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Credit expansion and financial stability in Malaysia

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ABSTRACT

This study investigated the degree of synchronization between credit expansion and financial stability in Malaysia at aggregated and disaggregated levels. The dynamic factor model and a broad range of macro-financial variables are adopted to construct a financial stability index to measure the stability of the Malaysian financial system. The non-parametric method is subsequently employed to gauge the degree of synchronization between credit and financial stability. The empirical findings indicated a negative synchronization between business credit and financial stability in Malaysia, suggesting that an expansion in business credit would lead to financial instability. The results implied that difficulties will arise in designing policies as business credit expands. On the other hand, there is insufficient evidence to show that increasing household credit has any negative influence on Malaysian financial stability.

1. Introduction

According to Francois Quesnay, "society was analogous to the physical organism. The circulation of wealth and goods in the economy was like the circulation of blood in the body, where both conformed to the natural order" (Brue and Grant, 2007, pp. 37). Likewise, a well-functioning financial system exhibits financial stability by utilizing socially productive investment opportunities; whereas a malfunctioning financial system leads to financial instability through the misallocation of scarce resources.

Financial intermediaries, especially the banking system, play a traditional intermediary role by channelling excess funds from depositors to households and investors to finance their consumption and investments respectively. By and large, credit plays a significant role in promoting economic growth through the credit channel, Mishra and Narayan (2015) suggested a positive effect of credit on growth after attaining a certain level of credit. However, it also influences financial stability. Both credit expansion and financial instability could give an impact on overall macroeconomic outcomes. The conflict could arise if credit expansion and financial instability are mutually exclusive that would cause policy-makers to face difficulties when designing financial development policies, where credit could promote growth as well as trigger financial instability.

The main transactions on the asset side of the balance sheet of the Malaysian banking system are loans to the public also known as credit. Economic agents, such as households and businesses, get access to credit services from banks mainly to support their consumption and investment. Before 2000, the amount of business credit to agriculture, manufacturers and services industries was relatively larger than household credit. However, household credit after that point began to grow and has beaten the growth of business credit since then. The credit trend is depicted in Fig. 1, in which the percentage of household credit-to-GDP was higher compared to the percentage of business credit-to-GDP since 2000. Moreover, household credit reached the peak of more than 15 percent of GDP in Malaysia in the year 2007, which is quite a significant amount. Household credit plays a role in promoting growth through household consumption. However, it is perceived to be more likely to cause financial instability (Buyukkarabacak and Valev, 2010), due to the lower ability of households to repay loans as compared to business credit, where businesses can generate profit for loan repayments.

The role of the financial sector was seldom highlighted in the dominance theories of the Classical and Keynesian schools. Evidently, growth theories view economic growth as a result of physical accumulation, human capital, and technological innovation. Adam Smith de-emphasizes the role of money in promoting the wealth of a nation, where money is important in facilitating payment and the circulation of goods in the economy but not promoting wealth. Additionally, Keynes viewed credit as "grease" for the wheels of economic growth. However, the recent 2007/08 global financial crisis has emphasized the importance of financial stability[1] as well as the role of credit growth in driving the business cycle, which has highlighted financial stability as a goal to

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[1] Creel et al. (2015) find that financial instability has a negative effect on economic growth in the European Union.

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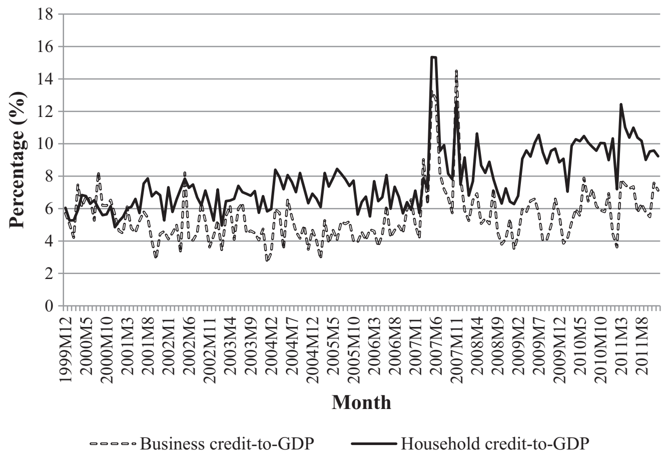
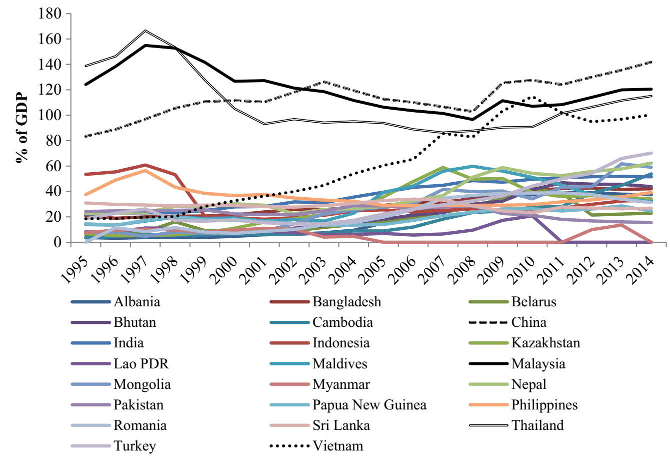


(Source: Various issues of Monthly Statistical Bulletin, Central Bank of Malaysia)

Fig. 1. Trend of credit approved by banking system in Malaysia.



(Source: World Development Indicators from the World Bank Online Databank)

Fig. 2. Trend of Domestic Credit to Private Sector by Banks from 1995 to 2014.

be pursued by central bankers, placing it at the center of academic discussions. Furthermore, the adoption of business diversification strategies by financial institutions has caused the financial system to evolve into a more complex system and hence to become less stable.

Furthermore, in the recent global financial crisis, modern macroeconomic analytical frameworks are found to be insufficient to predict future crises (White, 2009). In previous literature, many researchers have found that rapid credit growth is one of the leading indicators to determine a financial crisis (see, for example, Kaminsky et al., 1998; Kraft and Jankov, 2005; Hume and Sentence, 2009; Bernoth and Pick, 2011). Credit expansion contributes positively to growth. In the meantime, it also may lead to a financial crisis when the default probabilities are high among the credit borrowers, where it will disrupt the traditional intermediation role of financial institutions. Ultimately, systemic risk will be triggered in the financial system, whereby the risks spread to other financial institutions and eventually cause financial instability.

Credit conditions in Malaysia have been conducive to the financing needs of the economy, and they have reflected greater financial development in Malaysia. Since 2001, credit expansion has averaged around 9.2%.[2] This period of strong credit expansion coincides with a period of wide-ranging reforms undertaken to strengthen the banking sector following the 1997–1998 Asian financial crisis. The expansion of credit to businesses and households contributes to the financial development, acceleration of growth, improving investment and consumption activities. Nevertheless, excessive credit expansion that outperforms economic fundamentals and output potentially can pose destabilizing risks to the economy and financial system. While excessive credit growth is a useful indicator, studies have also demonstrated that a sustained period of high credit growth is more likely to increase the likelihood or severity of systemic distress if there are financial imbalances in the financial system.

This study investigates the degree of synchronization between credit expansion and financial stability in Malaysia. Also, we aim to gain an increased understanding of the behavior of the cycles of credit and fluctuations in financial stability and to guide policy-makers who face difficulties in designing financial development policies. We contribute to the literature in three important aspects. First, Malaysia was ranked first for five consecutive years (2009 – 2013) in the category of easily getting credit in the *Doing Business* report published by *World Bank*. Furthermore, Malaysia is ranked top three regarding supplying credit to the private sector domestically from the year 1990 to 2014. This trend is depicted in Fig. 2, in which Malaysia, China, and Thailand are the top three countries in the list of emerging economies. Therefore, it is important to evaluate the role of credit in influencing financial stability in a case of a high credit expansion emerging market. As a result, this study focused on the case of Malaysia. Second, this study constructed a financial stability index as a proxy to measure financial stability using fifteen indicators, this differs from Osorio et al. (2011) who used forecasting tests to test the predictive power of their index which are merely descriptive. Hence, the reliability and validity of their index is somewhat unconvincing. Meanwhile, Tng et al. (2012) who constructed financial stress indices only using financial variables could be insufficient information to capture financial crisis. Third, this study used the non-parametric statistics to analyze the degree of synchronization between credit and financial instability, namely a concordance index that does not require a stationary time series and suffers from sudden shocks in the series.

