

ASSESSING BANK STABILITY IN MALAYSIA IN THE FRAMEWORK OF DISTANCE TO DEFAULT

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ABSTRACT

Post global financial crisis central banks worldwide have been crucially concerned about ensuring financial stability in any economy. Malaysia is not an exception where Bank Negara Malaysia has been playing a pivotal role in ensuring continuing safety and soundness of the financial system of the country. In the present paper, we assess the stability of domestic banks in the country using the Distance to Default (DTD). No such analytical study on Malaysian banking has so far been reported in the literature. Using the data of the financial performance of banks during the period 2001 to 2014, their stock price information on daily basis and the corresponding KLCI index, and the daily yield of Malaysian Government Securities, we compute and analyse the DTD of banks at the individual level and also assess the contribution of individual banks to systemic risk. We also assess the robustness of the framework by analysing the cases of two banks which were merged during the period 2001 to 2010. The findings of the study are expected generate extensive research interest in this arena and would also be beneficial to the investor population at large who would be keen in knowing the underpinning of the systemic stability in the country.

Keywords: bank stability, distance to default, bank performance, systemic risk, Malaysia

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INTRODUCTION

Ensuring financial stability has become the centerpiece of the regulatory mandates of the central banks worldwide after the global financial crisis had disastrous consequences on the financial system worldwide. Malaysia is not an exception. One may recall here that the word “Financial Stability” has been incorporated in the series of reports on “Financial Stability and Payment Systems Report” of the Bank Negara Malaysia (BNM) since 2007. In its report for the year 2015, BNM has stated that “Domestic financial stability is preserved and well-supported by sound institutions and orderly financial market conditions”. The report continued by stating that “Banks, in particular, have shown a high degree of earnings resilience in spite of more challenging business conditions, allowing them to maintain strong buffers through conservative earnings retention policies”. In the said report for the year 2017, BNM has stated that “the financial sector remains robust with sound financial institutions that have strong buffers to weather potential shocks under extreme stress scenarios”. Given the affirmation about the continuing confidence of the central bank on the health of banks, it may be of interest to the researchers and policy planners of the country and also the institutional investors and the other investor’s community at large to have a look at the path traversed by domestic banks in the country ever since 2000. It may be recalled here BNM had to force consolidation in the Malaysian domestic banking space in the year 2000 to stave off the pressure of mounting non-performing loans in the books of domestic banks post-Asian financial crisis. In the present paper, we use the distance to default (DTD), a market-based indicator of corporate default risk, which is also used by financial authorities and regulatory agencies to monitor the risks of financial institutions (Harada & Ito, 2011), to assess the financial strengths of banks. The robustness of DTD in the prediction of rating downgrades of financial institutions in the emerging markets and developed economies has been reported in various empirical studies (Chan-Lau & Sy, 2007). Given the history of massive fiscal and social cost post-crisis, regulators have a natural concern and incentive to intervene quite in advance to prevent bank failure and have put in place the system of “Prompt-Corrective-Action”. Haldane and May (2011) argue that one of the major sources of systemic risk in the financial systems in the recent years is the rapid rise of “super-spreader institutions” which are too big, interconnected, and too important to fail. The second source is the turmoil in the real economy and the resultant cycle of booms and bursts. The authors also argue that the regulatory prescription of higher capital and liquid assets requirement is aimed at strengthening the health and resilience of the financial system as a whole by limiting the scope for network spillovers. However, they suggest that greater emphasis needs to be given on the objective of systemic diversity. By using the quarterly data of 15 British banks for Q1 to Q4 during 2001 to 2012, Duan and

Zhang (2013) find that the systematic risk is positively and directly related to market-wide factors of risk. They also find that when the systematic risk is large, the systemic risk becomes significant. The authors also show that banks can be ranked according to their individual systemic risk contributions.

Systemic risk was modelled by Acharya (2009) by asset correlations of various banks, and the author argues that in assessing systemic risk due regulatory attention needs to be paid on the endogenous choice of interbank contracts. Acharya, Pederson, Philippon and Richardson (2017) show that the propensity of undercapitalisation of individual financial institution in a situation when the entire system is undercapitalised, is the measure of its contribution to systemic risk. Blundell-Wignall, Atkinson and Roulet (2014) argue that interconnectedness risk resulting from changing models of the business of banks and their leverage are the core drivers of the global financial crisis. They also argue that in reforming Basel regulation, the Basel Committee on Banking Supervision (BCBS) continues to focus on complex models to control leverage of banks instead on the features of business models which have a strong independent effect on DTD.

The primary motivations of our paper are to assess whether the DTD framework can facilitate the assessment of systemic risk in the Malaysian banking system by capturing the underpinnings in the financial health of individual banks in Malaysia and their unique contribution to attenuate instability or to provide a counter-veiling force to maintain stability in the Malaysian banking system. Blundell-Wignall et al. (2014) argue that the regulatory policy is ultimately aimed at reducing bank risk. In view of the regulatory forbearance and the complexity associated with the valuation of illiquid assets, it is difficult to assess the risk of default purely from the annual report data. The DTD measure combines the annual report data with market information to compute the default point at which the observable value of assets of a bank equals the book value of its debt.

LITERATURE SURVEY

Predicting Corporate Default

In the first seminal review paper, Altman and Saunders (1997) argued that in earlier years, most financial institutions primarily relied on the subjective analysis of various characteristics of borrowers like character, capacity, capital, and collateral, commonly known as 4 “Cs” in their credit-granting decisions. With the passage of time, financial institutions moved progressively towards a more objective-based assessment of credit risk of its prospective clients. They refer to the study of Somerville and Taffler (1995), who showed that a subjective approach

makes the bankers “overly pessimistic” in their assessment of credit risk in case of less-developed countries (LDCs). The multivariate credit scoring model, in which key accounting ratios are combined and assigned weights to generate a risk metric or a likelihood of measure of default, performs better than the so-called expert system. Altman and Saunders (1997) report that there are four variants of the multivariate models like the linear model, logit model, probit model, and the discriminant model. Of these models, discriminant approach dominated the literature followed by the logit model. In their study of prediction of bank failures during 1975–1976, Martin (1977) used both discriminant and logit model. A combination of the logit model and factor analysis was used by West (1985) to assess the financial health of financial institutions. It has been pointed out by Altman and Saunders (1997) that the parameters identified by logit model are akin to the components of the extant CAMEL model used by bank examiners in assessing the strength of banks. There are, however, three major criticisms of the multivariate models. First, the ratios are based on discrete accounting data and hence fail to capture the dynamic nature of the borrower characteristics which is better reflected in the data in the capital market. Second, linear models fail to forecast reality which is arguably non-linear in character. The third criticism is that the predictions of bankruptcy models are not based on very sound theoretical foundation unlike the “risk of ruin” models (Wilcox, 1973; Santomero & Visno, 1977; Scott, 1981).

As reported by Altman and Saunders (1997), a separate class of models (Jonkhart, 1979; Littermann & Iben, 1991) aim to impute the implied probabilities of default from the yield spreads of the term structure between default free and risky corporate securities. In these models, the implied forward rates are computed on risky and risk-free bonds and are used to extract the expectations of the “markets” at different points of time in the future. Actuarial type default models based on past data on bond default across credit grades and remaining terms to maturity was developed by Altman (1989a, 1989b) and the “aging” approach by Asquith, Mullins and Wolff (1989). Rating agencies have adopted the modified mortality approach but it suffers from insufficiency of default data.

