Predicting stress in the banking sector: Malaysian evidence

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Abstract

This paper attempts to identify predictors of bank stress in Malaysia by computing a bank stress index and analyzing the index against bank specific variables and macroeconomic variables. This study utilizes the cointegrating VAR model to identify the existence of cointegrating relationships among both bank specific variables and macroeconomic variables towards bank stress. ARDL is also used to add robustness to the cointegration analysis. A forecast of the variables' dynamic relationship is quantified by applying both orthogonalized and generalized variance decomposition (VDC). The impact of a shock in macroeconomic variables is also portrayed via an impulse response function and a systemic shock is simulated based on persistence profile. It is found that based on the index, bank stress levels in Malaysia have increased over time within the recent 15 years period. In the short term, non-performing loans to total loans (NPL) and lending spread are found to be the main predictors of bank stress. However, in the longer term, NPL and bank capital and reserve variation are the main predictors of bank stress. Bank stress has been found to have a strong cointegrating relationship with all the macroeconomic variables used in this study, and when the macroeconomic variables were shocked individually, it was found that there is an increased volatility in bank stress. Based on persistence profile, external shocks are found to have a greater and longer effect on the economy compared to internal shocks such as a disruption in the financial market or bank failure.

Keywords: bank stress, macrovariables, ARDL, VECM, VDC, Malaysia

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1 Introduction

The banking system is an integral part of the financial system. For emerging market economies, the banking system plays a vital role in supporting the development of the country by providing the necessary channel to allow transmission and access of funds from surplus units to deficit units. Various studies (Allen & Gale, 1999; Bencivenga & Smith, 1991; Diamond, 1984; Ramakrishnan & Thakor, 1984; Sirri & Tufano, 1995) have highlighted the positive impact of banks on economic growth. A resilient banking system comprising of healthy financial institutions and supported with an encouraging financial regulatory system is essential, especially for developing countries and emerging markets.

However, the strength of a financial institution is highly dependent on the financial environment that it is in. Market conditions, the current economic state and various other factors affect the strength and livelihood of a financial institution. A financial institution is classified as robust or strong when it has the ability to weather adverse economic conditions.

In recent years, several studies have been done to identify the impact of financial fragility on the banking system (Goodhart, Sunirand, & Tsomocos, 2006; Tsomocos, 2003) and some attempts have been made to measure the level of bank stress in various countries such as Canada (Illing & Liu, 2003), Germany (Porath, 2006), South Korea (Lee, Ryu, & Tsomocos, 2013) and Switzerland (Hanschel & Monnin, 2005). This is to investigate whether its possible to detect increased levels of bank stress and financial fragility in order to rectify the situation before a full blown crisis occurs. As aptly stated by Hanschel and Monnin (2005) the absence of a full-blown crises does not mean that the condition of the banking sector is equally sound and stress-free.

A measure of the banking sector's stress gives a better picture of the sector's current financial condition. A stress indicator could be calculated to represent a continuum of states that describes the banking sector's condition at a given point in time. The banking system can be stressed due to two main reasons; macroeconomic factors and bank specific factors.

Macroeconomic factors are external factors that the bank is unable to control such as the current economic condition, monetary policy by the central bank, the government's fiscal policy and other external factors. Meanwhile, bank specific factors are internal factors that arise due to the operations and investment decisions of the bank. These factors create risks that are inherent in the business, but the risks are diversifiable by the bank if it changes its investment and operations policy.

This study is conducted to identify how both macroeconomic factors and bank specific factors impact bank stress levels. Both factors have been known to play a role in the development and growth of banking institutions but in the face of adverse macroeconomic conditions, how would the same factors that contribute towards growth, contribute to the detriment of the health of banking institutions? With that in mind, the main purpose of this study is to extend existing research on financial fragility and its impact to a developing country. This is because, a developing country with a small capital market is highly dependent on the banking sector to foster its economic growth. Compared to previous studies which have looked into financial fragility and banking stress in developed countries such as Canada, Germany, South Korea and Switzerland, financial fragility and banking stress in developed countries might be affected in a different manner due to different economic and financial landscape.

Thus this study is conducted to fulfill three objectives. Firstly, the paper aims to construct a bank stress index to summarize the current condition of the banking sector in Malaysia into one single measure. Secondly, the study aims to identify which bank specific variable is the index is most vulnerable to. And finally, the paper would also like to identify which macroeconomic variable that affects the index the most.

It is hoped that this study will be able to shed some light on the current condition of the banking sector in Malaysia and provide insight as to what factors affect the banking sector the most.

1.1 Background of the Study

This paper adopts the methodology used by Hanschel and Monnin (2005) in building a bank stress index and measuring the bank stress against bank-specific variables and macroeconomic variables for Switzerland. In their paper, the authors have divided the variables into four clusters; (1) market price data; (2) balance sheet data; (3) non-public data; and (4) other structural variables. For market price data the authors used the banks' stock price index and the yield spread for bank-issued bonds to reflect the risk that are inherent with the banking sector. For balance sheet data, total interbank deposits, return on assets, variation in bank capital and loan reserve coverage of non-performing loans was used as a measure to signify a banking crisis. Non-public data consists of total assets of banks who are under the observed list of the Swiss Federal Banking Commission as a measure to indicate the share of the banking sector considered to be in trouble by the banking supervisory authority. For other structural variables, the authors have used the variation in the number of bank branches.

Malaysia have been selected for this study due to several reasons. Firstly, previous studies have concentrated on developed countries such as Canada, Germany, South Korea and Switzerland and because of that, I would like to extend current literature by extending the sample to a developing country. The findings of this study are expected to be different from earlier findings by other researchers due to a different sample is used and that sample involves a country at a different economic state and financial growth level as compared to other countries which have been used. Secondly, Malaysia aims to be a developed country by the year 2020 and this study would provide much insight as to whether the current macroeconomic environment would help to lead the banking institution into providing support towards economic growth and development.

For this study, due to unavailability of data and not enough observations of the data, several changes have been made on the type of data/ variables used for this study compared to the earlier study made by Hanschel and Monnin (2005). Bank stress was derived based on only market data and balance sheet data where the bank stock price index and lending spread were selected to represent market data and variation in bank capital and reserves, non-performing loans to total loans and variation in interbank deposits were used to represent balance sheet data. There were not enough observations for us to use the variation in the number of bank branches. And due to various merger and acquisition activities which occurred in the beginning of the century as the central bank, Bank Negara Malaysia looked for ways to strengthen the banking institutions after the Asian financial crisis, several bank specific variables such as return on assets and loan reserve coverage to total loans were unavailable as the banks merged and transformed into new banking entities.

To improve on the sensitivity of the results, quarterly data was used. Figure 1 depicts the movement of bank specific variables over the period of 15 years from 2000 until 2015.

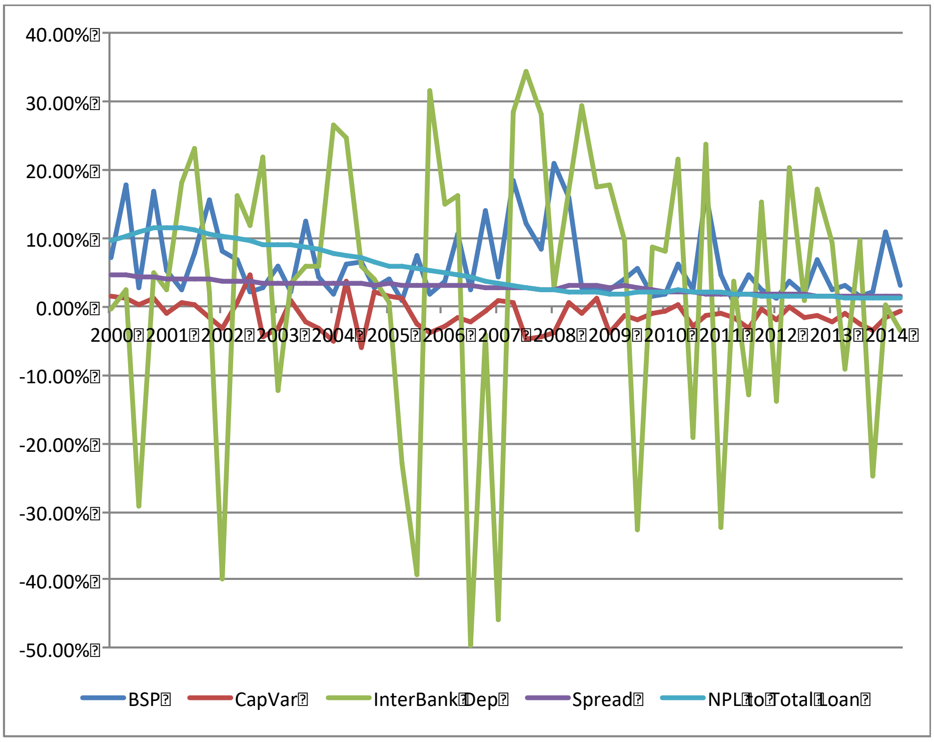


Figure 1 Bank Specific Variables

It can be seen that both the lending spread (Spread) and non-performing loan to total loan (NPL) has been on a decreasing trend. However, there are major fluctuations in the amount of interbank deposits (Inter Bank Dep) indicating a healthy movement of funds among the banking institutions where a fall in the amount of interbank deposits is immediately followed by an increase in interbank deposits. However, it should be noted that the fall in interbank deposits is higher (in percentage terms) compared to the consecutive rise in deposits. The bank stock price index (BSP) also showed a small level of volatility and a huge drop in bank stock price could be seen in 2008, corresponding to the global financial crisis at the time. A small movement in the banks' total capital and reserve variation could also be seen, however, the magnitude is quite small within the range of +5% and -5%.