The organization of this paper is as follows: Section 2 discusses the literature reviews, Section 3 lays out the empirical model, econometric methodology, and the data, Section 4 contains a discussion of the empirical findings, Section 5 provides a summary and conclusions.

2. Review of literature

2.1. *The construction of a financial stability index*

There has been increasing attention related to the study of financial stability in recent years, especially after the 2007/08 global financial crisis. The crisis particularly drew attention from researchers to develop an index to assess the current state of financial conditions, especially in the advanced countries such as United States, United Kingdom, and the European economies (see, for example, Matheson 2012; Brave and Butters 2011; Hatzius et al. 2010; Illing and Liu 2006). However, little attention has been paid to developing a financial stability index to measure the current states of financial conditions in Asian countries (see, for example, Osorio et al., 2011; Ghosh 2011; Tng et al., 2012).

Various methodologies can be adopted to construct a financial stability index. The two most commonly used methods are: (i) principal component approach[3] and (ii) weighted-sum approach[4]. A constructed

[2] Source: Financial Stability and Payment System Report, 2013, Central Bank of Malaysia. Jakubik and Moinescu (2015) show that a 3 percent (± 1 pp margin) quarterly increase in credit to the private sector is, in nominal terms, optimal for financial stability and sustainable growth in Romania.

[3] For example, Deutsche Bank Financial Conditions Index and Federal Reserve Bank of Kansas City Financial Stress Index employ the principal component approach to construct their financial condition indexes.

[4] For example, Bloomberg Financial Conditions Index, Citi Financial Conditions Index, Goldman Sachs Financial Conditions Index and OECD Financial Conditions Index use weighted-sum approach to develop their financial conditions indexes.

financial index summarizes the information contained in a set of indicators, be it financial or real variables, about the future state of an economy. Historical data of the indicators would contain the relevant predictive information.

Additionally, researchers from NBER and IMF adopted the dynamic factor model (DFM) to construct a financial conditions index in various countries. A wide array of financial indicators were employed from various parts of the financial system to reflect the financial conditions. With a large number of indicators, the problem of high dimensionality would arise and lead to unfavorable consequences for estimation methods such as ordinary least square (OLS), in which OLS when used with too many regressors would not lead to first-order forecast efficiency. Besides, some of the financial indicators are influenced by unobserved factors instead of observed variables. Hence, DFM is preferred due to its advantages that are 1) avoiding high dimensionality problems, and 2) estimating unobserved factors.

There are a number of indicators suggested by the Financial Stability Report (FSR) that can be used to identify and assess risks in the financial sector. Indicators include quantitative and qualitative indicators (Wilkinson et al., 2010). There are two common types of quantitative indicators, namely financial indicators and market-based indicators. In addition, the International Monetary Fund (IMF) has recommended a list of financial soundness indicators which are meant to assess the healthiness of a country's financial sector. Financial indicators include capital-to-asset ratios, return on assets and debt-to-equity ratios. These are considered to reflect only the current status – a snapshot – of the financial system. This means that financial indicators are unable to capture the dynamic future state and future risks of the financial system.

In contrast, market-based indicators include spreads on credit default swaps, stock price indexes and interest rate spreads. These are considered to have a higher power in predicting future outcomes compared to the financial indicators. Market-based indicators capture the expectations of investors based on financial market information. In other words, market-based indicators are perceived to be more forward-looking compared to the financial indicators because to some degree, they reflect the views of many highly proactive market participants – for instance, household and business sectors. By and large, financial variables only partially reflect economic activity. Therefore, relevant variables should be included in the index computation to measure the stability of the financial system as a whole. For instance, equity prices, effective exchange rate, the spread of lending rates over policy rates, bank credit to the private sector and stock market indices (Osorio et al., 2011).

A quantitative assessment of financial conditions in a group of 13 Asia-Pacific countries has been carried out by Osorio et al. (2011). The constructed financial condition index is found to have predictive power in forecasting GDP growth in the sample countries (including Malaysia) and has been used as a leading indicator. However, the forecasting tests used to examine the predictability of the indexes are merely descriptive, and are unconvincing. Likewise, Tng et al. (2012) constructed four financial stress indexes for ASEAN-5 economies. They found that stress was most severe during the Asian financial crisis, Dot Com bubble, and the global financial crisis of 2007/08, in which the constructed indexes were predictive for each of the crises. However, the variables that are employed are mainly focused from financial markets, namely stock market indexes, bank stock indexes, Treasury yields, foreign reserves and bilateral exchange rates; that may be insufficient to measure the stress level in the financial system. Meanwhile, some literature has pointed out that credit-based indicators and asset prices play a significant role in capturing financial risks, such as banking crises and systemic risk.[5]

The understanding of financial stability, especially in the context of managing credit risk, is important to avoid a crisis in the banking sector. Based on Ali and Daly (2010), a set of macroeconomic variables (i.e. interest rates, industrial production index and debt-to-GDP ratio) were statistically significant in affecting credit default rates in the United States and Australia. Furthermore, market-based information (i.e. macroeconomic determinants) complements the financial sector information by conveying market perceptions of market health and the stability of the financial system. Hence, macroeconomic determinants are crucial in explaining financial stability as well, where this information cannot be omitted in constructing a financial index.

Moreover, market-based information, such as the real exchange rate, the real interest rate, the inflation rate, money supply, foreign assets and domestic credit growth, are important in explaining the financial stability of an economy. This is supported by Beck et al. (2006) who reported that the level of the real interest rate is significantly related to the occurrence of banking crises; and large fluctuations in foreign assets or the money supply may indicate the existence of problems in the financial system. Other than that, Castelnuovo (2013) who examined the effects of the monetary policy shock on the financial conditions in the U.S. using the dynamic stochastic general equilibrium (DSGE) model. He found a negative and significant reaction of financial conditions to the unexpected tightening of monetary policy. In other words, an unexpected drop in the money supply would cause a negative effect on the financial condition due to tightening monetary policy would increase interest rates.

In addition, using a new early warning system model, Bussiere and Fratzscher (2006) suggested that overvaluation of exchange rate and domestic credit growth appear to be predictive variables in predicting financial crises, when considering the Asian financial crisis in 1997, the Russia/Brazil crisis in 1998 and the crisis in Turkey and Argentina in 2001. Furthermore, when using a qualitative response model, the empirical evidence of Klomp and de Haan (2009) found that change in exchange rate is a significant factor in accounting for financial instability.

Similarly, market-based variables, namely real effective exchange rate, domestic credit growth and growth rate of GDP are employed in forecasting the fragility of banking and insurance sectors (Bernoth and Pick, 2011). The findings report the positive sign of domestic credit, which suggests that domestic credit acts as a measure of the healthiness of the banking sector; whereas growth rate of GDP increases distance-to-default. More importantly, the authors highlighted that inclusion of unobserved common factors in the model is crucial in predicting the instability of the banking and insurance sectors, relative to a model with only observed variables. Besides, Babihuga (2007) empirically investigated the relationship between macroeconomic and financial soundness indicators (i.e. capital adequacy, asset quality and profitability). The results suggested that the real effective exchange rate and real interest rates play an important role in determining financial soundness in the sample countries.