In the neural network approach (Coats & Fant, 1993; Trippi & Turban, 1992), “hidden” correlations between the predictor variables are added as additional explanatory variables in a non-linear function of the prediction of bankruptcy. This approach is criticised because of its adhoc theoretical foundation and the manner in which it identifies the hidden correlation amongst the explanatory variables.

In the option pricing models proposed by Black and Scholes (1973), Merton (1974), and Hull and White (1995), the likelihood of default of a

company crucially depends on the initial market value of its assets (A) relative to outside debt (B) and the volatility of the market value of its assets (σ_A). In this formulation, the equity of a company is assumed as a call option upon the implicit value of the company with the book value of the debt of the company as the strike price. Two crucial inputs in the KMV model are A and σ_A , both of which are to be estimated from the publicly traded firms with adequate data on stock returns. It is argued that given the initial values of assets (A) and the short-term debt outstanding (B) and the diffusion of asset values over time (σ_A), one can compute the expected default frequency (EDF) for each borrowing unit. Default occurs in a future period when the market value of a company's asset falls below its outstanding short-term debt obligations. In reality, KMV uses an empirical estimate of the DTD assessment which is based on how many standard deviations asset values (A) are above B , and how much percentage of units that went bankrupt in a one-year time span with that many standard deviations of asset values above B . It is, however, of concern whether the volatility of the share price of a firm can be used as an accurate proxy of the implied volatility of the asset values of the firm and the efficacy of using a similar proxy for non-publicly traded companies. Bharat and Shumway (2008) examined the accuracy of the Merton (1974) DTD Model in forecasting bankruptcy and argued that the DD is a useful variable to forecast default but is not a sufficient statistic for default. They propose a naïve probability that captures both the functional form and the basic inputs proposed by Merton which outperforms the Merton Model. Jessen and Lando (2015) argue that despite simplifying assumptions, empirically DTD proved to be strong default predictor. The authors consider various deviations from the original Merton model like different dynamics of asset value, mechanism of default triggers, etc. and show that the ranking of default probabilities of firms using DTD is robust.

Default Studies in the Arena of Banking

Aspachs, Goodhart, Tsomocos and Zicchino (2007) argue that there is a need to develop a framework to measure financial fragility. The key component of the index of financial fragility proposed by the authors is the PD metric and they argue that it is possible to predict PD fluctuations. Wheelock and Wilson (2000) use competing risk hazard models with time-varying covariates to analyse factors that predict bank failures in the U.S. Using multivariate logit model, Demirgüç-Kunt and Detragiache (1998) evaluated the determinants of banking crisis around the globe during 1980–1994 and find that countries with low growth in gross domestic product (GDP), a high real rate of interest and explicit system of deposit insurance are more prone to a banking crisis. Based on a framework of analytical network process, Niemira and Satty (2004) propose a multicriteria decision-

making model to predict the financial crisis. Kosmidou and Zopounidis (2008) design a Utilities Additive Discriminants (UTADIS) model to predict bank failures and find that their model performs better than traditional multivariate models. Gaganis, Pasiouras and Zopounidis (2006) use a multicriteria decision aid model using UTADIS to classify 894 banks into three groups based on soundness from 79 countries and find that it outperforms decision analysis models. Zhao, Sinha, and Ge (2009) compare the performance of various factors that are used in predicting bank failures using Logit, Decision Tree, Neural Network, and K-Nearest Neighbours models and find that the choice of model is the key to the predictive power of the explanatory variables. Using a logit early warning model, Distinguin, Rous and Tarazi (2006) study the strength of stock market information, as a predictor of distress in the financial sector in the context of the safety net and the hypothesis of asymmetric information in the case of European banks. Some of their results support the use of market-based indicators and more so for banks whose liabilities are traded in the market.

Elsinger, Leharb and Summer (2006) analyse insolvency risk in 10 U.K. banks over a one-year horizon based on market data. Instead of assessing individual bank defaults, they analyse correlated exposures and interbank borrowing as major sources of systemic risk. Gropp, Vesala and Vulpes (2004) analyse the predictive power of “DTD” and the “spread” of subordinated debt issued by banks using logit model and proportional hazard model and conclude that the predictive power of negative DTD is robust in predicting downgrades between 6 and 18 months, but the predictive power is poor as default nears. To the contrary, the predictive power of “spreads” reduces beyond 12 months before downgrades for banks which are not covered by the federal safety net. As the predictive power of two together is more than on a standalone basis, bank regulators may use the signals from these models to identify banks that need closer scrutiny.

Chan-Lau and Sy (2007) argue that DTD overlooks the statutory actions taken by regulators to avoid the fiscal associated with defaults of banks under the Prompt Corrective Action (PCA) framework. They propose the concept of distance-to-capital and show that the same theoretical framework can be used to compute distance-to-capital applicable to individual banks. Using their framework, they demonstrate regulatory interventions in Japan pre-default during 2001–2003. Authors argue that though it is desirable to develop a systemic default measure which can be used to assess the stability of the financial system as a whole, aggregation of data from individual banks can mask key idiosyncrasies. Takami and Tabak (2007) in their study on the Brazilian banking sector argue that option and market-based vulnerability indicators are essential in monitoring banking risks and option-based models are preferable in classifying banks during

the period of high stress in the Brazilian banking sector during the period 1994–1995. Harada and Ito (2011) use DTD measure to assess whether the merger of banks in Japan during the 1990s and 2000s avoided failures and has added to the financial soundness of the merged entities. Using a probit model, Harada, Ito and Takahashi (2013) evaluate the predictive strength of DTD as a measure of the failure of Japanese banks.

Koutsomanoli-Filippaki and Mamatzakis (2009) in their study of default risk in EU banks find that DTD might act as an early warning mechanism both for financial instability and inefficiency in the operation of banks. The authors argue that monitoring DTD increases the ability of financial markets to be in a state of better preparedness to deal with a crisis. Blundell-Wignall and Roulet (2012) models the DTD of a sample of 94 banks controlling for the market beta of individual banks during the period 2004 to 2011 to shed light on the regulatory and policy issues. They find strong support for a policy approach on the unweighted leverage ratio of all banks but no support for Tier-I ratio under Basel-I as a predictor of DTD. Chan-Lau (2010) argue that in view of interconnectedness that exacerbates systemic risk, there is a need to impose an incremental capital charge to the individual financial institution regarding their incremental contribution to systemic risk. Saldías (2013) generates aggregated DTD series using the option prices information of systemically important banks and the STOXX Europe 600 Bank index. The author argues that systemic risk analysis is strengthened if both the measure of portfolio risk and Average DTD are put to use to monitor bank vulnerability. He also argues that information embedded in the prices of option imparts the series the property of forward-looking characteristics. Moreover, DTD series is quick to incorporate market expectations via option prices without distorting the overall position of risk in the banking system. Blundell-Wignall and Roulet (2014) argue that in view of the power of the results of the DTD models, the said approach may be used for the formulation of macro-prudential policy interventions. Betz, Oprică, Peltonen and Sarlin (2014) propose an early-warning model to predict vulnerabilities resulting in distress in European banks. They calibrate the cues from their model according to the preferences of the policymakers including the systemic relevance of individual banks as reflected in terms of their size. Their findings highlight that complementing bank-specific vulnerabilities with indicators for country-specific imbalances in the macroeconomy and vulnerabilities in the banking sector improves model performance. In addition, their model makes relevant out-of-sample predictions of distress in banks.