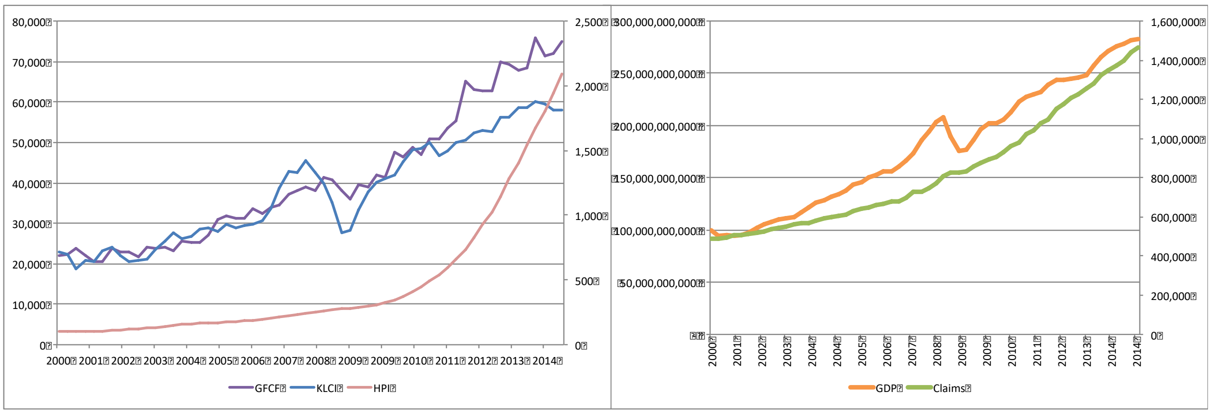


Figure 2 Macroeconomic Variables

For macroeconomic variables, it is evident from the chart on the left that there is a steady growth in Gross Fixed Capital Formation (GFCF), KLCI and exponential growth in the Housing Price Index (HPI). The chart on the right also shows a consistent growth in the claims from the private sector (Claims) and growth in GDP for Malaysia within the 15 year period. From both charts it could be said that from the year 2000, Malaysia is on a steady growth path with a promising future.

This paper is divided into three (3) parts, the first part measures the bank stress index and tabulates the level of bank stress in Malaysia from the period of 2000 until 2015. The second part looks at the impact of bank specific variables on bank stress and the third part looks at the influence of macroeconomic variables on bank stress. Finally the paper concludes on its findings and provides policy implications to the findings.

2 Literature Review

The recent U.S. financial crisis originated from both fragilities both in the banking sector and the real estate sector. When the housing bubble burst in the U.S., it caused a domino effect leading to a downward spiral from the evaporation of the value of securities which were tied to the real estate assets (mortgaged-backed securities and collateralized debt obligations), a massive tumble in real estate prices, and a liquidity emergency as banks and insurance

companies were unable to provide compensation on the financial commitments that they were making.
The 2008 global financial crisis provides clear evidence that there is a contagion effect between the banking sector and the economic wellbeing of a country. Despite being under constant regulatory supervision, the banking and insurance sector's fragility grew to unprecedented levels and as the economic conditions became overheated, it was discovered that the foundations of the banking and financial institutions were unable to shoulder their commitments and later led to the downfall of various financial institutions such as IndyMac, Lehman Brothers and AIG.
Previous studies on early warning systems (EWS) for banking crises have empirically established a link between the real economy and the financial sector (Hanschel & Monnin, 2005; Loayza & Ranciere, 2006; Tymoigne, 2011). This suggests that the economic environment corresponds to a common risk to all financial institutions and that it has the potential to forecast the stress. Therefore, if macroeconomic imbalances are prevailing and the economy is weak, the banking system is more prone to experience crises or stress in the near future.
It is important to distinguish the banking sector's stress from its fragility. Stress emerges from the combination of exogenous shocks and fragilities in the banking system (Goodhart et al., 2006). Hence a fragile banking sector does not systematically suffer stress if it benefits from a quiet and stable environment. Conversely, a solid banking system can undergo stress if it experiences extreme exogenous shocks (Aspachs, Goodhart, Tsomocos, & Zicchino, 2007). The interaction of the shock's magnitude and the banking system's fragility determines the stress level.
Based on literature, there are various methods which can be used to measure bank stress and the impact of macroeconomic factors on bank stress. Hanschel and Monnin (2005) developed a bank stress index in order to portray the fluctuations of bank stress in Switzerland. Their study is different from previous studies as they use variables that are exclusive to the banking sector and thus are able to demonstrate the movement is bank stress levels from tranquil to high levels of stress. The bank stress index is developed based on an aggregate of four variables representing market price data, balance sheet data,

non-public data of the supervisory authorities and other structural variables. The index is then tested against several variables that are selected as a potential symptom of bank crisis and also tried to forecast bank stress by using macroeconomic imbalances. They found that a banking crisis can show up in different ways, thus the variables used in the study may not correctly reflect a bank crisis and proposed that a stress index should be constructed on several variables and incorporate different types of information. They also found that on a macroeconomic perspective, a significant link exists between the macroeconomic environment and the banking sector’s condition.

Porath (2006) estimates default risk of German banks by using a discrete hazard model on a combined dataset of default events, balance sheet information, audit reports and macroeconomic variables. They found that capitalization, return, credit risk, market risk and macroeconomic context are relevant in estimating probabilities of default for German banks. They also found that models that exclusively utilizes bank-specific information provide good predictions for the relative risk of a bank but are unable to capture the risk level and risk level forecast greatly improves if macroeconomic variables are added to the model.

On the other hand, a study conducted by Lee et al. (2013) uses market data as proxies for probabilities of default and equity valuation of the Korean banking sector. The effect of probability of default was measured using a vector error correction model (VECM) and individual banks’ contribution to systemic risk is estimated using CoVar and MES (Marginal Expected Shortfall). They found that the composite financial stability index is highly significant in determining GDP and that it is possible to predict fluctuations in financial fragility via the same index.

Therefore it could be seen that there are various methods to compute bank stress and so far, there is no particular method that is able to perfectly capture the dynamics of bank stress. However, it is agreed that despite the limitations in the models used to capture bank stress, the ability to gain information from the current models outweighs any weaknesses of the model. It is found that bank specific variables are good at predicting bank stress and the forecast greatly improves if macroeconomic variables are also used in the model.

3 Methodology

Instead of taking the level or the growth rate of the variables, we follow the study done by Hanschel and Monnin (2005) which looks at the deviations from the longer-term trend, i.e. gaps. Gaps underline the cumulative process of the imbalances, a large trend deviation can develop either in one period with strong above (or below) trend growth or through a sequence of years with above (or below) trend growth.

The foundation of the stress index is based on the observation of crisis symptoms in the banking sector. Typically, there are several symptoms that signal banking crises i.e. bank run, fall in the banks' stock price, bank failures and many others. To measure the stress level, the gravity of the different crisis symptoms at a given date are estimated. If the symptoms are present and acute, the banking sector is likely to be in a crisis situation, and the stress level is likely to be high.

The variables that were used in representing crisis symptom have been identified and defined based on existing literature. Their intensity is then measured and aggregated to form the final stress index. Previous studies have identified that banking crises show up in many different ways and that identifying them implies a certain degree of subjectivity. A single variable would not be able to capture the complexity of crises. Thus a stress index is built by combining several types of variables (i.e. market prices and balance sheet data). The variables included in the index are: (1) Market price data represented by the banks' stock price index (BSP) and the lending spread (Spread). When the banking sector goes to a crisis, its intrinsic value diminishes causing the banks' stock prices to fall. In order to detect falling stock prices, we look at the biggest decline in 12 months observed during the year. This measure allows sharp falls to be exhibited more clearly than with raw data. For lending spread, the spread reflects the current liquidity levels and the ability of the banks to provide funds. During a crisis, a higher spread should be observed. The average spread over one year is used in the index. (2) Balance sheet data is represented by the number of total interbank deposits (Interbank), variation in the banks' total capital and reserves (CapVar) and an increased amount of non-performing loans over total loans (NPL). It is assumed that in a banking crisis, there would a loss of confidence by the depositors in the banking system i.e. a bank run would occur, causing a sudden drop in deposits. Similarly, if a bank is stressed, there would be negative variations in the banks' total capital and reserves as the bank would have to dig up into its own capital and reserves to finance its operations. One of the major indicators of a crisis is an increased level of non-performing loans to total loans. This is because, an increased level of NPL indicates that there banks are unable to recover the returns on their lending activities. This is detrimental to the banks' health as it eats up revenues (i.e due to non-payment) and erode profits as more costs are incurred in aiding collection activities.

A stress index for the Malaysian banking sector was then computed for the years between the 4th quarter of 2000 until the 1st quarter of 2015 based on both market price data and balance sheet data. Similar to an earlier study by Hanschel and Monnin (2005) and the same method is also common in literature, the variance-equal weight method is used to compute the index. The variables are first standardized so as to express them in the same units and then they are aggregated using identical weights. the index formula is computed as follows:

$$I_t = \sum_{i=1}^{k} \frac{X_{i,t} - \overline{X_\iota}}{\sigma_i}$$

where *k* is the number of variables in the index, $\overline{X_t}$ is the mean of the variable X_i and σ_i is its standard deviation. The final index is standardized to express it in terms of deviations from its mean. The results of the computed stress index for the Malaysian banking sector between 2000 until 2015 are as depicted in Figure 3 below. A level above zero means that the stress is higher than average. The index is expressed in terms of standard deviations from its mean.