Some previous literature has claimed that credit-based indicators and asset prices, such as house prices and equity prices are important ingredients in assessing banking crises, systemic banking crises and capturing the financial cycle. These correspond to Borio and Lowe (2002), Laina et al. (2015), Hiebert et al. (2014) and Stremmel (2015) respectively. Furthermore, Holopainen and Sarlin (2015) employ a range of macro-financial imbalance variables, namely asset prices (i.e. house and stock prices) and leverage (i.e. mortgages and private loans) in their early warning models. Similarly, to Alessi and Detken (2009), they also found that the global M1 gap and the global private credit gap are the best early warning indicators. Besides, M2, the real effective

[5] See, for example, Borio and Lowe (2002), Alessi and Detken (2009), Hiebert et al. (2014), Lo Duca and Peltonen (2013), Holopainen and Sarlin (2015), Laina et al. (2015) and Stremmel (2015).

exchange rate, credit to the private sector and real house prices are adopted in constructing a financial stress index and predicting systemic events (Lo Duca and Peltonen, 2013).

In conclusion, indicative and relevant variables should be adopted in constructing a financial index. Therefore, financial variables, such as capital ratio, non-performing loans, and market-based variables, such as money supply, interest rate spreads, credit-based indicators, asset prices and exchange rates are advisable to be included in constructing the index in order to reflect the stability of financial system.

2.2. Credit and financial stability

Many of the existing studies suggest that credit expansion is significant in predicting the likelihood of financial crises, such as a banking crisis and a currency crisis (Goldstein, 2001; International Monetary Fund, 2004; Kraft and Jankov, 2005; Bussiere and Fratzscher, 2006; Bernoth and Pick, 2011). More importantly, Kraft and Jankov (2005) found that rapid credit growth increases the risk of deterioration in the quality of credit and leads to current account and foreign debt problems. At the same time, it also leads to financial deepening that can help to promote long-term growth. These conflicting forces create a dilemma for policy-makers. According to Kraft and Jankov (2005), lending booms are identified as a frequent factor of banking and currency crises. Similarly, Beck et al. (2006) report that a large change in the money supply may indicate the existence of problems in the financial system.

In addition, Terrones (2004), credit booms are suggested to have negative effects on the economy, or even in the worst case they are associated with serious economic recession. Furthermore, credit booms are accompanied by a rise in real stock prices and a subsequent dramatic drop after the stock price reaches its peak level. Terrones (2004) concludes that credit booms pose significant risks for emerging countries because they are typically followed by sharp economic downturns and financial crises. Furthermore, Goldstein (2001) also provided evidence on the relationship between credit expansion and the likelihood of twin crises due to capital flows.

A prominent study by Kaminsky et al. (1998) used the signal approach to prove that the behavior of domestic credit and public sector credit is particularly useful for predicting crises. Likewise, using a new early warning system model, Bussiere and Fratzscher (2006) found that domestic credit growth appears to be a significant variable in predicting financial crises. Bernoth and Pick (2011) report the positive sign of domestic credit, which suggests it acts as a measure of the healthiness of the banking sector.

Specifically, Buyukkarabacak and Valev (2010) found that household credit expansions are statistically significant in predicting banking crises. Surprisingly, the effect is stronger and more robust than the effect of enterprise credit expansions. In support of the finding, there is evidence that banking crises are often preceded by rapid private sector credit expansions[6]. This is in line with the study done by Crowley (2008), in which credit growth financed consumer spending and home ownership instead of investment. However, it is believed that business credit can promote long-term growth rather than credit for the purpose of consumption. Besides, Kraft and Jankov (2005) found that rapid credit growth cast dilemmas for policy makers, where it increases the risk of deterioration of the quality of credit and leads to current account and foreign debt problems. Meanwhile, it also leads to financial deepening that can help to promote long-term growth.

Rousseau and Wachtel (2011) found the occurrence of financial crises is associated with the dampening effect of financial deepening on growth. Moreover, rapid credit expansion or excessive financial deepening may have led to inflation and may weaken the banking system which in turn gives rise to the growth-retarding effect of the financial crises. The 2008/09 global financial crisis was triggered by rapid credit expansion, what some economists call a financial deepening, is now considered as a credit build-up or credit boom. Additionally, Kim and Rousseau (2012) examined the relationship between credit deepening, stock markets and real activity in Indonesia, Korea, Malaysia and Thailand. Unsurprisingly, they found that traditional financial deepening has led to strong negative real outcomes for Indonesia and Korea.

3. Methodology and the data

3.1. Construction of a financial stability index

To construct an index for financial stability, the dynamic factor model (DFM) was used because of the ability of DFM to overcome the problem of high dimensionality and its greater predictability. The dynamic factor model is commonly used to model multivariate time series as linear functions of unobserved factors and idiosyncratic disturbances, where an unobserved factor may follow an autoregressive process. In general form, the model can be specified as follows:

$$X_t = AZ_t + \xi_t \tag{1}$$

$$Z_t = B_1 Z_{t-1} + B_2 Z_{t-2} + \ldots + B_{t-k} Z_{t-k} + \mu_t \tag{2}$$

$$\xi_t = C_1 \xi_{t-1} + C_2 \xi_{t-2} + \cdots + C_{t-q} \xi_{t-q} + \varepsilon_t \tag{3}$$

where X_t represents a vector of dependent variables ($n \times 1$), A represents a matrix of parameters ($n \times n_f$), Z_t represents a vector of unobservable factors ($n_f \times 1$), ξ_t represents a vector of disturbances ($n \times 1$), B_i represents a matrix of autocorrelation parameters for i ($n_f \times n_f$), μ_t represents a vector of disturbances ($n_f \times 1$), C_i represents a matrix of autocorrelation parameters for i ($n \times n$), and ε_t represents a vector of disturbances ($n \times 1$).

In particular, by following Stock and Watson (1989, 1991, 2002)[7], a range of fifteen financial variables are selected[8] and written as a dynamic factor model, estimated the parameters (factor loadings) using maximum likelihood (ML). A financial indicator called financial stability index is subsequently extracted using the Kalman filter. Then, the financial stability index is validated using several forecasting tests.[9]

In the simple model, a latent (unobserved) variable is postulated to follow an AR(3) process. Each financial variable is then related to the current value of that latent variable by a parameter called factor loading (λ_i). The state-space form of the dynamic factor model is as follows:

[6] See, for example, Demirguc-Kunt and Detragiache (1997), Kaminsky et al. (1998) and Kaminsky and Reinhart (1999).

[7] Using state-space model, the authors wrote a simple macroeconomic model as a dynamic factor model, estimated the parameters by ML, and extracted an economic indicator to predict the future economic activities.

[8] The relevance of the selected variables in constructing the index is discussed in Section 2.1, and the data description is discussed in Section 3.4.

[9] Forecasting tests included in-sample analysis, out-of sample analysis, and forecast rationality.

$$\begin{pmatrix} NPL \\ RWCR \\ MS \\ SMI \\ MMR \\ Spread1 \\ Spread2 \\ Spread3 \\ Spread4 \\ DC \\ REER \\ NIR \\ HPI \\ COP \\ PCF \end{pmatrix} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \\ \lambda_5 \\ \lambda_6 \\ \lambda_7 \\ \lambda_8 \\ \lambda_9 \\ \lambda_{10} \\ \lambda_{11} \\ \lambda_{12} \\ \lambda_{13} \\ \lambda_{14} \\ \lambda_{15} \end{pmatrix} Z_t + \begin{pmatrix} \xi_{1t} \\ \xi_{2t} \\ \xi_{3t} \\ \xi_{4t} \\ \xi_{5t} \\ \xi_{6t} \\ \xi_{7t} \\ \xi_{8t} \\ \xi_{9t} \\ \xi_{10t} \\ \xi_{11t} \\ \xi_{12t} \\ \xi_{13t} \\ \xi_{14t} \\ \xi_{15t} \end{pmatrix} \quad (4)$$

$$\begin{pmatrix} Z \\ Z_{t-1} \\ Z_{t-2} \end{pmatrix} = \begin{pmatrix} \theta_1 & \theta_2 & \theta_3 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} Z_{t-1} \\ Z_{t-2} \\ Z_{t-3} \end{pmatrix} + \begin{pmatrix} \mu_t \\ 0 \\ 0 \end{pmatrix} \quad (5)$$

$$Var \begin{pmatrix} \xi_{1t} \\ \xi_{2t} \\ \xi_{3t} \\ \vdots \\ \xi_{15t} \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & 0 & \cdots & 0 \\ 0 & 0 & \sigma_3^2 & \cdots & 0 \\ 0 & 0 & 0 & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{15}^2 \end{pmatrix} \quad (6)$$

where *NPL* is non-performing loans, *RWCR* is risk-weighted capital ratio, *MS* is money supply, *SMI* is stock market index, *Spread1* is 1 year Malaysian Government Securities (MGS)/3-months Treasury bills spread, *Spread2* is 10 years MGS/3-months Treasury bills spread, *Spread3* is money market rate (MMR)/3-months Treasury bills spread, *Spread4* is MMR/U.S. federal fund rate spread, *DC* is domestic credit to private sector, *REER* is real effective exchange rate, *NIR* is net international reserves, *HPI* is house price index, *COP* is crude oil price and *PCF* is private capital fund. Besides, Eqs. (4), (5) and (6) are corresponding to Eqs. (1), (2) and (3) respectively.

