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# **Do macroeconomic factors affect the credit risk of islamic banks? evidence from Malaysia**

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**Do macroeconomic factors affect the credit risk of islamic banks?  
evidence from Malaysia**

Safeza Sopian<sup>1</sup> and Mansur Masih<sup>2</sup>

**Abstract**

This paper makes an attempt to investigate whether the macroeconomic factors contribute to the credit risk exposure and non-performing financing (NPF) of Islamic banks. Malaysia is taken as a case study. The standard time series techniques are used to analyze the issue. The variables that have been chosen for the study are gross domestic product (GDP), Non-Performing Financing rate, Islamic financing rate (IFR) and unemployment rate (UMPT). The findings tend to indicate that Islamic Financing rate (IFR) stands out as the only factor that had a significant impact on the credit risk exposure and non-performing financing as well as the performance of Islamic banks in the context of Malaysia.

**Keywords:** Islamic Banks, Credit Risk, Non-performing Financing, Time Series Analysis, Malaysia

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## **1.0 OBJECTIVE AND MOTIVATION OF THE STUDY**

Since Islamic banks deal with a set of unique product characteristics and are bound by the *Shariah (Islamic law)* requirements, it is expected that the level of exposure to credit risk for Islamic banks could be different to that of the conventional banks.

The development of Islamic Banks in Malaysia since the first set up of Bank Islam Malaysia Berhad in 1983 (incorporated under the companies act 1965) had shown various efforts by the government , regulators in particular Bank Negara Malaysia (BNM) and the Islamic Banks themselves to strengthen credit risk management in line with local and international best practices. The adoption of Basel II (International Convergence of Capital Measurement Standard) which is in line with the practices adopted by the G10 countries, paved the way for BNM to establish Capital Adequacy Framework of Islamic Banks (CAFIB) in 2005 adopted by the Islamic Banks in Malaysia to better manage banking risk and compliant with regulatory capital requirement. On top of that BNM through numerous circulars and guidelines such as Best Practices for the Management of Credit Risk which was issued in 2001 and guidelines on Classification and Impairment Provision issued in 2007, has continuously guided the Islamic banks to improve the credit risk management standard to be at par with the conventional counterparts.

Credit risk is one of the common and significant risks in banking institutions which can be simply said to be the ability of borrowers to meet their financial obligations when they fall due. The inability could be due to personal specific factors such as, mismanagement, fraud or due to systematic or economy wide factors such as, recessions, high inflation etc. While the specific factors would normally be addressed by the banking institutions in Malaysia through best practices on credit risk management in line with regulatory requirements, there are lack of studies conducted to identify the default behavior owing to systematic or macroeconomic factors. Therefore, this paper will try to identify

and investigate the contributory factors to the credit risk for Islamic banks in Malaysia in terms of macroeconomics perspective.

Lack of attention and understanding in credit risk management would expose the banks to serious credit risk exposure as what happened in the US mortgage prime crisis in the past and even worst it has led to the global financial crisis. The nature of credit risk in Islamic banks is no different from its conventional counterparts and the same goes with its management in that it is based on the same analysis as the conventional banks. However, due to uniqueness of the products and their strict compliance with *Shariah* requirements, Islamic banks credit risk management tools are limited. While some of the fiqh related issues have to be resolved by the *Shariah* scholars, setting up infrastructure need to be continuously carried out by the government and regulatory authorities in the country. Credit risk arises due to borrowers' inability to meet financial obligations as they fall due. The inability could be due to personal as well as macroeconomic factors. Therefore, this paper will try to identify and investigate the contributory factors to the credit risk for Islamic banks in Malaysia from the perspective of macroeconomic factors.

## **2.0 LITERATURE REVIEW**

There were quite a number of studies conducted to analyze the relationship between the macroeconomic factors against the behavior of the default of the credits. While the impact of the credit risk had been studied elsewhere, it is hardly found that such a study has been carried out in the case of Malaysia.

Ali and Daly (2010) use econometric models to analyze the macroeconomic determinants of credit risk using a recent evidence from selected cross country study in the US and Australia. The result indicates that the same set of macroeconomic variables (GDP, interest rate, industrial production as well as debt to GDP ratio) display different default risk of the two economies. More

importantly, the study reveals that the US economy is much more susceptible to adverse macroeconomic shocks. Australian GDP variable is highly significant and negatively correlated with the default rate. The short term interest rate (nominal) and cyclical indicator has a negative coefficient yet insignificant to the default rates. Level of debt as indicated by the Debt-to-GDP ratio is positively correlated with the default rate. US GDP variable has negative coefficient with default and highly significant in explaining aggregate default. The nominal interest rate and Industrial production variables are both insignificant in explaining the default rate for the US economy. Debt to GDP ratio has a positive sign and is highly significant in explaining the default rate for the US economy.

Kunt and Detragianche (1998) studied the factors with regard to systemic banking crises in a large sample of develop and developing countries in developing countries for a 14 year period from (1980 – 1994) using a multivariate logit econometric model. From the study, it was noted that the banking crises tend to erupt when the macroeconomic environment is weak in particular when the growth is low and inflation is high. On top of that, it was also found that high real interest rates were also closely related to the systematic banking problems. It is argued that vulnerability to aggregate output shock is not necessarily the sign of the inefficient banking systems but due to its very nature which involves risk taking activities. With regard to the inflation, it was argued that it could be possibly due to the high and volatile nominal interest rate make it difficult for the banks to perform maturity transformation. The high real interest rates may be the result of host factors such as financial liberalization which is often associated with the fragility in the banking system.

Tang and Yang (2009) studied the impact on the interaction between markets and default risk on corporate credit spreads. The studied revealed that the GDP is significant determinant of average credit risk. Credit default swap (CDS) spreads decline in GDP growth rate. Other than it was also argued that the investors' sentiment is negatively associated with the credit spread.

