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Bank Failure: A New Approach to Prediction and Supervision

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Abstract

Bank failures are costly to customers and the wider market. Prevention is always better than cure but in light of recent economic downturns, it has become increasingly difficult for regulators to allocate more resources towards in-depth monitoring of banking practices. In this paper, we construct a tool that is able to predict bank failures ahead of time with reasonable accuracy. Through a logistic regression on a matched sample of 536 failed and non-failed US banks, we determine the financial indicators that most accurately predicts bank failure. From the regression, we construct a Bank Health Index that assesses a bank's propensity to failure. In-sample and out-of-sample tests show that our model is about 90% accurate two years prior to failure, and 95% accurate the year before failure. The accuracy and efficiency of the model and index provides a more efficient and effective tool for assessing a bank's propensity to failure besides requiring far less resources. With these methods, regulators will be able to take preventive measures at least one year before failure, saving the economy millions if not billions in the process.

Keywords: Bank failure, Financial crisis, Failure prediction, Commercial banks, Early warning system

1. Introduction

Are current risk management and monitoring devices adequate to avoid bank failures in light of increasing globalisation, market integration, and the use of innovative (and sometimes questionable) financial innovations used by banks and other financial institutions? Despite the well-meaning objectives of the Basel Capital Accord – now in its third iteration – many banks the world over have failed as a result of a number of financial crises such as the Asian Financial Crisis of 1997 (AFC) and the Global Financial Crisis of 2007 (GFC). Governments and central banks around the world resorted to billion-dollar liquidity injections and bailouts to avoid a severe tightening of credit and losses to customer deposits in their respective economies. Wary of bank failures, regulators have responded by introducing a multitude of risk management tools and benchmark financial indicators to ensure that banks remain adequately capitalised to absorb losses arising from credit, operational, and market risks. But as the large number of bank failures resulting from the recent crises shows, our ability to predict bank failure is severely lacking. If we are able to understand the factors related to bank failure, we could develop predictive methods to distinguish between sound and troubled banks (Thomas, 1991). With sufficient accuracy, these predictive methods will enable regulators to detect problems much allowing for remedial action to mitigate the risk of bank failure.

A number of works in predicting bank failure have been conducted (see Beaver, 1996; Altman 1968; Agarwal and Taffler, 2008; Andersen, 2008; Atiya, 2001; Balcaen and Ooghe, 2005; Bell and Pain, 2000; Bongini, Laeven and Majnoni, 2002; and Brossard, Ducrozef and Roche, 2007 for example) but despite the tremendous methodological developments in bank failure prediction models, bank failures persist; a strong indication of the inadequacy of existing models. Thus exists a need for a rethink and redesign of bank health evaluation using a new set of indicators, and subsequently, a unified device or tool that can be continuously used to monitor the soundness of individual banks.

In this study, we derive these key bank health indicators from 536 recent examples of bank failures resulting from the GFC in the U.S. by observing the changes to CAMEL (Capital, Asset, Management, Earnings and Liquidity) framework indicators in the 4 years leading up to the bank's failure. By estimating a logit model on a year by year basis, we find that the indicators that can best distinguish between healthy and unhealthy banks are Tier 1 capital ratio, impaired loans to equity, rate of loan growth, return on average assets, net interest margin, net loans to total assets, loans to deposits ratio, and impaired loans to gross loans. In-sample tests show that our model has a reasonably high chance of correctly predicting bank failure in the year of failure (89.86%) and the preceding year (81.30%). Out-of-sample tests validate our findings; showing a perfect accuracy of predicting bank failure in the year of failure (100%) and near-perfect accuracy in the preceding year (95.38%), with minimal Type I and II errors. On the basis of these indicators, we then construct a "Bank Health Index" to develop a more efficient method of assessing the soundness of a bank relative to other banks as well as the entire banking system. We used a sample of 20 domestic and foreign banks operating in Malaysia for this purpose as Malaysia's banking regulatory system has been regarded as one of the best in the world.

Our findings contribute to extant literature in a few ways. First, our model's accuracy in correctly predicting bank failure surpasses the predictive power of other failure-prediction models in the literature, with minimal error. Second, the simplicity of our variables and methods used in deriving the model makes ours more efficient and practicable for regulators and market observers alike. Finally, the "Bank Health Index" provides a quick and easy way for regulators to identify potentially unhealthy banks and take immediate remedial action at least one year before failure. The rest of this paper is structured as follows. Section 2 provides a review of relevant literature. Section 3 presents the theoretical framework and methodology used in this study. We present our findings and discussion in Section 4. Section 5 concludes.

2. Literature Review

Central to the existence of the modern economy is the role banks play as the primary intermediary for the distribution of funds. It is thus in the best interests of the regulators to avoid the possibility of a bank failure. But despite the regulators' best efforts, bank failures still occur. And when they do, the repercussions are far-reaching. In order to detect and prevent bank failure, we must first identify the aspects of bank operations and fund flows that are critical to the survival of the bank. The following discussion on relevant indicators is based on the CAMEL framework prescribed by central bankers and the International Monetary Fund (Gersl and Hermanek, 2006).

The first is its highly leveraged nature of business that is reliant on loans, advances and short-term investments, as assets that stem from liabilities held by the bank (e.g. deposits). The creation of assets from liabilities is simply a redistribution of wealth and is a system that has worked for centuries. However, an economic downturn may cause a rise in loan defaults, or falling asset values. Banks in response would have to make higher loan loss provisions and be prepared to write-off bad loans as collateral values are insufficient to cover bad loans; a prime indicator of insolvency (Kunt and Detragiache, 1998), and poor asset quality (Gonzalez-Hermosillo et al., 1996). Periods of economic growth meanwhile would see the growth of the banking system outpacing that of the country and even inflation. The exuberance may result in questionable lending practices and poor asset quality, creating potential loan repayment and recovery problems in the future (Bell and Pain, 2000; Jimenez and Saurina, 2006; Berg and Hexeberg, 1994; Logan, 2003). Studies (e.g. Foos et al., 2010; Andersen, 2010) have shown that aggressive lending during growth periods often lead to defaults two to four years after, resulting in a cooling and declining period of banking growth that may even amount to negative growth.