Using the econometric software package STATA, the parameters of the model are estimated using maximum likelihood (ML). The unobserved factor is subsequently predicted using the Kalman filter and all sample information, and hence, the financial indicator is extracted, Z_t, which also called the financial stability index to measure the stability in the Malaysian financial system. Finally, the index is tested for its predictive power towards the Malaysian business cycle and used to examine the effects of credit expansion on Malaysian financial stability.

3.2. Assessment of explanatory power of a financial stability index

Adapted from the idea of Stock and Watson (2002)[10], selected financial indicators (as described in Section 3.1 and Appendix Table A.1) are used to estimate factor (Z_t). The estimated factor measures common movements in the set of selected financial indicators. The estimated factor is subsequently used to assess its explanatory power in explaining the movement of the Malaysian business cycle.

Formal predictive tests are employed to investigate the ability of a financial stability index to forecast the business cycle. Specifically, in-sample and out-of-sample analyses are used to assess the explanatory power of the financial stability index respectively. According to Bernanke (1990), the following equation is estimated:

$$g_{t+h|t} = \alpha_0 + \sum_{i=1}^{k} \beta_i g_{t+1-i} + \sum_{i=1}^{p} \phi_i Z_{t+1-i} + \varepsilon_t \quad (7)$$

where g represents the Malaysian business cycle series, Z represents the estimated factor or the financial stability index and ε_t represents error term. Eq. (7) includes lags of g and lags of Z up until lag length of k and p respectively, where the optimal lag length is chosen based on the Schwarz Information Criterion (SIC). Three alternative models have been specified based on SIC, which are alternative model (I) with lag k=2 and p=1, alternative model (II) with lag k=2 and p=6 and alternative model (III) with lag k=6 and p=6.

The in-sample analysis includes t-test, F-test, breakpoint test and the Theil inequality coefficient. Based on Eq. (7), if the coefficients of Z (i.e.ϕ) are statistically significant, it would imply that the financial stability index has the explanatory power in predicting the business cycle even when the autoregressive part is taken into consideration.

Besides, there is the occurrence of structural changes or crises over the sample period, such as the 2007/08 global financial crisis that brought adverse impacts on the Malaysian economy in the third quarter of 2008, in order to detect the instabilities in the coefficients of Z in Eq. (7), the *Chow* breakpoint test is employed to test the stability of coefficients of Z over the sample period.

In addition, the Theil inequality coefficient measures the performance of forecasting. The coefficient always lies between zero (0) and one (1), where zero indicates a perfect fit of the forecast. In forecasting, a small bias proportion indicates a “good” forecast, which means the forecast value is closer to the actual value.

There are chances that one may over-estimate or under-estimate the performance of a model. Hence, the out-of-sample predictive test is carried out to evaluate the predictive power of the FSI on the business cycle. In order to do so, pseudo out-of-sample forecasting is adopted by estimating Eq. (7) recursively through the forecast period with different lag lengths, where the lags of k and p are chosen at each sample period using SIC to obtain the values of root mean squared error (RMSE).

Applying the same method of forecasting, an autoregressive (AR) model is estimated as a benchmark model for comparison purposes. To compare whether the AR model outperforms the alternative model (i.e. models with financial stability index) or the alternative model outperforms the AR model in predicting business cycle. A relative RMSE to benchmark model is calculated to indicate the performance of the alternative model, where a relative RMSE with lower than 1 indicates the alternative model performing better than the benchmark model or *vice versa*.

Given that the out-of-sample forecasting is merely descriptive, the concept of forecast rationality is applied, where forecast rationality covers unbiased forecast and efficient forecast. However, the traditionally used forecast rationality does not consider the marginal or incremental information provided by the forecast values at multiple horizons. Hence, a direct test is adopted in this study. The test was developed by Vuchelen and Gutierrez (2005) specifically to identify information content of a forecast in multiple-period ahead forecasts and additionally the properties of forecast rationality.

Vuchelen and Gutierrez (2005) showed that the general form for the direct test[11] can be expressed as follow:

$$A_{t+h} = \beta_1 + \beta_2 F_t^{t+h-1} + \beta_3 (F_t^{t+h} - F_t^{t+h-1}) + \mu_{t+h} \quad (8)$$

where the forecast values of the business cycle are generated using alternative models. Based on Eq. (8), three hypotheses can be tested simultaneously. Firstly, failure to reject the joint null hypothesis for forecast rationality $-\beta_1$=0 and β_2=β_3=1 – implies the forecasts are rational. Secondly, rejection of the null hypothesis of β_3=0 indicates that the forecast values at time $t+h$ made at time t (F_t^{t+h}) adds no incremental information relative to the forecast values at time $t+h-1$

[10] A large number of macroeconomic predictors are used to estimate factor using an approximate dynamic factor model, where the estimated factor is used to forecast a macroeconomic time series variable such as inflation and industrial production.

[11] Please see Vuchelen and Gutierrez (2005) for the model derivation of the direct test.

made at time t (F_t^{t+h-1}). In other words, there is no unique information contained in the incremental h-step ahead forecast horizon. Thirdly, failure to reject the null hypothesis of β_3=1 suggests that the h-step ahead forecast is properly scaled.

3.3. Stylized facts: The characteristics of the cycles

Preliminary, characteristics of the cycles[12] can be analyzed using the information obtained from y_t and S_t, where y_t is a series in level form and S_t is a cycle series. It is very important to describe the basic properties of the cycles. The cycles can be characterized through horizontal and vertical phase statistics. In particular, S_t can be used to measure the durations of the expansion and contraction phases for the horizontal phase; while for the vertical phase, y_t can be used to measure the amplitudes of expansion and contraction phases. In addition, the information can be used to further to measure the volatility of the cycles.

The horizontal phase statistics that measures the duration of the expansion phases can be defined as:

$$\widehat{D_e} = \frac{\sum_{t=1}^{T} S_t}{N} \tag{9}$$

where $\widehat{D_e}$ represents the sample average duration of expansion,$\sum_{t=1}^{T} S_t$ represents total time a cycle series remains in expansion phase and N represents the number of trough-to-peak occurrences, $\sum_{t=1}^{T-1} (1 - S_{t+1})S_t$. When S_t=1 and S_{t+1}=0, the equation $(1 - S_{t+1})S_t$ equals to unity, which indicates a peak occurs at time t (Harding and Pagan, 2001).

The vertical phase statistics that measure amplitude of the expansion phase can be written as follows

$$\widehat{A_e} = \frac{\sum_{t=1}^{T} S_t(\Delta y_t)}{N} \tag{10}$$

where $\widehat{A_e}$ represents the sample average amplitude during expansion.

Another important vertical phase statistic that measures the magnitude of changes of a cycle phase is the volatility of expansion or contraction phases within a cycle. This measure as proposed by Edwards et al. (2003), can be defined as

$$\widehat{\varphi_e} = \frac{\sum_{t=1}^{T} S_t|\Delta y_t|}{\sum_{t=1}^{T} S_t} \tag{11}$$

where $\widehat{\varphi_e}$ represents the sample volatility of an expansion phase in a cycle. Absolute value is included in these formulae to avoid occasional negative movements that are being hidden by the generally positive movements in a series or *vice versa*.