Milne (2014) evaluates the role of DTD of 41 largest global banks as a measure of bank performance during the financial crisis and finds that it only

provided an indication of difficulties much after the eruption of the crisis and concluded that the contingent claim models performed poorly as a market-based indicator of risk in the banks. The author also finds that Basel-II Tier-I Risk-weighted capital ratio is not useful for the prediction of default. Moreover, the argument that shareholders of major global banks were exploiting bank safety net before the crisis (Sinn Hypothesis) is incorrect; to the contrary shareholders were ignorant of the level of risk to which their banks were exposed to.

Singh, Gómez-Puig and Sosvilla-Rivero (2015) compute the individual bank level DTD and also the series at the aggregate level to assess the fragility in the EMU nations from 2004 to 2013. The authors argue that the cross-sectional differences of the respective DTD are a better predictor of fragility than the regulatory index which is based on the European level complex and large banking firms. The authors find DTD a forward-looking and intuitive measure of risk. Nagel and Purnanandam (2017) argue that the assumption of constant asset volatility in the traditional formulation of the structural model is incorrect and can significantly underestimate the default probability of banks during good times.

There are many studies (see Saha, Ahmad, & Dash, 2015) which address the issue of efficiency and also the drivers of the same in Malaysian banking. There are few studies which assess the effect of competition on financial stability in the Malaysian banking space. In their study to assess whether competition add to the banking stability across 45 countries (including Malaysia) during the period 1980 to 2005 using the H-statistic measure proposed by Panzar and Rosse (1987), Schaeck, Cihak and Wolfe (2009) conclude that higher is the level of competition in banking system lower is its proneness to systemic crisis. The authors also conclude that competition increases the time to crisis of the banking systems. Noman, Gee and Isa (2017) use H-statistic, and HHI as measures of competition and the equity ratio, and the ratio of non-performing loans as indicators of financial stability. In their analysis of possible linkage of competition and financial stability in ASEAN during the period 1990 to 2014 by applying the two-stage Generalised Method of Moments (GMM) technique, the authors also find support for the competition-stability hypothesis. The present study adopts a more generic DTD framework to assess banking stability in Malaysia.

METHODOLOGY

Database

Jessen and Lando (2015) argue that empirically DTD has been proven to be stronger in predicting default. In view of its extensive use in the literature as

documented above, we use the DTD framework to analyse the banking behaviour in our study. To obtain the “short-term liabilities” of individual banks, we use the annual reports of 10 domestic Malaysian banks including that of Bank-9 which was merged to Bank-2 in 2005–2006 and Bank-10 which was merged with Bank-4 in 2010–2011 for the period 2001 to 2014. In line with the definition adopted by Merton (1974), we compute short-term liabilities as the sum of current deposits, savings deposits, short-term debt (debt maturing within one year) and half of the long-term debt of the banks. For the risk-free rate, we take the daily yield of Malaysian Government Securities from FAST Database of BNM since 1 January 2001 to 31 December 2014. We have assumed a minimum return of 10% over risk-free rate as the expected return from the Malaysian Stock market. The daily share price of individual banks and the KLCI Index were collected from DataStream of the Thompson Reuters Database maintained at the Sultanah Bahiyah Library of the Universiti Utara Malaysia for the period under reference.

In our analysis, we compute Beta, Asset Volatility, Asset drift, DTD and the Default Probability of the banks for each year using the structural model using the iterative procedure as implemented in the software package by Löffler and Posch (2011), as detailed below.

To assess the systemic risk contribution of individual banks, we create two databases: one, the aggregate data for eight banks and in the other datasets of seven banks where we exclude one bank whose systemic risk contribution we intend to assess.

The Model (Löffler and Posch, 2011)

The foundation of the Merton model is that a firm default when the market value of its assets falls below the book value of the firm liabilities. In a simplified version of the Merton Model, we consider the firm’s liabilities consist of one zero-coupon bond with a principal value of L and maturing at time T . We assume that the equity holders wait until T before they take the decision either to default or not. The probability of default at T is then the probability that the market value of assets below the book value of liabilities. However, in general, firms do not default when the asset value reaches or fall below the book value of total liabilities of the firm; the long-term liabilities provide some elbow room. The default point, as a result, lies in between current liabilities and total liabilities of any firm. For illustrative purpose, we plot the book value of liabilities from the annual report in Figure 1 and we assume that the market value of its assets follows a lognormal distribution. The variance of the log asset value is denoted by σ^2 .

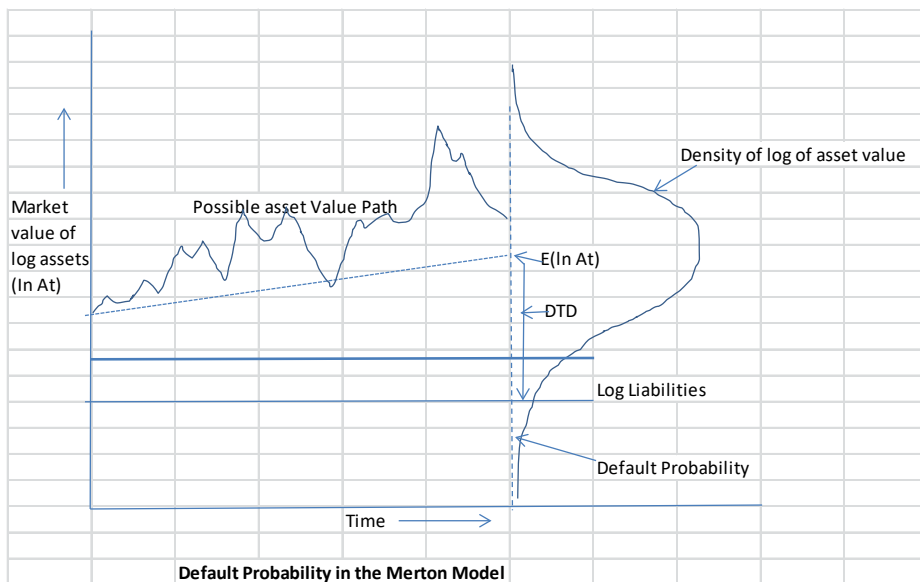


Figure 1. Profile of default probability

The expected per annum change in log asset value is denoted by $\mu - \frac{\sigma^2}{2}$, where μ is the drift parameter.

The standard deviation of the asset value measures the asset risk, and asset volatility is related to the size of the firm and its nature of the business. A firm's leverage magnifies the underlying volatility. Industries with lower asset volatility tend to assume a higher degree of leverage. Asset value, business risk, and the degree of leverage may be combined to arrive at a composite measure of default risk which is comparable to market net worth equivalent to one standard deviation movement in the asset value of a firm (Crosbie & Bohn, 2003). As it is not possible for banks to accurately discriminate between firms that would or would not default, firms pay a premium over the risk-free rate to banks to compensate in proportion to the default risk assumed by them.

