Impact of bank capital on non-performing loans: New evidence of concave capital from dynamic panel-data and time series analysis in Malaysia

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Impact of bank capital on non-performing loans: New evidence of concave capital from dynamic panel-data and time series analysis in Malaysia

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Abstract

Amid the steep expansion in Malaysia household debt, we investigate the role of bank capital in disciplining non-performing loans (NPLs) after controlling for the macroeconomic environment. Utilizing generalized method of moments (GMM) on a dynamic panel-data of 19 commercial banks and stress testing of NPLs using vector autoregression (VAR) on aggregated-monthly time series of the banking system, we provide new evidence that the capital (in the past and in the future) is a concave function of NPLs implying that increasing the capital will initially increase the NPLs until NPLs reach a maximum threshold (under the moral hazard effect), after which more capital buildups will succeed in decreasing NPLs (under the disciplinary or regulatory effect). We also find that higher levels in GDP growth and lending interest rate and are associated with more NPLs, while higher inflation is associated with less NPLs. Monetary expansion, i.e. higher money supply growth raises NPLs in banks, while competition between banks and higher liquidity of the stock market are NPLs reducing.

Keywords: Non-performing loans, Malaysia banking system, Bank capital, Macroeconomic determinants, Dynamic panel-data, Vector autoregression.
JEL classification: G21; C22; C23; E52

1. Introduction

The main risk a bank faces in the lending channel is the *ex post* credit risk that takes the form of non-performing loans (NPLs). In fact, NPLs' increase in banks' loan portfolio deteriorates banks' assets and capital, and represents greater risk that affects banks' liquidity and profitability. NPLs may act as an impediment to the development of the banking sector (Zhang et al., 2016), and they are one of the significant elements in causing a banking and financial crisis

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(Greenidge and Grosvenor, 2010). The literature agrees that the volumes of NPLs are often associated with bank failure and banking crisis. Ahmad (2002) empirically links NPLs to the financial crisis by the analysis the Malaysian banking system and concludes that NPLs had already started to accumulate at 4.1% before the onset of the 1997 Asian financial crisis (AFC) and became more serious as NPLs increased to 11.8% in 1998. Ghosh (2015) links NPLs to bank failure and indicates that NPLs can be used, among other factors as harbinger to a banking crisis. NPLs are therefore a measure of the stability of the banking system and the financial stability of a country. However, NPLs have been always remained especially since the 2008 global financial crisis (GFC) in the core interest of regulatory authorities concerned about financial stability as well as banks' management.

In addition to the general concerns regarding NPLs problem, there are concerns regarding the steep expansion in Malaysian household debt in recent years, which doubts the quality of loans granted and whether they are adequately evaluated by the banking system. This private debt reached 87% of GDP (amounting RM 854.3 billion) by the end period in 2013 compared to 57% of GDP in 2002 (Fig. 3). The high rate of household debt (the demand side) is actually driven by the credit expansion offered by banks (the supply side). Credit expansions which rightward shift both the demand and supply curves is leaded and driven by capital inflows to Malaysia from advanced economies which pumped easy money through quantitative easing (QE) in the aftermath of 2008-2009 GFC (Fig. 4). Nonetheless, the spillover of QE on Malaysian economy is that it decreases the domestic cost of financing due to the lower interest rates, and increases pressure on local currency due to the massive liquidity injections.

Attaining financial stability by banking regulatory authorities requires a constant monitoring of NPLs and consequently a policy response from them to solve NPLs problem. Monitoring NPLs and policy responses which come in the form of macro-prudential and micro-prudential regulations, first require a deep understanding of the fundamental macro and micro determinants of NPLs. Hence, investigating the impact of bank capital as well as macroeconomic environment on NPLs is an important issue for regulators concerned with financial stability, and for banks' management. This study is motivated by the mixed empirical results that prevail the literature in regard to the effect of bank capital on NPLs. The literature also argues that requiring banks to hold specified amount capital acts to both increase and decrease NPLs (Williams, 2014). We focus on the Malaysian banking system and use dynamic panel-data analysis (GMM) of 19 commercial banks over 2002-2011 in addition to time-series analysis (VAR) of the banking system over 1998M1-2015M8. The aim is to provide deeper investigation of the link between bank capital and NPLs after controlling for the macroeconomic environment and tests for the convex or concave capital, which is never tested before for Malaysian banks, and that allows to understand whether, when, and to what extent, capital acts to increase or decrease NPLs. Controlling for macroeconomic environment includes: GDP growth and inflation; monetary policy via lending interest rate and money supply growth; bank competition; and liquidity of the stock market.

The remainder of this paper is as follows: Section 2 is an overview of NPLs and the business cycle and Section 3 is the literature review. Sections 4 and 5 discuss the datasets and definition of variables, respectively. Section 6 is the methodology, Section 7 is the empirical results, and Section 8 is the analysis using VAR. Finally, Section 9 is the concluding remarks.

2. Non-performing loans and the business cycle

The researched period in this paper covers the period after the Asian Financial Crisis (AFC) that triggered in 1997, in addition to 2008 Global Financial Crisis (GFC) and the aftermath of this crisis up to the end of 2013. As a consequence of AFC, at the beginning of 2001, Malaysian banking system had been restructured associated with launching the Financial Sector Master Plan (FSMP) in March 2001 that consolidated 50 of 54 banks into 10 banking group. It was in regard to banks' capitalization, minimum capital adequacy requirements had been raised to 10% in 1999, where they were 8% in 1998. In addition to the re-regulation banks' capital, the period was associated with imposing controls on capital inflows into the country (see Kaplan and Rodrik, 2001; Ahmad et al., 2008). Although these inflows had been tightened after the AFC, it inflated (specifically foreign portfolio flows) in the aftermath of GFC driven by quantitative easing (QE) in the major economies leading to credit expansion in the Malaysian banking system. Considering the above major events, it can be assumed that NPLs determinants are changing over time. We believe that macroeconomic environment and the business cycle play a prominent role in determining banks' NPLs.

To understand the cyclical nature of banks' behaviour (specifically NPLs) over the business cycle, we utilize a set of monthly and aggregated time series data for NPLs ratio of the Malaysian banking system and data for economic indicators namely: GDP and lending rate. Capital ratio of the banking system is also used.[2] Fig. 1 plots a monthly time series (1998 M1-2015 M3) and shows NPLs ratio of the banking system over GDP growth[3], revealing that the period from 2002 to 2007 is a boom period, from the onset of 2008 until the end of 2009 is a bust period, and 2010 onwards is a boom period. However, Hahm et al. (2014) consider in their study that the period 2002-2008 is a boom period leading to 2008 GFC associated with fluctuations in capital inflows from advanced economies that formulated a credit boom-bust cycle in Malaysia. KIM and KIM (2013) find using VAR method that Malaysia experienced a boom-bust cycle since the 2000s. It is yet noticeable that banking system' capital ratio in Fig. 1 had significantly increased directly after the 2008 GFC; it could be to absorb any potential losses or the increased risk in the loan portfolio.

[2] Statistics of NPLs ratio, loan loss provisions, and capital ratio are from Bank Negara Malaysia website. Economy indicators are obtained from The Economist Intelligence Unit (EIU).

[3] GDP growth data are quarterly.

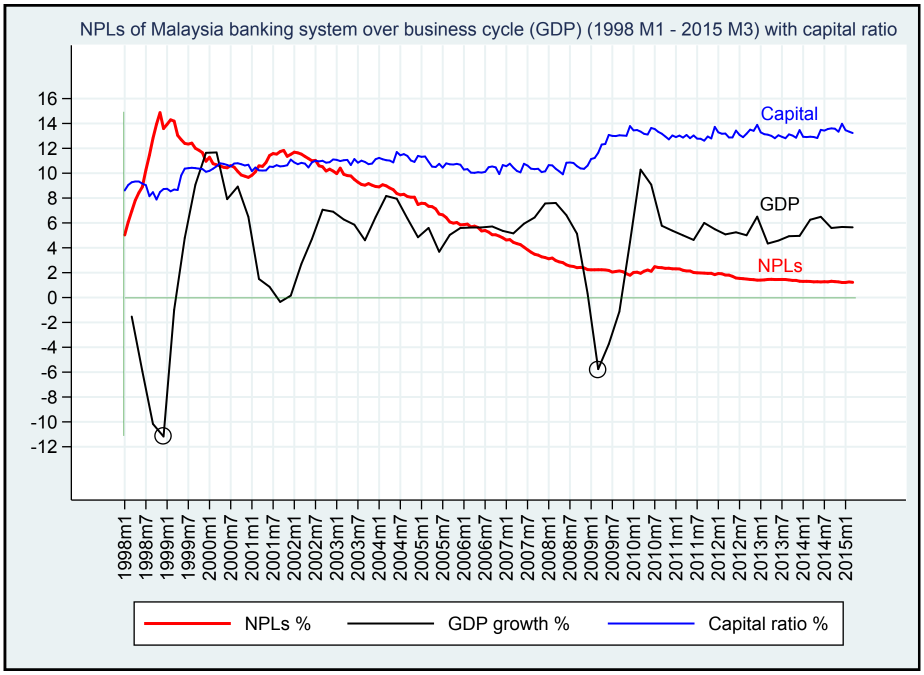

Figure 1: NPLs of Malaysia banking system over business cycle (GDP) (1998 M1-2015 M3) with capital ratio. Data source: Bank Negara Malaysia and The Economist Intelligence Unit.

It is considerable to mention that Malaysian banks did not experience a significant increase in NPLs ratio during the said bust period of GFC in 2008-2009, although they received a serious rise during the AFC (Fig. 1). Interestingly, plotting levels of banking system' loan loss provisions in Fig. 2 over (1998 M1-2015 M8) reveals that monthly amounts of loan loss provisions have dramatically increased in 2008-2009 GFC period. Generally, they are increasing over the full said period (1998 M1-2015M8).

In addition to the general concerns regarding NPLs problem, there are in fact further concerns regarding the steep expansion in household debt in recent years, which indeed doubts the quality of loans granted and whether they are adequately evaluated by the banking system. Fig. 3 depicts the household debt as a percentage of GDP in the period 2002-2013. This debt reached 87% of GDP (amounting RM 854.3 billion) by the end period in 2013 compared to 57% of GDP in 2002. However, this 'high rise' household debt forced Bank Negara Malaysia (BNM) in Jan 1, 2012 to tighten and restrict the lending behaviour by imposing new lending guidelines. The high rate of household debt (the demand side) is actually driven by the credit expansion offered by banks (the supply side). Credit expansions which rightward shift both the demand and supply curves is leaded and driven by capital inflows to Malaysia from advanced economies which pumped easy money through quantitative easing (QE) in the

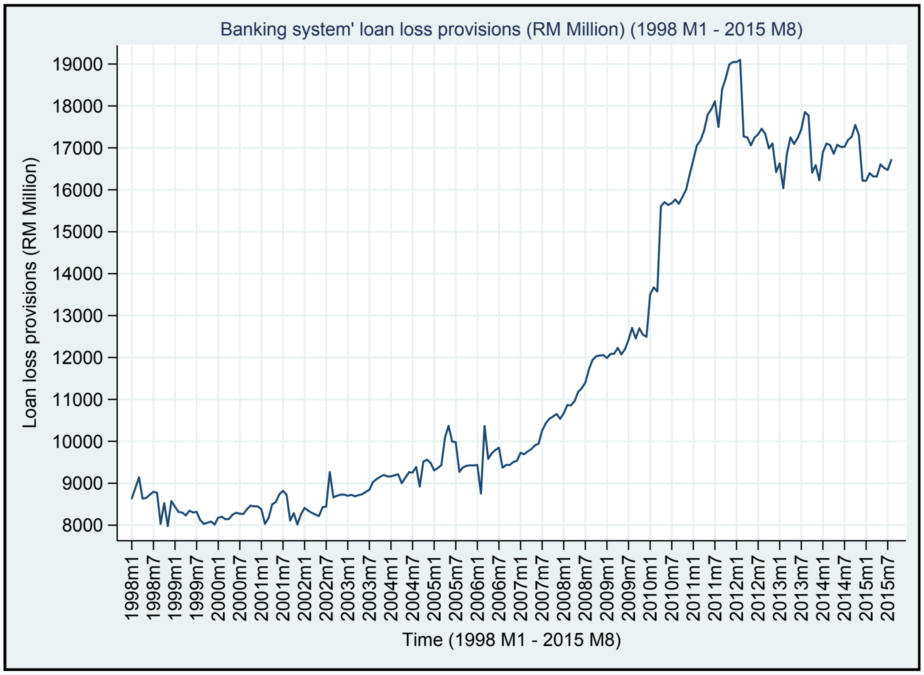

Figure 2: Banking system' loan loss provisions (RM Million) (1998 M1-2015 M8). Data source: BNM.

aftermath of 2008-2009 GFC. Fig. 4 depicts the cumulative net foreign portfolio inflows into selected emerging Asian countries over the period 2009 Q1-2013 Q1, particularly; those inflows to Malaysia has reached USD 71.9 billion by the end of Q1 2013. According to Bank Negara Malaysia (2014), "Asia received portfolio inflows, between 2009 and 2013, amounting to USD 597.7 billion, equivalent to 2.4% of its combined GDP". The spillovers of QE on Malaysian economy is considerable. QE contributes to decrease the domestic cost of financing due to the lower interest rates, in addition to the increasing of pressures on local currency because of the massive liquidity injections.