Similar concepts apply for computing the statistics for the duration of the contraction phase, the average amplitude of the contraction phase and the sample volatility of a contraction phase.[13]

3.4. Econometric approach

Non-parametric statistics, namely a concordance index, were used to analyze the degree of synchronization between a series of credit and financial instabilities, X_t and Y_t respectively. The advantages of this approach is that (1) it does not require a stationary time series and (2) it does not suffer from sudden shocks in the series as the statistic is computed based on the constructed binary variable (i.e. S_t) instead of the actual series (i.e. Y_t). Assuming that $S_{X_t}$is a binary variable that takes the value of one when there is an expansion phase in a cycle series and zero when it is in the contraction phase. With a similar concept applied toS_{Y_t}, the degree of concordance index can be written as,

$$\hat{I}_{X,Y} = \frac{1}{T}\left[\sum_{t=1}^{T} S_{X_t}S_{Y_t} + \sum_{t=1}^{T} (1 - S_{X_t})(1 - S_{Y_t})\right] \tag{12}$$

where $\hat{I}_{X,Y}$ represents the amount of time spent by the two series, X_t and Y_t, when they are in the same phase, and T represents the sample size. The concordance index, I, lies between zero and one, where the value of 1 indicates perfect synchronization or co-movement, while the value of 0 indicates non-synchronization or no co-movement and the value of 0.5 indicates independence between the two series. For instance, the interpretation of $\hat{I}_{x,y}$=0.6 is that 60 percent of the time S_{X_t} and S_{Y_t} are in the same phase. However, the shortcoming of the non-parametric statistics is that they do not show the statistical significance of the index or statistic. Therefore, to assess the significance of the concordance index, Harding and Pagan (2002) regressed the following equation:

$$S_{Y_t} = \beta_0 + \beta_1 S_{X_t} + \varepsilon_t \tag{13}$$

where β_0 represents the constant term, β_1 represents the coefficient of S_{X_t}, and ε_t represents the white noise error term. The null hypothesis when β_1 equals to zero implies no synchronization between the series of S_{Y_t} and S_{X_t}, hence, the rejection of null hypothesis here suggests synchronization between the two series. Specifically, if the null hypothesis of β_1=0 can be rejected, credit expansion would indeed have an effect on financial stability.

Two estimations were employed to regress Eq. (13), namely ordinary least square (OLS)[14] and generalized method of moments (GMM)[15]. In OLS estimation, the null hypothesis of β_1 equals to zero, ε_t might inherit the problem of serial correlation, which might be misleading. Hence, the method proposed by Newey and West (1987) can be adopted to obtain the heteroscedasticity and autocorrelation consistent (HAC) estimates to overcome this problem, where robust t-ratios are used to assess the statistical significance of the concordance index. On the other hand, there is an important consideration when estimating Eq. (13), where the regression of S_{Y_t} on S_{X_t} with a constant may not imply the same result as that the regression of S_{X_t} on S_{Y_t} with a constant. Therefore, GMM estimation was adopted because of the endogeneity problem can be solved (Hall and McDermott, 2004).

In GMM estimation, it is important to include a set of instrumental variables that must be orthogonal to the error process, which is also known as "instrument exogeneity". Additionally, the instrumental variables also must be correlated to the included endogenous variable, which is also known as "instrument relevance" (Goh et al., 2011). The "instrument exogeneity" can be tested using J-statistics, where if the instrument variable is exogenous the null hypothesis cannot be rejected. Meanwhile, the "instrument relevance" can be tested using the F-statistics. It can be obtained by regressing an OLS regression of S_{X_t} on the set of instrumental variables and computing the F-statistics for the joint significance of instrumental variables in the regression. If the F-statistics are greater than 10, it implies that the set of instrumental variables is relevant. It is claimed that lagged endogenous variables are weak instrumental variables for Malaysia (Goh et al., 2011). Therefore, a set of instrumental variables included U.S. federal fund rate (USFFR), U.S. stock price (USSP) and U.S. commercial bank credit (USANKC) are adopted in this paper. Intuitively, the justification for adopting this set of non-lagged endogenous instrumental variables is suggested by the fact that the U.S. is one of the major trading partners for Malaysia. As a result, changes in the U.S. federal fund rate, U.S. commercial bank credit, and the fluctuations in U.S. stock price may influence the level of bank credit and hence the financial stability in a small open economy such as Malaysia. Hence, theoretically, the instrumental variables are relevant yet exogenous, which fulfil the

[12] To determine the classical cycle of the series, the Bry and Boschan (BB) algorithm was employed in this paper using RATS software. In the appendix, Table A.5 presents the details of the classical cycles measured in months. In the BB program, their analysis is designed for monthly data, where k is set equal to 5.

[13] For further details, see Edwards et al. (2003).

[14] See Boshoff (2005)

[15] See Hall and McDermott (2004) and Augustine (2008).

requirements to be good instrumental variables.

3.5. The data

Fifteen variables are adopted to construct the financial stability index. The variables include non-performing loans (NPL) and risk-weighted capital ratio (RWCR) which measure the performance of the banking system, stock market index (SMI) which measures the performance of the share market, money supply (MS), money market rate (MMR) and interest rate spreads which reflect the situation in the money market, the real effective exchange rate (REER) which covers the foreign exchange market, domestic credit to private sector (DC) which exhibits the trend in the credit market, house price index (HPI) which shows the trend in the housing market, private capital fund (PCF) which covers the capital market, crude oil price (COP) which reflects the trends in the oil market and lastly net international reserve which measures the strength of the central bank in handling financial issues, such as currency pegging. Some variables are transformed into growth rates[16]. Meanwhile, all variables are de-meaned and standardised before estimating the dynamic factor model. Moreover, variables with quarterly data are linearly interpolated into a monthly frequency. High-frequency series are deemed to be more capable of providing timely estimates of financial conditions (Matheson, 2012). Therefore, all variables are measured in monthly frequency, where the sample period covered is April 1997 to December 2011. All data was obtained from *Bank Negara Malaysia (the Central Bank of Malaysia)* as well as *Thomson Reuters Datastream*.

On the other hand, to regress the synchronization between the credit expansion and financial stability, the total value of loans approved by the banking system, by purpose and by sector, was used as the proxy for aggregate credit,[17] business credit[18] and household credit[19] respectively. All series were obtained from *Bank Negara Malaysia (the Central Bank of Malaysia)*. They were measured at monthly frequencies and transformed into real terms, by deflating the series using the Consumer Price Index (CPI), and into logarithmic form,—except for the constructed financial stability index. Additionally, the instrumental variables for GMM estimation included the U.S. federal fund rate (USFFR), the U.S. stock price index (USSP) and the U.S. commercial bank loans and leases (USBANKC) obtained from the *Thomson Reuters Datastream*. Likewise, the series USSP and USBANKC are transformed into logarithmic form to compress the scale. In this part of the paper, the sample period covered is December 1999 to December 2011.

4. Empirical results

The first part of the empirical results section reports the results of the dynamic factor model estimation and is presented in Table 1. Based on the Wald *Chi*-square statistics, the null hypothesis of all parameters (i.e. the independent variables, the unobserved factors and the auto-regressive components) are zero is rejected at all conventional levels. Furthermore, the results indicated that the unobserved factors are persistent and significant in predicting for each of the observed variables, except for the money supply, the real effective exchange rate, net international reserves and private capital fund. In addition, a negative estimated sign indicated a tightening financial condition whereas a positive estimated sign suggested an easing financial condition in Malaysia. Interest rate spreads and domestic credit were found to contribute negatively to the Malaysian business cycle. In interpreting the estimated negative coefficient of money market rate (refer to Table 1), the increase of money market rate causes the money supply to drop and eventually lead to the tightening of the financial system.

Table 1
Result of dynamic factor model estimation.