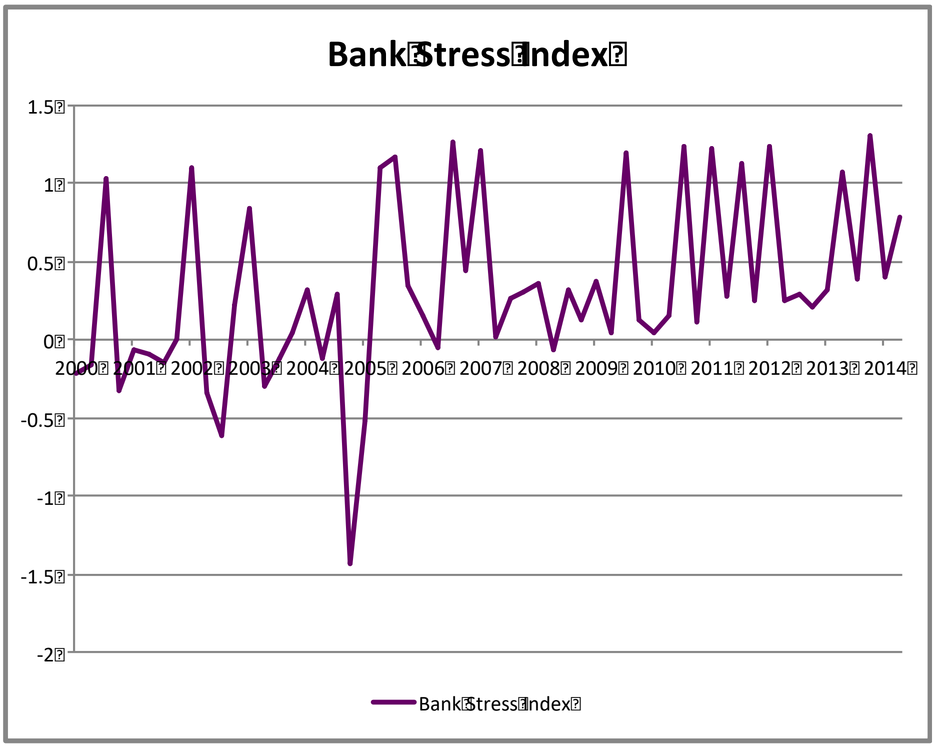


Figure 3 Stress Index for the Malaysian Banking Sector

It could be observed that the index identifies two periods where stress is above average, from 2003 to 2004 and from 2006 until 2015 while the year 2005 was the least stressful for the banking system in Malaysia. Despite many attempts to identify why the level of bank stress dropped significantly in 2005, we were unable to uncover the cause. However, based on our data, it is found that there is a significantly higher amount of interbank deposits between the last quarter of 2014 and the first quarter of 2015 which could contribute towards improving the liquidity in the banking system and thus reducing bank stress levels.

With the values computed for the bank stress index, the two relationships are examined; (1) the impact of bank specific variables on bank stress and to identify which variable would produce the most impact to bank stress; and (2) the impact of macroeconomic factors on bank stress and to identify which macroeconomic factor would have the greatest impact to bank stress. Cointegrating vector autoregressive (VAR) models were used to identify the relationships between the variables to bank stress and the autoregressive distributed lag (ARDL) estimators were used for robustness. Microfit 5 was used to analyze the variables.

3.1 Limitations of the Study

There are several limitations of the study that should be observed. Firstly, in the second part of this study which involves identifying the impact of bank specific variables on bank stress, there are multicollinearity issues as the variables used are highly correlated. However, multicollinearity does not reduce the predictive power or reliability of the model as a whole but it may not give valid results about any individual predictor or about which predictors are redundant with respect to others. Therefore we have decided to leave the model as it is, despite multicollinearity. This is because, the presence of multicollinearity doesn't affect the efficacy of extrapolating the fitted model to new data provided that the predictor variables follow the same pattern on multicollinearity in the new data as in the data on which the regression model is based.

Secondly, limitation exists on the selection of this particular time period. In this study, only the most recent time period is used because it will provide the most useful data to market regulators on what factors will affect bank stress. The level of development in Malaysia as well as the current financial system have changed significantly over time and thus the most recent period would be the most useful and applicable to regulators in formulating new policies for the future. However, due to that, this study is not able to capture the macroeconomic scenario and banking market information during the 1998 Asian financial crisis which would be useful for regulators to see whether financial conditions and the level of bank stress during that period have any similarities on the increased level of bank stress that we are currently experiencing.

Finally, due to unavailability of data and not enough observations on certain variables, this study is not able to utilize all the variables which was used in the study by Hanschel and Monnin (2005) thus the findings in this study might change if all variables that were used in that study are applied in this study.

4 Findings and Discussion

This section is divided into two parts, the first part discusses the bank specific variables which represents microeconomic factors affecting bank stress while the second part looks at the macroeconomic variables representing systematic risks or undiversifiable risks that affects bank stress.

4.1 Measuring Stress in the Malaysian Banking Sector

Six variables have been selected to represent bank specific variables; (1) BSP representing Bank Stock Price Index; (2) NPL representing non performing loans over total loans; (3) SPREAD representing the spread between bank lending rates and overnight rates (OPR); (4) CAPVAR representing the variations of bank capital and reserves; (5) INTERBANK representing movement in interbank deposits; and (6) STRESS representing the Bank Stress Index.

4.1.1 Preliminary Analysis for Bank Specific Variables

Three variables, BSP, SPREAD and NPL were logged (denoted as LBSP, LSPREAD and LNPL respectively) to make the variance of these variables constant, while the remaining three variables, CAPVAR, INTERBANK and STRESS were not logged because the variables contain negative values.

Unit root tests based on Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP) are conducted to identify whether the variables used in this study are stationary at I(1). In both tests, the t-statistics value is determined based on the highest absolute value under both Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

The hypothesis for both ADF and PP are as follows:

H_0 The variables are non-stationary

H_1 The variables are stationary

If the test-statistic is lower than the critical value, the null cannot be rejected and the variable is determined as non-stationary. If the test-statistic is higher than the critical value, the null hypothesis is rejected and the variable is deemed as stationary. To identify whether the variables are I(1), the variable must be stationary (i.e. the null is rejected) in differenced form.

Table 1 Unit Root Test using ADF

Variables	T-Statistics	Critical Value	Implication
		Level Form	
LBSP	2.3126	3.4969	Variable is non-stationary
LNPL	1.7977	3.4969	Variable is non-stationary
LSPREAD	1.8125	3.4969	Variable is non-stationary
CAPVAR	5.1289 (AIC) 6.1772 (SBC)	3.4969	Variable is stationary Variable is stationary
INTERBANK	5.7453	3.4969	Variable is stationary
STRESS	5.5719 (AIC) 2.6438 (SBC)	3.4969	Variable is stationary Variable is non-stationary
		First Differencing	
DBSP	5.6636 (AIC) 3.8656 (SBC)	2.9190	Variable is stationary Variable is stationary
DNPL	2.4672	2.9190	Variable is non-stationary
DSPREAD	4.4977	2.9190	Variable is stationary
DCAPVAR	6.6244	2.9190	Variable is stationary
DINTER	6.3195	2.9190	Variable is stationary
DSTRESS	7.3044	2.9190	Variable is stationary

In the first unit root test based on ADF, it was found that three variables (LBSP, LNPL and LSPREAD) are non-stationary at the level form while the remaining three variables (CAPVAR, INTERBANK and STRESS) are stationary at the level form. After first difference, only one variable is non-stationary (DNPL), while the remaining five variables (DBSP, DSPREAD, DCAPVAR, DINTER, DSTRESS) are stationary.

Table 2 Unit Root Test using Phillips-Peron

Variables	T-Statistics	Critical Value	Implication
Level Form			
LBSP	7.4975	3.4601	Variable is stationary
LNPL	2.5350	3.4601	Variable is non-stationary
LSPREAD	1.7375	3.4601	Variable is non-stationary
CAPVAR	9.3452	3.4601	Variable is stationary
INTERBANK	9.1721	3.4601	Variable is stationary
STRESS	11.9104	3.4601	Variable is stationary
First Differencing			
DBSP	26.3373	2.9029	Variable is stationary
DNPL	5.5952	2.9029	Variable is stationary
DSPREAD	6.6868	2.9029	Variable is stationary
DCAPVAR	30.7403	2.9029	Variable is stationary
DINTER	29.7486	2.9029	Variable is stationary
DSTRESS	35.4307	2.9029	Variable is stationary

For the PP test, some results are found to be different compared to the ADF test. Firstly, in the level form, the test showed that only two variables are non-stationary, LBSP and LNPL, while the remaining variables are stationary. After differencing, all the variables are shown to be stationary. To ensure the results are robust, another unit root test was conducted based on KPSS to confirm the data that will be used are I(1). Similar to ADF and PP, the hypothesis for KPSS are as follows:

H_0 The variables are non-stationary

H_1 The variables are stationary

Table 3 Unit Root Test based on KPSS

Variables	T-Statistics	Critical Value	Implication
Level Form			
LBSP	0.94761	0.16724	Variable is non-stationary
LNPL	0.098162	0.16724	Variable is stationary
LSPREAD	0.12085	0.16724	Variable is stationary
CAPVAR	0.14442	0.16724	Variable is stationary

INTERBANK	0.16850	0.16724	Variable is non-stationary
STRESS	0.15488	0.16724	Variable is stationary
First Differencing			
DBSP	0.12537	0.37853	Variable is stationary
DNPL	0.14745	0.37853	Variable is stationary
DSPREAD	0.13479	0.37853	Variable is stationary
DCAPVAR	0.17637	0.37853	Variable is stationary
DINTER	0.15009	0.37853	Variable is stationary
DSTRESS	0.13355	0.37853	Variable is stationary

Considering the existence of both stationary and non-stationary variables in the level form (refer to Table 1, Table 2 and Table 3), ARDL (Autoregressive Distributed Lag) will be used to test for cointegration and identify the long-run relationship between the variables.