In regard to the lending interest rates, Fig. 5 shows the time series of monthly lending interest rates over 2002 M1-2015 M8 in Malaysia. The Fig. clearly shows that interest rates had been sharply declined in the period accompanied with QE in the advanced economies, i.e. the period after the mid 2008. Consequently, the environment of lower interest rates and massive liquidity injections may have lead to the underpricing of risks and hence stimulating ample investments in risky assets and that in turn contributed to financial instabilities (Bank Negara Malaysia, 2014). Generally, the abundance of credit that offered during the boom periods: (2002 to 2007 and later it escalated: i.e. by the end of 2009 onwards) can be ascribed to the rightward shift in demand and supply curves. On the supply side: restructuring of financial system, bank competition, and quantitative easing has increased the credit growth. On the demand side: lower

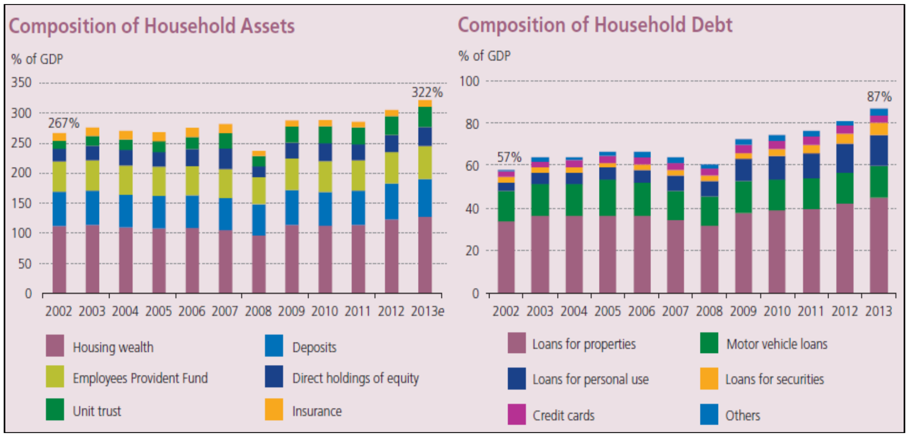

Figure 3: Malaysian household debt and assets (2002-2013). Source: Bank Negara Malaysia (2014).

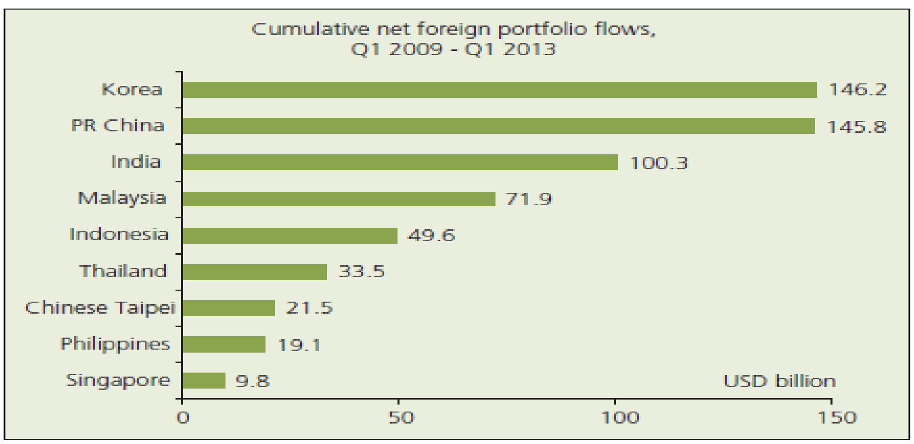

Figure 4: Impact of quantitative easing on Asia (2009 Q1-2013 Q1). Source: Bank Negara Malaysia (2014)

lending interest rate increased debt ceilings leading households to smooth their consumption via borrowing. Furthermore, good rate of growth in the boom periods encourage businesses for investments inducing business sector to higher debt obligations. Fig. 6 plots the overall bank lending (stock of domestic credit) over the period 1996M1-2015M8 in the Malaysian banking system which includes bank lending to public and private sectors, as well as lending in Ringgit to overseas. Fig. 7 graphs the actual demand curve with a confidence interval over the period 2002M1-2015M8 based on the linear regression of quantity of loans over interest rates. However, based on the fitted values in the Fig., the quantity of loans is about half trillion Ringgit with an interest rate of about

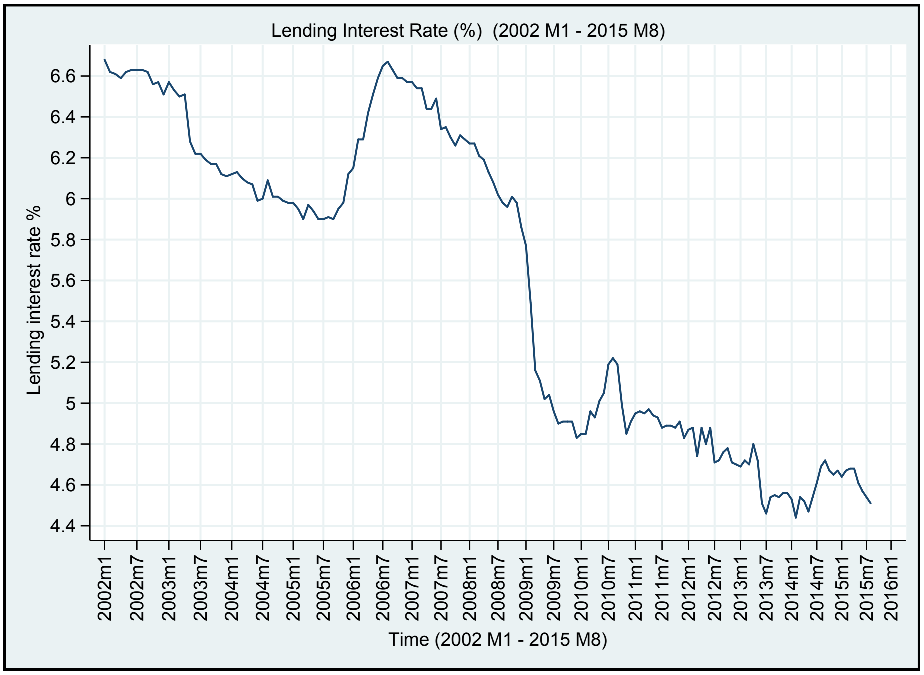

Figure 5: Lending interest rate (%) (2002 M1-2015 M8). Data source: EIU.

6.4%. The quantity of loans is tripled at nearly more than RM 1.6 trillion with the lowest rate of nearly 4%.

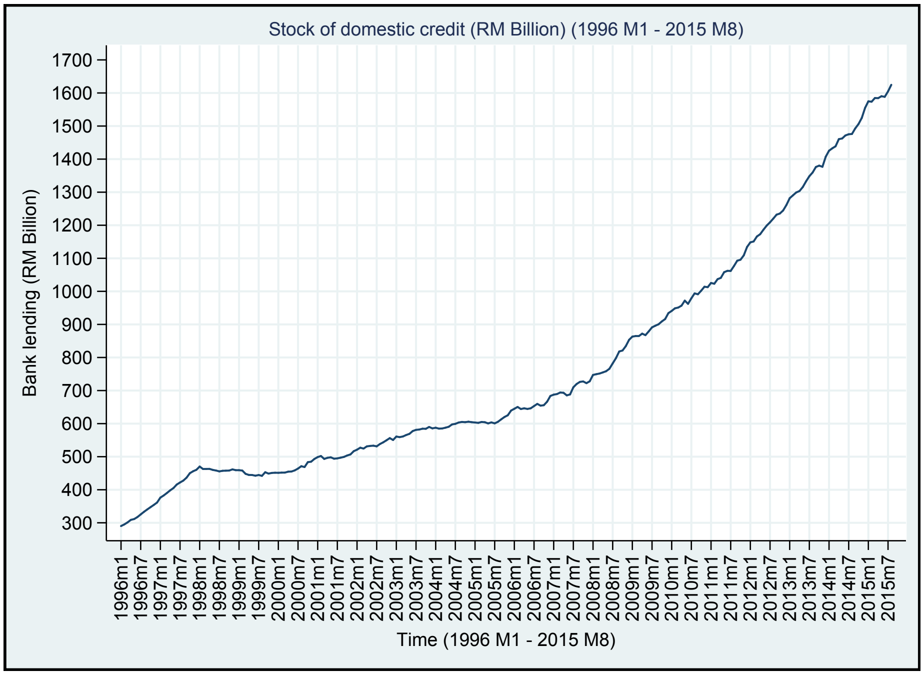

Figure 6: Bank lending (stock of domestic credit) (RM Billion) (1996 M1-2015 M8). Data source: EIU.

3. Literature review

Banking is one of the most regulated industries. The regulations on bank capital are the most important directions of regulating banking industry (Santos, 2001). According to Van Greuning and Bratanovic (2009), "Capital is one of the key factors to be considered when the safety and soundness of a particular bank is assessed". The bank capital's role is modifying the behavior of bank management, and in particular, modifying the risk of banks, has an academic and regulatory tradition over five decades long (VanHoose, 2007). Based on option-pricing theory, Merton (1977) and Diamond and Dybvig (1983) develop a theoretical model showing that banks are required to hold more capital to offset the moral hazards driven by deposit insurance or bank guarantees, i.e. to lower the implicit value of the put options created by actual or implicit deposit insurance. That is, holding more capital allows banks to reduce morally hazardous risk taking. Diamond and Rajan (2000) also introduce the theory of bank's capital in which a bank with more capital holdings reduces its liquidity creation, but that allows the bank to avoid risk and enjoy more loan repayments. Consequently, the traditional role of capital, on theory, is that it reduces the incentives of bank's management risk-taking behavior in engaging in riskier lending activities. Porter and Chiou (2012) conclude that bank capital is widely regarded as the cushion that prevents a decline in asset values from threatening

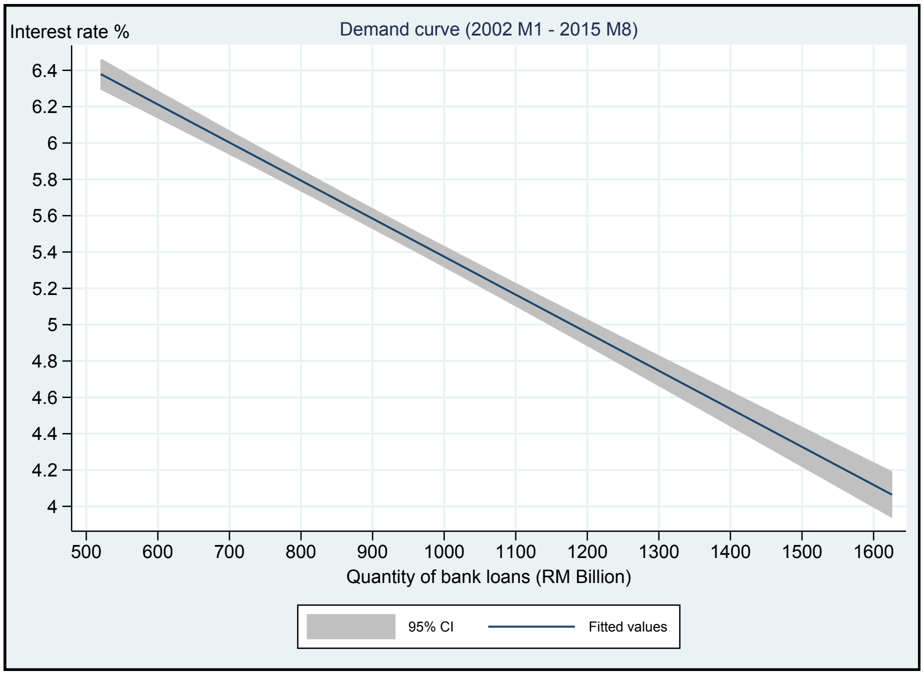

Figure 7: Demand curve (2002 M1-2015 M8). Data source: EIU.

the integrity of bank liabilities. However, the contrast between theory and reality is perhaps most apparent in the area of risk management (Allen and Santomero, 1997).