Financial variables	Coefficients (λ_i)	*p*-value
Non-performing loans (NPL)	0.0898**	0.000
Risk-weighted capital ratio (RWCR)	0.0303*	0.072
Money supply (MS)	0.0029	0.859
Stock market index (SMI)	0.0400**	0.019
Money market rate (MMR)	-0.0907**	0.000
1 year MGS/3-month T-bills spread (Spread1)	0.0583**	0.002
10 years MGS/3-month T-bills spread (Spread2)	0.2130**	0.000
MMR/3-month T-bill spread (Spread3)	-0.0348**	0.037
MMR/U.S. federal fund rate spread (Spread4)	-0.0944**	0.000
Domestic credit to private sector (DC)	-0.0361**	0.034
Real effective exchange rate (REER)	0.0142	0.388
Net international reserves (NIR)	0.0099	0.545
House price index (HPI)	0.0342**	0.044
Crude oil price (COP)	0.0622**	0.001
Private capital fund (PCF)	0.0129	0.430
Z_{t-1}	1.8280**	0.000
Z_{t-2}	-1.3127**	0.000
Z_{t-3}	0.4401**	0.000
Wald *Chi*-square	4180.28**	0.000

** and * represent 5% and 10% significance level.

From the estimation of the dynamic factor model, the financial stability index was extracted using the Kalman filter and the index is presented in Fig. 3. A reduction of the value in the constructed index indicates financial instability. Interestingly, the index showed up rather well on the recent financial downturns that occurred in Malaysia during the Asian financial crisis of 1997/98, the 2001/02 dot com bubble, and the 2008/09 global financial crisis as highlighted in the box area in Fig. 3.

The financial stability index is validated for its explanatory power on the Malaysian business cycle using a series of forecasting tests, including in-sample analysis, pseudo out-of-sample forecasting analysis and forecast rationality as described in Section 3.2. The results of the in-sample analysis, the out-of-sample analysis and forecast rationality are presented in Appendix Table A.2, Tables A.3 and A.4 respectively. Based on Table A.2, the financial stability index appeared to be a predictive index to the Malaysian business cycle as supported by significant F-tests, no structural breaks, and a near zero value of the Theil inequality coefficient (i.e. 0.0175). Additionally, based on Table A.3, the relative RMSE are lower than one at the 3- and 6-months forecast horizons for all alternative models. This result implied that the inclusion of the financial stability index improved the forecast performance in predicting the Malaysian business cycle. Lastly, based on Table A.4, the results suggested that the forecast of the business cycle using the financial stability index is rational, properly scaled and provide marginal information at the 3-month forecast horizon for all alternative models. In brief, the financial stability index is validated for its explanatory power on the Malaysian business cycle,

The relative contribution of each financial variable on the financial stability index was calculated using the weight that each financial variable has on the index that in proportion to its lambda coefficient, which is factor loading (λ_i) as estimated in Eq. (1). A negative factor loading suggests the financial condition tightens when the financial variable increases. Mainly, the financial variables with negative factor loading are from the interest rates group. Meanwhile, a positive factor loading indicates an easing financial condition when the financial

[16] For further details of data description, please refer to Appendix Table A.1.
[17] Aggregate credit consists of household and business credit.
[18] Business credit includes credit to the agriculture, manufacturing and services sector.
[19] Household credit includes loans approved for personal uses, credit cards, purchases of consumer durable goods, purchase of passenger cars, purchase of securities, purchase of transport vehicles, purchases of residential and non-residential properties.

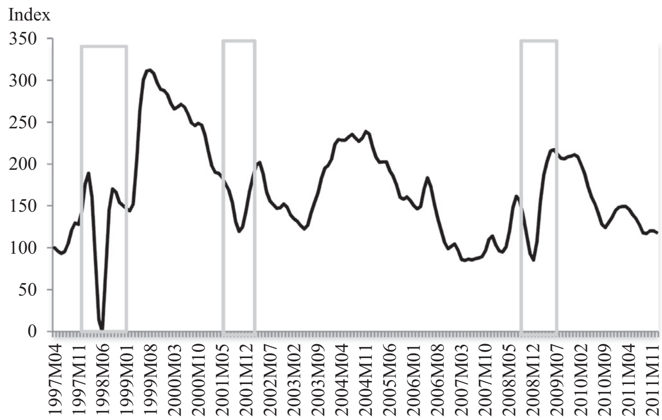


Fig. 3. Malaysian financial stability index from April 1997 to December 2011.

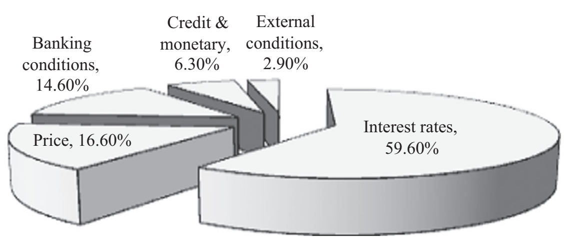


Fig. 4. Relative contribution of financial variables in financial stability index.

variable increases; and this is the case for the prices group. Fig. 4 shows the relative contribution of each group of financial indicators[20] to the financial stability index. From Fig. 4, the interest rate group is the major driver in influencing the financial condition in Malaysia, followed by price group, banking conditions group, and credit and monetary group; meanwhile external condition group is a minor contributor in the Malaysian financial system.

The second part of empirical results section reports the stylized facts about the cycles of the financial stability index, aggregate credit, business credit and household credit. The descriptive statistics, namely duration, amplitude and volatility for each phase and each series are presented in Table 2. A greater value of duration, amplitude and volatility showed a longer period, greater magnitude and greater fluctuation of the variables throughout the sample period or *vice versa*. For the cycle of financial stability index, the duration and amplitude of the contraction phases were greater compared to those of the expansion phases. The volatility of the expansion phases was slightly higher compared to that of the contraction phases. Conversely, for the cycle of credits, the duration, amplitude and volatility of the expansion phases were greater compared to those of the contraction phases, - except for household credit. Intuitively, one can infer that financial stability and credit does not spend most of the time in the same phase, suggesting that financial stability and credit are expected to move in opposite directions most of the time.

The third part of the empirical results section reports the concordance indexes. Recalling that a (rise) fall of the value in the financial stability index indicated the (stability) instability of the Malaysian financial system. Referring to Table 3; the indexes suggest that aggregate credit (expansion) and financial stability index (expansion) spent 38% of the time in the same phase, which is not significant. However, aggregate credit (expansion) and financial stability index (contraction) spent 62% of the time in the opposite phase, this result is significant. Similarly, the business and household credit, and financial stability index spent 67% and 64% of the time, respectively, in opposite phases. These results conclude that credit expansion would lead to financial instability most of the time regardless of if it is business or household credits.

The final part of the empirical results section shows the results of OLS and GMM estimations and are presented in Table 4. Based on the results of OLS estimation, the null hypothesis of β_1 equals to zero is rejected at a 5% significance level for business and household credit. This result implies that expansion in business and household credit will lead to financial instability as indicated by the negative sign of the estimated coefficients. However, the null hypothesis of β_1 equals to zero cannot be rejected for aggregate credit, suggesting insufficient evidence to reject the null hypothesis.

Based on the results of GMM estimation, the null hypothesis of the instrument variables is exogenous and cannot be rejected at all conventional levels as indicated by *J*-statistics. Hence, this result suggested that all three sets of instrumental variables fulfil the "instrument exogeneity" requirement. Meanwhile, *F*-statistics implied that all three sets of instrumental variables were relevant to the regression, where the *F*-statistics are greater than 10. Therefore, the robustness of GMM estimates was checked to fulfil the requirements of instrument exogeneity and instrument relevance.