Even if steps to ensure the quality of their loans and assets were taken, defaults inadvertently occur, hence the need for loan loss reserves to act as a buffer against writing down the bank's capital (Anglomkiew et al., 2008; Floro, 2010). During severe market downturns, loan loss reserves are insufficient; capital erosion becomes inevitable until loan losses significantly outweigh available capital resulting in insolvency and subsequently, failure. Common indicators of bank capital adequacy are the core capital ratio and the risk-weighted capital ratio, prescribed by the Basel II (and III) Capital Accords. These ratios are a good measure to determine the strength of a bank as adjustments for credit risk arising from off-balance sheet items have been considered in these ratios (Estrella, 2000). Thus, a greater amount of capital improves a bank's chance of survival (Andersen, 2008).

Another key aspect for bank survivability is liquidity. Bank liabilities, primarily stemming from customer deposits, are generally short term in nature vis-à-vis its assets that are longer term, thereby creating liquidity mismatch. As depositors have a right to withdraw funds without notice, banks must maintain sufficient liquidity at all times. But when revenue generated from loans and other assets fall short of liquidity demands, or when banks fail to convert liquid assets into cash on time, the liquidity shortage might result in a bank run (Lanine, 2005; Reed and Gill, 1989). Close observation of the loan-to-deposit ratio and the net-loans-to-assets ratio may provide indication of the bank's level of liquidity.

Bank profitability is reflected in the net interest margin (NIM). However, as NIM is dependent on the rate of interest charged on loans as well as the interest cost of sourcing loanable funds for distribution, high NIMs may be indicative of excessive risk taking and imprudent lending practices (Evans et al., 2000). During the AFC and GFC, banks dependent on short-term money market funds saw market interest rates rising to their detriment, reducing NIMs from two fronts: higher cost of funds, and greater loan defaults due to higher repayments. Extraordinarily high NIMs are possibly indicative of potential failure as banks hold a large portfolio of high-yield risky, as well as interest-bearing assets (Ross et al., 2007). High NIMs may also precede failure much earlier and fall significantly immediately before failure due to higher loan loss provisions (Despagne, 2010). Regardless, inclusion of NIMs into a failure-prediction model should provide additional explanatory power.

The literature is replete with off-balance sheet items (OBS) and short-term wholesale funding and its association with bank failures. Greater amounts of these assets are associated with a greater probability of failure. Similarly, studies (e.g. DeYoung and Toma, 2012; Allen and Jagtiani, 2000; Clark et al., 2007) have shown that reliance on volatile non-traditional income sources (i.e. non-interest income) such as insurance income, fees, commissions and other non-interest bearing income are associated with higher probabilities of bank distress. Failed banks are expected to have been more aggressive in their business diversification strategies and to have sought out the opportunities arising from scope deregulation. Banks have also diversified their sources of funding into non-traditional sources such as short-term money market funds. Given the volatile nature of these funding sources, over-reliance on such funds could place the bank in a risky liquidity position. Observation of the ratio of wholesale short-term liabilities to liquid assets (WST) is thus warranted.

But even with hawkish monitoring over these indicators, bank failures can and do occur as a result of inefficient bank management exemplified through poor operations, management, monitoring of loans and sub-optimal use of resources. Often observed through return on average assets (ROAA), management efficiency can be translated as the profits generated through efficient usage of assets. Operational efficiency on the other hand, can be observed through the cost to income ratio (CIR); an indication of how well the bank has kept growth of revenues ahead of rising expenses (Rahman, 2004).

3. Theoretical Framework and Methodology

3.1 Explanatory Variables

Based on the literature review in Section 2, the variables observed in this study, their definitions and their expected impact on the propensity of bank failure is summarised in Table 1 below.

Table 1. Definition of Variables

Variable	Variable abbreviation	Expected sign
Capitalization		
Total Capital Ratio (Tier 1 + Tier 2 capital / Risk-weighted assets)	TOTCAP	(-)
Core Capital Ratio (Tier 1 capital / Risk-weighted assets)	TIERCAP	(-)
Asset Quality/Credit Risk		
Impaired loans / Gross loans	IMPL	(+)
Loan loss reserves	LLR	(+)
Impaired loans / Total equity	IMPE	(+)
Loan Loss Reserves / Impaired loans	LLIMP	(+) / (-)
Loan growth (year-on-year)	LOANGROWTH	(+)
Asset growth rate (year-on-year)	AGR	(+)
Earnings or Profitability		
Net income / Average equity	ROAE	(-)
Net interest margin (NIM): (Net interest income – Net interest expense / Total earning assets)	NIM	(-) / (+)
Liquidity		
Net loans / Total assets	NETLOANS	(+)
Loans to deposit ratio	LOANDEP	(+)
Liquid funds (cash and short-term assets) / Total assets	LIQ	(-)
Reliance On Fee Income		
Non-interest fee income / Total income	INTEREST	(+)
Relience on off-balance sheet items		
Off-balance sheet items / Total assets	OBS	(+)
Reliance on short-term wholesale funds		
Volatile Wholesale short-term liabilties / Liquid assets	WST	(+)
Management Quality / Efficiency		
Return on average assets	ROAA	(-)
Cost to income ratio	CIR	(+)

We obtained a sample of 536 U.S. banks between the years 2004 to 2010, with an equal number of failed and non-failed banks, matched by total assets, from the Bankscope database. Because the U.S. saw a large number of bank failures during the GFC, it provides an ideal setting to the predictive power of our model. Malaysia alongside many other countries around Asia on the other hand, was relatively unscathed. Even during the AFC, Malaysia being one of the worst-hit did not see any bank failures due to rescue packages and bank mergers and acquisitions.

Because our purpose is to study the predictability of bank failure *a priori*, we collected data on the variables listed in Table 1 for the years before the bank failed. We denote the year of failure as $Year_0$, and the preceding years as $Year_{-1}$, $Year_{-2}$, $Year_{-3}$, and $Year_{-4}$; observing changes to the variables over the years for any significant changes or trends. Identifying the variables with considerable explanatory power is simply a matter of determining the statistically significant differences in the mean values between the failed and non-failed sample (Vilen, 2010).