Moral hazard theory in the bank lending channel justifies that more non-performing loans (NPLs) in the asset portfolio implies risky lending, declining loan quality, and instability of the financial system. Zhang et al. (2016) find empirically a support for the latter claim in Chinese commercial banks in the period 2006-2012. Considering the empirical literature of banking studies, the sign of the relationship between bank capital and bank risk taking (NPLs) is mixed. However, Williams (2014) notes that a large number of literature has argued that requiring banks to hold specified amounts of capital acts to both increase and decrease bank risk. That is, the empirical results in the literature are not only mixed, but also arguing that capital acts in both directions (increases and decreases the bank risk). VanHoose (2007) reviews the literature and questions the effectiveness of regulated capital on asset portfolio risk and the stability of the banking system, and reveals that this literature contains too much contradicting estimates and predictions. The issue of whether a higher capital ratio lowers bank risk is still widely undetermined. As the theoretical literature provides unobvious results of the impact of regulatory capital on risk taking of banks (Freixas and Rochet, 2008; Fiordelisi et al., 2011).

In contrast to the traditional view of capital, Porter and Chiou (2012) provide an empirical analyzing 25,000 company-year observations of bank holding company data over 1993-2008 in the United States using three different methods (stochastic frontier analysis, two-stages least squares regressions, and GMM estimation as a robustness tests). To determine the relationship between capital and seven measures of bank's risk-taking, they find a positive relationship between capital and risk while their hypotheses state that signs should be negative. They reveal that their results are consistent with the theory that banks are obliged to more capital by tendency to increase their asset portfolio risk and off-balance-sheet activities. This perverse result suggests that the bank regulation should be thoroughly re-examined and alternative tools should be developed to ensure a stable financial system. Williams (2014) finds that improvements in Asia national governance are risk reducing, but the improved national governance interacts with equity holdings to result in increased bank risk in 20 Asian countries over 1998-2012. Moreover, a U-shaped relationship is found between bank capital and bank risk (measured by the volatility of ROA and ROE). Increased bank holdings of capital will initially result in lower bank risk, followed by risk increases as capital levels increase. Hence, requiring banks to hold markedly increased capital as compared to the current levels of capital holdings is likely to result in banks increasing the risk profile of their portfolios. In his study on commercial banks of 50 American states over 1984-2013, Ghosh (2015) finds more capital leads to more NPLs. Moreover, on an international sample of 296 banks across 48 countries, Laeven and Levine (2009) show that capital regulations have a direct, positive association with bank stability, and they also increase the risk-taking incentives of bank owners. Their paper also shows that this capital-risk relationship depends crucially on the concentration of ownership structure for the banks. Tsai (2013)'s results doubt the success of capital regulation in reducing risk, in a way that it adversely affects the safety of the banking system. VanHoose (2007) also finds that these requirements do not essentially add value to stability and soundness developments.

The wisdom of banking regulation is to provide a cushion (the bank's capital) allowing to absorb losses and to protect depositors under the deposit insurance (Dewatripont et al., 2010). In this regard, various studies find a negative relationship between the regulated capital and bank's risk. Haq and Heaney (2012) provide evidence of factors determine European bank risk for 117 banks across 15 countries over 1996-2010. Results indicate an evidence of positive U-shaped relation between bank capital (square of regulated capital) and each of bank systematic risk and credit risk, and significant negative association between the regulated capital and their five measures of bank risk. In the financial crisis, the largest decline is the capital coefficient relative to credit risk. Demsetz and Strahan (1997) find a negative non-linear association between capital measured by log $(\text{capital/assets})^2$ and both bank-specific risk and bank systematic risk in bank-holding companies BHCs in the U.S., using pooled data over 1980-1993 with time fixed effects and regressions of factor analysis. In their study on 17 European countries over 1989-2004, Baele et al. (2007) find a negative association between bank capital (equity/assets) and bank systematic risk, idiosyncratic risk and bank total risk implying that higher capital adequacy lowers the risks.

They also find a positive non-linear association between capital measured by (equity/assets)^2 and bank risk, stating that an increase in capital raises bank risk for well capitalized banks.

Hoque et al. (2014) analyze whether regulation reduces risk during the credit crisis and the sovereign debt crisis for global banks (largest 378 banks by asset size at the end of 2006). Results show evidence that greater capital leads to lower bank risk during both crises, suggesting that banks having enough capital can insulate themselves from financial turmoil. During the global financial crisis (GFC), Altunbas et al. (2011) find for a sample of international banks with less capital have greater risk exposure, that is as concluded, undercapitalization *ex-ante* fosters the distress experienced during crisis. Espinoza and Prasad (2010) find negative impact of equity capital on NPLs of GCC (Gulf Cooperation Council) banks over 1995-2008. Finally, Fiordelisi et al. (2011) observe a bidirectional causality relationship between capital and non-performing loans of European banks, and a poor evidence of causality relationship between capital and bank market risk measured by Expected Default Frequency (EDF).

4. Datasets

We handle two datasets. First, yearly panel-data of 19 commercial banks[4] operating in Malaysia over 2002-2011. NPLs ratio and equity–to–assets ratio are obtained from BankScope database. Second, aggregated monthly time-series of NPLs ratio and core capital ratio of the banking system of Malaysia obtained from BNM spanning 1998 M1–2015 M8. Macroeconomic variables consist of yearly time series of GDP growth (code: DGDP), yearly and monthly lending interest rate (code: LRAT), and monthly money supply $M1$ growth (code: DMN1) obtained from The Economist Intelligence Unit (EIU) database. Yearly time series of inflation (code: NY.GDP.DEFL.KD.ZG) are obtained from the World Bank database. Yearly time series of bank concentration ratio and stock market turnover are obtained from Financial Development and Structure Dataset provided by Beck et al. (2010).

5. Variables definition

The proxy of the bank's non-performing loans[5] is what's called NPLs ratio, measured by dividing the value of the total amount of non-performing loans (impaired loans) over the total value of loans:

$$NPLs_{it} = \frac{\textit{Non-performing loans}_{it}}{\textit{Total loans}_{it}},$$

[4]We choose those 19 banks as a panel, because of the availability of data. Based on our own calculation, the approximate assets of the sample's banks are about 85% of the total assets of the banking system as of the end of 2013. We also believe that this sample represents the total commercial banking system in Malaysia as the actual total number of operating commercial banks are 27 (as of 12 November 2013). Banks' sample are listed in Table 2.

[5]A non-performing loan is a loan that has been not yet paid for 90 days or more.

where $NPLs_{it}$ is NPLs ratio for bank i in year t. *Non-performing loans*$_{it}$ is the value of non-performing loans for bank i in year t. *Total loans*$_{it}$ is bank i total loans in year t. NPLs ratio is the indicator of the bank's loan portfolio risk. It represents the bank's *ex post* credit risk and serves as the dependent variable in this study. NPLs is an indicator of bank fragility (Quagliariello, 2007).

The proxy of bank capital is the ratio of total bank's equity scaled to total assets. Bank capital's proxy is given by the following ratio:

$$CA_{it} = \frac{\textit{Total equity}_{it}}{\textit{Total assets}_{it}}.$$

This measure is used to capture bank i's capital in year t. The measure is the inverse of the leverage, that is, lower equity–to–asset ratio denotes more leverage and hence less resilient the bank to shocks as such a decline in bank's assets, *ceteris paribus*. According to Blum (2008), equity–to–asset ratio is the simplest and historically an oldest form of capital regulation. The legacy ratio represents the internal capital generation to satisfy the bank's solvency. Empirically, Williams (2014) finds a positive relationship between equity–to–asset ratio and asset quality measured by non-performing loans to total assets, for a sample of banks drawn from 20 Asian countries over 1998-2012. Louzis et al. (2012) observe no evidence of capital affects three different categories of Greece banks' NPLs.

The theoretical model of Calem and Rob (1999) calibrated with real data, suggests a U-shaped (convex) relationship exists between bank capital and bank risk taking: "As a bank's capital increases it first takes less risk, then more risk". However, the theoretical model of the optimal bank capital in case of recapitalization as of Peura and Keppo (2006) suggests "that recapitalization option may be valuable despite substantial fixed costs". To test whether the capital has convex or concave relationship that may exist with NPLs ratio, this study includes the square term of capital CA^2. Following Williams (2014), the square term is [equity–to–assets %]^2. That is,

$$CA_{it}^2 = \left(\frac{\textit{Total equity}_{it}}{\textit{Total assets}_{it}}\right)^2.$$

Regressing both variables CA in addition to CA^2 over $NPLs$ in one equation allows to understand the nature of the relationship between capital and NPLs. This relationship could be either convex (i.e. U-shaped) or concave one. Fig. 8 illustrates the difference between the convex (U-shaped) and concave function. For Asian banks, Williams (2014) finds that the relationship between capital variable and his two measures of risk (volatility of ROA and ROE) is negative; the square term of capital is found to be in a positive relationship with risk. That suggests a convex (U-shaped) relationship rules the function between capital and risk. That is, increased bank holdings of capital will initially result in lower risk, followed by risk increases as capital levels increase. For European banks, Haq and Heaney (2012) also find a convex (U-shaped) relationship between regulated capital and each of systematic risk and bank credit risk (measured by loan loss

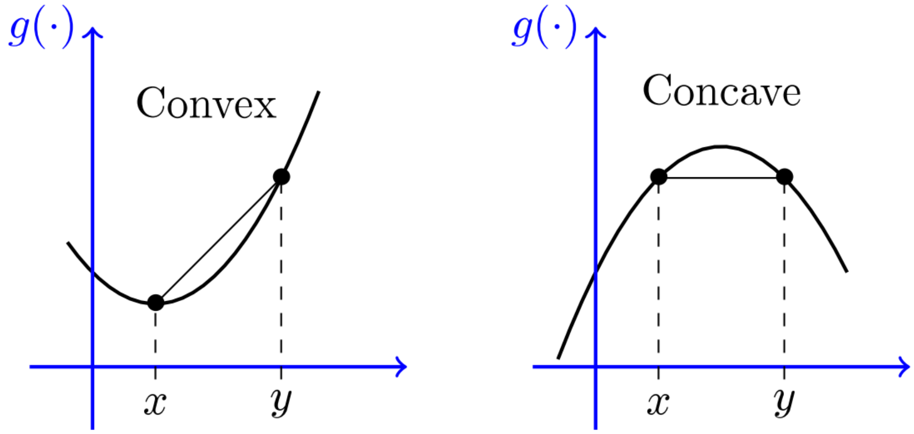

Figure 8: Illustration of a convex and a concave function. Source: probabilitycourse.com

provisions over total assets). That is, they find a negative sign of capital variable and positive sign of capital squared on their two bank risk measures, concluding that "for low levels of capital as a bank's capital increases, it takes on less risk, reflecting the disciplinary effect of bank capital, but as capital continues to rise, banks eventually reach a point where further increases in bank capital result in increasing risk". However, this study tests the following hypothesis:
'Concave Capital' Hypothesis: *NPLs continue to increase with increases in capital until NPLs reach a threshold (moral hazard effect), after which more capital buildups decrease NPLs (disciplinary or regulatory effect).*

GDP growth is included to control for macroeconomic shocks and the country's macroeconomic performance. GDP growth variable is the percentage change in real GDP over previous year (non-seasonally adjusted). Louzis et al. (2012) find a negative effect of GDP growth on NPLs of Greece banks. Similarly, Anastasiou et al. (2016) find that GDP growth negatively affects NPLs of European Banks using GMM on quarterly data over 1990-2015. While, Castro (2013) finds for banks from five European countries that higher GDP growth increases the credit risk of those banks. However, Beck et al. (2015) find that GDP growth of 75 countries significantly affects the NPLs, and it is the main driver of NPLs of these countries.