Referring to Table 4 under the GMM estimation, the null hypothesis of β_1 equals to zero is rejected at a 5% significance level for business credit under the three sets of instrumental variables and for the aggregate credit under the first and third set of IVs (i.e. IV(1) and IV(3)). In other words, synchronization between credit and financial stability in Malaysia is negative, as indicated by the negative sign of the coefficient (β_1). Furthermore, the results indicated that on average business credit and financial stability spent approximately 74% of the time in the opposite phase. However, the null hypothesis of β_1 equals to zero cannot be rejected for household credit, which suggests no synchronization between household credit and financial instability in Malaysia. Conversely, according to Harding and Pagan (2002), the failure to reject the null hypothesis implies that an increasing level of household credit would not lead to financial instability. In summation, we concluded that there is insufficient evidence to reject the null hypothesis—that there is no synchronization occurring between the two series – household credit and financial stability index.

There is insufficient evidence and inconsistent results for aggregate credit and household credit. However, there is consistency for the results of business credit, where both OLS and GMM estimations suggested that business credit would lead to financial instability. In other words, an increasing level of business credit would tighten the financial condition and ultimately lead to financial instability.

5. Conclusions

This study examined the role of credit in influencing financial stability in Malaysia. The theory of credit expansion has been gaining popularity in recent years, especially in promoting economic growth. Nevertheless, there is limited econometric evidence tracing the link between credit expansion and financial stability at the disaggregated level, particularly in an emerging market, such as Malaysia, which from 2009 – 2013 ranked first in the *Doing Business* report published by *World Bank* for obtaining credit easily.

A financial stability index is constructed to measure financial stability, using a broad range of financial and market-based variables. Based on the dynamic factor model, a negative (positive) estimated coefficient indicated that the Malaysian financial system tightens (relaxes). By adopting a series of forecasting tests, the index appears to be predictive of the Malaysian business cycle as well as showing up rather well regarding the events of financial downturns in Malaysia. The non-parametric statistics, namely a concordance index, OLS and GMM estimations are subsequently adopted to measure the degree of

[20] Interest rates group consists of money market rate and all the four interest rate spreads; price group includes house price index, crude oil price and stock market index; NPL and RWCR represents the conditions of banking system; credit and monetary group consists of domestic credit to private sector, private capital fund and money supply; REER and net international reserves represents the group of external conditions.

Table 2
Statistics for cycles characteristics.

Series	Financial stability index	Aggregate credit	Business credit	Household credit
Duration of expansion ($\widehat{D}_e$)	16.67	37.33	36.33	52.50
Duration of contraction ($\widehat{D}_c$)	31.67	11.00	12.00	13.33
Amplitude of expansion ($\widehat{A}_e$)	6.88	1.56	3.43	2.10
Amplitude of contraction ($\widehat{A}_c$)	24.81	-0.44	-0.77	-0.20
Volatility of expansion ($\widehat{\varphi}_e$)	1.66	0.15	0.26	0.13
Volatility of contraction ($\widehat{\varphi}_c$)	1.30	0.12	0.19	0.13

Table 3
Concordance indexes.

Types of credits	Financial stability index	
	Same phase	Opposite phase
Aggregate credit	0.38	0.62
Business credit	0.33	0.67
Household credit	0.36	0.64

synchronization between credit and financial stability. Based on the concordance index, OLS and GMM estimation, the empirical results indicated that there is insufficient evidence to prove that household credit is influencing financial stability in Malaysia. The results were rather surprising.

Conversely, the results suggest that business credit plays a significant role in influencing the stability of the Malaysian financial system. An expansion of business credit would cause the financial conditions to tighten, which may lead to financial instability. In other words, business credit expansion is detrimental to Malaysian financial stability. Therefore, policy-makers face difficulties, and they should carefully consider their policy actions, as financial instability occurs when business credit expands. It is especially crucial when it involves expansionary policy actions for the purposes of financial deepening and financial development.

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Table 4
Synchronization between credit and financial stability.

Types of credits		OLS estimation	GMM estimation		
			IV (1)	IV (2)	IV (3)
Aggregate credit	β_1	-0.103	-0.7088	-0.4254	-0.5222
	SE	0.097	0.3440	0.2945	0.2778
	p-value	0.288	0.0393**	0.1486	0.0602*
	J-statistics	–	1.3396	4.4441	5.3231
			[0.2471]	[0.1084]	[0.2557]
	F-statistics	–	26.282	215.888	148.309
Business credit	β_1	-0.243	-0.7761	-0.6632	-0.7925
	SE	0.094	0.3331	0.3265	0.2915
	p-value	0.009**	0.0198**	0.0422**	0.0065**
	J-statistics	–	1.1438	3.8261	4.3891
			[0.2849]	[0.1476]	[0.3559]
	F-statistics	–	28.747	152.478	102.378
Household credit	β_1	-0.180	-6.0174	0.2734	0.0795
	SE	0.091	57.9771	0.3630	0.3007
	p-value	0.047**	0.9173	0.4513	0.7915
	J-statistics	–	0.0351	3.7568	5.4078
			[0.8515]	[0.1528]	[0.2479]
	F-statistics	–	16.318	132.255	101.395

Note: The results were obtained by regressing Eq. (13). The p-values of J-statistics are reported in square brackets. Instrumental variables for IV (1): {USFFR, USFFR(−1), USFFR(-2)}; IV (2): {USFFR, USFFR(−1), USFFR(−2), USSP}; IV (3):{USFFR, USFFR(−1), USFFR(-2), USSP, USBANKC, USBANKC(−1)}.
F-statistics is obtained by regressing an OLS regression of S_{X_t} on the set of IVs and obtain the F-statistics for the joint significance of IVs in the regression. ** and * denote significant at 5% and 10% levels, respectively. The bandwidth (q) is based on the number of observations in the sample, via the Newey-West formula: q=4(T/100)$^{2/9}$. The fixed bandwidth is 4 in this study.

Appendix

See Table A1–A5.

Table A.1
Data description for selected 15 indicators to construct financial stability index.

Indicators/Variables	Frequency	Transformation	Timing	Source
Non-performing loans	Monthly	Level	Lagging	BNM
Risk-weighted capital ratio	Monthly	Level	Lagging	BNM
Money supply	Monthly	Growth	Leading	DataStream
Stock market index	Monthly	Growth	Leading	DataStream
Money market rate (MMR)	Monthly	Level	Leading	BNM
MMR/3-months T-Bill spread	Monthly	Level	Leading	BNM
MMR/U.S. federal fund rate spread	Monthly	Level	Leading	BNM/ DataStream
1-year Malaysian Government Securities/3-months T-Bill spread	Monthly	Level	Leading	BNM
10-years Malaysian Government Securities/3-months T-Bill spread	Monthly	Level	Leading	BNM
Real effective exchange rate (REER)	Quarterly	Growth	Leading	DataStream
International reserves	Monthly	Growth	Leading/ Coincident	BNM
Domestic credit to private sector	Monthly	Growth	Lagging	DataStream
House price index	Quarterly	Growth	Leading/ Coincident	BNM
Crude Oil Price	Quarterly	Growth	Leading/ Coincident	DataStream
Private Capital Fund	Monthly	Growth	Lagging	BNM

Note: BNM – Central Bank of Malaysia

Table A.2
Results of in-sample analysis for financial stability index.