3.2 Empirical Model

We use a logistic regression model to identify the financial ratios that can most effectively discriminate between failed and non-failed banks in the most reliable (Frydman et al, 1985; Marais et al, 1984; Ohlson, 1980; Casey and Bartczak, 1985; Zavgren, 1985; Glezakos et al, 2010) manner. The model specification is:

$$Y_i = \beta_0 + \sum_{i=1}^{k} \beta_i X_i \tag{1}$$

where Y_i is a binary variable with a value of "1" for a failed bank and "0" for a non-failed bank, while X_i is a vector of the explanatory variables that have been determined to possibly have the strongest explanatory power in predicting bank failure. If the probability of bank i failing is $P(Y_i = 1) = \hat{p}$ and the probability of bank i not failing is $P(Y_i = 0) = 1 - \hat{p}$, then

$$\hat{p} = \frac{e^{\beta_0 + \sum_{i=1}^{k} \beta_i X_i}}{1 + e^{\beta_0 + \sum_{i=1}^{k} X_i}} \tag{2}$$

Logit models are sensitive to extreme multicollinearity (Balcaen and Ooghe, 2005) and thus, Espahbodi (1991) advocates the use of more than one measure in studying bank health to avoid issues related to multicollinearity. As we seek to construct a model as an early warning system, we estimate the regression for the year of failure as well as for each of the four years preceding failure. To test the reliability and external validity of our method, we re-estimate the logit model using a hold out sample (Jones, 1987).

3.3 Constructing the Bank Health Index

To construct the "Bank Health Index", we first define the value ranges of the statistically significant variables from the logit estimates by computing 95% confidence intervals around the mean values of each variable for the failed and non-failed sample. We only compute value ranges for $Year_{-1}$ and $Year_{-2}$ as the predictive power of variables diminish beyond two years preceding failure (Espahbodi, 1991). This confidence level for the variables is constructed base on the following expression.

$$\text{Upper bound} = \bar{x} + 1.96 * \frac{s}{\sqrt{n}} \;;\quad \text{Lower bound} = \bar{x} - 1.96 * \frac{s}{\sqrt{n}} \tag{3}$$

The computed value ranges will be further classified into a risk continuum ranging from critical to excellent depending on the correlation of the significant variable ratios to failure.

The value ranges computed above need to be interpreted with respect to each of the ratios. For example, for variables negatively related to bank failure such as capitalization ratios, a higher ratio indicates better health. Hence, a ratio falling below the "failed" range will be categorised as "critical" while a ratio value above the "non-failed" range is categorised as "excellent". For variables positively related to bank failure such as impaired loans to total equity (IMPE), a ratio above the "failed" range would be categorised as "critical" while a ratio below the "non-failed" range is categorised as "excellent".

We then convert the value ranges into scores (0 to 10). To ensure an even spread, the median value of each variable is given a score of 5. For variables that are negatively related to failure, any value that falls above the median obtained a score higher than 5 and the rest obtained scores lower than 5. With *x* as the variable value and *m* as the median value for the variable, the score is calculated as follows:

if $x < m$ then the score for the bank = 5 - $\left(\frac{m-x}{m-min} * 5\right)$; and

if $x > m$ then the score for the bank = 5 + $\left(\frac{x-m}{max-m} * 5\right)$.

For example, if TOTCAP had a maximum of 25%, a minimum of 0% and a median of 13%, the score for the bank is = 5-$\left(\frac{13-x}{13-0}\right) * 5$. If $x < 13$ or if $x > 13$ then the score for the respective bank is = 5+$\left(\frac{x-13}{25-1} * 5\right)$.

Thus, a bank with a TOTCAP ratio below the median would receive a score below 5 while a bank with a ratio above the median would receive a score higher than 5. Hence, the higher the TOTCAP ratio, the higher the score a bank achieves. The scores for the variables which have a positive correlation with bank failures is calculated as follows;

if $x < m$, then the score for the bank = 5+ $\left(\frac{m-x}{m-min} * 5\right)$; and

if $x > m$, then the score for the bank = 5- $\left(\frac{x-m}{max-m} * 5\right)$.

That is to say, the lower the ratio, the better the bank's health. Hence, a bank with a lower *x* would receive a higher score than a bank with a higher *x*.

The calculation of scores for the variable LOANGROWTH, poses a problem as too high or too low a ratio would point to failure. The score for LOANGROWTH is thus calculated as follows:

if $x < m$, then the score for the bank = 10 - $\left(\frac{m- x}{m-min} * 10\right)$; and if $x > m$, then the score for the bank = 10 - $\left(\frac{x-m}{max-m} * 10\right)$.

Here, the median value gets a score of 10. Any value further away from the median in either direction would result in a lower score.

With the scores computed, we then construct a micro-soundness index for each bank as well as a macro-soundness index for the entire banking industry. The soundness index will consist of the five main aspects of bank health prescribed by the CAMEL framework i.e. capitalisation, asset quality, management efficiency, earnings and liquidity. The micro-soundness index is constructed by summing the component scores for each health aspects of the bank. Where a health component is represented by more than one variable (e.g. asset quality), the component score is calculated by taking an average of the scores. With a maximum score of 10 for each significant variable, the maximum total health score will be 50. This score will then be converted into a scale ranging from 0 to 100. In this instance, the maximum score of 50 would be defined as 100 on the health scale, which will be the soundness index for individual banks. The macro-soundness index is constructed by taking the summation of individual bank health scores, weighted by the ratio of total assets of the bank and the total assets of the banking industry. The weighted average health score would be on a continuum of 0 to 100, with 0 representing poor health and 100 excellent health.

4. Analysis and Findings

4.1 Descriptive Statistics

To determine the independent variables that have the greatest explanatory power to predict bank failure, we first determined whether there are statistical significant differences in the mean values of the two samples (Vilen, 2010) on a year-by-year basis, beginning in $Year_{-4}$ until $Year_0$, by observing changes to the financial ratios over the years for the failed and non-failed banks. We then conduct a student *t*-test at the 1% level of significance (Note 1). We present these in Tables 2 – 7 below. Since not all variables were statistically significant in all the five years, we omit those that: (1) did not show a statistically significant difference in any of the years; (2) showed significant difference only in the year of failure; and (3) showed significant difference in just one of the years. The variables employed in this study were strictly required to show a statistically significant difference between the two data samples (failed and non-failed banks) (Note 2). For brevity purposes, we only discuss the variables that from the *t*-test, has sufficient power to predict bank failure.