Lending interest rate is included as macroeconomic variable in order to help predict NPLs. The measure is the end period average lending rate in percentage. Louzis et al. (2012) find that lending interest rate positively influences Greece banking' NPLs. Castro (2013) finds that interest rate positively affects the credit risk of banks drawn from five European countries. Beck et al. (2015) find that lending interest rate of 75 countries significantly affects the NPLs of these countries.

This study includes money supply $M1$ growth as a macroeconomic variable to test its impact on NPLs. Money supply or money stock impacts the business cycle and represents the central bank' monetary policy as the measure linked to inflation. It allows testing the effect of monetary growth on banks' asset risk. By definition, the measure is the percentage change in total supply of notes and coins plus demand deposits at end-period, over previous year. That is, the measure is the percentage change in stock of money $M1$. Our measure, i.e. $M1$ is narrower than M2 (broad money) which is $M1$ plus quasi money. Demirgüç-Kunt and Detragiache (2005) find that the stock of money can predict banking crisis. Specifically, they find that M2 scaled to foreign exchange reserves has a positive impact on the probability of the banking crisis on their study of banking crisis worldwide. However, Kaminsky and Reinhart (1999) find that monetary growth measured by excess $M1$ (i.e. $M1$ deflated by inflation minus estimated money demand) is very high in the months before a banking crisis. Kauko (2012) uses M2 scaled to GDP as a control variable to predict the banking crisis during GFC, and finds it insignificant on affecting his special measure of non-performing loans (relative share of NPLs in 2009) for a sample of 34 countries.

Inflation variable is included to control for macroeconomic environment. The measure used is the annual inflation (GDP deflator). Baselga-Pascual et al. (2015) find that higher inflation increases NPLs for a sample of European Banks. Castro (2013) finds no evidence of a significant effect of inflation on NPLs for a sample of 5 south European countries. However, Gerlach et al. (2005) find that higher inflation (CPI) reduces NPLs ratio of Hong Kong banks over 1995-2002.

Banking concentration ratio is included to represent the structure of banking markets in the country and the competition among them. The ratio could also account for monopoly power in the banking system (Boyd et al., 2006). The variable is measured by ratio of assets of largest three banks to assets of all banks. Haq and Heaney (2012) find a negative impact of banking concentration on the credit risk of the European banks.

Finally, we include the financial stock market turnover ratio as a macroeconomic variable to control for financial market liquidity and thus the business cycle in the economy. This variable is the ratio of the value of total shares traded to average real market capitalization. Haq et al. (2014) find a positive impact of stock market turnover on credit risk (measured by NPLs over total assets) for 15 Asia-Pacific 218–quoted banks. Table 1 shows the variables definition, and Table 3 shows the descriptive statistics of the used variables.

6. Methodology

6.1. Dynamic panel data model description

In order to test the research hypothesis regarding the impact of bank capital on non-performing loans NPLs of a panel of 19 banks, the following general regression is considered:

$$NPLs_{it} = f(MV_t + CAPITAL_{it}), \tag{1}$$

where subscripts i and t refer to a bank and a year in the sample respectively. The general regression in (1) sets the relationship between non-performing loans

Table 1: Variables definition.

Variables	Exp. sign	Definition	Data source
Non-performing loans		$NPLs_{it} = \frac{Non\text{-}performing\ loans_{it}}{Total\ loans_{it}}$	BankScope and BNM*
Capital	(+)	$CA_{it} = \frac{Total\ equity_{it}}{Total\ assets_{it}}$	BankScope and BNM
Capital squared	(–)	$CA^2_{it} = \left(\frac{Total\ equity_{it}}{Total\ assets_{it}}\right)^2$	
GDP Growth	(+)	GDP_t: is the percentage change in real GDP over previous year.	EIU†
Lending interest rate	(+)	$LENR_t$: is the end period average lending rate.	EIU
Money supply M1 growth	(+)	$M1_t$: is the percentage change in total supply of notes and coins plus demand deposits.	EIU
Inflation	(–)	INF_t: "is the annual inflation deflated by the implicit annual growth rate of GDP. It shows the rate of price change in the economy as a whole".	World Bank
Bank concentration ratio	(–)	$CONC_t$: is "Assets of three largest banks as a share of assets of all commercial banks".	Beck et al. (2010)
Stock market turnover	(–)	SMT_t: "Ratio of the value of total shares traded to average real market capitalization".	Beck et al. (2010)

Note: Except for CA^2, all variables are expressed in percentage (%).
*Bank Negara Malaysia (BNM). †The Economist Intelligence Unit (EIU).

NPLs and each of a specified macroeconomic variables MV_t and bank capital: $CAPITAL_{it}$. To control for the unobserved panel-level effects and the panel time persistence, a dynamic panel data model is applied. The unobserved bank's fixed effects could be a banks managers preference to maximize profit or growth, or banks managers risk aversion. Time persistence is the strong tendency of an observation this year to be correlated with the observation next year. Following the literature on dynamic panel-data studies for NPLs (e.g., Louzis et al., 2012),

Table 2: 19 banks in the sample

No.	Commercial banks	Ownership type
1	Affin Bank Berhad	Local
2	Alliance Bank Malaysia Berhad	Local
3	AmBank (M) Berhad	Local
4	CIMB Bank Berhad	Local
5	Hong Leong Bank Berhad	Local
6	Malayan Banking Berhad	Local
7	Public Bank Berhad	Local
8	RHB Bank Berhad	Local
9	Bank of America Malaysia Berhad	Foreign
10	Bank of Tokyo-Mitsubishi UFJ (Malaysia) Berhad	Foreign
11	Citibank Berhad	Foreign
12	Deutsche Bank (Malaysia) Berhad	Foreign
13	HSBC Bank Malaysia Berhad	Foreign
14	J.P. Morgan Chase Bank Berhad	Foreign
15	OCBC Bank (Malaysia) Berhad	Foreign
16	Standard Chartered Bank Malaysia Berhad	Foreign
17	The Bank of Nova Scotia Berhad	Foreign
18	The Royal Bank of Scotland Berhad	Foreign
19	United Overseas Bank (Malaysia) Berhad	Foreign

Source: Bank Negara Malaysia (BNM) (2013) website: http://www.bnm.gov.my.

a dynamic panel-data model with panel-level fixed effects has the form:

$$NPLs_{it} \;=\; \alpha \; NPLs_{it-1} + \beta_1 \; MV_t + \beta_2 \; CAPITAL_{it} + \eta_i + \varepsilon_{it}, \qquad (2)$$

where, $|\alpha| < 1, \quad i = 1, ..., N, \; t = 1, ..., T$, and, $NPLs_{it}$ is the non-performing loans ratio in bank i at the end of year t and $NPLs_{it-1}$ is the lagged dependent variable, α is a parameter to be estimated, MV_t is macroeconomic variables: a vector contains a set of exogenous explanatory variables, $CAPITAL_{it}$ is bank capital, β_1 and β_2 are vectors of parameters to be estimated, ε_{it} is the error term, η_i is a panel-level fixed effect which may be correlated with the regressors including the dependent variable, η_i and ε_{it} are assumed to be independent for each bank i over all years t. Equation (2) does not contain endogenous variables as both macroeconomic and bank capital variables are treated as exogenous variables. In (2), the lagged dependent variable $NPLs_{it-1}$ is by construction correlated with the panel-level fixed effects η_i (such as banks managers' risk aversion) making standard estimators inconsistent.

To remove panel-level fixed effects η_i , and to estimate (2) when T is not large, the literature (e.g., Anderson and Hsiao, 1981) suggests two instrumental variable method by first-differencing (2) (i.e. applying Δ the first difference operator), that gives the following transformed form:

$$\Delta \; NPLs_{it} = \alpha \; \Delta \; NPLs_{it-1} + \beta_1 \; \Delta \; MV_t + \beta_2 \; \Delta \; CAPITAL_{it} + \Delta \; \varepsilon_{it}. \quad (3)$$

Table 3: Descriptive statistics.

	Variables used in GMM						
	$NPLs$	GDP	INF	$LENR$	SMT	$CONC$	CA
Mean	6.54	5.10	4.43	5.87	32.86	63.57	10.18
Median	3.96	5.49	4.88	6.05	32.53	68.17	7.80
Maximum	57.33	7.43	10.39	6.53	53.47	76.21	35.34
Minimum	0.08	-1.51	-5.99	4.92	22.65	49.39	3.57
Standard deviation	7.47	2.35	4.17	0.61	7.78	8.45	6.44
Skewness	3.18	-2.12	-1.17	-0.60	1.59	-0.45	2.11
Kurtosis	17.12	6.55	4.57	1.70	5.38	1.92	7.03
Jarque-Bera	1877.94	239.63	62.46	24.54	123.36	15.58	266.51
Observations	188	188	188	188	188	188	188

	Variables used in VAR				
	$NPLs$	CA	CA^2	$LENR$	$M1$
Mean	5.86	11.42	132.45	6.32	10.59
Median	4.99	10.91	118.95	6.09	11.53
Maximum	14.87	13.97	195.28	13.54	35.67
Minimum	1.17	7.88	62.11	4.44	-18.00
Standard deviation	4.11	1.44	32.95	1.85	8.05
Skewness	0.38	0.03	0.21	2.06	-1.22
Kurtosis	1.65	2.05	1.84	8.01	6.83
Jarque-Bera	21.27	8.08	13.48	369.40	179.92
Observations	212	212	212	211	210

Equation[6] (3) which is a transformed form from (2) is needed to be estimated, Arellano and Bond (1991) Generalized Method of Moments (GMM) is used to estimate α, β_1, and β_2 in (3) using the moment conditions that formed from the first-differencing errors from (2) (i.e. $\Delta\varepsilon_{it}$ in (3)). Lagged levels of the dependent variable are used to form GMM-type instruments. First differences of the exogenous variables are used as standard instruments.

The advantages of utilizing dynamic model are to control for both the unobserved panel-level fixed effects (bank-specific effects η_i) as well as the panel's time persistence. Moreover, utilizing dynamic panel-data model allows better understand the dynamics of adjustment (Baltagi, 2008). However, this study uses GMM[7], in estimating its dynamic panel-data model in (3), for the following advantages: (i) GMM allows differentiating between exogenous and endogenous explanatory variables. That is, GMM allows dealing with potential endogeneity issues (Bouvatier et al., 2014). (ii) GMM estimator allows the precision in choosing the optimal lag length of the dependent variable and in other explanatory variables as well. (iii) GMM estimator deals with collinearity or multicollinearity properly, as the estimator drops the variables that are highly correlated to each other and causing collinearity.