Based on the test results from the ADF, PP and KPSS test, it is concluded that all the variables used in this analysis are I(1) and could be used for further testing. Although it was found that in some instances for the ADF test the AIC and SBC gave different result (i.e. at level form the STRESS variable is found to be stationary based on AIC and non-stationary based on SBC), and ADF and PP test gave different results (e.g. DNPL is found to be non-stationary in the ADF test but stationary in the PP test), the stationarity or non-stationarity of the variable is established based on all three tests. It is concluded that the implications of the variables as I(1) are consistent.

Before proceeding with the test of cointegration, the order of the vector auto regression (VAR) is first identified. This will determine the number of lags to be used in the following tests. The optimal order is determined based on the highest absolute value for AIC and SBC.

Table 4 Selecting the Order of the VAR Model

	Choice Criteria		
	AIC	**SBC**	**Adjusted LR test**
Optimal Order	6	0	0

Based on AIC, 6 lags should be used while based on SBC and Adjusted LR test, 0 lag should be used. As there is clearly a conflict between the recommendation of AIC and SBC, serial correlation for each variable is tested and the results are as follows:

Table 5 Identification of Serial Correlation

Variable	Chi-Sq p-value	Implication at 10%
DBSP	0.000	There is serial correlation
DNPL	0.000	There is serial correlation
DSPREAD	0.098	There is serial correlation
DCAPVAR	0.001	There is serial correlation
DINTER	0.000	There is serial correlation
DSTRESS	0.000	There is serial correlation

Based on the results in Table 5, there exists autocorrelation in all 6 variables. If a lower order is used, there could be effects of serial correlation and if a higher order is selected, there is a risk of over-parameterization. As this study has 58 observations it is decided that a higher order would be selected to avoid the effects of serial correlation.

4.1.2 Cointegration Test

In the first part of this study it has been identified that the variables are I(1) and the optimal VAR order as 6. The next step is to test for cointegration. When a series of variables are cointegrated, it is said that over time, the variables move together i.e. they do not drift apart in the long run.

Table 6 Johansen Cointegration Test

Criteria	Maximal Eigenvalue	Trace	AIC	SBC	HQC
No. of cointegrating vectors	1	1	6	2	6

Based on the results in Table 6, it can be safely assumed that there is at least one cointegrating vector in the model. This is because, based on the variables selected on this study and previous literature on the similar studies, the variables do have an effect on each other. For example, the amount of interbank deposits act as a measurement on the level of liquidity in the market and should the level of liquidity increase, the lending spread should be lower (i.e. the values for INTERBANK variable would be smaller) as there are more funds to be lent out while if liquidity levels decrease, the lending spread would be bigger as there are less funds available.

On a statistical level, the cointegration results indicate that the variables used in this study, in some combination, result in a stationary error term and they tend to move together in the long run.

4.1.3 Autoregressive Distributed Lag (ARDL) estimators for Cointegration

For robustness, we have decided to utilize the autoregressive distributive lag (ARDL) approach to further confirm the presence cointegration, testing the presence of long-run relationships among the variables.

Table 7 Test of Long-Run Relationships between the Variables

Dependent Variables	F-Statistics	Critical Value		Implication
		Lower bound	Upper bound	
DBSP	4.0392	2.476	3.646	Cointegration exists among the variables
DNPL	0.39683	2.141	3.250	There is no cointegration
DSPREAD	0.76693	2.141	3.250	There is no cointegration
DCAPVAR	1.4263	2.141	3.250	There is no cointegration
DINTER	1.0241	2.141	3.250	There is no cointegration
DSTRESS	1.2874	2.141	3.250	There is no cointegration

Based on the results in the above table, one cointegrating vector has been found indicating that the six variables are theoretically related, and they tend to move together in the long term. This means that their relations to one another is not merely spurious or by chance. This finding has important implications because given that the variables are cointegrated, the movement of any of the variables would affect the banks' stress levels in Malaysia.

For robustness, an ARDL bounds test was conducted to identify the existence of cointegration among the variables. The existence of a level effect relationship among the variables is identified using the following hypothesis:

H_0 There exists no level effect relationship among the variables

H_1 There exists level effect relationship among the variables

Table 8 ARDL Approach to Cointegration based on AIC

Dependent Variables	F-Statistics	Critical Value		Decision
		Lower bound	Upper bound	
LBSP	3.3949	2.8562	4.1393	Test results are inconclusive
LNPL	0.63071	2.8562	4.1393	There is no cointegration among the set of I(0) and I(1) variables
LSPREAD	4.3787	2.8562	4.1393	Cointegration exists among the I(0) and I(1) variables
CAPVAR	12.8205	2.8562	4.1393	Cointegration exists among the I(0) and I(1) variables
INTERBANK	3.7720	2.8562	4.1393	Test results are inconclusive
STRESS	4.3549	2.8562	4.1393	Cointegration exists among the I(0) and (1) variables

To test the level effect relationship among the variables, each variables were made as dependent and regressed against the remaining variables in the model. Similar to the previous test, the optimal VAR order 6 was used. If the F-Statistic is lower than the lower bound, there is no cointegration among the variables. However, if the F-Statistic is higher than the upper bound, thus rejecting the null and indicating that cointegration exists among the variables. Based on the results in Table 8, we conclude that there exists at least long run or short run relation among the variables.

Next, diagnostic tests for auto-correlation, normality, specification and heteroskedasticity are examined to identify the existence of any issues that may arise. The chi-square p-value of both the LM Version (LM) and the F Version (F) have been tabulated in Table 9 below.

Table 9 Diagnostic Tests based on AIC

Variables	Serial Correlation	Functional Form	Normality	Heteroskedasticity
LBSP	0.208 (LM) 0.38301 (F)	0.041 (LM) 0.271 (F)	0.000 (LM) N/A (F)	0.405 (LM) 0.414 (F)
LNPL	0.944 (LM) 0.11844 (F)	0.002 (LM) 0.009 (F)	0.761 (LM) N/A (F)	0.074 (LM) 0.077 (F)
LSPREAD	0.072 (LM) 0.608 (F)	0.653 (LM) 0.800 (F)	0.808 (LM) N/A (F)	0.417 (LM) 0.426 (F)
CAPVAR	0.013 (LM) 0.316 (F)	0.120 (LM) 0.348 (F)	0.549 (LM) N/A (F)	0.381 (LM) 0.391 (F)
INTERBANK	0.000 (LM) 0.125 (F)	0.62 (LM) 0.333 (F)	0.894 (LM) N/A (F)	0.790 (LM) 0.795 (F)
STRESS	0.000 (LM) 0.063 (F)	0.189 (LM) 0.516 (F)	0.583 (LM) N/A (F)	0.684 (LM) 0.691 (F)

Based on the results in the diagnostics test, it was found that there is an issued of autocorrelation in the STRESS variable, functional form in the LNPL variable, normality in the LBSP variable and heteroskedasticity in the LNPL variable.

As mentioned earlier, a higher VAR order is used to mitigate the issue of autocorrelation. In regards to the functional form issue for LNPL, this could be due to many reasons such as LNPL may be better explained using a different function, more than one function or a non-linear function. However, it is the STRESS variable which is the main variable that is being studied in this paper, and we have decided to ignore the functional form issue for LNPL. The AIC criterion was adopted to obtain the following cointegrated equation:

$$\mathbf{STRESS_t = 2.287 + 0.0722LBSP_t + 0.856LSPREAD_t - 0.533\ LNPL_t - 27.669CAPVAR_t - 6.535INTERBANK_t + e_t}$$

se = (1.6795) (0.10707) (0.60048) (0.19044) (14.9900) (2.6663)

t = [0.195] [0.511] [0.176] [0.014] [0.086] [0.028]

4.1.4 Identification of Long Run Relationships

The relationship among the variables is quantified using the Long Run Structural Modeling (LRSM) component in MicroFit. One cointegration level is used based on the results of Maximal Eigenvalue and Trace. One cointegration means that the variables are moving together in one direction in the long run. The variable of interest i.e. Bank Stress (STRESS) was normalized and the results are shown in the next table:

Table 10 Long Run Structural Modeling: Exact Identification

Variable	Coefficient	Standard Error	t-ratio	Implication
LBSP	1.2904	19.0763	0.0676	Variable in insignificant
LNPL	3.3758	22.3814	0.1508	Variable in insignificant
LSPREAD	-14.3402	276.8052	0.0518	Variable in insignificant
CAPVAR	377.6031	5746.0	0.0657	Variable in insignificant
INTERBANK	64.3135	1008.1	0.0638	Variable in insignificant
STRESS	-	-	-	-

It was surprising to discover that all the variables used in the study are found to be statistically insignificant. This means that based on these results, there are no meaningful (or cointegrating) relations found between these variables.

The significance of the results are further tested by subjecting the estimates to over identifying estimates. Based on over-identification approach, we found that when the BSP and SPREAD variables were dropped, the remaining three variables, NPL, CAPVAR and INTERBANK were significant. The imposed restriction were found to be correct as the Chi-square p-value was found to be 0.255 i.e. we do not reject the null that the restrictions are correct.

Table 11 Long Run Structural Modeling: Over Identification

Variable	Coefficient	Standard Error	t-ratio	Implication
LBSP	-	-	-	-
LNPL	1.3170	0.43217	3.0474	Variable in significant
LSPREAD	-	-	-	-
CAPVAR	59.1730	25.7830	2.2950	Variable in significant
INTERBANK	9.5493	3.4924	2.7343	Variable in significant
STRESS	-	-	-	-

4.1.5 Vector Error Correction Model (VECM)

So far it has been established that the variables in this model are cointegrated to a certain degree. However, the cointegrated equation reveals nothing about causality, i.e. which variable is the leading variable and which is the laggard variable.

Thus the next step identifies the process of how the variables adjust in the short run to bring about equilibrium in the long run. It can be used to identify endogenous and exogenous variables in the model. By knowing which variable is endogenous and exogenous, it would be easier to predict the expected impact that the variable would have on the bank stress level in Malaysia. The exogenous variable would be the variable which is of interest by the industry stakeholders because they could closely monitor the performance of the variable as it would have a significant bearing on the expected movement of the other variables which would trigger bank stress.

