11%	11%	14%	100%	20.60%	6
LPPI	24	0.16%	38%	54%	6%	1%	1%	100%	53.57%	4
LINT	24	0.13%	31%	1%	65%	0.21%	2.35%	100%	65.00%	2
LEXCH	24	0.18%	45%	6%	1%	45%	2%	100%	44.66%	5
LM2	24	0.04%	34%	6%	3%	2%	56%	100%	55.84%	3

	Horizon	LNPLR	LCPI	LPPI	LINT	LEXCH	LM2	TOTAL	SELF DEP	RANKING
LNPLR	36	83%	11%	5%	1%	0.36%	0.11%	100%	82.92%	1
LCPI	36	0.11%	14%	46%	13%	12%	15%	100%	13.72%	6
LPPI	36	0.18%	41%	50%	6%	2%	2%	100%	49.90%	4
LINT	36	0.17%	36%	1%	59%	0%	3%	100%	59.02%	2
LEXCH	36	0.21%	50%	7%	1%	39%	3%	100%	38.68%	5
LM2	36	0.03%	38%	7%	3%	2%	50%	100%	50.36%	3

Table 11 depicts the forecasted error VDCs for horizon 24 and 36 months. The results exhibit in the table is consistent across the horizons where the most exogenous variable is non-performing loan ratio then followed by interest rate, money supply, producer price index, exchange rate and consumer price index. Ranking is consistent with throughout long term period. Besides that, this result is consistent with the results obtained from the VECM findings above.

5.6 Impulse Response Function (IRF)

In this section a series of impulse respond techniques are presented where Impulse Reponse Functions describe the time profile of all variables returning to equilibrium value after a one period shock to a particular variable (Masih, 2006). The information obtained through IRF may be equivalent to variance decomposition except that IRF presented in graphical manner as shown in Figures below.