6.2. GMM moment conditions

In the differenced (3), the first-differenced errors $\Delta\varepsilon_{it}$ is now correlated with the lagged dependent variable $\Delta NPLs_{it-1}$, this suggests instrumenting for $\Delta NPLs_{it-1}$ with both $\Delta NPLs_{it-2}$ and $\Delta NPLs_{it-3}$, which are uncorrelated with $\Delta\varepsilon_{it}$. That is, lag order of 2 (and maximum 2) for the dependent variable $\Delta \mathrm{NPLs}_{it}$ are used as instruments and satisfies the following moment condition:

$$E\big[NPLs_{it-s}\ \Delta\varepsilon_{it}\big] = 0 \qquad \text{for} \quad t = 3, ..., T \quad \text{and} \quad s \geqslant 2. \tag{4}$$

For macroeconomic variables which are treated as (strictly) exogenous variable, 1 lag for macroeconomic variables is used[8] and that satisfies the following moment conditions:

$$E\big[\mathrm{MV}_{t-s}\ \Delta\varepsilon_{it}\big] = 0 \qquad \text{for} \quad t = 3, ..., T \quad \text{and} \quad s \leqslant 1. \tag{5}$$

For bank capital variables which are exogenous but with a weak form of exogeneity, only current and lagged values of $CAPITAL_{it}$ (up to 4 lags) are valid

[6] Equation (3) is equivalent to the following:
$(NPLs_{it} - NPLs_{it-1}) = \alpha\ (NPLs_{it-1} - NPLs_{it-2}) + \beta_1\ (MV_t - MV_{t-1}) + \beta_2\ (CAPITAL_{it} - CAPITAL_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$.

[7] Generalized Method of Moments (GMM) is firstly introduced by Arellano and Bond (1991) (the Difference GMM) and later Arellano and Bover (1995) and Blundell and Bond (1998) generalize it (the System-GMM).

[8] We tried to add more than 1 lag to macroeconomic variables but instrumenting for $\Delta\ MV_t$ in (3) leads to dropped variables due to collinearity in addition to autocorrelation as denoted by the corresponding test. The models seem to fit/be content with the first differencing of MV_t i.e. $\Delta\ MV_t$. Autocorrelation test should ensure that $\Delta\ MV_t$ does not autocorrelate with $\Delta\varepsilon_{it}$ and satisfies the moment conditions of zero autocorrelation.

instruments and that satisfies the following moment conditions:

$$E\big[CAPITAL_{it-s}\ \Delta\varepsilon_{it}\big] = 0 \qquad \text{for} \quad t = 3, ..., T \quad \text{and} \quad s \geqslant 2. \qquad (6)$$

Applying the moment conditions described in (4 - 6) i.e. the new lag length to (3) will give the following equation:

$$\Delta\, NPLs_{it} = \sum_{j=1}^{2} \alpha_j\ \Delta\, NPLs_{it-j} + \beta_1\ \Delta\, MV_t + \sum_{j=0}^{4} \beta_2\ CAPITAL_{it-j} + \varepsilon_{it}. \quad (7)$$

6.3. Arellano-Bond one-step GMM robust VCE estimator and moment conditions validation

Arellano and Bond (1991) introduced the one-step and the two-step GMM estimators. One-step GMM estimator is used because, for small samples (as our case), the estimated asymptotic standard errors of two-step GMM estimator can be severely downward biased (Windmeijer, 2005; Blundell and Bond, 1998). Yet, Judson and Owen (1999) apply Monte Carlo simulation experiment for different sets of cross sections time series, and show that one-step GMM performs better than the two-step GMM with respect to less standard deviation and less bias in the estimated parameters. For the one-step GMM estimator, Arellano and Bond (1991) has two versions, homoskedastic one-step version and robust VCE[9] version. This study applies the robust VCE estimator because we do not believe that the errors have the same finite variance (i.e. the homogeneity of variance which is the assumption of homoskedastic one-step version). That is, the assumption of homoskedastic errors (residuals) is not applicable. Instead, the one-step GMM robust VCE estimator will be applied as it fits more our data. However, higher standard errors are expected (when using of 'robust' standard errors estimator) compared to those that assume homoscedasticity in the error term.

Arellano-Bond test for first-, second-, and third-order for zero autocorrelation in the first-differenced errors $\Delta\varepsilon_{it}$ is used to validate GMM moment conditions those described in (4 - 6) and to check for any misspecification in the one-step robust VCE estimator that uses these moments (instruments). That test, the test of autocorrelation of order m_1, m_2, and m_3 is run under the null hypothesis H_0 of no autocorrelation. Autocorrelation in the first-differenced errors on an order higher than 1 (m_2 and higher) implies that the moment conditions used by the one-step GMM estimator are not valid. That is m_2 and higher should fail to reject H_0, i.e. p-value should be more than 0.05. However, we report 3 orders tests (m_1, m_2, and m_3). In the case of autocorrelation of order 1 (m_1) in the differenced-errors (the case of rejecting H_0, i.e. p-value of m_1 ¡ 0.05), the idiosyncratic errors are independently and identically distributed (i.i.d). It should be noted that the Sargan test (Sargan, 1958) of overidentifying restrictions cannot be computed for robust VCE model because Sargan test

[9]VCE stands for the estimate of the variance–covariance matrix.

asymptotic distribution is not known under the assumptions of robust VCE (StataCorp., 2015). We believe that homoskedastic estimator relaxes the heteroskedasticity in the data-generating process, and that is why we consider the robust case assumption for our one-step GMM estimator.

6.4. Empirical model

The approach is to estimate a baseline model that contains only macroeconomic variables; capital variables are then added to the baseline model to examine the additive explanatory magnitude that capital can contribute and add to the model. The assumption held here is that macroeconomic environment and business cycle play a crucial role in determining NPLs. Thus, the purpose is to determine the significant impact of capital on NPLs, after controlling for the macroeconomic environment. Based on (7), baseline Model is specified as:

$$\Delta\ NPLs_{it} = \sum_{j=1}^{2} \alpha_j\ \Delta\ NPLs_{it-j} + \beta_1\ \Delta GDP_t + \beta_2\ \Delta\ INF_t + \beta_3\ \Delta\ LENR_t + \beta_4\ \Delta\ SMT_t + \beta_5\ \Delta\ CONC_t + \eta_i + \varepsilon_{it}, \tag{8}$$

where, $|\alpha_j| < 1, \quad i = 1, ..., 19,\ t = 1, ..., 10$. $\Delta NPLs_{it}$ is the first difference of non-performing loans ratio, the dependent variable in (8). $\Delta NPLs_{it-j}$ is the lagged dependent variable. ΔGDP_t is the real GDP growth rate. ΔINF_t is the change in the inflation rate. $\Delta LENR_t$ is the change in the lending interest rate. ΔSMT_t is the change in the stock market turnover ratio. $\Delta CONC_t$ is the change in the bank concentration ratio.

We are interested in checking for evidence of either concave or convex (U-shaped) capital, forming the relationship with NPLs. For this purpose, 3 lagged values of capital variable, 3 lagged values of the square term of capital variable CA^2, as well as the current level of both capital CA and capital squared CA^2 are all added to baseline model (8). Thus, the following specification is estimated for Model 1:

$$\Delta\ NPLs_{it} = \sum_{j=1}^{2} \alpha_j\ \Delta\ NPLs_{it-j} + \beta_1\ \Delta\ GDP_t + \beta_2\ \Delta\ INF_t + \beta_3\ \Delta\ LENR_t + \beta_4\ \Delta\ SMT_t + \beta_5\ \Delta\ CONC_t + \sum_{j=0}^{3}\ \beta_{6j}\ CA_{it-j} + \sum_{j=0}^{3}\ \beta_{7j}\ CA^2_{it-j} + \eta_i + \varepsilon_{it}. \tag{9}$$

We are interested in the cumulative impact of macroeconomic and capital variables on current NPLs ratio. To achieve this objective, long-run coefficients are calculated (following Merkl and Stolz (2009)) based on the estimated short run coefficients. To construct each long-run coefficient β_j^{LR} in the previous 2 equations (8 - 9), short-run coefficients are first estimated and then applying the following formula:

$$\beta_j^{LR} = \sum_{j=1}^{J} \beta_j \Bigg/ \left(1 - \sum_{j=1}^{2} \alpha_j\right). \tag{10}$$

Long-run impact of each explanatory variable is accordingly calculated by dividing the sum product of its estimated coefficients (lagged and current if any) over one minus the sum product of the coefficients of the lagged dependent variables (two coefficients in all equations). The standard errors and the statistical significance are derived by Delta method. The statistical inference provided by the Delta method attains an accurate overall effect of lagged variables. The null hypothesis will be that NPLs ratio does not react along the lines of macroeconomic variable, neither the capital. Based on the long-run coefficient β_j^{LR} in (10), the following null and alternative hypotheses (for each respective explanatory variable) will be tested:

$$H_0: \quad \beta_j^{LR} = 0, \quad H_1: \quad \beta_j^{LR} > or < 0.$$

Table 4 presents the panel-data unit-root tests for the variables. We use Fisher-type unit-root test for the used variables based on augmented Dickey-Fuller test. The test's p-value should allow rejecting the null hypothesis of the test which is "all panels contain unit root". For bank-specific variables (NPLs, CA, and CA^2), we apply the unit-root test to the variable in level, and in 1-lag, 2-lag, 3-lag, and 4-lag forms. All results of the test's p-value confirm that we can reject the null hypothesis of the test since the p-value ¡ 0.05. Macroeconomic variable is tested in both level and in 1-lag. Augmented Dickey-Fuller test is used for the variable and the result reveals that macroeconomic variables do not follow a unit-root process and the data are stationary in level and in 1-lag form. We use the test of Harris-Tzavalis unit-root test to test $LENR$ in level and in 1-lag form. The p-value of the test rejects the test's null hypothesis under which panels contain unit roots. The test of levels for $LENR$ fails to reject the null hypothesis. However, we do not use the level of $LENR$ in the specifications.

7. Empirical results

Table 5 contains the results of baseline model, whose Equation is (8). The coefficient of the first lag of the dependent variable is positive and statistically significant at 5% level. The second lag of the dependent variable is statistically insignificant. The short run coefficients for all the 5 macroeconomic variables are statistically significant and have the expected sign. The overall impact in the long run for each of the macroeconomic variables is also significant and has the expected sign. Moreover, long-run coefficients reveal that these coefficients are more pronounced (i.e. has a greater coefficient than the one in the short run), and statistically more significant. On the long run, lending interest rate has a significant positive impact on NPLs at 5% level. GDP growth has a significant positive impact at 0.1% level. Inflation negatively affects NPLs and statistically

Table 4: Fisher-type unit-root test for the variables based on augmented Dickey-Fuller tests.

	Level	1-lag	2-lag	3-lag	4-lag
$NPLs$	235.95*	280.37*	202.7*	175.3*	258.8*
CA	64.75*	96.14*	64.7*	90.2*	174.3*
CA^2	61.93*	171.82*	62.6*	69.0*	60.0*
GDP	206.79*	81.72*			
$LENR^{\dagger}$	0.97	0.14*			
INF	201.02*	81.28*			
$CONC$	103.42*	102.2*			
SMT	126.18*	55.72*			

†Harris-Tzavalis unit-root test is used for $LENR$ instead of augmented Dickey-Fuller test.*significant at less than 5%.

significant at 0.1% level. The relationship between stock market turnover and NPLs is negative at 0.1% significance level (99.9 confidence level).

In regard to lending interest rate; GDP growth; inflation; stock market turnover; and bank concentration ratio, the results of the baseline model in Table 5 give evidence that higher levels in GDP growth and lending interest rate, raise NPLs in banks. While a rise in inflation; banking concentration; and stock market turnover, reduce NPLs.

Model 1 in Table 5 presents the estimation of (9) which resulted from adding 3 lags of capital squared CA^2 and 3 lags of capital variable CA. The current value of capital and current value of capital squared are also included in the estimation of model 1. All these variables (8 variables) are added to the baseline model. Results indicate that macroeconomic variables are all still significant. The AR (m_1) test reveals that the p-value (of m_1) is less than 5% inducing that the idiosyncratic errors, in model 1, are independently and identically distributed (i.i.d). The sign of CA in the long run is positive at coefficient of 1.0181 and is significant at 5% level. The sign of CA^2 in the long run is negative and significant at 0.1% level with coefficient -0.0490. The results denote that the relationship between capital CA and NPLs is positive, and the relationship between capital squared CA^2 and NPLs is negative.

Consequently, we accept 'Concave Capital' hypothesis that NPLs continue to increase with increases in capital until NPLs reach a threshold (moral hazard effect), after which more capital buildups decrease NPLs (disciplinary or regulatory effect).