Table 12 Error Correction Model for Bank Specific Variables

Variable	Coefficient	ECM (-1) t-ratio p-value	Implication
dLBSP	-1.4949	0.003	Variable is endogenous
dLNPL	0.38121	0.300	Variable is exogeneous
dLSPREAD	0.21384	0.434	Variable is exogeneous
dCAPVAR	-0.30221	0.045	Variable is endogenous
dINTERBANK	0.44145	0.702	Variable is exogeneous
dSTRESS	0.81573	0.815	Variable is exogeneous

Based on the above results, it was found that there are four (4) variables that are exogenous that should be of interest to the industry stakeholders. The variables are the level of non-performing loans to total loan (NPL), lending spread (SPREAD), variation in the level of interbank deposits (INTERBANK), and bank stress (STRESS). What it means is that for industry stakeholders and market participants in the banking industry, changes in the exogenous variables would affect the level bank capital and reserve and the bank stock price in a significant way. Thus any news, events and developments in both indicators would like be of interest to industry stakeholders and market participants. However, we do not fully agree to the findings in VECM as we feel that bank stress should be an endogenous variable as the level of bank stress should be impacted by the movement in all the other variables. Thus the next step will tell us more on the endogeneity and exogeneity of a variable.

From the results depicted by the error correction coefficient it was also found that BSP has a faster speed of adjustment, while a moderate speed of convergence was found for the remaining variables.

4.1.6 Variance Decomposition (VDC)

In the previous section it has been established that both the NPL, SPREAD, INTERBANK and STRESS are exogenous variables while the remaining variables, BSP and CAPVAR are endogenous variables. However, we have not established the relative exogeneity and endogeneity of the variables. In other words, which variables is the most leading variable and which variable is the most laggard variable.

Relative exogeneity and endogeneity will be determined by variance decomposition (VDC). VDC decomposes the variance of forecast error of each variable into proportions attributable to shocks from each variable in the system, including its own. The least endogenous variable is the variable whose variation is explained mostly by its own past variations.

Orthogonalized VDC is applied and the following results have been obtained:

Forecast Horizon = 2 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	66.72%	0.91%	1.48%	5.67%	18.55%	6.67%
LNPL	0.71%	94.72%	0.85%	0.85%	3.48%	0.16%
LSPREAD	0.96%	22.74%	75.44%	0.61%	0.75%	0.18%
CAPVAR	15.93%	3.77%	0.24%	58.39%	16.93%	4.74%
INTER	4.10%	7.52%	14.40%	7.57%	63.77%	2.63%
STRESS	0.96%	22.74%	75.44%	0.61%	0.75%	0.18%

Forecast Horizon = 4 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	50.64%	11.05%	6.10%	7.98%	18.28%	5.95%
LNPL	1.28%	85.46%	1.44%	2.97%	8.49%	0.37%
LSPREAD	0.56%	27.19%	67.29%	0.33%	4.27%	0.36%
CAPVAR	20.75%	3.50%	4.98%	49.69%	15.02%	6.06%
INTER	6.94%	13.65%	17.70%	9.75%	48.90%	3.06%
STRESS	0.56%	27.19%	67.29%	0.33%	4.27%	0.36%

Forecast Horizon = 8 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	40.43%	15.18%	5.76%	10.29%	22.71%	5.63%
LNPL	3.91%	63.89%	1.74%	12.11%	17.48%	0.88%

LSPREAD	0.70%	35.81%	58.94%	0.33%	3.90%	0.33%
CAPVAR	19.99%	4.30%	6.85%	45.41%	15.11%	8.33%
INTER	8.09%	10.31%	29.86%	8.48%	39.45%	3.80%
STRESS	0.70%	35.81%	58.94%	0.33%	3.90%	0.33%

For the above tables, the rows display the percentage of the variance error forecast of each variable into proportions attributable to shocks from other variables (in columns) including its own. The columns display the percentage in which that variable contributes to other variables in explaining observed changes. The diagonal line of the matrix (highlighted) represents the relative exogeneity. Based on the results, the ranking of the variables by degree of exogeneity (i.e. the extent to which its variation is explained by its own past variations or lags) is presented in the table below:

Table 13 Ranking of the Variables by Degree of Exogeneity based on Orthogonalized VDC

No.	2 Quarters	4 Quarters	8 Quarters
1	NPL	NPL	NPL
2	Lending Spread	Lending Spread	Lending Spread
3	Bank Stock Price	Bank Stock Price	Capital Variation
4	Interbank Deposit	Capital Variation	Bank Stock Price
5	Capital Variation	Interbank Deposit	Interbank Deposit
6	Bank Stress	Bank Stress	Bank Stress

The results are found to be partly inconsistent with earlier findings. This is because, from the previous analysis, four variables were found to be exogenous, non-performing loans to total loans (NPL), lending spread (SPREAD), interbank deposits (INTERBANK) and bank stress (STRESS). However in VDC, it is found that although NPL is ranked first in terms of exogeneity, bank stress ranks as the most endogenous variable, which is consistent with other studies and previous literature. NPL and SPREAD are found to be consistent with the earlier findings in

VECM, both variables are ranked as the most exogenous variable according to orthogonalized VDC.

However, due to inconsistencies between the findings in VECM and orthogonalized VDC, we would like to see whether the same results hold true in generalized VDC. This is because, there are two limitations of orthogonalized VDC that must be recognized. Firstly, orthogonalized VDC assumes that when a particular variable is shocked, all other variables are “switched off”. And secondly, orthogonalized VDC does not produce a unique solution. The results are generated based on the ordering of variables in the VAR. Thus the first variable would report the highest percentage and would most likely be specified as the most exogenous variables.

Therefore the results from generalized VDCs are also taken into consideration as they are invariant to the ordering of the variables. However, in interpreting the numbers generated by the generalized VDC, there are additional computations that needs to be performed. This is because, the numbers do not add up to 1.0 such as the results found in orthogonalized VDC. For a given variable, at a specified horizon, the numbers in the given row is summed up and then divided by the number for that variable (representing the magnitude of variance that is explained by its own past). In this way, the numbers in a particular row will now add up to a total of 1.0 or 100%. The results are as tabulated below:

Forecast Horizon = 2 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	56.73%	2.01%	1.27%	14.51%	14.08	11.50%
LNPL	0.67%	88.17%	2.79%	4.85%	1.78%	1.73%
LSPREAD	0.71%	17.31%	63.75%	0.42%	15.06%	2.74%
CAPVAR	12.48%	2.37%	0.12%	57.65%	12.56%	14.81%
INTER	2.64%	4.80%	10.02%	6.41%	51.41%	24.73%
STRESS	0.55%	8.04%	2.54%	14.67%	24.06%	50.13%

Forecast Horizon = 4 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	39.91%	10.65%	4.95%	14.73%	15.82%	13.94%
LNPL	1.22%	79.09%	6.70%	9.95%	1.14%	1.89%

LSPREAD	0.37%	17.93%	53.11%	0.45%	22.88%	5.26%
CAPVAR	15.95%	2.43%	3.74%	50.89%	12.51%	14.48%
INTER	4.69%	8.72%	11.39%	10.76%	42.32%	22.12%
STRESS	1.60%	9.18%	6.09%	12.69%	25.44%	44.99%

Forecast Horizon = 8 (quarters)

	LBSP	LNPL	LSPREAD	CAPVAR	INTER	STRESS
LBSP	29.67%	13.08%	4.70%	15.87%	18.04%	18.64%
LNPL	3.62%	55.60%	2.55%	23.14%	5.28%	9.81%
LSPREAD	0.45%	22.74%	48.19%	0.66%	22.09%	5.86%
CAPVAR	16.29%	3.08%	5.04%	49.35%	12.97%	13.27%
INTER	6.04%	7.37%	20.91%	10.62%	34.72%	20.33%
STRESS	1.44%	8.11%	16.25%	12.10%	21.09%	41.01%

From the results that were obtained based on the generalized VDCs, the variables are ranked by relative exogeneity (refer to Table 14).

Table 14 Ranking of the Variables by Degree of Exogeneity based on Generalized VDC

No.	2 Quarters	4 Quarters	8 Quarters
1	NPL	NPL	NPL
2	Lending Spread	Lending Spread	Capital Variation
3	Capital Variation	Capital Variation	Lending Spread
4	Bank Stock Price	Bank Stress	Bank Stress
5	Interbank Deposit	Interbank Deposit	Interbank Deposit
6	Bank Stress	Bank Stock Price	Bank Stock Price

Based on the results tabulated, several observations can be made. Firstly, the generalized VDC results confirms the orthogonalized VDC results that both NPL and lending spread (SPREAD) are the most exogenous variable.

Secondly, the relative rank in exogeneity maintains its stability over time. Between 2 quarters and 4 quarters, there is only two changes in ranking, i.e. (1) capital variation became more exogenous compared to lending spread over time, and (2) bank stress also became more exogenous compared to interbank deposits and bank stock price index over time.

Thirdly, the difference between exogeneity between the variables are quite substantial. In the horizon of 2 quarters, the difference between the most exogenous variable and the most endogenous variable is 38.04%. However, this difference is reduced over a longer horizon, the value drops to 25.93% in the horizon of 8 quarters.

Finally, different variables explain the variation of bank stress over time forecast horizons. Despite NPL and SPREAD being the most exogenous variable, in the shorter run (over a forecast horizon of 2 quarters), bank stress variation levels are explained more by the interbank deposits and total capital and reserve variation while in the longer run, (over a forecast horizon of 8 quarters), bank stress variation levels are explained more by interbank deposits and lending spread.