Table 2. Descriptive Statistics and *t*-test for Capital Adequacy

Capital Adequacy	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
TIERCAP0	16.126	11.604	-3.19%	5.800	4.129	44.58%	13.69***
TIERCAP-1	16.658	16.824	2.77%	10.465	3.189	29.59%	5.91***
TIERCAP-2	16.208	11.375	-6.75%	14.863	15.841	6.00%	1.12
TIERCAP-3	17.381	13.748	-1.90%	14.022	18.080	26.04%	2.41****
TIERCAP-4	17.717	15.642		18.958	39.822		0.47
TOTCAP0	17.291	11.519	-2.61%	7.023	4.317	40.11%	13.64 ***
TOTCAP-1	17.755	16.711	2.75%	11.726	3.150	26.61%	5.79 ***
TOTCAP-2	17.279	11.280	-6.48%	15.978	15.786	5.31%	1.09
TOTCAP-3	18.475	13.655	-1.81%	15.172	18.002	24.42%	2.39***
TOTCAP-4	18.817	15.535		20.074	39.668		0.48

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Capital Adequacy variables from $Year_{-4}$ to $Year_0$. TIERCAP is the core capital ratio and TOTCAP is the total capital ratio. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 2 presents the descriptive statistics, the percentage change in mean values and *t*-statistics for the Capital Adequacy variables in this study from $Year_{-4}$ to $Year_0$. From Table 2, we can see that TIERCAP and TOTALCAP for non-failed banks remained relatively constant even until $Year_0$. Failed banks in contrast exhibited falling TIERCAP and TOTALCAP values from year to year; falling below the minimum of 8% in the year of failure. These changes seemingly support the proposition that failed banks are poorly capitalised i.e. they have a much smaller buffer against potential losses arising from credit or economic risk. We also recorded statistically significant differences between the mean TIERCAP and TOTCAP values of failed and non-failed banks, allowing both to be reasonable indicators of bank health.

Table 3 presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Asset Quality variables in this study from $Year_{-4}$ to $Year_0$. Impaired loans for non-failed banks have risen steadily over the years (up to 21 times of total equity in $Year_0$). IMPE for failed banks on the other hand, rose exponentially up to 227 times in $Year_0$. *t*-tests also reveal a statistically significant difference in IMPE values between both samples – an indicator of their suitability in distinguishing bank failure. Similar trends were observed for impaired assets to gross loans (IMPL). Failed banks recorded tremendous growth in this regard, leading up to $Year_0$; suggestive of the variable's power in explaining bank failure. The trend observed for LOANGROWTH is consistent with our earlier discussion. Failed banks were lending aggressively in the years prior to failure, finally leading to negative growth in the year of failure as a result of loan defaults. While a similar trend is observed for non-failed banks, the rate of change was more subdued. Asset growth rate (AGR) displayed a similar trend and statistical significance over the years. The *t*-statistics support the proposition that high loan growths as well as asset growth in preceding years are indicators of failure.

Table 3. Descriptive Statistics and *t*-test for Asset Quality

Asset Quality	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
IMPE0	21.251	35.105	60.48%	227.144	214.575	320.69%	15.47***
IMPE-1	13.242	22.221	91.46%	53.993	68.580	297.95%	9.24 ***
IMPE-2	6.916	13.124	78.62%	13.568	19.428	148.21%	4.64 ***
IMPE-3	3.872	5.896	22.12%	5.466	7.990	21.28%	2.62 ***
IMPE-4	3.171	4.656		4.507	7.179		2.552 ***
IMPL0	2.861	4.065	68.01%	13.898	8.887	162.14%	18.46 ***
IMPL-1	1.703	2.174	74.86%	5.302	5.514	229.70%	9.93 ***
IMPL-2	0.974	1.748	66.90%	1.608	2.217	135.13%	3.67 ***
IMPL-3	0.583	0.838	18.52%	0.684	0.964	20.99%	1.29 **
IMPL-4	0.492	0.707		0.565	0.927		1.02 *
LOANGROWTH0	3.834	19.646	-64.29%	-6.112	23.072	-136.34%	5.36 ***
LOANGROWTH-1	10.734	25.111	-40.30%	16.821	63.718	-49.08%	1.45 **
LOANGROWTH-2	17.981	51.372	-8.68%	33.033	71.026	-1.49%	2.81 ***
LOANGROWTH-3	19.690	66.928	45.00%	33.533	50.839	-27.76%	2.69 ***
LOANGROWTH-4	13.580	21.365		46.420	101.342		5.18 ***
LLR0	1.676	0.826	17.25%	3.572	2.245	7782.00%	12.96 ***
LLR-1	1.429	0.653	12.44%	2.009	1.358	4742.00%	6.28 ***
LLR-2	1.271	0.512	0.57%	1.363	0.647	1130.00%	1.81 **
LLR-3	1.264	0.499	-2.20%	1.224	0.374	-124.00%	1.03
LLR-4	1.292	0.514		1.240	0.403		1.32 **
LLIMP0	0.296	1.139	-42.46%	0.042	0.080	-90.45%	3.63 ***
LLIMP-1	0.515	1.589	-29.10%	0.444	2.832	-23.53%	0.36
LLIMP-2	0.726	2.116	-17.91%	0.580	1.660	-77.64%	0.89
LLIMP-3	0.885	3.124	-53.28%	2.594	14.178	16.29%	1.92 ***
LLIMP-4	1.894	4.671		2.231	7.104		0.65
AGR0	6.457	13.847	-45.11%	-1.465	18.665	-109.71%	5.57 ***
AGR-1	11.762	23.277	-8.48%	15.088	41.322	-35.65%	1.15 *
AGR-2	12.852	32.472	-23.23%	23.445	34.852	-27.73%	3.63 ***
AGR-3	16.740	61.890	26.91%	32.439	49.044	-2.86%	3.25 ***
AGR-4	13.190	28.513		45.118	45.118		9.77 ***