Fig. 9 plots the function of capital in relation to NPLs ratio based on the estimated parameters of CA and CA^2 in the long run. That is, the figure graphs the following simple equation: $\left[NPLs = 1.0181\ CA - 0.0490\ CA^2\right]$. The Fig. shows that the capital function in relation to NPLs ratio is a concave relationship

Table 5: 1-step GMM estimation for dependent variable $\Delta NPLs_{it}$.

Baseline model				Model 1			
		Long-run coefficients				Long-runcoefficients	
Constant	-0.888***			*Constant*	-5.003		
	(0.258)				(4.122)		
$\Delta NPLs_{it-1}$	0.080*			$\Delta NPLs_{it-1}$	-0.042		
	(0.035)				(0.134)		
$\Delta NPLs_{it-2}$	-0.043			$\Delta NPLs_{it-2}$	-0.096		
	(0.039)				(0.074)		
$\Delta LENR_t$	1.854*	*LENR*	1.926*	$\Delta LENR_t$	1.993**	*LENR*	1.753***
	(0.767)		(0.754)		(0.611)		(0.515)
ΔGDP_t	0.449**	*GDP*	0.467***	ΔGDP_t	0.324*	*GDP*	0.285**
	(0.153)		(0.141)		(0.137)		(0.111)
ΔINF_t	-0.359**	*INF*	-0.373***	ΔINF_t	-0.262**	*INF*	-0.231**
	(0.115)		(0.107)		(0.094)		(0.080)
ΔSMT_t	-0.107**	*SMT*	-0.111***	ΔSMT_t	-0.074**	*SMT*	-0.065**
	(0.034)		(0.032)		(0.028)		(0.025)
$\Delta CONC_t$	-0.180**	*CONC*	-0.187***	$\Delta CONC_t$	-0.116†	*CONC*	-0.102†
	(0.059)		(0.053)		(0.065)		(0.054)
				CA_{it}	0.666*		
					(0.291)		
				CA_{it-1}	0.667**		
					(0.257)		
				CA_{it-2}	-0.701		
					(0.566)		
				CA_{it-3}	0.526	*CA*	1.018*
					(0.328)		(0.486)
				CA^2_{it}	-0.020*		
					(0.008)		
				CA^2_{it-1}	-0.023**		
					(0.007)		
				CA^2_{it-2}	0.010		
					(0.013)		
				CA^2_{it-3}	-0.023*	CA^2	-0.049***
					(0.009)		(0.013)
Obs.	112			*Obs.*	112		
Wald χ^2	86.2			*Wald* χ^2	18986.2		
	[0.000]				[0.000]		
AR (m_1)	-1.775			*AR* (m_1)	-2.660		
	[0.076]				[0.008]		
AR (m_2)	0.419			*AR* (m_2)	-1.609		
	[0.675]				[0.108]		
AR (m_3)	-0.268			*AR* (m_3)	-0.523		
	[0.789]				[0.601]		

Robust standard errors in parentheses. The p-values for the *Wald* χ^2, m_1, m_2, and m_3 tests are reported in brackets. † $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

and it is surely not a convex (U-shaped) relationship. The figure shows that increasing the capital ratio (equity–to–assets %) from 1% up to 10% leads to increase in NPLs ratio, but up to a maximum threshold of 5.28%. Afterwards, more increases in capital and up to 20% lead to decreases in NPLs ratio till it reaches 0.76% (when the capital ratio is 20%). The figure shows also that the

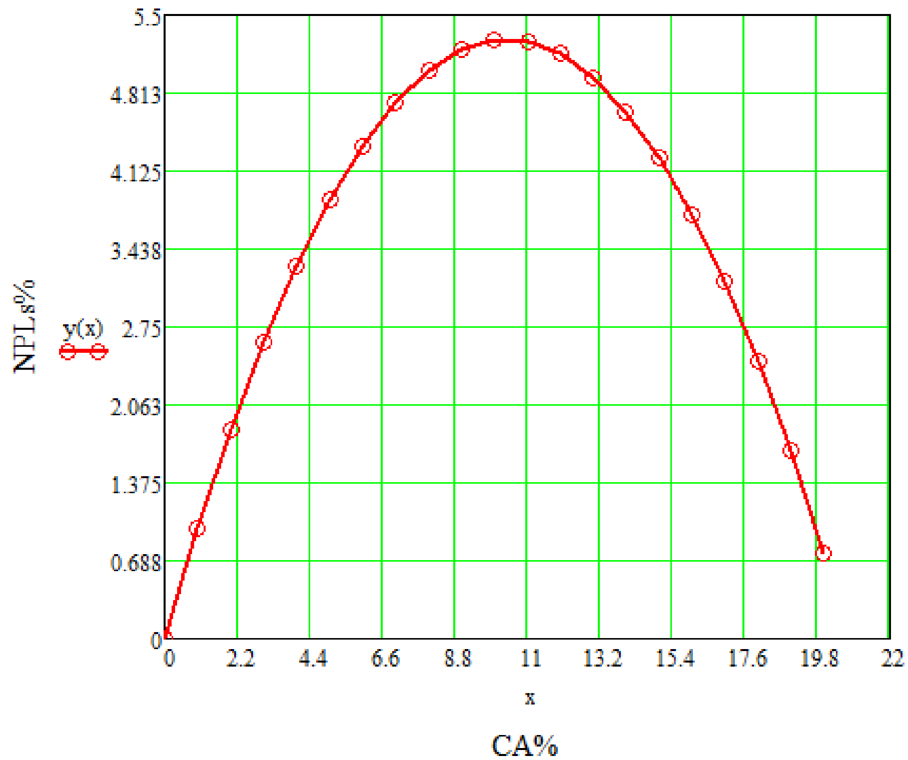

Figure 9: The concave capital based on GMM estimation.

minimum capital ratio should be 11% in order to absorb NPLs. Capital below 10% will increase NPLs, and capital higher than 11% will start to decrease NPLs ratio. We provide empirical evidence that the function between bank's capital and NPLs ratio is concave, i.e., there is a threshold level of NPLs after which NPLs ratio begins to decline with the further capital buildups.

8. Further analysis using VAR on aggregated time series

'Concave Capital' hypothesis will be further tested, we utilize aggregated-monthly time series data spanning 1998 M1–2015 M8 to implement multivariate time series analysis using, in application, a vector autoregressive (VAR) model. The VAR model contains a system of five endogenous variables. Bank-specific variables include: aggregated-monthly time series of both Malaysia banking system' NPLs as well as the core capital ratio. Square term of the core capital ratio is added to the system. Macroeconomic variables include: monthly data of both the lending interest rate as well as the money supply $M1$ growth. The model is verified via model selection criteria, and then unit roots are tested. VAR model is then estimated followed by check of stability conditions and Granger causality tests. Forecast-error variance decompositions (FEVDs) of NPLs and impulse response functions (IRFs) of NPLs to exogenous shocks (in NPLs itself, capital, capital squared, lending rate, and $M1$ growth) are forecasted in horizon of 30 months using 1000 reps of Monte-Carlo simulation of the estimated VAR model. FEVDs of NPLs are to be tabulated and IRFs of NPLs will be graphed. This section aims to check for robustness of the concave capital empirical results that obtained in the dynamic panel-data model. The section tests further the 'Concave Capital' and tries to ascertain that bank capital function in relation to non-performing loans–NPLs is a concave function. The concavity of capital implies that, NPLs continue to increase with increases in capital until NPLs reach a threshold (moral hazard effect), after which more capital buildups decrease NPLs (disciplinary or regulatory effect). However, this implication is a contrary to the implication of convex (U-shaped) capital which is found empirically by other studies, for example Haq and Heaney (2012) on European banks, in that, capital first reduces bank risk, and then with more capital buildups, it increases the risk. The check in this section tries to prove the opposite of capital convexity. However, we generally believe that the optimal capital regulation function should be a concave function and not a convex function.

We utilize aggregated-monthly time series data spanning 1998 M1–2015 M8 of Malaysia banking system to implement a vector autoregressive (VAR) model. The VAR model, which contains a system of endogenous variables, is given by the following equation:

$$Y_t = v + \sum_{j=1}^{n} A_j \; Y_{t-j} + u_t, \quad Y_t = \left[NPLs_t, \; CA_t, \; CA_t^2, \; LENR_t, \; M1_t\right], \tag{11}$$

where, $t \in \{-\infty, \infty\}$. v and A_j are vectors of parameters. u_t is a white noise $E[u_t] = 0$. Y_t is a vector of 5 endogenous variables, all represents a monthly ratio over 1998 M1–2015 M8. These variables are: $NPLs_t$ is the ratio of net impaired loans (non-performing loans) to net total loans (%) of Malaysia banking system. CA_t is the core capital ratio (%) of Malaysia banking system. CA_t^2 is the square term of CA_t. $LENR_t$ is the lending interest rate, and $M1_t$ is the money supply $M1$ growth. Table 3 shows the descriptive statistics of VAR variables.

8.1. Model selection

The criteria of selection-order statistics test is applied to obtain the optimal lag-order of variable in the VAR model. Table 6 reveals that the smallest AIC, HQIC, and SBIC values are at the lag order of 2. Consequently, we select the lag-order of 2 of the variables that form Y_t vectors in the VAR equation (11). That is, second-order VAR model is the preferred model selection. Table 7 presents the full estimates of the VAR model. At 0.1% statistical significance level, in NPLs equation in Table 7, $NPLs_{t-1}$ affects NPLs positively, CA_{t-2} affects NPLs positively, CA_{t-2}^2 affects NPLs negatively, and $LENR_{t-2}$ affects NPLs positively. These intuitive results (for NPLs equation) are consistent with the results of the GMM panel data model.

Table 6: Model selection-order criteria.

Lag	LL	LR	DF	p-value	FPE	AIC	HQIC	SBIC
1	-680.5	2966.2	25	0.000	0.001	6.898	7.095	7.383
2	-610.7	139.6	25	0.000	0.000*	6.463*	6.823*	7.352*
3	-588.6	44.2	25	0.010	0.000	6.491	7.014	7.784
4	-563.0	51.3*	25	0.001	0.000	6.485	7.171	8.182

8.2. Stability conditions of the estimated VAR model

This subsection checks the stability condition of the estimated VAR model. Table 8 and Fig. 10 show that all the eigenvalues lie inside the unit circle. Therefore, the VAR model estimate is stable and satisfies stability conditions.

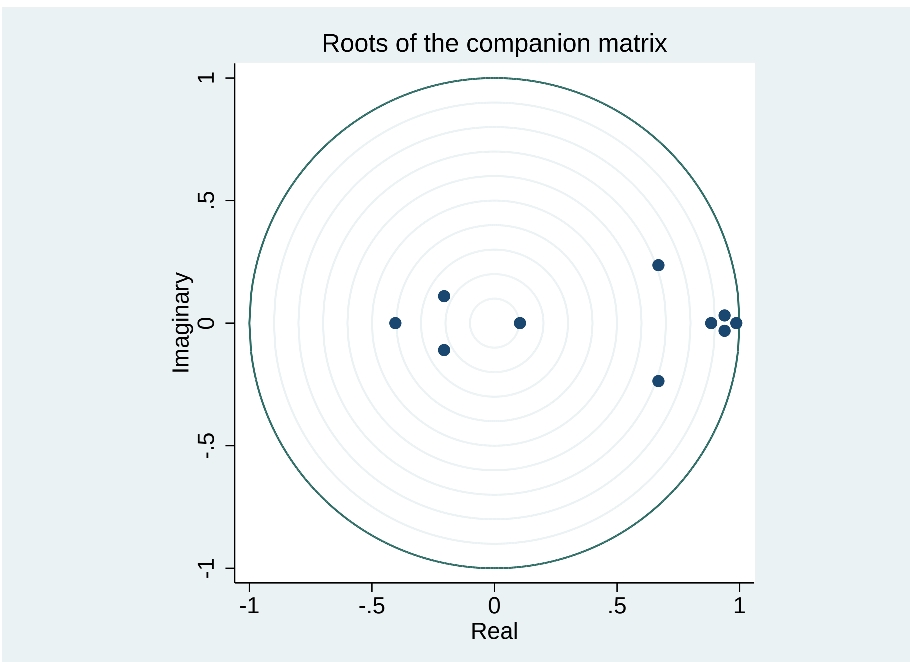

Figure 10: VAR stability condition unit circle.