There are several implications of the results which would be beneficial to industry stakeholders and participants in the banking industry. As far as bank stress is concerned, in the short run, bank stress levels could be identified by observing the value of interbank deposits and total capital and reserve variation. As the value of interbank deposits fall and banks are obliged to utilize their own capital and reserves to finance operations, there is less liquidity in the market and banking activities become constrained by the low levels liquidity. This also signals a tightening in the market and a higher levels of cautiousness as market participants bear themselves to unfavorable market conditions.

In the longer run, persistent low levels of interbank deposits and increased lending spread would increase bank stress. It signals a general slow down in economic activities and due to lower levels of liquidity, the cost of lending have increased as banks become more hesitant in providing financing facilities to borrowers (thus increasing the lending spread).

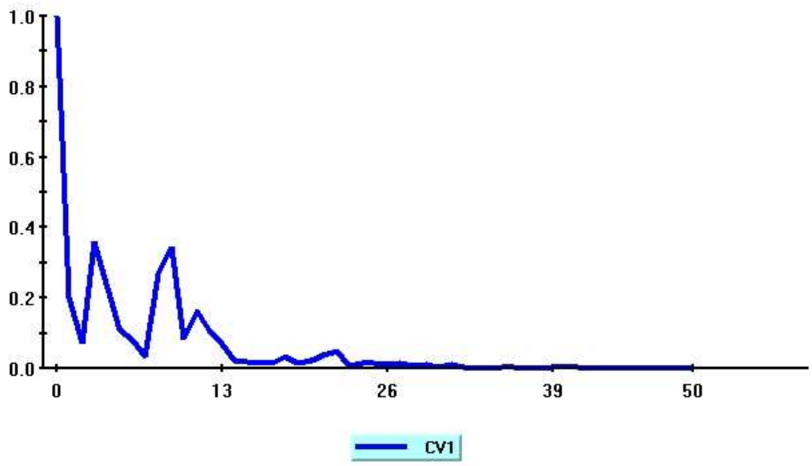
4.1.7 Impulse Response Function (IRF)

The impulse response function provides the same information as the VDC except that it is in graphical form. The IRFs for all six variables have been included in the appendix.

4.1.8 Persistence Profile (PP)

The persistence profile provides information where if all the variables in the cointegrating equation is shocked, how long would it take for the relationship to fall back to equilibrium. The focus of PP is to show the impact of a system-wide shock (such as an economic recession, a bank crash or bank run) on the long-run relations of the variables. It is different from the earlier analysis in IRF which only looks at variable-specific shocks. The PP for the cointegrating variables are shown in the table below.

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



The chart indicates that it would take approximately 14 quarters for the cointegrating relationship to return to equilibrium following a system-wide shock.

4.2 Measuring Macroeconomic Factors Affecting Bank Stress

Five variables have been selected to represent macroeconomic variables; (1) CLAIMS representing claims on the private sector; (2) GDP representing the gross domestic product for Malaysia; (3) GFCF representing the gross fixed capital formation; (4) HPI representing the house price index; and (5) KLCI representing stock market information. Another variable is added to the list, i.e. STRESS representing the Bank Stress Index which was computed in the first part of this study.

4.2.1 Preliminary Analysis for Macroeconomic Variables

All variables have been converted to log at the level form to make the variance of the variables constant, except for STRESS which was not logged because the variable contains negative values.

Table 15 Unit Root Test using ADF

Variables	T-Statistics	Critical Value	Implication
Level Form			
LCLAIMS	1.7548	3.4969	Variable is non-stationary
LGDP	2.2562	3.4969	Variable is non-stationary
LGFCF	2.2932 (AIC) 2.9833 (SBC)	3.4969	Variable is non-stationary
LHPI	0.93357	3.4969	Variable is non-stationary
LKLCI	4.2749	3.4969	Variable is stationary
STRESS	6.0636	3.4969	Variable is stationary
First Differencing			
DCLAIMS	2.4511 (AIC) 4.4707 (SBC)	2.9190	Variable is non-stationary Variable is stationary
DGDP	5.8326	2.9190	Variable is stationary
DGFCF	3.6746	2.9190	Variable is stationary
DHPI	1.3850	2.9190	Variable is non-stationary
DKLCI	4.7812	2.9190	Variable is stationary
DSTRESS	6.8786	2.9190	Variable is stationary

Based on the ADF test, it was found that four variables (LCLAIMS, LGDP, LGFCF and LHPI) are non-stationary at level form while two variables (LKLCI and STRESS) are stationary. After first differencing, only DHPI remained non-stationary while the remaining five variables are stationary.

Table 16 Unit Root Test using Phillips-Peron

Variables	T-Statistics	Critical Value	Implication
Level Form			
LCLAIMS	2.0504	3.4601	Variable is non-stationary
LGDP	2.2402	3.4601	Variable is non-stationary
LGFCF	3.4164	3.4601	Variable is non-stationary
LHPI	0.35228	3.4601	Variable is non-stationary
LKLCI	2.3357	3.4601	Variable is non-stationary
STRESS	11.9104	3.4601	Variable is stationary
First Differencing			
DCLAIMS	7.2512	2.9029	Variable is stationary
DGDP	4.8684	2.9029	Variable is stationary
DGFCF	10.7079	2.9029	Variable is stationary
DHPI	1.4665	2.9029	Variable is non-stationary
DKLCI	5.5896	2.9029	Variable is stationary
DSTRESS	35.4307	2.9029	Variable is stationary

Based on the PP test, at level form, five variables (LCLAIMS, LGDP, LGFCF, LHPI and LKLCI) are non-stationary while the remaining variables (STRESS) is stationary. After first difference, five variables

(DCLAIMS, DGDP, DGFCF, DKLCI and DSTRESS) are found to be stationary while one variable (DHPI) remained non-stationary. This indicates that the five variables are I(1) while HPI is I(2). To confirm this, KPSS test is done to confirm that HPI is truly I(2).

Table 17 Unit Root Test Using KPSS

Variables	T-Statistics	Critical Value	Implication
Level Form			
LCLAIMS	0.14570	0.16724	Variable is stationary
LGDP	0.13236	0.16724	Variable is stationary
LGFCF	0.14194	0.16724	Variable is stationary
LHPI	0.14285	0.16724	Variable is stationary
LKLCI	0.11710	0.16724	Variable is stationary
STRESS	0.15488	0.16724	Variable is stationary
First Differencing			
DCLAIMS	0.40830	0.37853	Variable is non-stationary
DGDP	0.13955	0.37853	Variable is stationary
DGFCF	0.21471	0.37853	Variable is stationary
DHPI	0.38811	0.37853	Variable is non-stationary
DKLCI	0.13776	0.37853	Variable is stationary
DSTRESS	0.13355	0.37853	Variable is stationary

Although there are some conflicting results found in KPSS compared to ADF and PP, the main focus of is to identify whether the variable Housing Price Index (HPI) is consistently found to be non-stationary in differenced form or I(2). Due to HPI the being found non-stationary at differenced form in both ADF test, PP test and KPSS, the variable is dropped from the model.

Next the order of the vector auto regression (VAR) is identified to determine the number of lags to be used in the following tests. The optimal order is determined based on the highest absolute value for AIC and SBC.

Table 18 Selecting the Order of the VAR Model

	Choice Criteria		
	AIC	**SBC**	**Adjusted LR test**
Optimal Order	6	1	0

Based on AIC, 6 lags should be used while based on SBC, 1 lag should be used and Adjusted LR test, 0 lag should be used. As there is clearly a conflict between the recommendation of AIC, SBC, and Adjusted LR Test, serial correlation for each variable is tested and the results are as follows:

Table 19 Identification of Serial Correlation

Variable	**Chi-Sq p-value**	**Implication at 10%**
DCLAIMS	0.061	There is serial correlation
DGDP	0.001	There is serial correlation
DGFCF	0.086	There is serial correlation
DKLCI	0.127	There is no serial correlation
DSTRESS	0.087	There is serial correlation

Based on the results in Table 19 it was found that autocorrelation exists in four out of the five variables. It is decided that a higher order would be selected to mitigate the effects of serial correlation.

4.2.2 Cointegration Test

Based on results in the unit root test, it is confirmed that the variables used in this study are I(1) and the optimal VAR order is determined as 6. It is known that the performance of the banking sector is somewhat connected to the performance of other variables used in this study such as GDP (Gross Domestic Product) and other economic activities such as the stock market, claims on the private sector and capital formation. Hence, it is expected that at least one cointegration will be found in the following test.

Table 20 Johansen Cointegration Test

Criteria	Maximal Eigenvalue	Trace	AIC	SBC	HQC
No. of cointegrating vectors	1	1	5	3	3

It is found that there exists one cointegrating vector based on Maximal Eigenvalue and Trace test while according to AIC there are 5 cointegrating vectors and according to both SBC and HQC, there are 3 cointegrating vectors (Table 20). Therefore based on the results and the fact that only five variables are used in this study, a one cointegration vector is accepted.

Cointegration means that in some combination, the variables used in this study would results in a stationary error term. This means that, the variables tend to move together in the long run. Thus the relationship between one another is not merely spurious or by chance. This discovery is important to regulators as given that the variables are cointegrated, a movement in any one of the variables would affect bank stress levels i.e. an improvement in the variable is expected to reduce bank stress levels and vice versa.

4.2.3 Autoregressive Distributed Lag (ARDL) estimators for Cointegration

Similar to the earlier test on bank specific variables affecting the levels of bank stress, for macroeconomic variables, the autoregressive distributive lag (ARDL) approach is also used for robustness to further confirm the presence of cointegration i.e. to test for the presence of long-run relationships among the variables.

Table 21 Test of Long-Run Relationships between the Variables

Dependent Variables	F-Statistics	Critical Value		Implication
		Lower bound	Upper bound	
DCLAIMS	0.56338	2.262	3.367	There is no cointegration
DGDP	0.88478	2.262	3.367	There is no cointegration
DGFCF	2.0587	2.262	3.367	There is no cointegration
DKLCI	0.52877	2.262	3.367	There is no cointegration
DSTRESS	2.0374	2.262	3.367	There is no cointegration

Based on the results in the above table, no cointegration was found indicating that the five variables are not theoretically related, and they do not move together in the long term. This finding is contradictory to our earlier findings in the Johansen cointegration test (Table 20).