Let us assume that t denotes today. The log asset value in T thus follows a normal distribution with the following parameters:

$$\ln A_T \sim N\left(\ln A_t + \left(\mu - \frac{\sigma^2}{2}\right)(T - t), \sigma^2(T - t)\right) \dots \quad (1)$$

If we know L , A_t , μ and σ^2 it would be easier to compute the default probability. In general, the probability that a normally distributed variable x falls

below z is given by $\Phi[(z - E[x])\sigma(x)]$, where Φ denotes the cumulative standard normal distribution.

Applying this result to our case, we get

$$\begin{aligned} \text{Prob. of Default} &= \Phi\left[\frac{\ln L - A_t + (\mu - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}\right] \dots \quad (2) \\ &= \Phi\left[\frac{\ln L/A_t + (\mu - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}\right] \end{aligned}$$

DTD measures the number of standard deviations the expected asset value is away from the default.

We can therefore write

$$\text{DTD} = \frac{\ln A_t + (\mu - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} \dots \quad (3)$$

$$\text{Prob. of Default} = \Phi[-\text{DTD}]$$

Mathematically, the pay-off to equity holders can be described as

$$E_T = \max(0, A_T - L) \dots \quad (4)$$

This is the pay-off of a European call option. The underlying of the call are the assets of the firm and the strike price of the call is L . The pay-off to the holders of bond correspond to a portfolio composed of a risk-free zero-coupon bond with principal L and a short put on the firm's asset with a strike price of L .

If the firm pays no dividends, the equity value can be determined with the standard Black-Scholes call option formula:

$$E_T = A_t \cdot \Phi(d_1) - L e^{-r(T-t)\Phi(d_2)} \dots \quad (5)$$

$$d_1 = \frac{\ln(A_t/L) + (r - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} \dots \quad (6)$$

$$d_2 = d_1 - \sigma\sqrt{T-t}$$

Where r denotes the logarithmic risk-free rate of return.

However, the problem is to determine the asset value A_t and the asset volatility σ and we now have an equation that links an observable value (the equity value) to those two unknowns [σ enters Equation (5) via Equation (6)]. But, we have only one equation, with two unknown variables.

Implementing the Merton model with a one-year time horizon: The iterative approach:

Rearranging the Black-Scholes Equation (5), we get

$$A_t = [E_t + L e^{-r(T-t)} \phi(d_2) / \phi(d_1)] \dots \quad (7)$$

If we go back in time, say that there are 260 trading days in a year, then we get a system of equations:

$$\begin{aligned} A_t &= [E_t + L e^{-r(T-t)} \phi(d_2) / \phi(d_1)] \\ A_{t-260} &= [E_{t-260} + L_{t-260} e^{-rt260[T-(t-260)]} \phi(d_2)] / \phi(d_1) \dots \end{aligned} \quad (8)$$

The equation system (8) consists of 261 equations with 261 unknowns (asset values). The additional unknown variable, the asset volatility σ can be estimated from the time series of A_s . Thus, the system of equation can be solved.

In general, firms have liabilities that mature at a different point in time. However, we make an ad-hoc assumption that maturity of liability is one year and we apply it on a retrospective basis on the assumption that the firm has a stable liability structure and issue debt when some part of the debt is retired. Setting $(T-t)$ to one for each day in the preceding 12 months, Equation (8) simplifies to

$$\begin{aligned} A_t &= [E_t + L_t e^{-rt} \phi(d_2)] / \phi(d_1) \\ A_{t-1} &= [E_{t-1} + L_{t-1} e^{-rt-1} \phi(d_2)] / \phi(d_1) \dots \\ A_{t-260} &= [E_{t-260} + L_{t-260} e^{-rt-260} \phi(d_2)] / \phi(d_1) \end{aligned} \quad (9)$$

This system of equation can be solved through the following iterative procedure:

Iteration 0: We set the starting values of A_{t-a} for each $a = 0, 1, 2, \dots, 260$. It is sensible to set the A_{t-a} equal to sum of the market value of equity E_{t-a} and the book value of liabilities L_{t-a} . We also set σ equal to the sum of the log asset returns computed with the A_{t-a} .

For any further iteration: $k - 1, 2, 3, \dots$ till the end.

Iteration k: We would insert A_{t-a} and σ from the previous iteration into the Black-Scholes formula d_1 and d_2 . We input these d_1 and d_2 into Equation (7) to compute the new A_{t-a} to compute the asset volatility.

We continue on until the asset values from one iteration to the next converges to below the value of 10^{-10} . The iterative procedure is implemented through the macro “iterate” in the software. With the asset values obtained through the iterative procedure, we compute the beta of the assets with respect to KLCI index and use the Capital Asset Pricing Model (CAPM) to compute the expected return using the formula, $E[R_i] - R = \beta_i (E[R_M] - R)$, where R denote the simple risk-free rate of return.

Analysis and Findings

The overall profile of riskiness of individual domestic Malaysian banks under the structural model presented in the previous section is presented in Table 1. The profile of three parameters viz. Beta, Asset Volatility, and Asset drift of the domestic banks as computed in Tables 2, 3, 4 and the corresponding Figures 2, 3 and 4 depicting these profiles are presented. Tables 5 and 6 present the profile of asset volatility and asset drift of the individual domestic Malaysian banks. A close look at the tables would provide an insight into the changing risk in the Malaysian banking system over time.

Table 5 indicates that of the four major domestic banks in terms of market share, Bank-1, Bank-2, and Bank-4 appeared 9, 6 and 5 times respectively amongst the top three in terms of asset volatility and in contrast Bank-3 appeared only once during the entire period of 2001 to 2014. In fact, the Bank-3 was at the bottom of the table in as many as 7 years. It needs to be qualified that Bank-2 was amongst the bottom three in 5 years in terms of asset drift.

Bank-1 was amongst the top three banks in terms of the size of asset drift in 11 out of 14 years followed by Bank-2 which was amongst the top three in 7 out of these years. In contrast, Bank-3 was amongst the bottom three in 9 out of these 14 years under reference. Amongst the smaller banks, in terms of asset volatility, Bank-5 was amongst top three in 10 out of the 14-year period and in terms of asset drift, it was amongst bottom three in 7 years. It is interesting to note that Bank-8 was amongst the bottom three in 11 years in terms of asset volatility and 9 years in terms of asset drift.