		Aggregated	**Disaggregated/Sectoral**		
		Business cycle (All sectors)	**Business cycle (Primary sector)**	**Business cycle (Manufacture sector)**	**Business cycle (Services sector)**
F-test		2.014*	1.961*	2.945***	1.811*
		[0.0565]	[0.0637]	[0.0063]	[0.0886]
t-test	Z_t	2.369**	2.580**	2.848***	0.304
		[0.0190]	[0.0108]	[0.0050]	[0.7617]
	Z_{t-1}	-3.055***	-2.994***	-3.515***	-1.500
		[0.0026]	[0.0032]	[0.0006]	[0.1356]
	Z_{t-2}	3.515***	3.317***	4.071***	2.432**
		[0.0006]	[0.0011]	[0.0001]	[0.0161]
	Z_{t-3}	-3.564***	-3.471***	-4.045***	-2.738***
		[0.0005]	[0.0007]	[0.0001]	[0.0069]
	Z_{t-4}	3.144***	3.150***	3.374***	2.395**
		[0.0020]	[0.0020]	[0.0009]	[0.0178]
	Z_{t-5}	-2.444**	-2.526**	-2.341**	-1.705*
		[0.0156]	[0.0125]	[0.0205]	[0.0901]
	Z_{t-6}	1.835*	1.962*	1.432	1.030
		[0.0684]	[0.0515]	[0.1541]	[0.3047]
Sum of coefficients		1.800	2.018	1.824	0.218
Chow test		1.681	2.134**	2.010*	2.072**
2008M7		[0.1178]	[0.0433]	[0.0574]	[0.0499]
		1.719	1.934*	1.910*	1.680
2008M8		[0.1086]	[0.0680]	[0.0717]	[0.1180]
		1.700	1.563	1.827*	1.681
2008M9		[0.1129]	[0.1506]	[0.0860]	[0.1176]

Note: The results are obtained by estimating $y_t = \alpha_0 + \sum_{i=1}^{6} \beta_i \Delta y_{t-i} + \sum_{i=0}^{6} \delta_i Z_{t-i} + \varepsilon_t$ with lags of k and p equal to 6. However, the results of the lags of y are excluded in this table due to the emphasis on Z. All p-values are reported in squared brackets. ***, **, and * denote significant at 1%, 5%, and 10% levels, respectively.

Table A.3
Results of pseudo out-of-sample forecasting error measures of financial stability index on all sectors business cycle.

Sample period		1997:4–2008:12	1997:4–2009:3	1997:4–2009:6	1997:4–2009:9	1997:4–2009:12	1997:4–2010:3	1997:4–2010:6	1997:4–2010:9	1997:4–2010:12
Model	Horizon	Root Mean Squared Errors (RMSE)								
Benchmark Model	*h*=3	0.0502	0.0388	0.0030	0.0027	0.0389	0.0106	0.0047	0.0148	0.0214
	h=6	0.0579	0.0337	0.0045	0.0258	0.0406	0.0117	0.0146	0.0118	0.0178
	h=9	0.0540	0.0286	0.0235	0.0308	0.0344	0.0156	0.0133	0.0099	0.0170
	h=12	0.0476	0.0393	0.0288	0.0276	0.0323	0.0143	0.0117	0.0114	0.0193
Model	Horizon	Relative RMSE to Benchmark Model								
Alternative Model I	*h*=3	1.07	0.98	0.93	1.11	1.01	1.01	1.11	1.03	0.99
	h=6	1.10	0.96	1.16	1.04	1.02	1.04	1.08	1.04	0.98
	h=9	1.10	0.99	1.05	1.04	1.02	1.07	1.09	1.06	1.01
	h=12	1.10	1.02	1.05	1.04	1.02	1.08	1.09	1.08	1.03
Model	Horizon	Relative RMSE to Benchmark Model								

(continued on next page)

Table A.3 *(continued)*

Sample period		1997:4–2008:12	1997:4–2009:3	1997:4–2009:6	1997:4–2009:9	1997:4–2009:12	1997:4–2010:3	1997:4–2010:6	1997:4–2010:9	1997:4–2010:12
Alternative Model II	h=3	1.06	1.01	2.00	1.30	1.01	1.07	0.43	0.97	0.87
	h=6	1.07	1.07	0.98	1.10	1.02	1.02	0.77	0.98	0.83
	h=9	1.03	1.05	0.99	1.10	1.03	0.94	0.79	1.10	1.08
	h=12	1.01	1.02	1.05	1.11	1.01	0.93	0.86	1.34	1.19
Model	Horizon	Relative RMSE to Benchmark Model								
Alternative Model III	h=3	1.25	0.81	1.97	1.22	0.87	1.42	0.40	1.12	0.78
	h=6	1.35	0.79	0.98	0.69	0.82	1.54	0.79	1.20	0.74
	h=9	1.36	0.80	0.77	0.66	0.81	1.31	0.84	1.43	1.09
	h=12	1.35	0.80	0.73	0.65	0.83	1.30	1.01	1.60	1.18

Note: Selected lag length for benchmark model is k=2; for alternative model I is k=2 and p=1; for alternative model II is k=2 and p=6 and for alternative model III is k=6 and p=6. Lag length selection is based on Schwarz Information Criterion (SIC).

Table A.4
Evaluation of all sectors business cycle forecast using financial stability index.

Horizon	**Alternative model I**				
	Coefficient estimates			**Hypothesis tests**	
	β₁	**β₂**	**β₃**	**β₁=0, β₂=β₃=1**[a]	**β₃=1**[b]
h=3	-1.46E-05 [0.9973]	0.8508 [0.0000]	0.8113 [0.0000]	3.9486 [0.2671]	2.2326 [0.1426]
h=6	-0.0066 [0.3883]	0.4859 [0.0971]	0.4118 [0.3892]	4.2926 [0.2316]	1.5463 [0.2211]
h=9	-0.0165 [0.0245]	-0.2066 [0.6961]	0.1420 [0.7884]	12.8308 [0.0050]	2.6714 [0.1109]
h=12	-0.0216 [0.0058]	0.7331 [0.1940]	0.3156 [0.5023]	12.8021 [0.0051]	2.1645 [0.1507]
	Alternative Model II				
	Coefficient estimates			**Hypothesis tests**	
	β₁	**β₂**	**β₃**	**β₁=0, β₂=β₃=1**[a]	**β₃=1**[b]
h=3	0.0009 [0.8442]	0.8504 [0.0000]	0.7901 [0.0000]	4.1585 [0.2448]	2.5899 [0.1150]
h=6	-0.0062 [0.4315]	0.2853 [0.2861]	0.0485 [0.9085]	7.3937 [0.0604]	5.1410 [0.0290]
h=9	-0.0167 [0.0244]	-0.0689 [0.8647]	0.2649 [0.5282]	11.0620 [0.0114]	3.1250 [0.0856]
h=2	-0.0174 [0.0147]	0.9952 [0.0202]	0.2335 [0.5713]	12.5934 [0.0056]	3.5267 [0.0693]
	Alternative model III				
	Coefficient estimates			**Hypothesis tests**	
	β₁	**β₂**	**β₃**	**β₁=0, β₂=β₃=1**[a]	**β₃=1**[b]
h = 3	0.0004 [0.9349]	0.8481 [0.0000]	0.8415 [0.0000]	3.1956 [0.3624]	1.2092 [0.2778]
h=6	-0.0079 [0.3022]	-0.1604 [0.5946]	-0.7494 [0.1400]	15.4366 [0.0015]	12.3691 [0.0011]
h=9	-0.0163 [0.0032]	-1.8699 [0.0000]	-1.5339 [0.0001]	88.0844 [0.0000]	52.7706 [0.0000]
h=12	-0.0169 [0.0223]	-0.6214 [0.1946]	-1.0220 [0.0970]	26.8592 [0.0000]	11.4178 [0.0019]

Note: Results are obtained by regressing $A_{t+h} = \beta_1+\beta_2 F_t^{t+h-1} + \beta_3(F_t^{t+h} - F_t^{t+h-1}) + \mu_{t+h}$. For horizon h=3, F_t^{t+h-1} is replaced by A_t. This forecast method is developed by Vuchelen & Gutierrez (2005), see this paper for further details. All p-values are reported in square brackets.

[a] reports Chi-squared test statistics with its p-value in square brackets.

Table A.5
Expansions, contractions and cycles using Bry and Boschan (BB) algorithm (in months).

Series	Peak (P)	Trough (T)	Expansion T to P	Contraction P to T	Cycle P to P
Financial		2001:10	–	–	–
stability	2002:04	2003:05	6	13	–
index	2004:11	2007:04	18	29	31
	2009:06		26	–	55
Aggregate	2000:08	2001:10	–	14	–
Credit	2005:09	2006:02	47	5	61
	2007:11	2009:01	21	14	26
Business	2000:08	2001:10	–	14	–
Credit	2004:06	2005:02	32	8	46
	2007:11	2009:01	33	14	41
Household		2000:12	–	–	–
Credit	2005:06	2006:02	54	8	–
	2007:06	2009:01	16	19	24

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