8.3. Granger causality postestimation tests

Granger causality (after VAR) Wald test in Table 9 shows that NPLs Granger causes each of CA, CA^2, $LENR$, $M1$, and all the variables jointly. And, while each of CA and CA^2 does not Granger cause $NPLs$, each of $LENR$ and and $M1$

Table 7: Vector autoregression.

Log likelihood:	-638.4	Obs.:	208		
AIC:	6.6672	HQIC:	7.0240	SBIC:	7.5497
Equation	*NPLs*	*CA*	CA^2	*LENR*	*M1*
RMSE	0.2099	0.2893	6.6399	0.1430	2.8116
R-squared	99.75%	96.04%	96.05%	99.38%	87.97%
Chi-square χ^2	84262.9	5049.0	5062.9	33236.1	1520.6
Prob. $> \chi^2$	0.0000	0.0000	0.0000	0.0000	0.0000
	NPLs	*CA*	CA^2	*LENR*	*M1*
NPLs					
L1	0.9691***	-0.0887	-1.6317	0.0309	-1.3374
	(0.0634)	(0.0874)	(2.0069)	(0.0432)	(0.8498)
L2	0.0001	0.0842	1.4626	-0.0312	1.5417†
	(0.0621)	(0.0855)	(1.9630)	(0.0423)	(0.8312)
CA					
L1	-0.8684*	0.9683†	10.2295	1.4315***	-5.1369
	(0.3585)	(0.4941)	(11.3406)	(0.2443)	(4.8021)
L2	2.0262***	-0.6860	-18.9422†	-1.2494***	-3.8072
	(0.3365)	(0.4638)	(10.6457)	(0.2293)	(4.5079)
CA^2					
L1	0.0378*	-0.0103	0.2782	-0.0587***	0.1742
	(0.0156)	(0.0215)	(0.4927)	(0.0106)	(0.2086)
L2	-0.0830***	0.0374†	1.0172*	0.0504***	0.1968
	(0.0147)	(0.0202)	(0.4637)	(0.0100)	(0.1963)
LENR					
L1	-0.1669*	0.0263	-0.4191	1.4260***	0.4450
	(0.0824)	(0.1135)	(2.6054)	(0.0561)	(1.1032)
L2	0.3486***	-0.0879	-0.7009	-0.4528***	-1.2242
	(0.0877)	(0.1209)	(2.7747)	(0.0598)	(1.1749)
M1					
L1	-0.0089†	0.0079	0.1526	0.0002	0.7324***
	(0.0051)	(0.0070)	(0.1611)	(0.0035)	(0.0682)
L2	-0.0024	-0.0085	-0.1942	0.0005	0.1610*
	(0.0051)	(0.0070)	(0.1618)	(0.0035)	(0.0685)
Constant	-8.1135***	5.0570*	69.3601	-0.8473	57.9606**
	(1.5834)	(2.1823)	(50.0893)	(1.0789)	(21.2100)

Notes: Standard errors are reported in parenthesis. $^\dagger p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Granger causes $NPLs$. However, CA Granger causes all variables jointly, and CA^2 Granger causes all variables jointly at 10% significance level. Moreover, each of $LENR$ and $M1$ Granger causes all variables jointly.

8.4. Unit roots tests

Table 10 presents the Dickey-Fuller unit root tests for the used variables in the VAR model. We use for $NPLs$, CA, and CA^2 the modified Dickey-

Table 8: Eigenvalue stability condition.

Eigenvalue			Modulus
0.9865395			0.986539
0.9386796	+	0.03133982i	0.939203
0.9386796	−	0.03133982i	0.939203
0.8840361			0.884036
0.6688319	+	0.236441i	0.709394
0.6688319	−	0.236441i	0.709394
-0.4043713			0.404371
-0.205542	+	0.1099687i	0.233111
-0.205542	−	0.1099687i	0.233111
0.1039485			0.103949

All the eigenvalues lie inside the unit circle (see Fig. 10). VAR satisfies stability condition.

Table 9: Granger causality Wald tests.

Equation	Excluded	Chi-square χ^2	Degree of freedom	Prob. $> \chi^2$
NPLs	*CA*	43.80	2	0.0000
NPLs	CA^2	38.67	2	0.0000
NPLs	*LENR*	81.26	2	0.0000
NPLs	*M1*	17.52	2	0.0000
NPLs	ALL	146.51	8	0.0000
CA	*NPLs*	1.10	2	0.5760
CA	ALL	17.72	8	0.0230
CA^2	*NPLs*	1.16	2	0.5600
CA^2	ALL	13.58	8	0.0930
LENR	*NPLs*	0.60	2	0.7420
LENR	ALL	47.46	8	0.0000
M1	*NPLs*	12.36	2	0.0020
M1	ALL	23.73	8	0.0030

Fuller test that transforms the time series by GLS (generalized least-squares) regression. We use for $LENR$ and $M1$ the augmented Dickey-Fuller test. All the variables pass the test and allow rejecting the null hypothesis that a variable follows a unit root process, since the absolute value of the test statistic is larger than the absolute value of the critical value. $M1$ cannot reject the null at 1% critical value level; whereas it can reject the null at 5% and 10% critical value level.

Table 10: Dickey-Fuller unit roots tests.

	Test statistic	1% Critical value	5% Critical value	10% Critical value
	Modified Dickey-Fuller test			
NPLs				
Lag 1	-3.787	-3.480	-2.924	-2.636
Lag 2	-4.033	-3.480	-2.931	-2.642
CA				
Lag 1	-3.021	-2.611	-2.181	-1.880
Lag 2	-3.261	-2.611	-2.198	-1.895
CA^2				
Lag 1	-3.022	-2.611	-2.181	-1.880
Lag 2	-3.266	-2.611	-2.198	-1.895
	Augmented Dickey-Fuller test			
LENR				
Level	-3.528	-3.473	-2.883	-2.573
Lag 1	-3.528	-3.473	-2.883	-2.573
Lag 2	-3.526	-3.474	-2.883	-2.573
M1				
Level	-3.027	-3.474	-2.883	-2.573
Lag 1	-3.027	-3.474	-2.883	-2.573
Lag 2	-3.027	-3.474	-2.883	-2.573

For further diagnostic of VAR estimates, Table 11 shows the Wald test of the null-hypothesis that the endogenous variables at a given lag are jointly zero for each equation and for all equations jointly. The results pass the test that the VAR variables are different from zero, since p-values¡0.05 reject the test's null-hypothesis.

8.5. Forecast-error variance decompositions (FEVDs) and impulse response functions (IRFs)

Vector autoregression model estimates (in Table 7) are seldom interpreted by itself (Love and Zicchino, 2006). For that reason, we estimate the forecast-error variance decompositions (FEVDs), as well as the impulse response functions (IRFs) based on the estimated VAR model. The purpose is to measure and forecast the impact of the exogenous shocks on each of the endogenous variables that form the VAR system. This section will focus on the impact of these shocks on NPLs of the banking system, particularly. For FEVD, we apply Cholesky FEVDs and for IRF, we apply orthogonalized IRFs. The forecast horizon is 30 months in the future. The 5% errors of this forecast (at 95% confidence interval) are computed by Monte-Carlo simulation of our VAR model with 1000 reps (draws). Table 12 presents the FEVDs of NPLs equation only. Table 12

Table 11: Wald lag-exclusion test.

	Lag	Chi-square χ^2	Degree of freedom	Prob. $> \chi^2$
Equation: $NPLs$	1	276.64	5	0.0000
	2	49.79	5	0.0000
Equation: CA	1	124.28	5	0.0000
	2	12.20	5	0.0320
Equation: CA^2	1	119.63	5	0.0000
	2	14.12	5	0.0150
Equation: $LENR$	1	710.19	5	0.0000
	2	79.15	5	0.0000
Equation: $M1$	1	131.10	5	0.0000
	2	11.95	5	0.0350
Equation: All	1	1367.43	25	0.0000
	2	202.10	25	0.0000

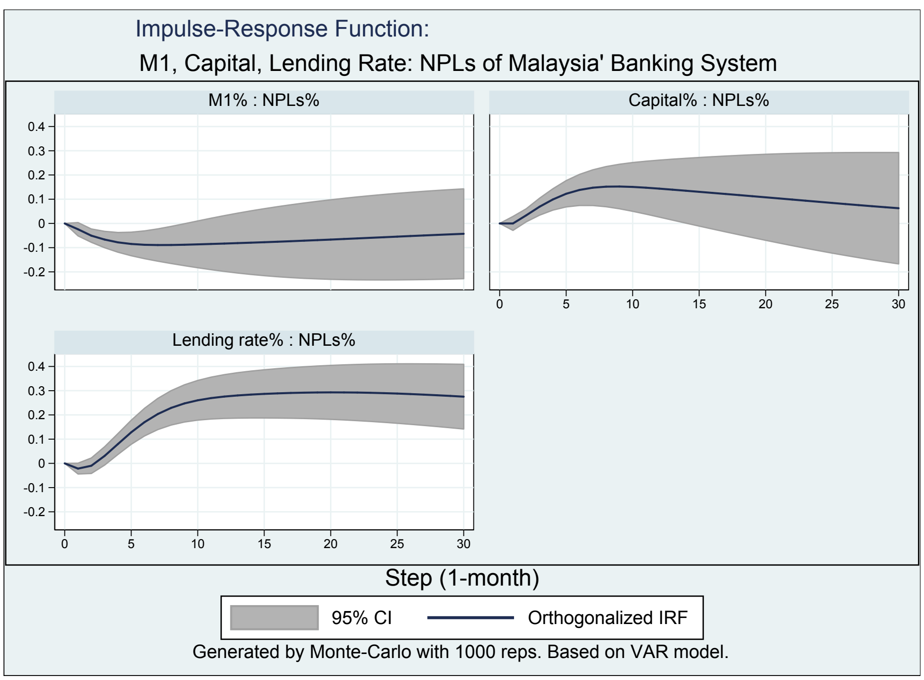

Figure 11: Impulse–response functions. $M1$, capital, lending rate–NPLs.

shows the responses of NPLs (NPLs is the response variable) to a shock on itself, and to a shock on each of CA, CA^2, $LENR$, and $M1$, over a time horizon of

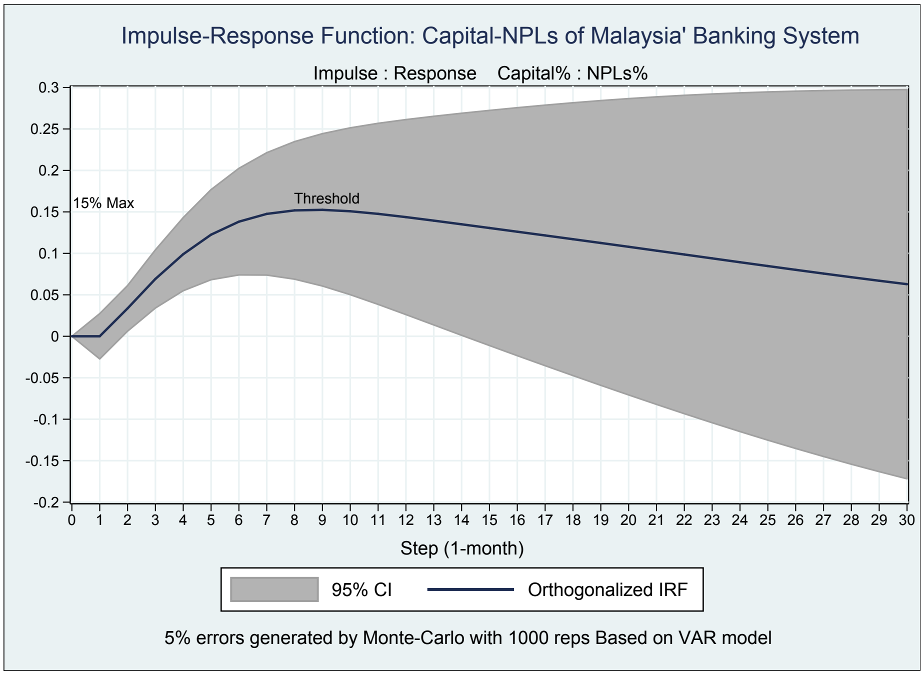

Figure 12: Impulse–response function. capital–NPLs of Malaysia' banking system.