Due to this, an ARDL bounds test was conducted to further identify the existence of cointegration among the variables. The existence of a level effect relationship among the variables is identified using the following hypothesis:

H_0 There exists no level effect relationship among the variables

H_1 There exists level effect relationship among the variables

Table 22 ARDL Approach to Cointegration based on AIC

Dependent Variables	F-Statistics	Critical Value		Decision
		Lower bound	Upper bound	
LCLAIMS	1.4190	3.1312	4.3792	There is no cointegration among the set of I(0) and I(1) variables
LGDP	7.4677	3.1312	4.3792	Cointegration exists among the I(0) and I(1) variables
LGFCF	2.0727	3.1312	4.3792	There is no cointegration among the set of I(0) and I(1) variables
LKLCI	2.5831	3.1312	4.3792	There is no cointegration among the set of I(0) and I(1) variables
STRESS	8.1341	3.1312	4.3792	Cointegration exists among the I(0) and (1) variables

In the bounds test, each variables were made as a dependent and regressed against the remaining variables in the model. Similar to the previous test, the optimal VAR order 6 was used. If the F-Statistic is lower than the lower bound, there is no cointegration among the variables. However, if the F-Statistic is higher than the upper bound, thus rejecting the null and indicating that cointegration exists among the variables. Based on the results in Table 22, we conclude that there exists at least long run or short run relation among the variables.

Next, diagnostic tests for auto-correlation, normality, specification and heteroskedasticity are examined to identify the existence of any issues that may arise. The chi square p-value of both the LM Version (LM) and the F Version (F) have been tabulated in Table 23 below.

Table 23 Diagnostic Tests based on AIC

Variables	Serial Correlation	Functional Form	Normality	Heteroskedasticity
LCLAIMS	0.951 (LM) 0.973 (F)	1.4224 (LM) 1.0968 (F)	0.004 (LM) N/A (F)	0.619 (LM) 0.627 (F)
LGDP	0.263 (LM) 0.598 (F)	0.339 (LM) 0.485 (F)	0.195 (LM) N/A (F)	0.420 (LM) 0.430 (F)
LGFCF	0.143 (LM) 0.264 (F)	0.530 (LM) 0.588 (F)	0.589 (LM) N/A (F)	0.788 (LM) 0.793 (F)
LKLCI	0.063 (LM) 0.341 (F)	0.051 (LM) 0.163 (F)	0.280 (LM) N/A (F)	0.296 (LM) 0.305 (F)
STRESS	0.568 (LM) 0.666 (F)	0.194 (LM) 0.236 (F)	0.010 (LM) N/A (F)	0.861 (LM) 0.864 (F)

Based on the results in the diagnostics test, it is confirmed that we do not face any serial correlation, functional form or heteroscedasticity issues. However, it was found that there are normality issues in the LCLAIMS and STRESS variables. For this study, normality issues is mitigated by using a large sample size and hence ignored in this study.

4.2.4 Identification of Long Run Relationships

Now that the existence of cointegration in our model is confirmed, the relationship among the variables is quantified using the Long Run Structural Modeling (LRSM) component in MicroFit. One cointegration level is used based on the results of Maximal Eigenvalue and Trace. One cointegration means that the variables are moving together in one direction in the long run. The variable of interest i.e. Bank Stress (STRESS) was normalized and the results are as tabulated in the table below:

Table 24 Long Run Structural Modeling: Exact Identification

Variable	Coefficient	Standard Error	t-ratio	Implication
LCLAIMS	8.0720	4.5091	1.7901	Variable in insignificant
LGDP	13.7645	6.3498	2.1677	Variable in significant
LGFCF	6.2090	3.2314	1.9215	Variable in insignificant
LKLCI	8.6544	4.9954	1.7325	Variable in insignificant
STRESS	-	-	-	-

It was surprising to discover that out of all the variables used in the study, only one variable is found to be significant. This means that based on these results, there is only one meaningful (or cointegrating) relations found between these variables.

The significance of the results are further tested by subjecting the estimates to over identifying estimates. We were unable to find a suitable restriction in over-identification approach as either all restrictions are found to be incorrect, i.e. based on the restrictions results, all restrictions displayed the p-value to be lower than 0.05 or even if the restrictions are correct (p-value higher than 0.05), the variables turn out to be insignificant. Therefore no restrictions were imposed and we moved on towards the error correction model using the exact identification results.

4.2.5 Vector Error Correction Model (VECM)

So far it has been established that bank stress and macroeconomic factors used in this model are cointegrated to a certain degree. This step identifies the process of how the variables adjust in the short run to bring about equilibrium in the long run. It can be used to identify endogenous and exogenous variables in the model. By knowing which variable is endogenous and exogenous, it would be easier to predict the expected impact that the variable would have on the bank stress levels in Malaysia. The exogenous variable would be the variable which is of interest by the regulators because the variable would have a significant bearing on the expected movement of the other variables and would trigger bank stress.

Table 25 Error Correction Model for Macroeconomic Variables

Variable	Coefficient	ECM (-1) t-ratio p-value	Implication
dLCLAIMS	0.013419	0.025	Variable is endogenous
dLGDP	0.016004	0.132	Variable is exogeneous
dLGFCF	0.063687	0.016	Variable is endogenous
dLKLCI	-0.027115	0.354	Variable is exogeneous
dSTRESS	-1.0652	0.005	Variable is endogenous

Based on the above results, it was found that there are two variables that are exogenous that should be of interest to the regulators. The variables are GDP and the stock market performance (KLCI). What it means is that, changes in the exogenous variables would affect the levels of claims to the private sector, gross fixed capital formation and bank stress in a significant way. Thus any news, events and developments in both indicators would like be of interest to market regulators. The next step will tell us more on the endogeneity and exogeneity of a variable.

From the results depicted by the error correction coefficient it was also found that with the exception of bank stress, all other variables experience a slow speed of convergence from the short run to the long run. This is consistent with the fact that the other variables are macroeconomic variables, thus any changes to the macroeconomic variables in the short run would result in a slower convergence to long-term trends compared to bank stress.

4.2.6 Variance Decomposition (VDC)

In the previous section it has been established that both GDP and KLCI are exogenous while the remaining variables, CLAIMS, GFCF and STRESS are endogenous variables. However, we have not established the relative exogeneity and endogeneity of the variables. This will be determined by variance decomposition (VDC).

Orthogonalized VDC is applied and the following results have been obtained:

Forecast Horizon = 2 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	93.22%	3.00%	0.37%	2.66%	0.76%
LGDP	13.05%	78.98%	0.79%	3.08%	4.10%
LGFCF	1.14%	5.98%	78.16%	10.27%	4.45%
LKLCI	12.50%	9.92%	8.48%	65.21%	3.90%
STRESS	8.34%	16.90%	3.14%	4.26%	67.36%

Forecast Horizon = 4 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	87.73%	2.51%	0.36%	4.44%	4.97%
LGDP	12.54%	58.10%	3.50%	16.28%	9.58%
LGFCF	7.72%	8.60%	67.49%	10.03%	6.16%
LKLCI	19.21%	6.82%	16.06%	54.08%	3.83%
STRESS	7.07%	15.60%	6.85%	4.40%	66.08%

Forecast Horizon = 8 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	77.41%	1.20%	0.25%	16.66%	4.49%
LGDP	11.59%	49.12%	8.83%	23.74%	6.72%
LGFCF	7.06%	8.69%	65.89%	13.82%	4.54%
LKLCI	14.24%	5.72%	34.53%	42.44%	3.07%
STRESS	8.70%	16.83%	9.77%	4.20%	60.51%

Based on the results, the ranking of the variables by degree of exogeneity (i.e. the extent to which its variation is explained by its own past variations or lags) is presented in the table below:

Table 26 Ranking of the Variables by Degree of Exogeneity based on Orthogonalized VDC

No.	2 Quarters	4 Quarters	8 Quarters
1	CLAIMS	CLAIMS	CLAIMS
2	GDP	GFCF	GFCF
3	GFCF	Bank Stress	Bank Stress
4	Bank Stress	GDP	GDP
5	KLCI	KLCI	KLCI

The results are found to be inconsistent with earlier findings as well as literature. This is because, from the previous analysis, two variables were found to be exogenous, GDP and KLCI. However in VDC, GDP and KLCI are the two most endogenous variables (in the 4^{th} and 8^{th} quarter respectively).

However, due to inconsistencies between the findings in VECM and orthogonalized VDC, and the limitations of orthogonalized VDC, we would like to see whether the same results hold true in generalized VDC. Therefore the results from generalized VDCs are also taken into consideration as they are invariant to the ordering of the variables.

The results are as tabulated below:

Forecast Horizon = 2 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	84.50%	8.54%	1.37%	3.80%	1.79%
LGDP	8.38%	58.65%	0.83%	25.56%	6.57%
LGFCF	1.18%	4.44%	83.31%	4.63%	6.44%
LKLCI	12.88%	12.89%	11.10%	59.14%	3.98%
STRESS	8.28%	8.14%	2.39%	8.59%	72.59%

Forecast Horizon = 4 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	77.39%	13.80%	1.86%	2.09%	4.86%
LGDP	8.87%	47.94%	2.52%	30.29%	10.38%
LGFCF	7.35%	11.37%	70.13%	3.32%	7.82%
LKLCI	20.20%	13.71%	22.02%	39.93%	4.15%
STRESS	6.88%	8.10%	6.21%	8.27%	70.54%

Forecast Horizon = 8 (quarters)

	LCLAIMS	LGDP	LGFCF	LKLCI	STRESS
LCLAIMS	72.86%	14.22%	1.95%	6.79%	4.18%
LGDP	8.44%	42.09%	4.24%	37.34%	7.89%
LGFCF	6.78%	11.70%	69.64%	5.54%	6.35%
LKLCI	14.68%	9.93%	37.13%	35.23%	3.03%
STRESS	8.21%	10.07%	8.46%	8.08%	65.19%

From the results that were obtained based on the generalized VDCs, the variables are ranked by relative exogeneity (refer to Table 27).