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Asset Quality variables from Year$_{-4}$ to Year$_0$. IMPE is the ratio of impaired loans to total equity, IMPL is the ratio of impaired loans to gross loans, LOANGROWTH is the bank's year-on-year growth in loans, LLR is the loan loss reserves, LLIMP is the ratio of loan loss reserves to impaired loans, and AGR is the bank's year-on-year asset growth rate. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 4. Descriptive Statistics and *t*-test for Management Efficiency

Management Efficiency	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
CIR0	76.530	36.966	0.81%	147.782	96.926	66.46%	11.22 ***
CIR-1	75.916	28.791	2.47%	88.779	46.882	19.76%	3.82 ***
CIR-2	74.089	27.039	2.18%	74.131	38.475	-4.25%	0.01
CIR-3	72.509	29.078	3.08%	77.422	60.374	0.91%	1.19
CIR-4	70.342	24.524		76.721	70.988		1.38 **
ROAA0	0.449	1.235	-11.84%	-4.119	3.347	623.34%	20.92 ***
ROAA-1	0.509	1.942	-43.20%	-0.569	2.009	-205.16%	6.31 ***
ROAA-2	0.896	1.983	-10.95%	0.542	1.507	-32.80%	2.32 ***
ROAA-3	1.006	1.946	-0.74%	0.806	1.608	-6.75%	1.29 **
ROAA-4	1.013	1.696		0.864	1.731		1.01

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Management Efficiency variables from $Year_{-4}$ to $Year_0$. CIR is the cost to income ratio and ROAA is the return on average assets. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 4 presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Management Efficiency variables in this study from $Year_{-4}$ to $Year_0$. The cost to income ratio (CIR) for failed banks rose drastically in the years leading to failure, doubling from about 77 to 147 in just 5 years, as compared to the CIR for non-failed banks which rose albeit at a much slower pace. In contrast, return on average assets (ROAA) for both failed and non-failed banks over 5 years. However, non-failed banks recorded negative ROAAs in $Year_{-1}$ and $Year_0$. Statistically significant *t*-statistics for CIR and ROAA is indicative of their suitability in predicting management efficiency and subsequently, bank failure.

Table 5 presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Liquidity variables in this study from $Year_{-4}$ to $Year_0$. We can see that net loans to total assets (NETLOANS) for non-failed banks to remain relatively unchanged as opposed to failed banks who failed banks which recorded about a 7% fall in NETLOANS in $Year_0$. The loan to deposit ratio (LOANDEP) for both failed and non-failed banks meanwhile fell in $Year_{-1}$ and $Year_0$, with failed banks recording a much greater fall than non-failed banks. *t*-statistics for both variables suggest that both are good indicators of potential bank failure.

Table 5. Descriptive Statistics and *t*-test for Liquidity

Liquidity	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
NETLOANS0	62.766	14.411	-2.62%	70.718	10.400	-6.84%	7.31 ***
NETLOANS-1	64.453	15.845	-1.83%	75.908	10.014	1.49%	9.99 ***
NETLOANS-2	65.657	15.816	2.42%	74.792	13.205	-2.07%	7.24 ***
NETLOANS-3	64.103	16.283	1.57%	76.371	11.761	4.72%	9.98 ***
NETLOANS-4	63.111	16.585		72.927	16.021		6.96 ***
LIQ0	0.009	0.008	12.50%	0.010	0.007	42.86%	1.59 **
LIQ-1	0.008	0.008	14.30%	0.007	0.005	0.00%	2.77 ***
LIQ-2	0.007	0.007	-12.50%	0.007	0.009	-12.50%	0.14
LIQ-3	0.008	0.008	0.00%	0.008	0.009	-11.11%	0.28
LIQ-4	0.008	0.008		0.009	0.013		0.95
LOANDEP0	79.510	23.250	-7.67%	84.500	14.780	-11.33%	2.97 ***
LOANDEP-1	86.120	49.100	-0.31%	95.300	18.050	-3.57%	2.87 ***
LOANDEP-2	86.380	44.190	4.82%	98.830	28.670	5.19%	3.86 ***
LOANDEP-3	82.410	25.380	3.30%	93.950	18.340	2.44%	6.02 ***
LOANDEP-4	79.780	22.470		91.710	21.760		6.23 ***

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Liquidity variables from $Year_{-4}$ to $Year_0$. NETLOANS is the ratio of net loans to total assets, LIQ is the ratio of liquid funds to total assets, and LOANDEP is loans to deposits ratio. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 6 presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Earnings and Net Interest Income variables in this study from $Year_{-4}$ to $Year_0$. Net income to average equity (ROAE) stands out in particular. We can see that in the years leading up to $Year_0$, both failed and non-failed banks recorded falling ROAEs. However, non-failed banks were able to maintain a positive ROAE. Failed banks in contrast, recorded a fall of more than 1,000% from $Year_{-1}$ to $Year_0$. Though not to this extent, a similar trend can be observed for net interest margins (NIM) for both samples; indicating that holding high-risk, high-yield assets initially increases the NIM of banks but when the bank faces financial distress, increasing funding costs and high levels of defaults deteriorate NIM. (Despagne, 2010). The magnitude of change observed for both variables is suggestive of their explanatory power. Outside the CAMEL framework, other financial items may provide indication as to the health of the bank. Non-interest income have often been perceived as riskier (Allen & Jagtiani, 2000; Clark et al, 2007; DeYoung & Torna, 2012) but may also be seen as a diversification of business, if carefully executed (Gamra and Plihon, 2011). Our non-failed bank sample seem to fall into the latter category, recording much higher levels of non-interest income as compared to failed banks. It is possible that a well-diversified mix of interest and non-interest sources of income lowers insolvency risks whilst improving profitability (Sanya and Wolfe, 2010).