Although the study were concentrated more on the firm level as implied volatility due to investors sentiments are the most significant determinant of default risk, it also recognized macroeconomic variables are directly responsible albeit on a lesser portion.

Volainen (2004) studied on the macro stress testing with a macroeconomic credit risk model for Finland. In the studied they employed data on industry specific corporate sector bankruptcy for 18 years period from 1986 to 2003. They used estimated model to analyze corporate credit risks reflective the current economic conditions during the study. The samples include data from severe recession period with significantly higher than average default rates in early 1990s. It was revealed for the study that, there are significant relationships between corporate sector default rates and macroeconomic factors which include GDP, interest rates and corporate indebtedness. The Interest rates shock and extreme GDP shock would significantly increase the default rates for the corporate debts.

Gerlach et. al (2004) studied the impact of macroeconomic conditions and banking performance in Hong Kong with a focus on the impact of macroeconomic developments on the net interest margin and asset quality. The study employed financial information on all retail banks in Hong Kong between the years 1994 – 2002. It was found that both the interest margin and asset quality are affected by the macroeconomic and financial development. It was revealed from the study that the default rates rises with increase in GDP, inflation and nominal interest rate. However the rises in the property prices reduce the NPL ratio as a result of the related bank's exposure to the real estate sector.

Babouček and Jancar (2005) conducted a study to investigate transmission involving set of macroeconomic variables describing the development of the Czech economy and the functioning of its credit channel from 1995 to 2004. It provides the first systematic assessment of the links between loan quality and the macroeconomic shock in the Czech Republic. Unemployment, real GDP growth, exports, imports, the real effective exchange rates, the CPI and credit

growth has been chosen as indicators of ratios performance against an unrestricted VAR methodology. It was showed from the study that the appreciation of real effective exchange rate does not deteriorate the NPL ratios; increasing unemployment and Inflation would increase the NPL ratio, while fasters GDP growth would decelerates NPL ratio. Thus the importance factors indirectly influencing financial stability and loan portfolio quality are the dynamic of inflation and interest rate.

### **3.0 METHODOLOGY**

#### **3.1 Data Descriptions**

For the purpose of this study, the 3 months gross non performing financing (NPF) would be taken as the dependent variable, while the macroeconomic determinants would be considered as independent. Based on the literature discussed above, we decided to select some macroeconomic determinants that reflect the macroeconomic forces onto the behavior of the default rates in credits such as, quarterly gross domestic products (GDP), Islamic financing rates (IFR) and unemployment rates (UMPT).

All the data are obtained from the Bank Negara Malaysia's website<sup>1</sup>.

#### **3.2 Stationarity test of Variables**

The first step in time series techniques is the unit root test. Under this test we need to determine the stationarity or non-stationarity of variables chosen. Generally, economic data of a stochastic time series or a trend is not stationary, meaning that the data have unit roots. So, in order to estimate a

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<sup>1</sup> <http://www.bnm.gov.my>

model using these data, we need to test the stationarity of the variables or known by the unit root test. If the variables used contain root element of the unit, it will be difficult to estimate a model because these data trends not tend to fluctuate around its average value. Then it can be concluded that the variables which are stationary will have a tendency to approach the average value round mean values (Gujarati, 2003).

When a time series data is stationary, it means that the mean, variance and covariance is constant and does not vary with time. A stationary series tends to return to its mean and fluctuate around it within more-or-less constant range. On the other hand, a non-stationary series would have a different mean at different point of time. In the unit root test, the null hypothesis ( $H_0$ ) is non-stationary or it has a unit root and the alternative hypothesis ( $H_1$ ) is stationary. Both hypotheses can be shown as below:

**$H_0$ : Non stationary**

**$H_1$ : Stationary**

### **3.3 Determination of the Order of the VAR Model**

Before proceeding with test of cointegration, we need to first determine the optimal order lag of the variables which means the number or lags to be used. We use the most recommended Akaike Information Criterion (AIC) as well as Schwarz Bayesian Criterion (SBC) test to determine the lag length of the VAR system to make sure the model is well specified. The lag will commonly be determined by the “Highest” value of AIC whereas the SBC test is more refined and extended test. On top of that, in determining the level of optimum lag, number of sample observations need to be considered as the number of lag will minimize the degree of freedom.

### **3.4 Cointegration Test**



Once we have determined the optimum order lag of the variables, we should be ready for the next step which is to test whether the variables are cointegrated with each other or not or in other words is to evaluate whether there have a linear combination of integration variables that is stationary in their long-term relationship. In general, a variable is said to be integrated of order  $n$ , if it requires differencing  $n$  times to achieve stationary. Therefore we can say that our variables are cointegrated if they are non-stationary integrated of the same order and yet their linear combination is stationary.

Under this test, it also shows that the variables are not moving away from each other arbitrarily. If a variable deviates from the long run relationship, it will result in some other variables adjusting to return back to the long run path. Cointegration test not only tells us information on the long run relationship between the variables it also tells us that the variables have some significance in the economic theory and it does not happen spuriously. However, Cointegration test does not indicate the direction of causality between variables. This direction of the Granger (or temporal) causality can be detected through the vector error correction model derived from the long run cointegrating vectors.

The objective of this test is to reject the null hypothesis ( $H_0$ )= no cointegration between variables.

### **3.5 Long-Run Structural Modelling (LRSM)**

After we have determined the number of lags and cointegrating relationship between variables, we need to move on to Long-Run Structural Modelling (LRSM). The purpose of conducting this test is to determine the coefficient of variables against theoretical expectations in the long run. In this test we will start by assuming which variable that we want to treat as a dependent variable and put a restriction on it relations within other variables.

### **3.6 Vector Error-Correction Modelling (VECM)**

Under this step, it holds an assumption that all variables are “endogenous” (dependent) in the long run. “Exogenous” variables can be observed when the error correction coefficient in any equation shows an insignificant result. On the other hand, if the coefficient is significant, it implies that the corresponding dependent variable is “endogenous”. The size of the coefficient of the error correction term indicates the spread of a short term adjustment to bring about long term equilibrium and it represents the proportion by which the disequilibrium in the dependent variable is being corrected in each short period.