Table 1
Profile of riskiness of individual domestic Malaysian banks during 2001–2014

Bank name	Profile	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-1	Beta	0.119	0.098	0.153	0.199	0.289	0.155	0.113	0.139	0.23	0.199	0.172	0.131	0.26	0.337
	Asset volatility	3.37%	1.88%	3.03%	3.79%	3.34%	2.46%	3.29%	4.52%	4.26%	2.43%	2.78%	1.61%	7.99%	3.88%
	Asset drift	4.05%	3.91%	4.36%	4.15%	6.01%	4.97%	4.56%	4.19%	4.32%	4.73%	4.45%	3.30%	5.47%	6.63%
	DTD	3.566	6.393	6.395	5.593	6.093	7.505	4.848	2.501	4.749	9.174	6.603	12.059	4.854	10.804
	Default probability	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.62%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Bank-2	Beta	0.047	0.108	0.114	0.13	0.087	0.119	0.158	0.138	0.129	0.34	0.269	0.26	0.336	0.212
	Asset volatility	1.66%	2.32%	1.72%	2.18%	1.68%	2.09%	4.49%	4.24%	2.71%	4.24%	4.48%	2.76%	3.86%	3.03%
	Asset drift	3.34%	3.93%	3.99%	3.48%	4.09%	4.62%	4.99%	4.18%	3.35%	6.06%	5.37%	5.45%	6.19%	5.45%
	DTD	2.444	2.862	4.615	3.769	5.654	5.324	3.464	2.015	5.478	8.063	6.095	8.783	6.366	5.524
	Default probability	0.73%	0.21%	0.00%	0.01%	0.00%	0.00%	0.03%	2.20%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Bank-3	Beta	0.067	0.13	0.108	0.169	0.088	0.089	0.084	0.092	0.07	0.08	0.072	0.066	0.067	0.068
	Asset volatility	3.21%	3.05%	2.44%	3.20%	2.07%	1.62%	2.13%	3.08%	1.74%	1.25%	1.30%	0.90%	0.99%	1.45%
	Asset drift	3.53%	4.15%	3.93%	3.90%	4.10%	4.34%	4.28%	3.74%	2.78%	3.59%	0.29%	3.61%	3.63%	4.07%
	DTD	4.029	4.911	7.748	7.16	6.939	8.623	6.87	4.011	8.263	10.787	8.117	17.316	17.143	8.649
	Default probability	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

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Table 1 (continued)

Bank name	Profile	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-4	Beta	0.068	0.174	0.114	0.123	0.063	0.082	0.147	0.083	0.056	0.196	0.17	0.139	0.239	0.224
	Asset volatility	3.35%	3.88%	3.67%	3.49%	2.05%	2.68%	4.62%	3.21%	3.01%	2.95%	3.48%	2.22%	3.67%	4.29%
	Asset drift	3.55%	4.57%	3.98%	3.42%	3.85%	3.76%	4.88%	3.65%	2.65%	4.70%	4.43%	4.30%	5.27%	5.56%
	DTD	3.595	3.925	5.051	4.719	5.913	5.196	3.333	2.967	5.374	6.594	4.324	8.115	5.787	5.373
Bank-5	Default probability	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.04%	0.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Beta	n.a	0.08	0.124	0.094	0.132	0.098	0.163	0.158	0.155	0.194	0.223	0.125	0.233	0.151
	Asset volatility	n.a	1.98%	3.11%	4.26%	2.92%	2.14%	5.18%	1.94%	3.94%	3.39%	4.32%	2.50%	4.73%	3.41%
	Asset drift	n.a	3.66%	4.08%	3.13%	4.52%	4.43%	5.03%	4.37%	3.60%	4.68%	4.94%	4.17%	5.21%	4.87%
Bank-6	DTD	n.a	2.187	3.389	3.548	4.853	6.661	3.408	7.112	4.477	5.658	5.315	9.101	4.974	6.058
	Default probability	n.a	1.44%	0.04%	0.02%	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Beta	0.065	0.113	0.072	0.17	0.165	0.166	0.149	0.18	0.129	0.235	0.213	-0.053	0.185	0.129
	Asset volatility	1.98%	1.96%	1.50%	3.18%	2.48%	2.53%	4.15%	5.53%	2.97%	3.57%	3.63%	2.70%	2.71%	2.17%
Bank-7	Asset drift	3.52%	3.99%	3.58%	3.87%	4.84%	5.08%	4.90%	4.58%	3.35%	5.07%	2.10%	2.40%	4.76%	4.66%
	DTD	2.487	2.63	4.445	4.038	4.428	5.129	3.242	2.135	7.302	7.542	5.11	8.36	8.234	8.905
	Default probability	0.64%	0.43%	0.00%	0.00%	0.00%	0.00%	0.06%	1.64%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Beta	0.172	0.144	0.119	0.086	0.098	0.072	0.094	0.113	0.094	0.101	0.149	0.033	0.109	0.081
Bank-7	Asset volatility	5.20%	3.37%	2.23%	1.68%	1.42%	1.57%	4.26%	3.98%	2.48%	2.13%	3.39%	1.53%	1.99%	1.96%
	Asset drift	4.50%	4.28%	4.03%	3.05%	4.19%	4.18%	4.37%	3.94%	3.01%	3.79%	4.23%	3.29%	4.03%	4.20%
	DTD	2.05	2.069	3.453	4.222	4.47	5.004	3.445	2.628	4.951	8.077	3.906	7.684	6.621	5.617

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Table 1 (continued)

Bank name	Profile	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-8	Beta	0.05	0.064	0.056	0.071	0.091	0.052	0.131	0.092	0.091	0.074	0.116	0.072	-0.018	0.069
	Asset volatility	2.09%	1.77%	1.29%	1.83%	1.64%	1.28%	3.99%	2.79%	2.86%	1.82%	2.84%	1.52%	1.96%	1.63%
	Asset drift	3.37%	3.52%	3.43%	2.91%	4.13%	3.99%	4.73%	3.73%	2.99%	3.53%	3.92%	3.66%	3.86%	4.08%
	DTD	2.298	2.424	3.079	3.253	4.254	6.855	3.003	2.576	3.777	6.201	3.603	6.733	6.129	5.304
	Default probability	1.08%	0.77%	0.10%	0.06%	0.00%	0.00%	0.13%	0.50%	0.01%	0.00%	0.02%	0.00%	0.00%	0.00%

Table 2
Comparative profile of beta of domestic Malaysian Banks 2001–2014

Bank name	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-1	0.119	0.098	0.153	0.199	0.289	0.155	0.113	0.139	0.23	0.199	0.172	0.131	0.26	0.337
Bank-2	0.047	0.108	0.114	0.13	0.087	0.119	0.158	0.138	0.129	0.34	0.269	0.26	0.336	0.212
Bank-3	0.067	0.13	0.108	0.169	0.088	0.089	0.084	0.092	0.07	0.08	0.072	0.066	0.067	0.068
Bank-4	0.068	0.174	0.114	0.123	0.063	0.082	0.147	0.083	0.056	0.196	0.17	0.139	0.239	0.224
Bank-5	n. a.	0.08	0.124	0.094	0.132	0.098	0.163	0.158	0.155	0.194	0.223	0.125	0.233	0.151
Bank-6	0.065	0.113	0.072	0.17	0.165	0.166	0.149	0.18	0.129	0.235	0.213	-0.053	0.185	0.129
Bank-7	0.172	0.144	0.119	0.086	0.098	0.072	0.094	0.113	0.094	0.101	0.149	0.033	0.109	0.081
Bank-8	0.172	0.144	0.119	0.086	0.098	0.072	0.094	0.113	0.094	0.101	0.149	0.033	0.109	0.081

Table 3
Comparative profile of asset volatility of domestic Malaysian Banks 2001–2014