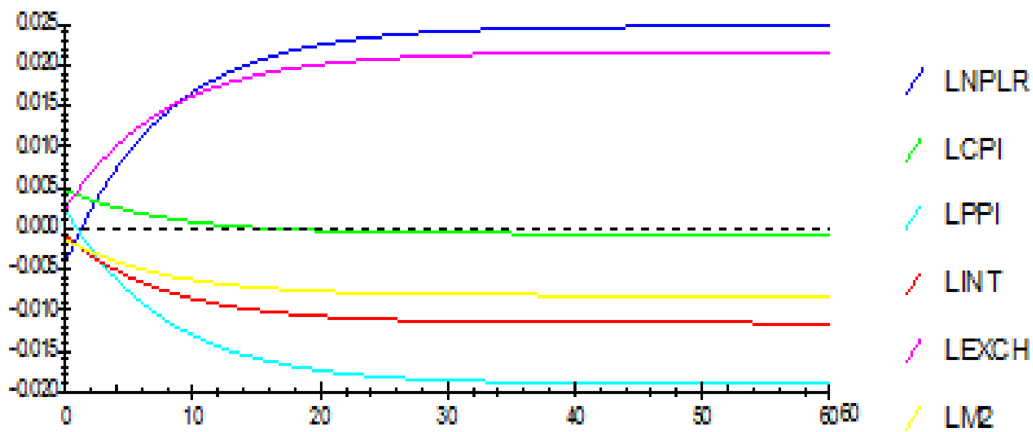


Figure 1 Generalized Impulse Response to one S.E shock in the equation for LCPI

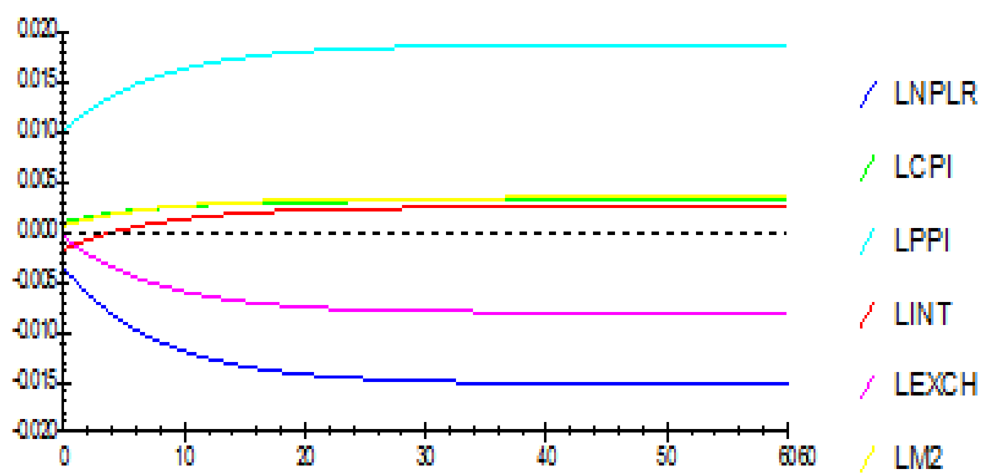


Figure 2 Generalized Impulse Response to one S.E shock in the equation for LPPI

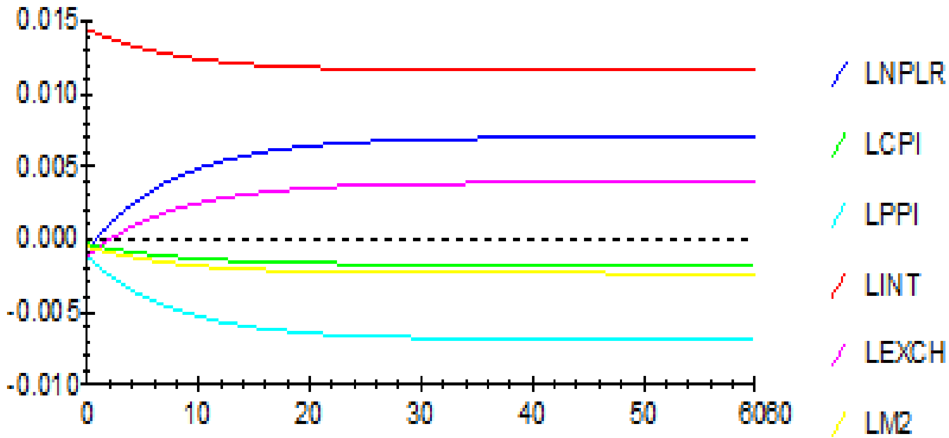


Figure 3 Generalized Impulse Response to one S.E shock in the equation for LINT

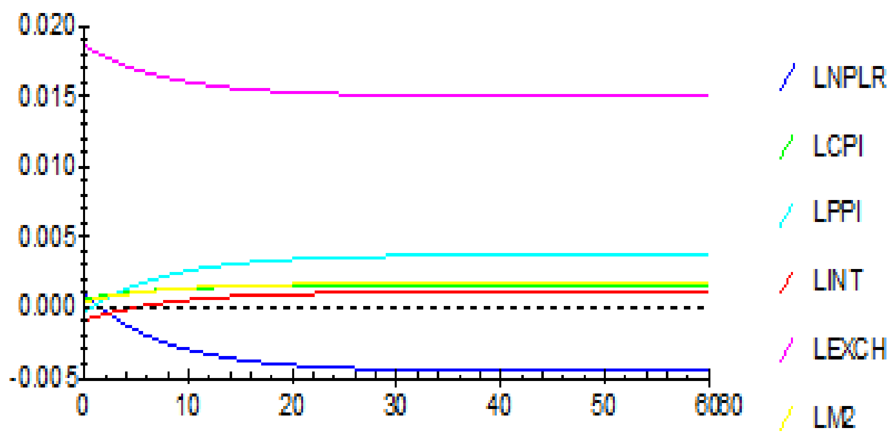


Figure 4 Generalized Impulse Response to one S.E shock in the equation for LEXCH

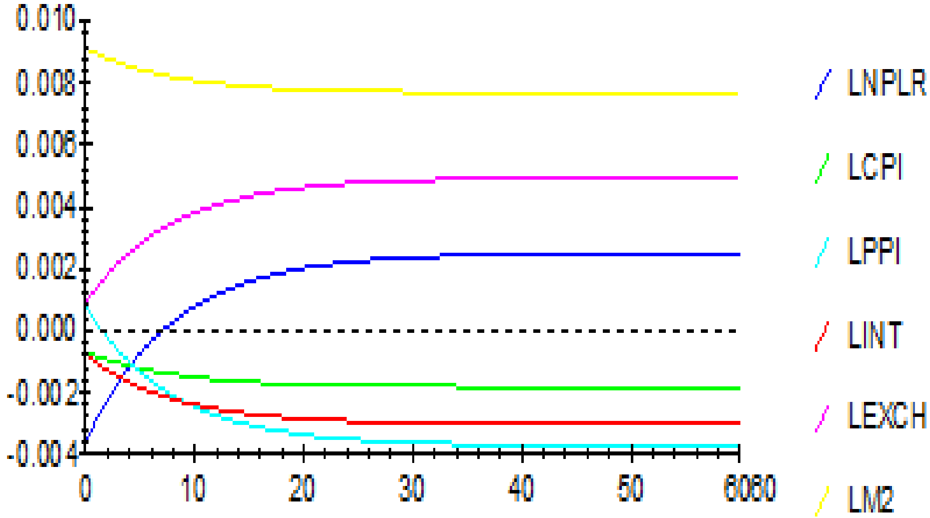
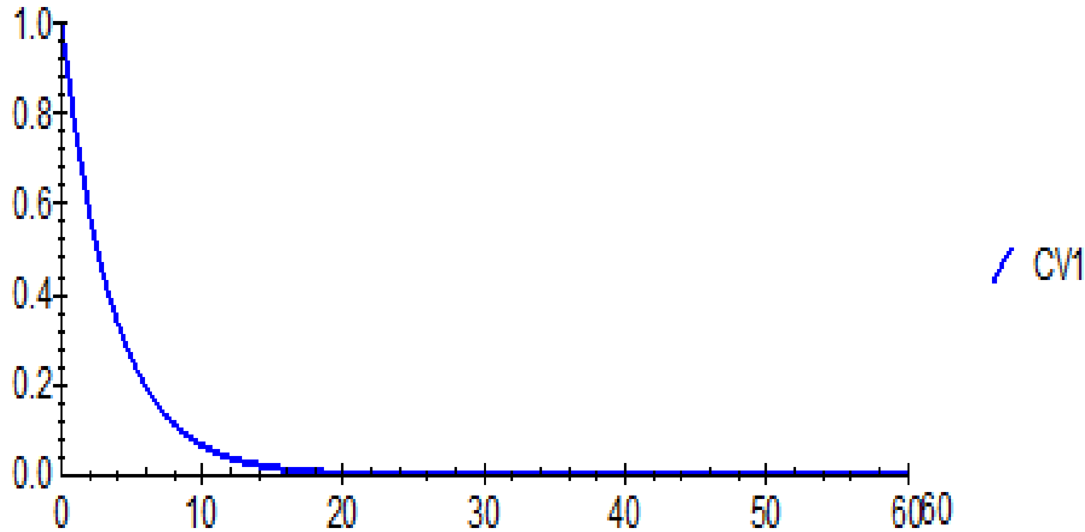


Figure 5 Generalized Impulse Response to one S.E shock in the equation for LM2

5.7 Persistence Profile

The PP deals with effects of system-wide shock in the long run rather than of variable-specific shock as it is done in IRF. The results indicate that if the long-term convergence between the variables is disturbed by any shocks, it will take about approximately about 14 months to restore the equilibrium.



6. Conclusion

The objective of the study is to identify and investigate which macroeconomic variables would be the most influential that contribute to credit risk exposure that is proxied by Non-performing loan ratio (NPLR). The variables used in this study are non-performing loan ratio, consumer price index, production price index, real interest rate, exchange rate and money supply. In this study we found that there are three endogenous variables identified in this study; (i) the consumer price index; (ii) the producer price index; and (iii) exchange rate. However, NPLR, interest rate and money supply are relatively exogenous variables. The results are also consistent across the horizons where the most exogenous variable is non-performing loan ratio followed by interest rate, money supply, producer price index, exchange rate and consumer price index. In particular, the non-performing loan ratio being the most exogenous can't be explained by any macroeconomic shocks. The results have strong policy implications.

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