### **3.7 Variance Decompositions (VDCs)**

After we have determined which variables are endogenous and which variables are exogenous, we will proceed to the next step, Variance Decompositions (VDCs). Both VECM and VDCs are testing on causality but VDCs test is more specific where it will determine which variables is the most exogenous and which variable is the most endogenous. On the other hand, VECM does not give us any information about the relative exogeneity or endogeneity of each variable. The variable which is explained mostly by its own shocks is deemed to be the most exogenous of all variables. The variable that have a lot of decomposed proportions in other variables are said to be endogenous.

### **3.8 Impulse Response Functions (IRFs)**

The Impulse Response Functions (IRFs) essentially produce the same information as the VDCs, except that they can be presented in graphical form. It will show us when we shocked one variable, what will happen to the other variables or in other words, it mapped out the dynamic response of a variable owing to one period standard deviation shock to another variable.

### **3.9 Persistence Profiles (PP)**

The Persistent Profile trace out the effects of a system wide shock on the long run relations between the variables. Under this step we would be able to see how long it will take to get back to equilibrium when the entire cointegrating variables are shocked.

#### 4.0 ANALYSIS AND FINDINGS

Under this section, I will explain in great detail the analysis and findings in this study.

##### 4.1 Step 1: Testing the non-stationarity/stationarity of each variable

As mentioned in the earlier section, most of macroeconomic series appeared to be non-stationary. Thus, in order to start running the data, first and foremost we need to check for the stationarity of the series whether it is stationary or non stationary. According to an example stated by Masih (2010), if the series is ‘stationary’, the demand-side short run macroeconomic stabilization policies are likely to be effective but if the series is ‘non-stationary’, the supply-side policies are more likely to be effective. Here, I have applied the Augmented Dickey-Fuller (ADF) (1981) test to examine the stationarity characteristics of the series. The test will be done for each variable (in both level and differenced form). In **table I** below show the summary of the results.

**Table 1**

Variable	Test Statistic	Critical Value	Implication
<b>Variables in Level Form</b>			
LGDP	-1.3172	-2.9499	Variable is non-stationary
NPF	-2.8879	-2.9499	Variable is non-stationary
UMPT	-2.4397	-2.9499	Variable is non-stationary
IFR	-2.4808	-2.9499	Variable is non-stationary
95% critical value for the augmented Dickey-Fuller statistic = -2.9499			

Variable	Test Statistic	Critical Value	Implication
<b>Variables in Differenced Form</b>			
LGDP	-3.8847	-2.9528	Variable is stationary
NPF	-7.6401	-2.9528	Variable is stationary
UMPT	-4.1793	-2.9528	Variable is stationary
IFR	-3.0827	-2.9528	Variable is stationary
95% critical value for the augmented Dickey-Fuller statistic = -2.9528			

Again, it is important to note that in this step 1, there are 2 important objectives to be observed:

- When testing the stationarity in the level form, the objective is to **accept** the **null hypothesis (Ho)** which is **non stationary**. In the level form, we need the variables to be **non stationary**.
- When testing the stationarity in the first order difference form, **I(1)** the objective is to **reject** the **null hypothesis (Ho)** which is **non stationary**. In the difference form, we need the variables to be **stationary**.

Thus, from the above table, the result has suggested that, at 5% significance level, the null hypothesis of a unit root (i.e., non stationary) is accepted when the series LGDP, NPF, IFR and UMPT are in level form, but it is rejected when they are in first differences form. Therefore, we can move to the next step that is to determine the lag order.

**4.2 Step 2: Determination of the order (or lags) of the VAR model** In order to investigate whether there is cointegration between LGDP,

NPF, UMPT and IFR we need to know the order of Vector Auto Regression (VAR) which means the number of lags to be used.

**Table 2** below shows the summary of the result.

**Table 2**

	Choice Criteria	
	AIC	SBC
Optimal order	6	0

Given the limitation of the number of my observation which is total of 40 observations as well as looking at this apparent conflict between recommendation of AIC and SBC, I have decided to choose **order 2**. As from my understanding and explanation given by Professor Mansur, the more lag we take, the more we will lose the **degree of freedom** and again due to this, the fair order to choose is 2.

### **4.3 Step 3: Testing the Cointegration**

The third step is to determine the value of cointegrating relationship of the current model. We use 'multivariate' with VAR order 2 to get the results based on 'Eigen values' and the 'trace' statistics to determine the value of  $r$  (cointegrating relationship). If  $r = 0$  is accepted, there is no cointegration among the variables. If  $r = 0$  is rejected, there is cointegration among the variables.

Basically, this test is conducted to see whether NPF, LGDP, IFR and UMPT have long-term relationship or not. The test will be done by following the

Engle Granger and Johansen method. In Engle Granger method we are testing the stationary on the residual where as under Johansen method, determination of cointegration seen from the trace statistic and maximum Eigenvalue statistics. Eigenvalue and trace statistics that exceeds the critical value indicate that there is cointegration in the model used. However, in residual-based method, we can only draw a conclusion for one cointegrating relationship.

As summarized in the **table 3** and **table 4** below, it shows the result for Engle Granger Method (Residual-based) and Johansen Method.

**Table 3**

<b>Error Term</b>	<b>Test Statistic</b>	<b>Critical Value</b>	<b>Implication</b>
ADF(1) (based on SBC)	6.8849	-4.4347	Variable is stationary

From the result, looking at the error term test of stationarity on the residual we found that at lag 1 the stationarity test on residual found to be stationary which implies that there is one cointegrating relationship between variable Y and independent variable or the regression.

As time goes by, if the error term found to be stationary, it implies that the error term is not permanent and transitory in nature.