Bank name	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-1	3.37%	1.88%	3.03%	3.79%	3.34%	2.46%	3.29%	4.52%	4.26%	2.43%	2.78%	1.61%	7.99%	3.88%
Bank-2	1.66%	2.32%	1.72%	2.18%	1.68%	2.09%	4.49%	4.24%	2.71%	4.24%	4.48%	2.76%	3.86%	3.03%
Bank-3	3.21%	3.05%	2.44%	3.20%	2.07%	1.62%	2.13%	3.08%	1.74%	1.25%	1.30%	0.90%	0.99%	1.45%
Bank-4	3.35%	3.88%	3.67%	3.49%	2.05%	2.68%	4.62%	3.21%	3.01%	2.95%	3.48%	2.22%	3.67%	4.29%
Bank-5	n.a.	1.98%	3.11%	4.26%	2.92%	2.14%	5.18%	1.94%	3.94%	3.39%	4.32%	2.50%	4.73%	3.41%
Bank-6	1.98%	1.96%	1.50%	3.18%	2.48%	2.53%	4.15%	5.53%	2.97%	3.57%	3.63%	2.70%	2.71%	2.17%
Bank-7	5.20%	3.37%	2.23%	1.68%	1.42%	1.57%	4.26%	3.98%	2.48%	2.13%	3.39%	1.53%	1.99%	1.96%
Bank-8	2.09%	1.77%	1.29%	1.83%	1.64%	1.28%	3.99%	2.79%	2.86%	1.82%	2.84%	1.52%	1.96%	1.63%

Table 4
Comparative profile of asset drift of domestic Malaysian Banks 2001–2014 (%)

Bank name	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-1	4.05	3.91	4.36	4.15	6.01	4.97	4.56	4.19	4.32	4.73	4.45	3.30	5.47	6.63
Bank-2	3.34	3.93	3.99	3.48	4.09	4.62	4.99	4.18	3.35	6.06	5.37	5.45	6.19	5.45
Bank-3	3.53	4.15	3.93	3.90	4.10	4.34	4.28	3.74	2.78	3.59	0.29	3.61	3.63	4.07
Bank-4	3.55	4.57	3.98	3.42	3.85	3.76	4.88	3.65	2.65	4.70	4.43	4.30	5.27	5.56
Bank-5	n.a.	3.66	4.08	3.13	4.52	4.43	5.03	4.37	3.60	4.68	4.94	4.17	5.21	4.87
Bank-6	3.52	3.99	3.58	3.87	4.84	5.08	4.90	4.58	3.35	5.07	2.10	2.40	4.76	4.66
Bank-7	4.50	4.28	4.03	3.05	4.19	4.18	4.37	3.94	3.01	3.79	4.23	3.29	4.03	4.20
Bank-8	3.37	3.52	3.43	2.91	4.13	3.99	4.73	3.73	2.99	3.53	3.92	3.66	3.86	4.08

Table 5
Relative ranks of domestic Malaysian banks in terms of their Asset Volatility during 2001–2014

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-7	Bank-4	Bank-1	Bank-5	Bank-1	Bank-5	Bank-4	Bank-5	Bank-6	Bank-1	Bank-2	Bank-2	Bank-2	Bank-1	Bank-4
Bank-1	Bank-7	Bank-5	Maybank	Bank-5	Bank-6	Bank-4	Bank-4	Bank-1	Bank-5	Bank-6	Bank-6	Bank-6	Bank-5	Bank-1
Bank-4	Bank-3	Bank-1	HLBB	Bank-6	Bank-1	Bank-2	Bank-2	Bank-4	Bank-4	Bank-5	Bank-6	Bank-5	Bank-2	Bank-5
Bank-3	Bank-2	Bank-3	PUB	Bank-3	Bank-5	Bank-7	Bank-7	Bank-6	Bank-6	Bank-4	Bank-4	Bank-4	Bank-4	Bank-4
Bank-8	Bank-5	Bank-7	AMMB	Bank-4	Bank-4	Bank-2	Bank-6	Bank-4	Bank-8	Bank-1	Bank-7	Bank-1	Bank-6	Bank-6
Bank-6	Bank-6	Bank-2	CIMB	Bank-2	Bank-3	Bank-3	Bank-8	Bank-3	Bank-2	Bank-7	Bank-8	Bank-7	Bank-7	Bank-7
Bank-2	Bank-1	Bank-6	Bank-8	Bank-8	Bank-7	Bank-1	Bank-1	Bank-8	Bank-7	Bank-8	Bank-1	Bank-8	Bank-8	Bank-8
n.a.	Bank-8	Bank-8	Bank-7	Bank-7	Bank-8	Bank-3	Bank-3	Bank-5	Bank-3	Bank-3	Bank-3	Bank-3	Bank-3	Bank-3

Table 6
Relative ranks amongst domestic Malaysian banks in terms of their Asset Drift during 2001–2014

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-7	Bank-4	Bank-1	Bank-1	Bank-1	Bank-1	Bank-6	Bank-5	Bank-6	Bank-1	Bank-2	Bank-2	Bank-2	Bank-2	Bank-1
Bank-1	Bank-7	Bank-5	Bank-3	Bank-6	Bank-1	Bank-1	Bank-2	Bank-5	Bank-5	Bank-6	Bank-5	Bank-4	Bank-1	Bank-4
Bank-4	Bank-3	Bank-7	Bank-6	Bank-6	Bank-5	Bank-2	Bank-6	Bank-1	Bank-2	Bank-1	Bank-1	Bank-5	Bank-4	Bank-2
Bank-3	Bank-6	Bank-2	Bank-2	Bank-2	Bank-7	Bank-5	Bank-4	Bank-2	Bank-6	Bank-4	Bank-4	Bank-8	Bank-5	Bank-5
Bank-6	Bank-2	Bank-4	Bank-4	Bank-4	Bank-8	Bank-3	Bank-8	Bank-7	Bank-7	Bank-5	Bank-7	Bank-3	Bank-6	Bank-6
Bank-8	Bank-1	Bank-3	Bank-5	Bank-3	Bank-3	Bank-7	Bank-1	Bank-3	Bank-8	Bank-7	Bank-8	Bank-1	Bank-7	Bank-7
Bank-2	Bank-5	Bank-6	Bank-7	Bank-6	Bank-2	Bank-8	Bank-7	Bank-8	Bank-3	Bank-3	Bank-6	Bank-7	Bank-8	Bank-8
Bank-5	Bank-8	Bank-8	Bank-8	Bank-8	Bank-4	Bank-4	Bank-3	Bank-4	Bank-4	Bank-8	Bank-3	Bank-6	Bank-3	Bank-3

Table 7
Profile of distance to default of domestic Malaysian banks 2001–2014

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Bank-1	3.566	6.393	6.395	5.593	6.093	7.505	4.848	2.501	4.749	9.174	6.603	12.059	4.854	10.804
Bank-2	2.444	2.862	4.615	3.769	5.654	5.324	3.464	2.015	5.478	8.063	6.095	8.783	6.366	5.524
Bank-3	4.029	4.911	7.748	7.16	6.939	8.623	6.87	4.011	8.263	10.787	8.117	17.316	17.143	8.649
Bank-4	3.595	3.925	5.051	4.719	5.913	5.196	3.333	2.967	5.374	6.594	4.324	8.115	5.787	5.373
Bank-5	n.a.	2.187	3.389	3.548	4.853	6.661	3.408	7.112	4.477	5.658	5.315	9.101	4.974	6.058
Bank-6	2.487	2.63	4.445	4.038	4.428	5.129	3.242	2.135	7.302	7.542	5.11	8.36	8.234	8.905
Bank-7	2.05	2.069	3.453	4.222	4.47	5.004	3.445	2.628	4.951	8.077	3.906	7.684	6.621	5.616
Bank-8	2.298	2.424	3.079	3.253	4.254	6.855	3.003	2.576	3.777	6.201	3.603	6.733	6.129	5.304