30 months (1-month step). Based on the orthogonalized IRFs, three graphs are generated and drawn, Fig. 11 depicts the impulse response function response of NPLs to a shock on each of money supply $M1$ growth, capital, and lending interest rate $LENR$. Fig. 12 depicts the impulse response function of NPLs to a shock on capital CA. While Fig. 13 depicts the complete IRFs of the VAR system model.

8.6. NPLs variance decomposition

Table 12 presents the variance decomposition of NPLs equation. Variance decomposition of NPLs measures the impact of the exogenous shocks of each of NPLs itself, CA, CA^2, $LENR$, and $M1$ on $NPLs$, based on Cholesky FEVDs. The table shows that in the end of 30-month time horizon, in the future, 55.14% of variations in NPLs can be explained by the lending interest rate. Then, 18.80% of variations in NPLs can be explained by bank capital (11.21% by CA and 7.59% by CA^2). Then, 4.35% of variations in NPLs can be explained by money supply $M1$ growth.

8.7. Response of NPLs to shocks in lending interest rate

Table 12 and Fig. 11 show that a shock in the lending interest rate $LENR$ have a persistent and positive impact on future NPLs. A shock in $LENR$ will increase NPLs 26.09% at month 10, 46.29% at month 20, and 55.14% at month

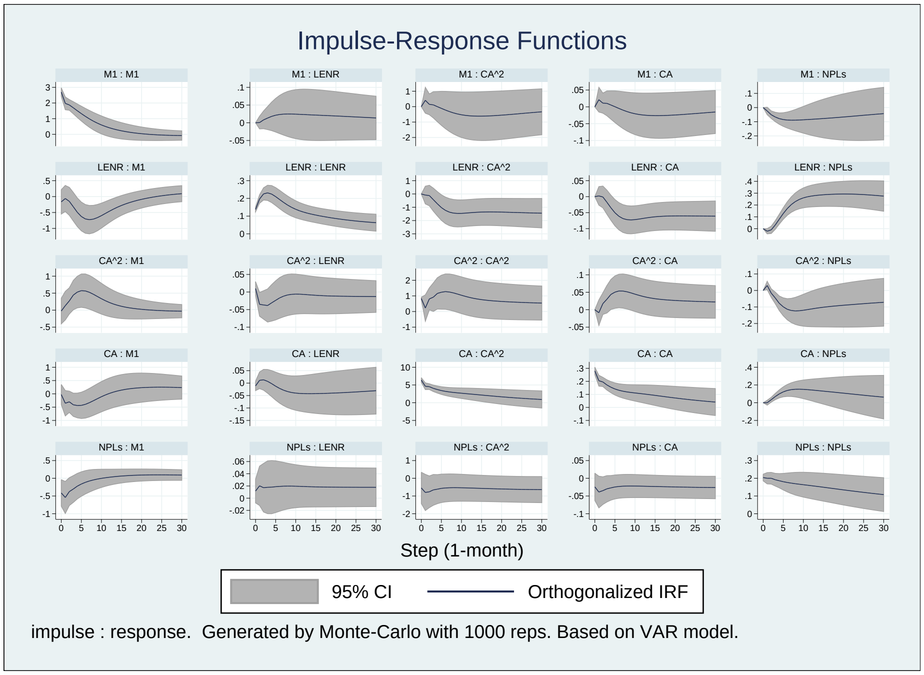

Figure 13: Impulse–response functions.

30, at the end of the forecasted horizon. IRF plot in Fig. 11 (LENR : NPLs) shows the positive effect of a shock in LENR on NPLs (the upward response function). The results of FEVDs and IRFs confirm the positive relation that exists between LENR and NPLs.

8.8. Response of NPLs to shocks in money supply M1 growth

Table 12 shows that a shock in money supply $M1$ growth has a positive impact on NPLs, it leads to 6.80% increase in NPLs at horizon 8. Overall impact of the shock in $M1$ growth on NPLs is that it increases NPLs 4.35% at the end of the forecasted horizon (at month 30). IRF plot in Fig. 11 shows that a negative shock on $M1$ growth leads to decreases in NPLs (positive relationship), although it is a short-lived shock. The positive yet long-lived shock in $M1$ growth leads to increases in NPLs. The above results provide evidence of the positive relationship that exists between money supply $M1$ growth and NPLs.

8.9. Response of NPLs to shocks in capital

Table 12 and Fig. 12 show that a positive shock in capital leads to increase NPLs 6.56% in horizon 5, and 14.76% in horizon 10 until NPLs reach a maximum threshold. At that threshold, NPLs increase to 15.06% at horizon 12. From horizon 13 till 30, the impact of capital shock on NPLs decreases NPLs to a 11.21% level. The IRF plot of NPLs response to shocks in capital, in Fig. 12,

Table 12: Forecast-error variance decomposition for NPLs equation.

Response variable $NPLs$	Impulse variable				
Time horizon	$NPLs$	CA	CA^2	$LENR$	$M1$
0	0	0	0	0	0
1	1	0	0	0	0
2	0.9766	3.14^{-11}	0.0109	0.0055	0.0069
3	0.9532	0.0089	0.0092	0.0044	0.0244
4	0.8975	0.0334	0.0180	0.0085	0.0426
5	0.8065	0.0656	0.0384	0.0328	0.0568
6	0.7045	0.0958	0.0592	0.0758	0.0648
7	0.6112	0.1185	0.0760	0.1266	0.0678
8	0.5349	0.1335	0.0870	0.1766	0.0680
9	0.4755	0.1426	0.0933	0.2218	0.0668
10	0.4299	0.1476	0.0964	0.2609	0.0652
11	0.3947	0.1499	0.0974	0.2945	0.0635
12	0.3672	0.1506	0.0972	0.3233	0.0618
13	0.3452	0.1501	0.0962	0.3482	0.0603
14	0.3273	0.1489	0.0948	0.3700	0.0589
15	0.3124	0.1472	0.0933	0.3894	0.0576
16	0.2998	0.1452	0.0917	0.4068	0.0564
17	0.2889	0.1430	0.0901	0.4226	0.0553
18	0.2793	0.1407	0.0886	0.4371	0.0542
19	0.2709	0.1383	0.0872	0.4505	0.0532
20	0.2633	0.1358	0.0858	0.4629	0.0522
21	0.2566	0.1333	0.0845	0.4744	0.0512
22	0.2504	0.1308	0.0833	0.4852	0.0502
23	0.2449	0.1283	0.0821	0.4954	0.0493
24	0.2398	0.1258	0.0811	0.5049	0.0484
25	0.2352	0.1234	0.0800	0.5138	0.0475
26	0.2310	0.1210	0.0791	0.5222	0.0467
27	0.2271	0.1187	0.0782	0.5302	0.0459
28	0.2235	0.1164	0.0774	0.5376	0.0451
29	0.2202	0.1142	0.0766	0.5447	0.0443
30	0.2171	0.1121	0.0759	0.5514	0.0435

shows that capital increases NPLs until a threshold of 15%, after which NPLs decline. Fig. 12 shows clearly that capital function is a concave function. The results of FEVDs and IRFs, regarding the capital, confirm that capital increases NPLs up to a threshold of 15%, then capital begins to decrease NPLs. Therefore, VAR model gives evidence supporting 'Concave Capital' hypothesis, and that is consistent with the result of the dynamic panel data model.

9. Concluding remarks

We investigate the impact of bank capital on NPLs using a panel of 19 commercial banks and aggregated time series of Malaysia banking system. The study provides a strong evidence that the capital function is a concave function implying that, increasing the capital will initially increase the NPLs until NPLs reach a maximum threshold (under the moral hazard effect), after which more capital buildups will succeed in decreasing NPLs (under the disciplinary or regulatory effect). The findings of the dynamic panel-data model of 19 commercial banks using GMM suggest that the minimum capital ratio should be at least 11% in order to be allowed to absorb NPLs. The capital concavity is confirmed when aggregated NPLs of the banking system are stress tested and forecasted by using the impulse-response function based on the VAR model. The forecasting reveals that a positive shock in capital ratio will act to increase NPLs until a threshold of 15%. After which NPLs will decline with the more capital buildups. The findings, in regard to the evidence of capital concavity, suggest that when the capital holdings act to affect NPLs negatively, i.e. in the disciplinary effect phase, the capital holdings succeed to act their traditional role as a reducer of the appetite of the bank's management risk-taking. The result supports the theory of Diamond and Dybvig (1983) that banks are required to hold more capital to offset the moral hazards driven by deposit insurance or bank guarantees. The result also supports the theory of bank capital by Diamond and Rajan (2000) in which banks with more capital holdings reduce their liquidity creation, but that allows the bank to avoid risk and enjoy more loan repayments. However, our result supports the theoretical model of the optimal bank capital in case of costly recapitalization as of Peura and Keppo (2006). As a policy implication, the *status quo* of commercial banks' capitalization is good, but it is recommended to enhance the capital regulation a bit more in order to more absorb the NPLs.

With regard to the impact of macroeconomic variables on NPLs, the study finds empirically that: higher levels in GDP growth; lending interest rate; money supply M1 growth, raise NPLs in banks. A rise in inflation; banking concentration; and stock market turnover, reduce NPLs. First, we find that higher economic growth measured by GDP growth lead to increases of NPLs in commercial banks. The positive sign between Malaysia GDP growth and NPLs is consistent with Castro (2013) who finds for banks from five European countries that higher GDP growth increases the credit risk of those banks. The result suggests that NPLs is procyclical in terms of GDP under the business cycle theory. The result also supports the theory and the argument of Quagliariello (2007) that the impact of GDP on NPLs is asymmetrical, and that NPLs may form a cyclical behavior.

Second, higher lending interest rate is found foster the increases in NPLs and will continue to do so in the future as denoted by stress testing and forecasting the NPLs based on the VAR model on aggregated-monthly time series. The positive sign between Malaysia lending interest rate and NPLs is consistent with Louzis et al. (2012) who find that lending interest rate positively influences

Greece banking' NPLs. Third, money supply M1 growth is found to be leading to increases in NPLs as denoted by forecasting and stress testing of aggregated NPLs. Suggestive of that, the central bank policy of expansionary money supply (higher monetary growth) leads to higher rates of NPLs in banks. The result supports the prediction of the theoretical monetary DSGE (dynamic stochastic general equilibrium) model of Abbate and Thaler (2015) that monetary policy expansion increases the asset-risk taking of bank managers. As a policy implication, the central bank is advised to take steps towards both decreasing the lending interest rates as well as decreasing the monetary growth, specifically via reducing the expansion of money supply M1.

Fourth, the inflation deflated by GDP is found reduce NPLs in banks. That is consistent with the impact of inflation (measured by the consumer price index–CPI) on NPLs of Hong Kong' banks in Gerlach et al. (2005) study over 1995-2002. Fifth, more competition (captured by bank concentration ratio) between banks is evidenced to reduce NPLs of those banks. The empirical result (i.e. the negative sign between bank concentration ratio and NPLs) is consistent with Haq and Heaney (2012) who find a negative impact of banking concentration on the credit risk of the European banks. This finding supports the predictions of the concentration-stability theory (against the concentration-fragility theory) that economies with more concentrated banking system have more stable banking systems. Further, banks are less risky as their banking system becomes more concentrated (Boyd and De Nicolo, 2005). However, the findings suggest that the more competition between banks, the more stable the banking system is. Finally, the findings reveal that more financial market liquidity (captured by stock market turnover) reduces NPLs of banks. The result is intuitive on the grounds that a business cycle associated with higher liquidity in the financial market drives to more loan repayments and thus less NPLs in banks. The result is inconsistent with Haq et al. (2014) who find a positive impact of stock market turnover on credit risk measured by NPLs over total assets for Asia-Pacific banks.

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