**Table 4**

<b>Ho</b>	<b>H<sub>1</sub></b>	<b>Statistic</b>	<b>95% Critical Value</b>	<b>90% Critical Value</b>
<b>1. Maximal Eigenvalue</b>				
r = 0	r = 1	<b>49.5752</b>	31.7900	29.1300
r <= 1	r = 2	<b>29.4432</b>	25.4200	23.1000
r <= 2	r = 3	12.4495	19.2200	17.1800
r <= 3	r = 4	3.8656	12.3900	10.5500
<b>2. Trace Statistic</b>				
r = 0	r >= 1	<b>95.3335</b>	63.0000	59.1600
r <= 1	r >= 2	<b>45.7584</b>	42.3400	39.3400
r <= 2	r >= 3	16.3151	25.7700	23.0800
r <= 3	r = 4	3.8656	12.3900	10.5500

From the result above, both Eigenvalue and trace statistic states that there are 2 cointegrating relationship. Statistical value in **bold**, denote significance at the 5% and 10% significance level respectively, while r stands for the rank or the number of cointegrating vectors present. However, this particular study is focusing on contributing factors to credit risk which emphasized on 1 variable to be endogenous. Thus, it is more practical to assume only one cointegrating relationship.

#### **4.4 Step 4: Long-Run Structural Modelling (LRSM)**

The fourth step is to test the Long Run Structural Modeling. This test is needed in order to compare our statistical findings with theoretical (or intuitive) expectations by imposing on those long-run relations (and then testing) both identifying and over-identifying restrictions based on theories and information of the economies under review.

**Table 5**

<b>Variable</b>	<b>Coefficient</b>	<b>Standard Error</b>	<b>t-ratio</b>	<b>Implication</b>
LGDP	-2.6535	2.1669	-1.225	Variable is insignificant
IFR	0.37794	0.13557	<b>2.788</b>	<b>Variable is significant</b>
UMPT	-0.15348	0.11712	-1.310	Variable is insignificant

\*The dependent variable (NPF) has been normalized.

From the table above (Exact identifying test), after calculating the t-ratios manually, I found two variables to be insignificant - LGDP and UMPT and one variable to be significant - IFR.

Looking at the result, I was very curious as to why the LGDP and UMPT were found to be insignificant. Therefore, driven by curiosity, I have decided to verify the significance of the variables by subjecting the estimates to over-identifying restrictions. I did this for all the variables (making one over-identifying restriction at a time) and the results confirmed the earlier findings that only IFR were significant, as detailed in the **table 6** below:

**Table 6**

<b>Variable</b>	<b>Chi-Sq p-value</b>	<b>Implication</b>
LGDP	0.089	Variable is insignificant
UMPT	0.066	Variable is insignificant

#### **4.5 Step 5: Vector Error-Correction Modelling (VECM)**



The vector error correction models (VECM) is an econometric model used to capture the evolution and the interdependencies between multiple time series. It specifies the short-run dynamics of each variable in the system, and in a framework that anchors the dynamics to long-run equilibrium relationships suggested by economic theory.

In this test, if the error-correction coefficient is insignificant, the corresponding dependent variable is ‘exogenous’. But if that coefficient is significant, that implies that the corresponding dependent variable is ‘endogenous’ (it does depend on the deviations of other variables). In other words the ECM term contain long run information. If the ECM term is found to be **significant**, the value of **T-ratio** should be **more than 2 or the error term** should be **less than 0.05**. On the other hand, if the ECM term is found to be **insignificant** the value of T-ratio should be less than 2 or **the error term** should be **more than 0.05**. This result implies that the variable is **exogenous**. Therefore, IFR is an exogenous which it does not depend on the deviation of other variable. It also implies that is a leading variable and initially receives the exogenous shocks resulting in deviations from equilibrium and transmits the shocks to other variables. Please refer to **table 7** below for summary of the results. This result implies that the variable is **endogenous**. Therefore in this particular study, the **NPF** is an **endogenous** variable and IFR is an exogenous variable. To make it more clearly, NPF is depending on other exogenous variable which is IFR. This shows that, IFR would have significant bearing on the expected movement of NPF.

**Table 7**

<b>Variable</b>	<b>ECM(-1) t-ratio p-value</b>	<b>Implication</b>
NPF	0.000	Variable is endogenous
IFR	0.294	Variable is exogenous

#### 4.6 Step 6: Variance Decompositions (VDCs)

In previous step, I have found that IFR is the exogenous variable but I have less assurance on the relative endogeneity of the other variable. According to Masih (2008), the Vector Error-correction Modelling can tell us which variable is exogenous (i.e., leader) and which variable is endogenous (i.e., follower), but the error-correction model cannot tell us the relative exogeneity or endogeneity of the variables. Since the VECM test could not give the relative endogeneity of the variable, I need to move to the next test which is Variance Decomposition (VDCs).

The decomposition results have been summarized in **table 8** below:

**Table 8**

<b>Horizon</b>	<b>NPF</b>	<b>IFR</b>
<b>Relative variance in NPF (Follower)</b>		
5	0.76302	0.23698
10	0.62938	0.37062
15	0.53868	0.46132
20	0.47194	0.52806
<b>Horizon</b>	<b>NPF</b>	<b>IFR</b>
<b>Relative variance in IFR (Leader)</b>		

5	0.043199	0.95680
10	0.034072	0.96593
15	0.030980	0.96902
20	0.029427	0.97057

From the table shows that as the time horizon increased, the follower variable (NPF) is depending on IFR which explains the variance forecast error of IFR keep on increasing as the horizon increased whereas, for the leader variable (IFR), as time horizon increased, we can see that the variables (IFR) is explained mostly by its own shocks which shows it is exogenous where it depends on its own past and not depending on NPF. For example, from the result, variance of forecast error for horizon 20, IFR is 97% explained by itself which deemed to be most exogenous whereas NPF is only 2%.