Table 6. Descriptive Statistics and *t*-test for Earnings & Net Interest Income

Earnings & Net Interest Income	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
ROAE0	3.527	13.422	-23.99%	-76.054	89.775	1017.24%	14.33 ***
ROAE-1	4.640	13.078	-40.27%	-6.807	23.196	-164.05%	7.02 ***
ROAE-2	7.768	8.124	-20.63%	10.628	10.593	58.30%	3.49 ***
ROAE-3	9.787	7.686	-8.26%	6.714	12.306	-41.34%	3.46 ***
ROAE-4	10.668	8.223		11.445	9.656		1.01
NIM0	3.951	1.048	2.28%	2.976	1.183	-20.31%	10.08 ***
NIM-1	3.863	1.055	-2.33%	3.734	1.107	-13.54%	1.37 **
NIM-2	3.955	1.055	-3.18%	4.319	1.157	-4.07%	3.80 ***
NIM-3	4.085	1.375	0.22%	4.503	1.212	2.24%	3.73 ***
NIM-4	4.076	1.229		4.404	1.241		3.07 ***
INTEREST0	14.922	35.863	-11.22%	9.828	80.088	-17.66%	0.94 *
INTEREST-1	16.808	17.201	-0.54%	11.936	25.600	-1.42%	2.58 ***
INTEREST-2	16.898	12.844	-4.51%	12.108	9.855	-9.04%	4.84 ***
INTEREST-3	17.696	12.435	0.28%	13.311	10.652	-6.02%	4.38 ***
INTEREST-4	17.647	13.688		14.164	11.035		3.24 ***

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Earnings and Net Interest Income variables from $Year_{-4}$ to $Year_0$. ROAE is ratio of net income to average equity, NIM is ratio of net interest margin to total earning assets, and INTEREST is the ratio of non-interest fee income to total income. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 7 presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Off-balance Sheet Items and Short-term Wholesale Funds variables in this study from $Year_{-4}$ to $Year_0$. Off-balance sheet items (OBS) have similarly been perceived as risky as their true nature is often not made publicly known. Our sample shows both failed and non-failed banks to hold an almost equal amount of OBS. Although *t*-tests show statistically significant differences between the two in the earlier years, the magnitude seems to have fallen leading up to $Year_0$. A similar trend can be observed for the banks' reliance on short-term wholesale funding (WST). Although WST mean values suggest failed banks rely heavily on WST, *t*-tests do not indicate a statistically significant difference between the two samples.

Table 7. Descriptive Statistics and *t*-test for Off-Balance Sheet Items & Short-term Wholesale Funds

Off-Balance Sheet Items & Short-term Wholesale Funds	Non-Failed Banks			Failed Banks			*t*-stat
	Mean	Std. Dev.	% Change	Mean	Std. Dev.	% Change	
OBS0	0.015	0.035	22.71%	0.011	0.023	-16.87%	1.55 **
OBS-1	0.012	0.011	5.63%	0.013	0.009	-23.25%	1.15 *
OBS-2	0.012	0.008	-3.80%	0.017	0.019	-18.68%	4.45 ***
OBS-3	0.012	0.008	-0.32%	0.021	0.042	13.75%	3.52 ***
OBS-4	0.012	0.008		0.019	0.011		7.86 ***
WST0	50.960	111.527	-45.07%	61.991	137.521	-39.03%	1.02 *
WST-1	92.770	169.877	-12.97%	101.671	169.800	-5.56%	0.61
WST-2	106.595	171.197	39.52%	107.657	182.345	6.11%	0.07
WST-3	76.399	133.777	-7.24%	101.461	174.821	-5.69%	1.86 **
WST-4	82.360	139.420		107.581	176.327		1.83 **

The table presents the descriptive statistics, percentage change in mean values and *t*-statistics for the Off-Balance Sheet Items and Short-term Wholesale Funds variables from $Year_{-4}$ to $Year_0$. OBS is ratio of off-balance sheet items to total assets and WST is the ratio of volatile wholesale short-term liabilities to liquid assets. Full variable definitions are in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

4.2 Logistic Regression Estimation

The discussion of the descriptive statistics above provides early insight into which variables can discriminate between failed and non-failed banks. To identify the variables that can provide early warning signals of bank distress in advance, we perform a cross-sectional logistic regression for each of the 5 years preceding bank failure. Although our *t*-tests identified a number of financial ratios that may have strong explanatory power in predicting bank failure, we only use one measure for every aspect of bank health (Espahbodi, 1991) since logit models are sensitive towards multicollinearity (Balcaen and Ooghe, 2005). The regression estimates are presented in Table 8 below.

Table 8. Logistic Regression Estimation

Explanatory Variables	***Year₀***	***Year₋₁***	***Year₋₂***	***Year₋₃***	***Year₋₄***
TOTCAP	-0.222***	-0.172***	0.012	-0.095***	-0.009
	(0.081)	(0.042)	(0.013)	(0.031)	(0.022)
IMPE	0.016***	0.024***	0.023***	0.016	0.046**
	(0.004)	(0.006)	(0.008)	(0.016)	(0.019)
LLR	-0.117	0.245	0.216	0.384	0.138
	(0.159)	(0.174)	(0.209)	(0.276)	(0.254)
LOANGROWTH	0.15	0.013***	0.007***	0.003	0.025***
	(0.011)	(0.005)	(0.002)	(0.002)	(0.005)
ROAA	-0.661***	-0.239**	-0.311**	-0.192	-0.033
	(0.124)	(0.116)	(0.157)	(0.198)	(0.178)
CIR	0.005	-0.001	-0.006	0.004	0.004
	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)
NIM	-0.108	0.032	0.445***	0.424***	0.287**
	(0.196)	(0.121)	(0.120)	(0.127)	(0.127)
NETLOANS	0.029	0.054***	0.046***	0.060***	0.040***
	(0.018)	(0.011)	(0.009)	(0.011)	(0.010)
Constant	-1.526	-2.902**	-5.359***	-5.631***	-5.170***
Log likelihood	187.847	503.16	607.308	541.216	518.826
Nagelkerke R Square	0.837	0.446	0.24	0.315	0.297
Prob. > χ^2	0.000	0.000	0.000	0.000	0.000

Variable definitions are in Table 1. Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

From Table 8, we can see that in the years where the coefficient estimates were significant, the coefficient signs are as argued earlier. TOTCAP and ROAA were negative i.e. higher levels of capitalization and greater management efficiency mitigates the probability of failure. NETLOANS, LOANGROWTH and IMPE meanwhile were positive as expected. Interestingly, NIM estimates suggest that higher levels of NIM in the earlier years is indicative of risky behaviour which eventually leads to failure i.e. positive coefficient sign from $Year_{-4}$ to $Year_{-1}$ and subsequently, negative in $Year_0$. LLR and CIR however, did not show any statistically significant power in predicting bank failure.