Table 8
Profile of distance to default of Bank-2, Bank-9, Bank-4, and Bank-10

Bank name	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Bank-2	2.44	2.84	4.62	3.6	5.04	5.29	3.43	2.01	5.33	8.09
Bank-9	n.a.	n.a.	2.8	4.75	5.68	n.a.	n.a.	n.a.	n.a.	n.a.
Bank-4	3.59	3.9	5.02	4.66	5.61	5.35	3.3	2.89	5.31	6.6
Bank-10	n.a.	n.a.	3.69	5.16	4.74	5.48	3.39	1.07	4.89	8.54

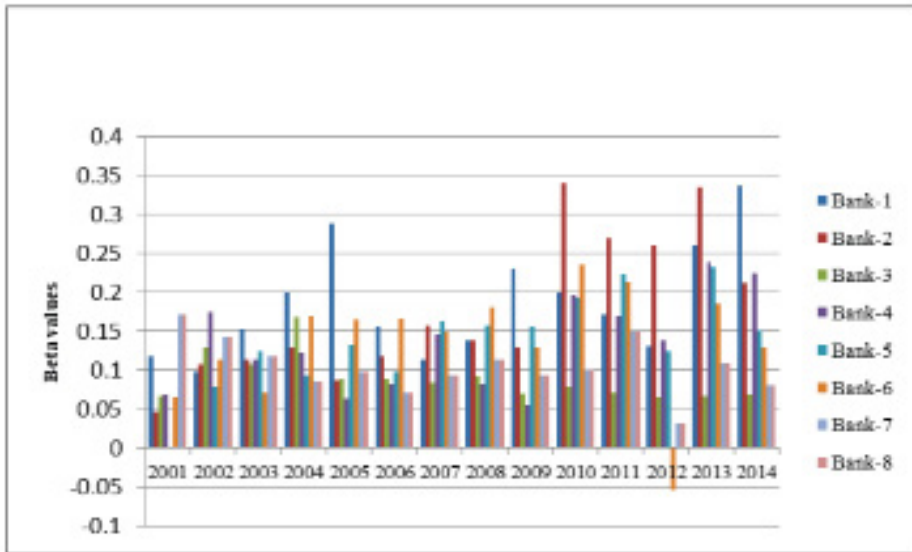


Figure 2. Comparative profile of beta of domestic Malaysian banks for 2001–2014

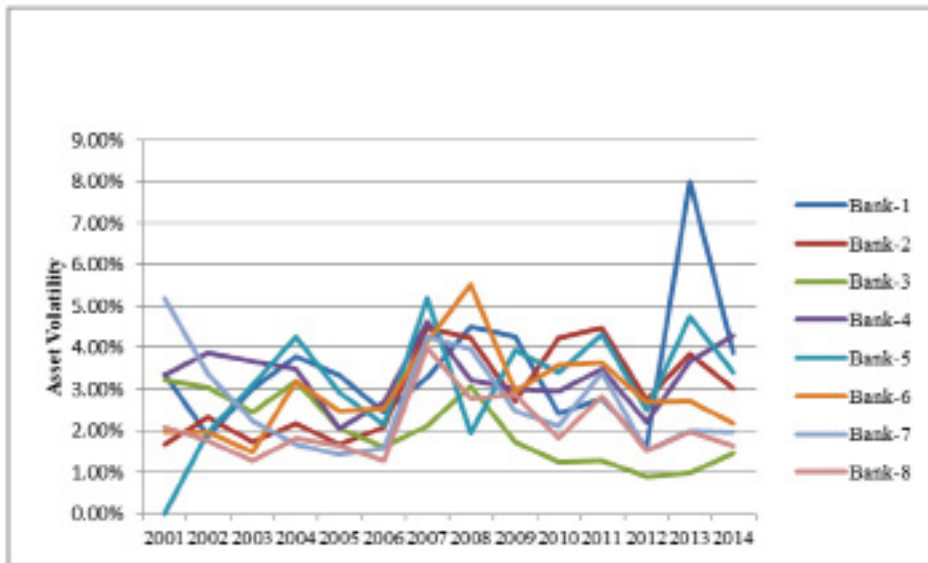


Figure 3. Comparative profile of asset volatility of domestic Malaysian banks for 2001–2014

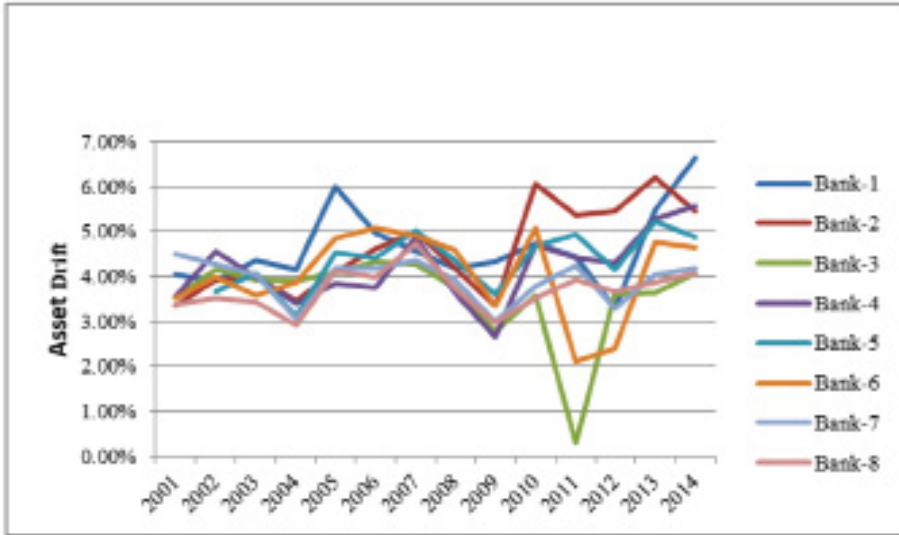


Figure 4. Comparative profile of asset drift of domestic Malaysian banks for 2001–2014

A close look at Table 7 on the profile of the DTD of the domestic Malaysian banks and the corresponding Figure 5 would indicate that the overall direction of movement of the DTD curve is bundled. On the whole, DTD started moving up from 2001 until 2006 and there was a sharp drop in its values across the banks during the period of global financial crisis and bottomed out in 2008. Since then though there was a marked improvement in the overall profile of the position in case of domestic banks, the profile was however erratic from 2010 to 2014. On the whole, Bank-3’s DTD profile dominated all the banks followed by Bank-1 and Bank-4.