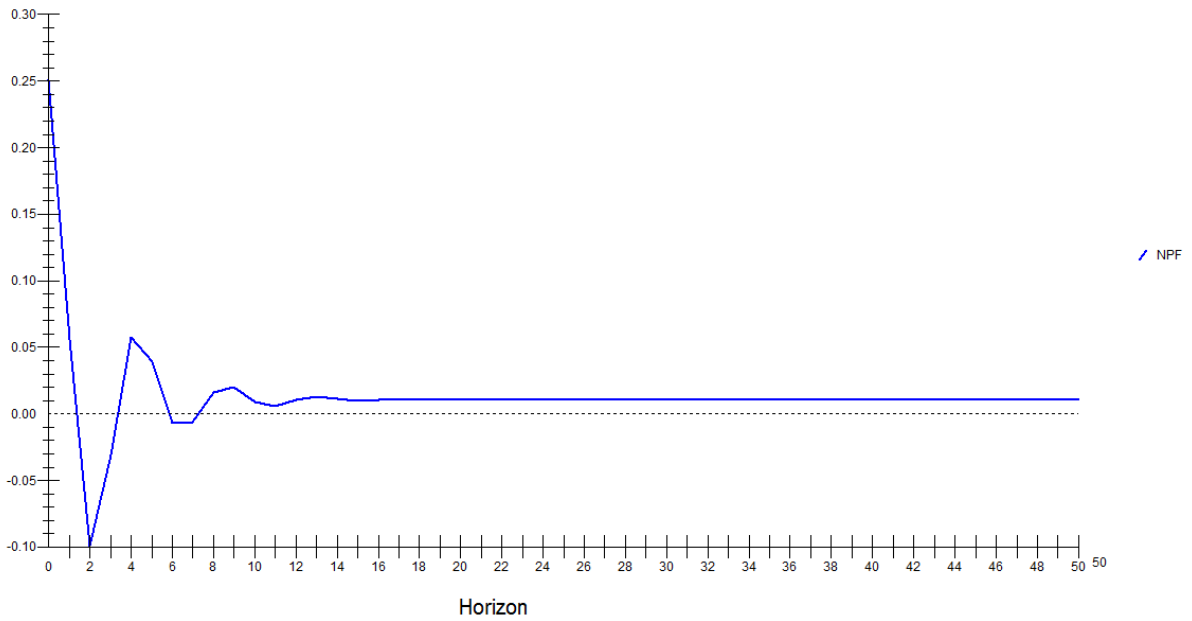
#### **4.7 Step 7: Impulse Response Functions (IRFs)**

In this section a series of impulse response analysis functions and their interpretations are presented. Impulse Response Functions described the time profile of all variables returning to its equilibrium value after a one period shock to a particular variable (Masih, 2006).

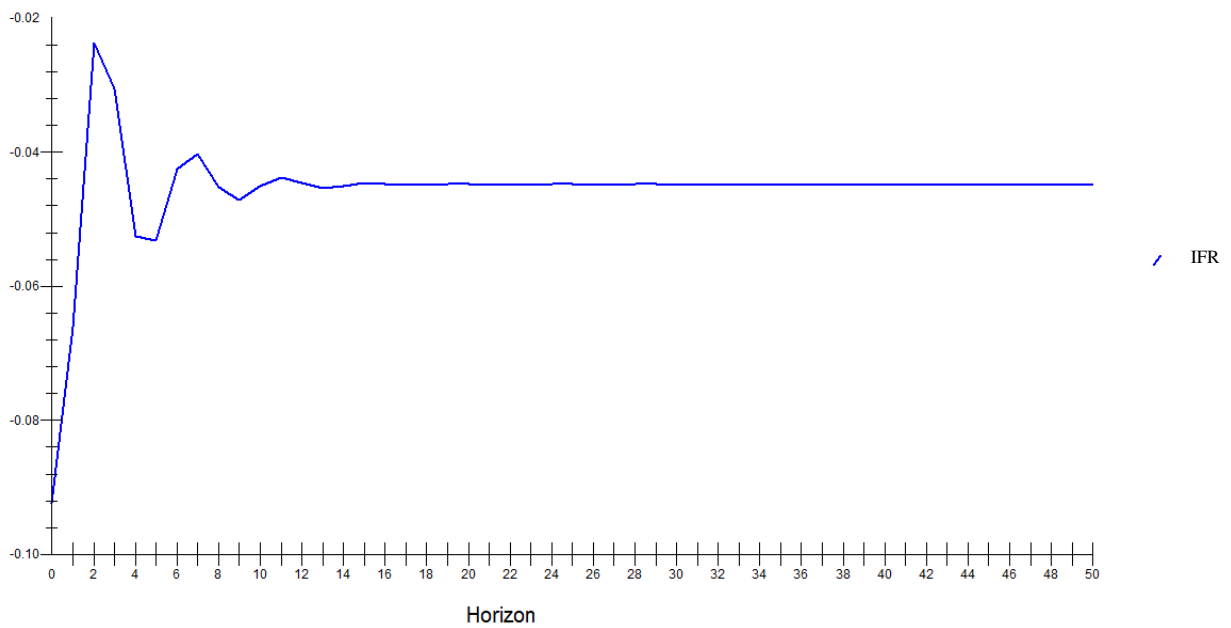
The information contained in the VDCs can be equivalently represented by IRFs only that it has presented in graphical manner (Please refer to the graphs below). IRFs essentially map out the dynamic response path of a variable owing to a one-period standard deviation shock to another variable. The IRFs are normalized such that zero represents the steady-state value of the response variable (Masih and Masih, 2008).