We re-estimated the logit model twice to avoid multicollinearity, each time using a different proxy to represent a particular aspect of bank health. In Model 1, we replaced NETLOANS with LOANDEP to represent liquidity while in Model 2, we used IMPL as a proxy for asset quality instead of IMPE. The estimates of Model 1 and 2 are consistent with those presented in Table 8, with both LOANDEP and IMPL showing a statistically significant positive relationship to bank failure (Note 3). From our regression estimates, we can conclude that eight financial ratios are significant predictors of bank failures: TOTCAP, IMPE, LOANGROWTH, ROAA, NIM, NETLOANS, LOANDEP; and IMPL.

The classification accuracy of the model for the year of failure and the four years preceding it are illustrated in the Table 9 below.

Table 9. Classification Accuracy

Panel A: In-Sample					
	$Year_0$	**$Year_{-1}$**	**$Year_{-2}$**	**$Year_{-3}$**	**$Year_{-4}$**
Overall classification accuracy	91.82%	71.81%	72.41%	73.40%	73.20%
Correct classification of failed banks	89.86%	81.30%	73.73%	76.92%	66.36%
Correct classification of non-failed banks	93.46%	78.29%	71.09%	70.12%	79.18%
Type I error	10.14%	18.70%	26.27%	23.08%	33.64%
Type II error	6.54%	21.71%	28.91%	29.88%	20.82%
Panel B: Out-of-Sample					
	$Year_0$	**$Year_{-1}$**	**$Year_{-2}$**	**$Year_{-3}$**	**$Year_{-4}$**
Overall accuracy	96.15%	87.69%	76.15%	81.54%	72.31%
Correct classification of failed banks	100%	95.38%	89.23%	96.92%	84.62%
Correct classification of non-failed banks	92.31%	80.00%	63.08%	66.15%	60.00%
Type I error	0%	4.62%	10.77%	3.02%	15.38%
Type II error	7.69%	20%	36.92%	33.85%	40.00%

In-sample tests (Panel A, Table 9) show that the model displays fairly reasonable predictive power considering past studies have suggested that failure-prediction models are only reliable up until two years before failure (Altman, 2000; Espahbodi, 1991; Meyer & Pifer, 1970). Overall, our model is about 70% accurate, increasing to 91.82% in $Year_0$. Our model also seems to be more accurate in predicting failure even up to as far as $Year_{-1}$. It is however expected that accuracy of correct classification will fall the further away it is from $Year_0$. We have also managed to keep Type I errors i.e. the probability of incorrectly classifying a failed bank as non-failed, lower than Type II errors i.e. the probability of incorrectly classifying non-failed banks as failed, in the years preceding failure. As misclassification costs arising from Type I error are greater (Barr and Siems, 1997; Fidrmuc and Sub; 2011), relatively lower Type I errors in our model suggests greater predictive power. Although the model has high in-sample accuracy, we conduct further tests to evaluate its reliability and validity in classifying out of sample data (Jones, 1987). The out-of-sample predictive accuracy was tested using a sample of U.S. commercial banks from 2011. The hold out sample consists of 65 failed banks in year 2011, matched by a sample of 65 non-failed banks according to asset size in the same year. The results presented in Panel B, Table 9 show that our model has a high overall rate of accuracy even up to $Year_{-1}$ with minimal Type I error. Accuracy of correctly classifying a failed bank is near perfect in $Year_{-1}$ and perfect in $Year_0$. Type I errors were well below Type II errors and are also much lower than what was observed in the in-sample test. The accuracy of our model is greater than that of Glezakos et al. (2010) i.e. ours is able to predict failure at a higher degree of accuracy (100% - 85%) as compared to theirs (60% - 55%). We must note however that the accuracy of our model in correctly classifying healthy banks is similar to theirs.

4.3 The Soundness of Malaysian Banks

Having identified the financial variables that are able to effectively distinguish between healthy and unhealthy banks, we then construct 'value ranges' to assess the soundness of Malaysian commercial banks by computing 95% confidence intervals around the mean values of each variable for both the failed and non-failed sample banks. Since the predictive power of the variables diminish beyond two years prior to failure, we only computed value ranges for $Year_{-1}$ and $Year_{-2}$, although a few variables were only significant for just one year. The value ranges are presented in Table 10 below.

Table 10. Value Ranges of Bank Distress Indicators

	Non-failed (%)		**Failed (%)**	
	Lower boundary	Upper boundary	Lower boundary	Upper boundary
$TOTCAP_{-1}$	15.73	19.78	11.35	12.11
$TOTCAP_{-2}$	**N/S**		**N/S**	
$NETLOANS_{-1}$	62.53	66.73	74.70	77.11
$NETLOANS_{-2}$	63.73	67.58	73.17	76.41
$LOANGROWTH_{-1}$	**N/S**		**N/S**	
$LOANGROWHT_{-2}$	11.67	24.29	24.33	41.74
$ROAA_{-1}$	0.2739	0.7437	-0.81	-0.33
$ROAA_{-2}$	**N/S**		**N/S**	
NIM_{-1}	**N/S**		**N/S**	
NIM_{-2}	3.83	4.08	4.18	4.46
$IMPE_{-1}$	10.55	15.93	45.74	62.24
$IMPE_{-2}$	5.32	8.52	11.22	15.91
$LOANDEP_{-1}$	80.15	92.08	93.13	97.47
$LOANDEP_{-2}$	80.99	91.78	95.36	102.29
$IMPL_{-1}$	1.74	2.52	4.62	5.94
$IMPL_{-2}$	1.13	1.63	1.33	1.87