To assess the robustness of the framework of DTD in capturing the potential distress of banks in Malaysia, the analysis was extended to the case of two banks which were merged during the first decade of this century: Bank-9 was merged with Bank-2 in 2005–2006 and Bank-10 was taken over by Bank-4 in 2010–2011. Table 8 presents the profile of DTD of these banks for the period for which the data was available. It is interesting to note that framework is able to clearly capture the pending distress and vulnerability for Bank-10 especially during the financial crisis when its DTD fell down to as low as 1.07, the lowest amongst all the domestic banks during the said year, by the end of 2008 dropping from the level of 5.35 during the pre-crisis year of 2006.

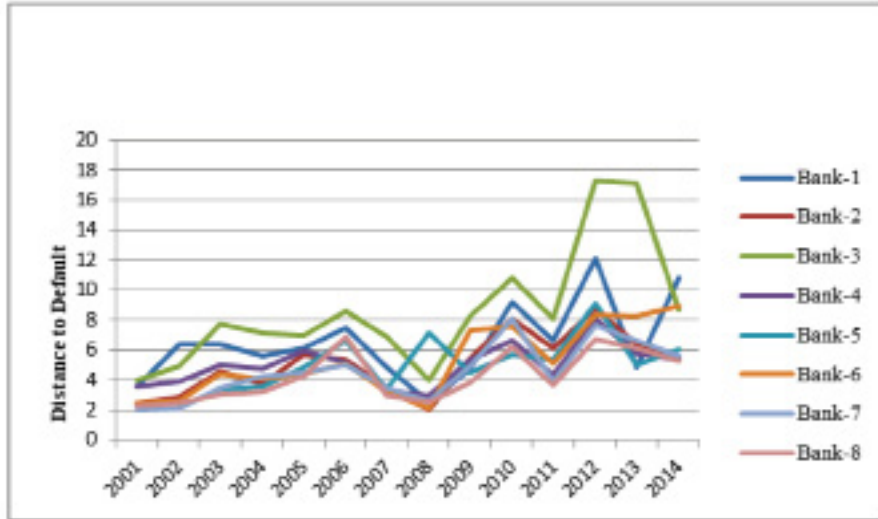


Figure 5. Comparative profile of distance to default of Malaysian banks 2001–2014

Table 9
Systemic risk contribution of individual domestic Malaysian banks

Year	Particulars	Aggregate	Excl. Bk-1	Excl. Bk-2	Excl. Bk-3	Excl. Bk-4	Excl. Bk-5	Excl. Bk-6	Excl. Bk-7	Excl. Bk-8
2002	DTD	5.88	4.75	5.88	5.45	5.43	5.83	4.14	6.02	5.82
2003	DTD	7	4.12	7.4	7.31	6.77	7.01	7.13	6.99	7.02
2004	DTD	7.67	7.22	7.47	6.8	7.37	7.52	7.8	7.69	7.66
2005	DTD	9.57	9.33	9.17	8.52	9.21	9.46	9.48	9.56	9.53
2006	DTD	11.35	10.45	11.4	10.33	10.83	11.18	11.34	11.22	11.2
2007	DTD	7.01	6.71	7.27	5.96	6.94	6.98	7.13	6.91	7.03
2008	DTD	3.92	4.02	4.08	3.29	3.73	3.88	3.98	3.83	3.87
2009	DTD	8.55	10.11	8.24	7.49	8.16	8.49	8.21	8.38	8.51
2010	DTD	12.71	12.35	13.13	11.5	12.47	12.63	12.64	12.44	12.63
2011	DTD	8.76	8.59	8.86	7.8	8.73	8.73	8.8	8.87	8.76
2012	DTD	17.09	16.54	19.26	15.06	16.35	10.37	16.67	15.61	17.04
2013	DTD	12.15	11.52	13.71	10.78	11.76	12.22	12.1	12.07	12.09
2014	DTD	12.79	12.07	13.73	12.8	9.32	12.7	12.46	12.62	12.75

Note: DTD = Distance to default

Having analysed the riskiness/robustness of individual banks under the DTD framework, it was felt imperative to analyse and assess the contribution of individual banks towards the systemic profile of banks in the country. It can be

seen from Table 9 that the DTD at the aggregate level increased gradually from 5.88 to 11.35 by 2006 but dropped significantly down to 3.92 by the end of 2008. The effect of the financial crisis on the systemic risk in domestic commercial banking space is therefore quite vivid. The situation, however, improved quite rapidly in the subsequent years by the end of 2014. In terms of the contribution of an individual institution to systemic risk would indicate, of the four bigger banks, Bank-2 has been contributing to systemic risk in most of the years during the period under reference. Bank-1 had also added to the systemic risk during 2008 and 2009. Most significantly, Bank-4 and Bank-3, especially the Bank-3 has been providing a cushion to the system throughout the period under reference and have reduced the systemic risk at the aggregate level.

CONCLUSIONS AND DISCUSSIONS

As the economy of Malaysia is entering into a new phase of reckoning, the robustness of the health of individual banks and hence systemic stability would be of crucial importance. The International Monetary Fund (IMF) Report (IMF, 2014) on the performance of financial sector of the country notes that comfortable macroeconomic environment, strong oversight of regulation since the consolidation exercise in 2000 to meet the shocks arising out of the Asian Financial crisis in 1997–1998, and favourable policies of the government has resulted in a rapid progress in the financial sector of the country. The report notes that as per the baseline projected GDP growth rate of 5% and the projected growth of credit of 8% per annum, Malaysian banks would be able to meet the requirements of Basel-III core Tier-I capital requirement and would at the same time be able to meet the growth requirement of the economy. In a high growth scenario, however, banks may have to skip dividend or raise additional capital of around USD260 million to meet the growth requirements of the economy. The report also notes that as the credit cycle in the economy steps into late expansionary phase, there is a need to bolster the resilience of the domestic banks through counter-cyclical policies of capital retention, raising capital base and restrain exuberance in lending.

The trajectories of banks as assessed using the framework of distance to default clearly reflect that despite the apparent strength of banks at the overall level, the banking system did face the stress post-global financial crisis. The low default probability as observed during the entire reference period is extremely low, but this is not surprising given the low asset volatilities and low leverage ratios of the Malaysian banks. Besides, the Merton Model tends to underestimate empirical PDs. So, whereas the model as implemented in the software could suggest the PDs as zero, practical applications of the model would recalibrate

PDs, and possibly assume some minimum value in addition to the recalibration. Moody's KMV, for example, uses a minimum PD of 0.01%. Based on the analysis of 22 largest investment banks and bank holding companies, Patro, Qi and Sun (2013) found that correlation of daily stock return is a timely and forward-looking indicator of systemic risk. Adrian and Brunnermeier (2016) proposed a ΔCoVaR measure of systemic risk and argued that it is a robust indicator to predict systemic risk in the financial system. Researchers may like to explore these approaches in their assessment of systemic risk in Malaysian banking.

We are sure that the present paper being the first of its kind would attract the attention of the scholars engaged in the research work on banking stability in Malaysia. Moreover, given the robustness of the framework of DTD as a predictor of impending stress in the banking system, the findings of the study would also attract the attention of the regulator and the policy planners in the country. The investors' community at large would undoubtedly be watching the findings of the present study with keen interest.

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