### i) Orthogonalized Impulse Response

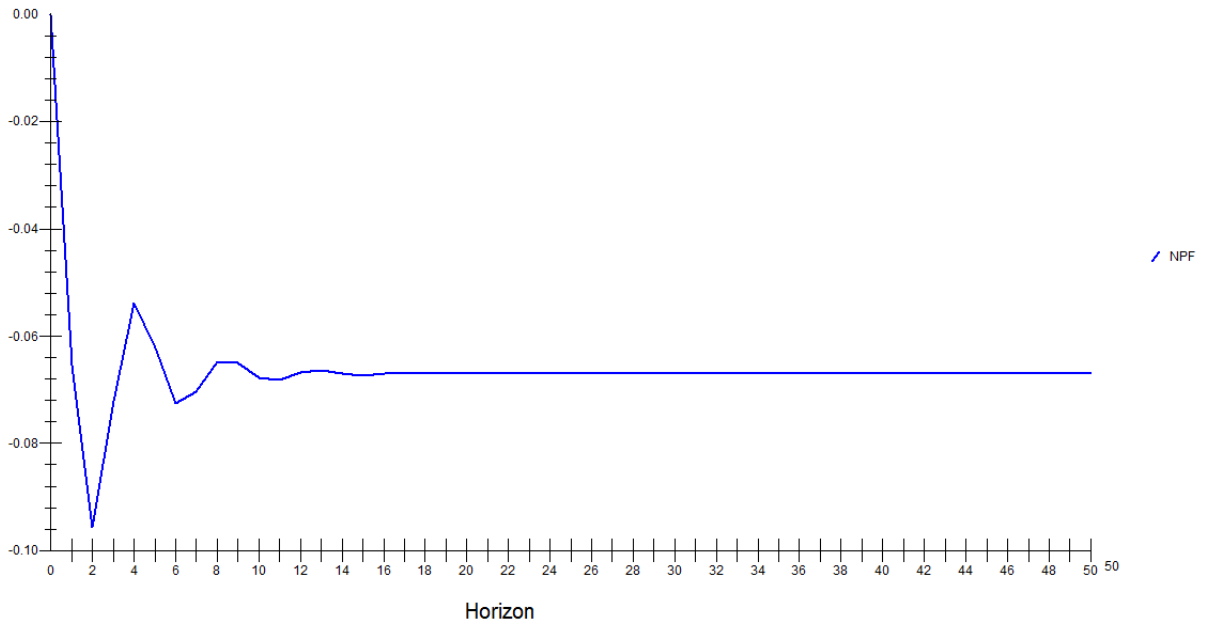
Orthogonalized Impulse Response(s) to one S.E. shock in the equation for NPF



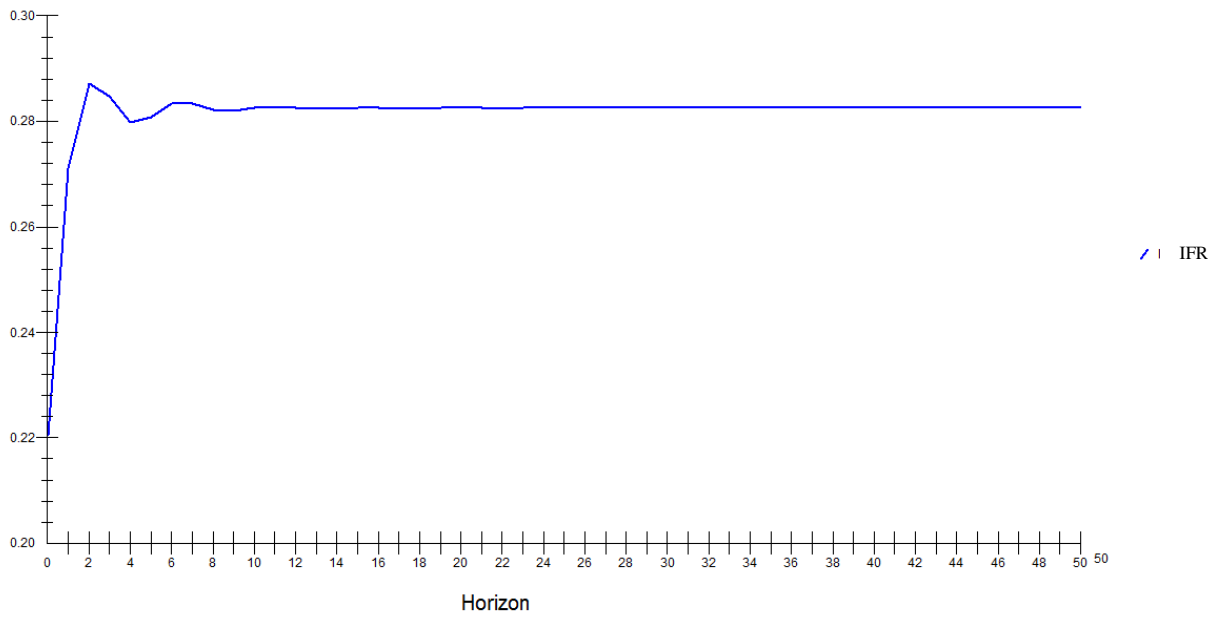
Orthogonalized Impulse Response(s) to one S.E. shock in the equation for NPF