Table 27 Ranking of the Variables by Degree of Exogeneity based on Generalized VDC

No.	2 Quarters	4 Quarters	8 Quarters
1	CLAIMS	CLAIMS	CLAIMS
2	GFCF	Bank Stress	GFCF
3	Bank Stress	GFCF	Bank Stress
4	KLCI	GDP	GDP
5	GDP	KLCI	KLCI

Based on the results tabulated, several observations can be made. Firstly, the generalized VDC and orthogonalized VDC are consistent in a longer horizon (4^{th} and 8 quarters respectively) but results in the shorter horizon, 2 quarters are different.

Secondly, the difference between exogeneity among the variables increases over time. In the horizon of 2 quarters, the difference between the most exogenous variable and the most endogenous variable is 25.85%. However, this difference is increased to 37.63% over a longer horizon, i.e. 8 quarters.

Thirdly, different variables affect the variation of bank stress differently over time forecast horizons. In terms of percentage proportion, in the shorter run (over a forecast horizon of 2 quarters), bank stress variation levels are affected more by the KLCI, claims on the private sector and GDP while in the longer run, (over a forecast horizon of 8 quarters), bank stress variation levels are explained more by GDP, gross fixed capital formation and claims on the private sector.

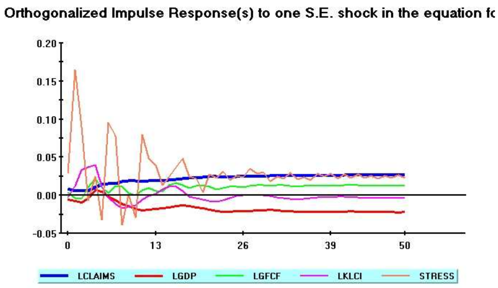
There are several implications of the results which would be beneficial to regulators. Firstly, bank stress appears to be more exogenous than we earlier assumed. This means that the variation in bank stress is seen to be influenced due to its own lags more than the macroeconomic variables.

As far as bank stress is concerned, in the short run, bank stress levels are influenced more by variations in the stock market and claims on the private sector. This is indeed true as the performance of the stock market and claims on the private sector can be used as yardstick to see current state of the economy i.e. bank stress levels are more closely associated to the performance of the stock market and claims on the private sector compared to the other macroeconomic variables such as GDP and gross fixed capital formation in the short run. However in the longer run, the roles are switched and GDP and gross fixed capital formation plays a bigger role in influencing the levels of bank stress.

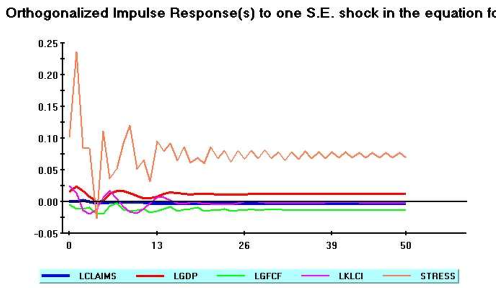
4.2.7 Impulse Response Function (IRF)

The impulse response function provides a graphical representation of the impact if one of the variables is shocked to the other variables in the model i.e. the impact of a single variable shock to the other variables. As there is not much variation in the earlier VDC results of both orthogonalized and generalized VDC, it appears that the results in both orthogonalized and generalized impulse response are also similar therefore only the orthogonalized impulse response chart is presented below. Both charts are available in the appendix.

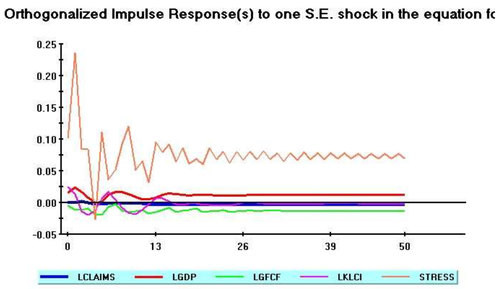
Figure 4 Orthogonalized Impulse Response to one S. E. shock in the equation



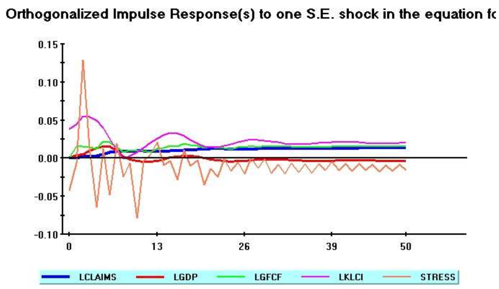
Variable shocked: LCLAIMS (blue line)



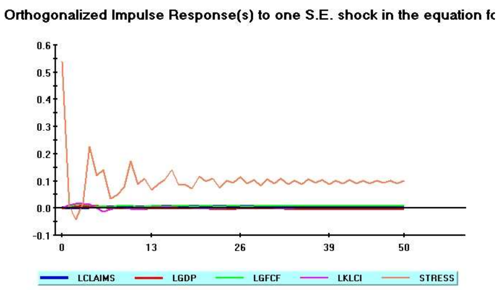
Variable shocked: LGDP (red line)



Variable shocked: LGFCF (green line)



Variable shocked: LKLCI (purple line)

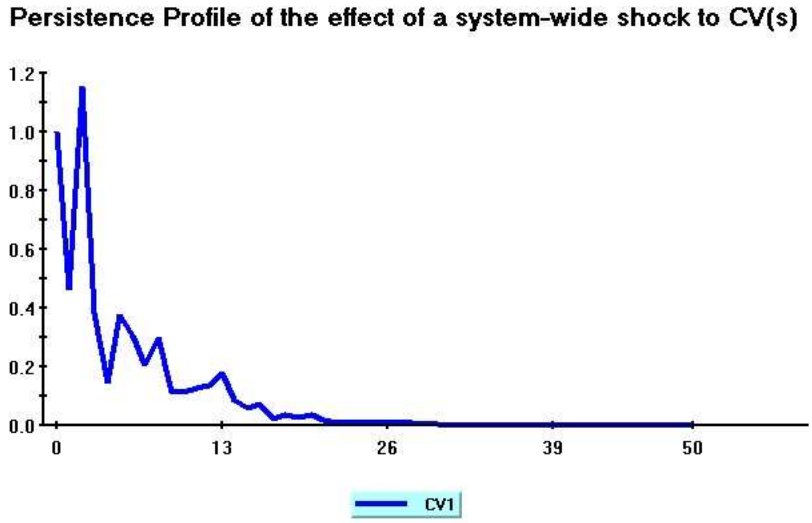


Variable shocked: Bank Stress (orange line)

Consistent with literature, when macroeconomic variables (CLAIMS, GDP, GFCF, and KLCI) are shocked, based on the volatility depicted in the charts, bank stress is affected significantly and requires an adjustment period of at least 13 quarters or 3 years and 3 months. However, when bank stress is shocked, it could be clearly seen that, the macroeconomic variables are not affected by bank stress.

4.2.8 Persistence Profile (PP)

The persistence profile provides information where if all the variables in the cointegrating equation is shocked, how long would it take for the relationship to fall back to equilibrium. The focus of PP is to show the impact of a system-wide shock (such as a global or regional economic recession or financial crisis) on the long-run relations of the variables. It is different from the earlier analysis in IRF which only looks at variable-specific shocks. The PP for the cointegrating variables are shown in the table below.



The chart indicates that it would take approximately 20 quarters or five years for the cointegrating relationship to return to equilibrium following a system-wide shock. The impact of a system-wide macroeconomic shock is larger and longer than the first persistence profile that was conducted based on bank specific variables. This is because, the earlier persistence profile indicated an internal shock to the country i.e. the country falls into an economic recession or if there is a significant slowdown in the economy. If the country's fundamentals are strong, a country like Malaysia would be able to recover quickly from a financial or economic crisis that was caused by internal factors. However, the second persistence profile which was conducted based on macroeconomic indicators indicate that if there is a global economic crisis or if externally, there is a cumulative slowdown in global activity, Malaysia would be receiving a greater impact negative impact and thus would require a longer period to recover from the shock.

5 Policy Implications and Conclusion

Based on the findings of this study, it could be concluded that non-performing loans to total loans and lending spread are the main predictors of bank stress in the short to medium term. However, in the longer term, non-performing loans to total loans and bank capital and reserve variation are the main predictors of bank stress. This study highlights the importance of banks maintaining low levels of non-performing loans to total loans if it wants to mitigate bank stress. This is because a higher level of non-performing loans to total loans indicate the adverse market conditions where there is an increase level of borrowers who are unable to repay their obligations to the bank. Non-performing loans are bad for the banking institutions, banks lose out on potential profits and at the same time incur costs in recovering the loans. A higher level of non-performing loans have damaging impact to the operations of the bank as it lowers the banks' revenues and erode their profits.

From a macroeconomic perspective, due to its exogeneity, bank stress is found to have a strong cointegrating relationship with macroeconomic variables such as claims on the private sector, GDP, gross fixed capital formation and the stock market. In terms macroeconomic impact to bank stress, all macroeconomic variables used in this study have been found to have a strong negative impact to bank stress, i.e. when the macroeconomic variables are shocked individually, it was found that there is increased volatility in bank stress.

On a wider perspective, external shocks such as a global or regional economic financial crisis is deemed to have a greater and longer effect on the economy compared to internal shocks such as a stock market crash or bank failures.

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