Orthogonalized Impulse Response(s) to one S.E. shock in the equation for **IFR**

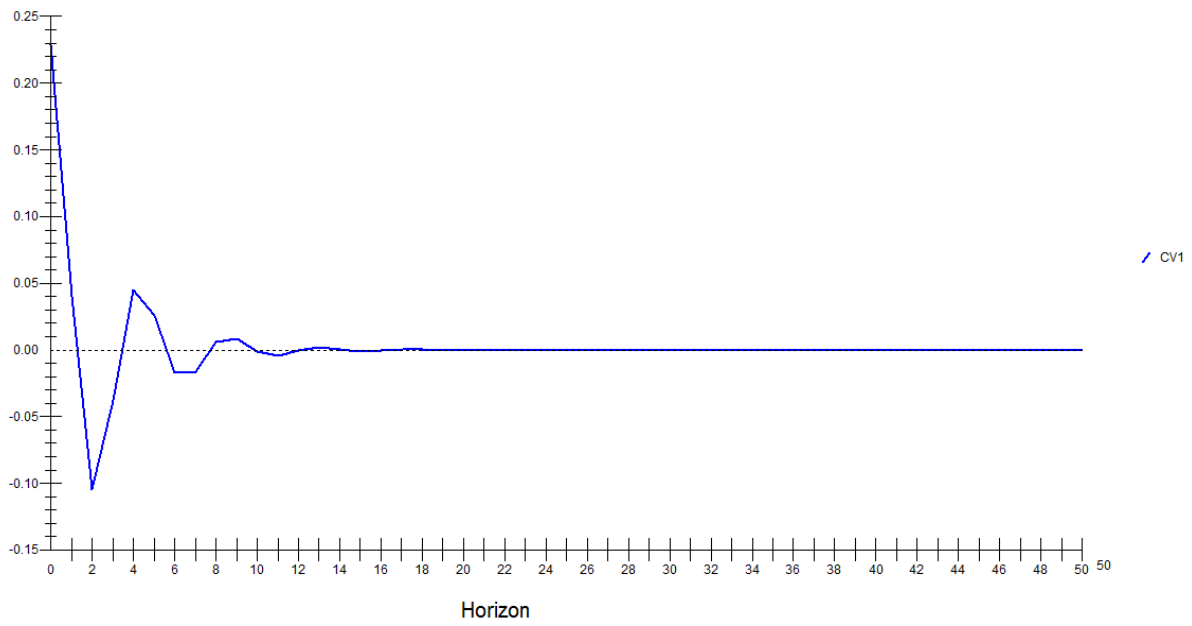


Orthogonalized Impulse Response(s) to one S.E. shock in the equation for **IFR**

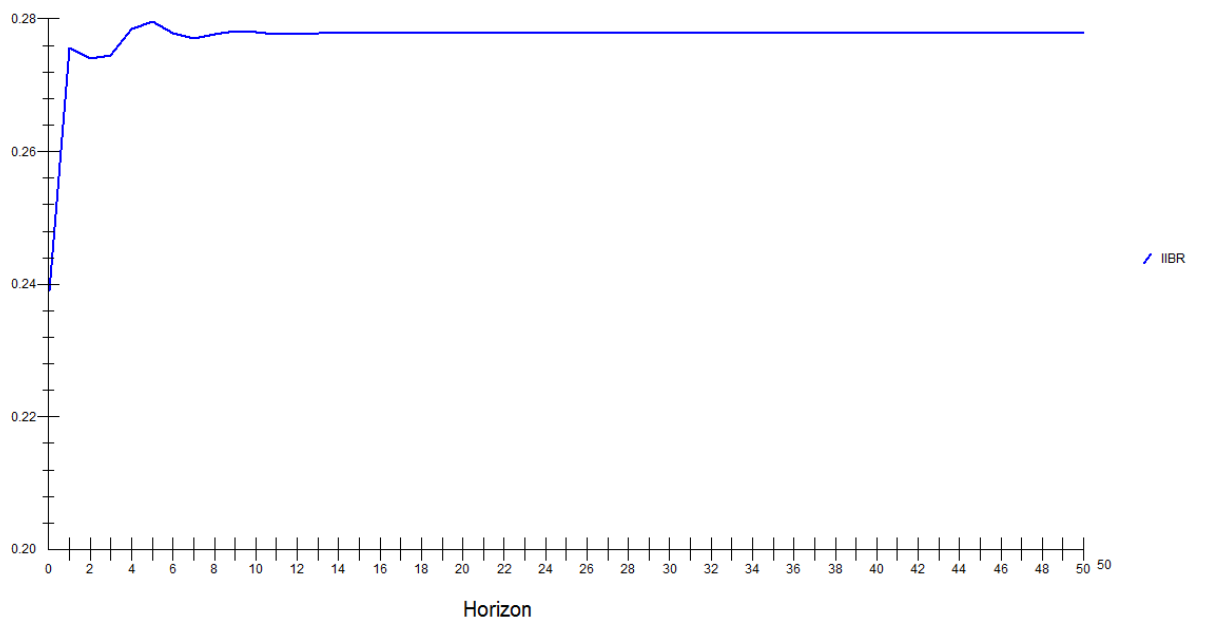


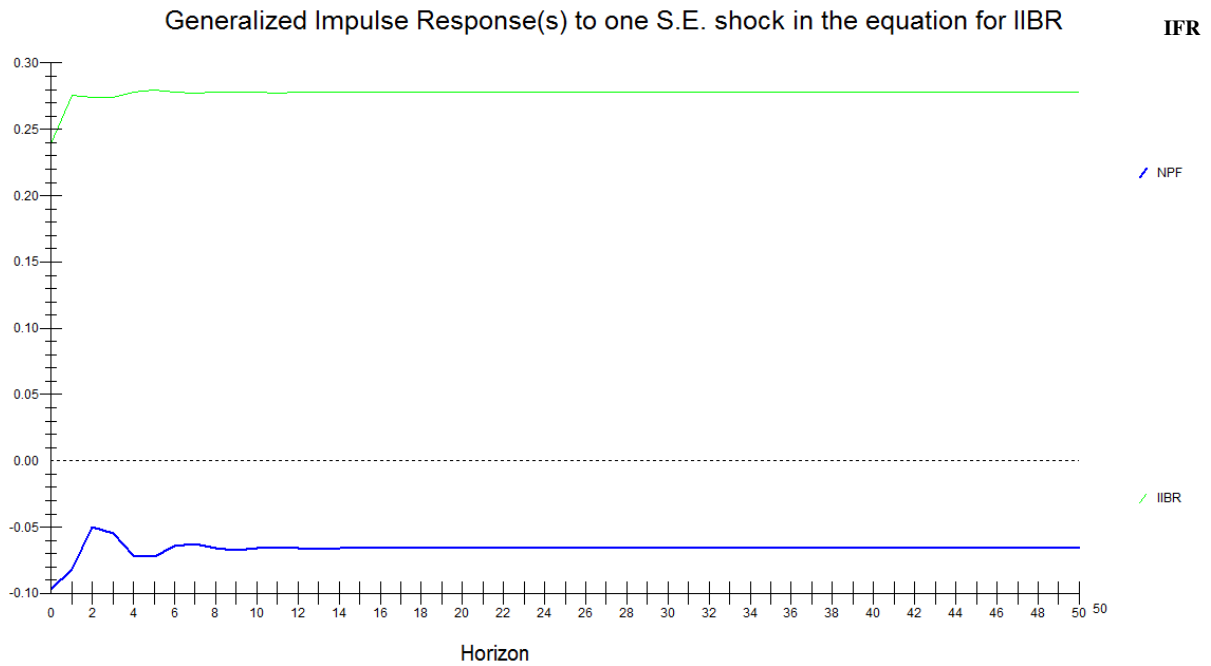
## ii) Generalised Impulse Response

Generalized Impulse Response(s) to one S.E. shock in the equation for NPF



Generalized Impulse Response(s) to one S.E. shock in the equation for IIBR

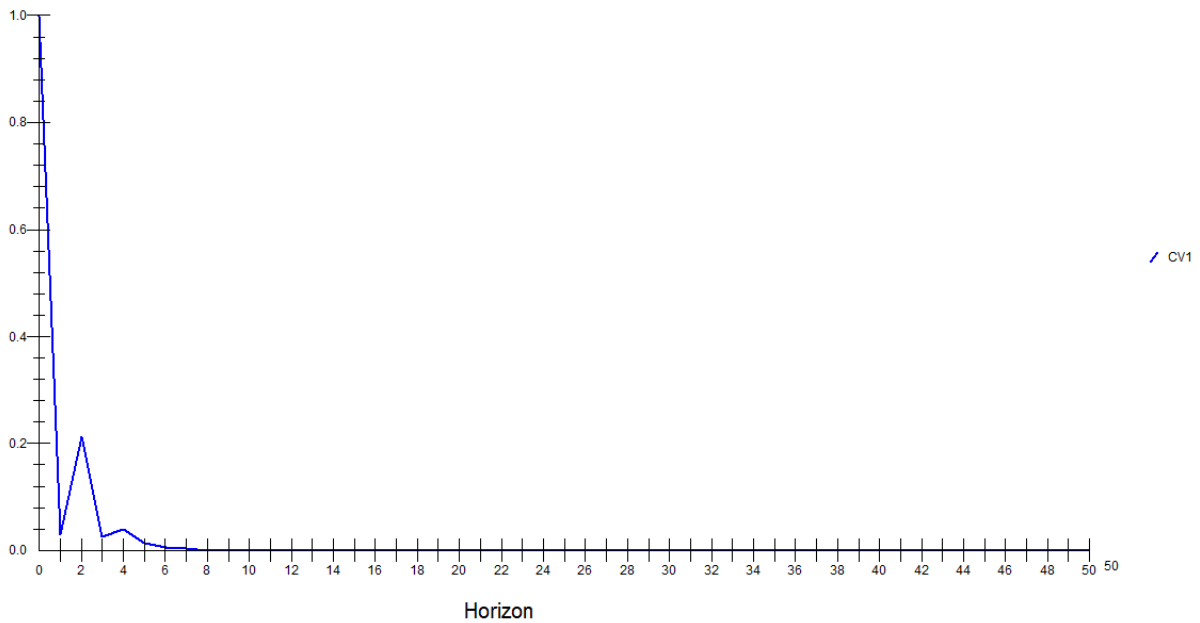




#### 4.8 Step 8: Persistence Profiles (PP)

Persistence Profiles (PPs) presented a view of the model in the long run under the external force whole shock of the entire equations. It gives the dynamic response over the shock and tells us on how long does it takes for the whole equation to return to equilibrium after the shock. It will explain that variables are cointegrated in a vector for the long run. The Persistent Profile trace out the effects of a system wide shock on the long run relations between the variables. In the graph below, it shows that after the shocked was made for NPF and IFR, it will converge to equilibrium at 7.5 periods.

Persistence Profile of the effect of a system-wide shock to CV'(s)



## 5.0 CONCLUSION

The objective of this study is to identify and investigate which macroeconomics factor would be the most influential that contribute to credit risk exposure and non-performing financing (NPF) as well as affect the performance of Islamic banks in Malaysia.

Among the factors that have been chosen for the study are gross domestic products (GDP), Non-Performing Financing rate, Islamic financing rates (IFR) and unemployment rates (UMPT). The findings tend to indicate that Islamic Financing rate (IFR) became the only factor that would have a significant impact on the credit risk exposure and non-performing financing as well as the performance of Islamic banks in Malaysia.



The cointegration test has proved that NPF and IFR both have cointegrating relationship. This shows that both variables are cointegrating in the long-run. The results in both analyses have documented a positive long-run association between NPF and IFR. The IFR appears to be significant and exogenous in nature from the VECM test. From the VDCs test shows clearly that the NPF is the follower and highly depending on IFR which means IFR has very strong causality relationship. IFR is explained mostly by its own shocks which show it is exogenous where it depends on its own past and not depending on NPF.

Overall, the findings has led me to conclude that eventhough the GDP and UMPT has been rejected to be the contributing factors to the credit risk, my intuition and personal beliefs still thinks that GDP and UMPT could also become the contributing factors maybe not so significant but at least there are small percentage that the two factors are also macroeconomic determinants for credit risk. Referring to the study done by Babouchek and Jancar (2005), they found that increasing in unemployment and Inflation would increase the NPL ratio, whilest fasters GDP growth would decelerates NPL ratio.

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