Note: N/S indicates non-statistically significant coefficient estimate

We then categorise the value ranges in Table 10 into five distinct tranches, colour-coded for ease of presentation: (1) critical i.e. recorded ratio is worse than failed banks (in red); (2) unsound i.e. ratio is within failed banks' range (in pink); (3) moderate i.e. ratio is between failed and non-failed range (in yellow); (4) sound i.e. ratio is within non-failed range (in light green); and (5) excellent i.e. ratio is better than non-failed banks (in dark green). Interpretation of the value ranges is variable-specific. For variables negatively related to the likelihood of failure, higher ratios indicate better health. Ratios falling below the 'failed' range will thus be considered 'critical' while ratios above 'non-failed' are considered 'excellent'. For variables positively related to bank failure, ratios above the 'failed' range are considered 'critical' while ratios below 'non-failed' are considered 'excellent'. Interpreting LOANGROWTH however, requires more discretion as too low a value may indicate inability in generating profits while too high a value may indicate poor lending practices.

We assessed the soundness of 20 domestic and foreign commercial banks in Malaysia as of 2011 based on our colour-coded categories above. The results of the assessment are presented in Table 11 below.

Table 11. Malaysian commercial bank soundness assessment

Bank	**Capital** TOTCAP	**Asset quality** LOANGROWTH	**Asset quality** IMPE	**Asset Quality** IMPL	**Management** ROAA	**Earnings** NIM	**Liquidity** LOANDEP	**Liquidity** NETLOANS
Affin	yellow	light green	yellow	yellow	dark green	dark green	light green	dark green
AmBank	yellow	red	yellow	yellow	dark green	dark green	pink	yellow
Alliance	light green	red	yellow	yellow	dark green	dark green	dark green	dark green
Bangkok	dark green	light green	dark green	yellow	light green	dark green	pink	light green
Bank of America	dark green	red	dark green	dark green	dark green	red	dark green	dark green
Bank of Nova Scotia	dark green	light green	dark green	dark green	dark green	dark green	red	pink
Bank of Tokyo Mitsubishi	dark green	red	dark green	dark green	dark green	dark green	dark green	dark green
CIMB	light green	light green	yellow	yellow	dark green	dark green	light green	dark green
Citibank	yellow	red	light green	yellow	dark green	pink	dark green	dark green
Deutsche	yellow	yellow	dark green	dark green	light green	dark green	dark green	dark green
Hong Leong	yellow	light green	yellow	yellow	dark green	dark green	dark green	dark green
HSBC	yellow	light green	light green	light green	dark green	dark green	dark green	dark green
JP Morgan Chase	dark green	light green	dark green	yellow	dark green	dark green	dark green	dark green
Maybank	yellow	light green	yellow	yellow	dark green	dark green	yellow	dark green
OCBC	light green	light green	yellow	yellow	dark green	dark green	light green	light green
Public Bank	light green	light green	dark green	dark green	dark green	dark green	light green	yellow
RHB	light green	light green	yellow	yellow	dark green	dark green	light green	light green
Royal Bank of Scotland	yellow	yellow	dark green	red	dark green	dark green	dark green	dark green
Standard Chartered	yellow	yellow	light green	dark green	dark green	dark green	light green	dark green
United Overseas Bank	yellow	pink	yellow	light green	dark green	dark green	light green	yellow

The soundness of Malaysian commercial banks is assessed on 8 categories formed on the basis of the value ranges in Table 10. Each category is divided into 5 tranches: Critical (in red); Unsound (in pink); Moderate (in yellow); Sound (in light green); and Excellent (in dark green).

The bank soundness assessment in Table 11 shows that for the most part, Malaysian commercial banks seem to be reasonably sound. A few problem areas exist however, especially in terms of capitalisation and asset quality. We can see that banks such as AmBank, Alliance, Bank of America, Bank of Tokyo and Citibank have very low or even negative loan growth rates (-12.63%; 4.92%; -36.86%; 6.51% and 4.29% respectively), while United Overseas Bank recorded exceptionally high loan growth rates (35.4%). Other aspects of asset quality seem to be acceptable with the exception of Royal Bank of Scotland which recorded a high amount of IMPL (11.65%). Earnings wise, Bank of America recorded high levels of NIM (8.18%) while Citibank was just the opposite (4.26%). With regards to liquidity, we can see that both AmBank and Bangkok Bank recorded high levels of LOANDEP (96.79 and 97.82 respectively) while the Bank of Nova Scotia is seemingly facing liquidity problems with high levels of LOANDEP and NETLOANS (>200%). The above assessment shows that 35% (7 out of 20 banks) of the commercial banks in Malaysia have asset quality issues, 20% (4 banks) have problem liquidity issues and 10% (2 banks) have problems with earnings.

4.4 Constructing the Bank Soundness Index

Although the construction of a soundness assessment framework for banks has provided us some insight to the bank's health, there is still a need for assessments from a wider perspective that allows for inter-bank comparisons to be made. We thus construct a 'Bank Health Index' that gives regulators and interested parties a birds-eye view of the soundness of the overall banking industry in the country. The Bank Health Index is computed on a score ranging from 0 to 10 for each component - capital; asset quality; management efficiency; earnings; and liquidity – its summation an overall "health score" for the individual bank. With each bank's health score, an industry score can be computed, allowing for comparisons against the overall banking system to be made. The health scores for each bank are presented in Table 12 below.

Table 12. Bank Health Index Scores

		Ownership	Capialization	Management Efficiency	Asset Quality	Earnings	Liquidity	Total Score	Health Score	Total Assets	Weighted Score
1	Bank of Tokyo-Mitsubishi	F	9.25	8.06	8.54	7.57	10	43.42	86.85	2919	0.46
2	JP Morgan Chase	F	10	7.06	7.19	6.61	10	40.86	81.73	2366	0.35
3	Royal Bank of Scotland	F	6.07	6.19	5.46	9.56	10	37.29	74.57	1434	0.2
4	HSBC	F	5.25	8.26	6.27	7.06	10	36.84	73.68	25094	3.37
5	Standard Chartered	F	5.23	7.82	6.9	7.5	8.69	36.13	72.26	15531	2.05
6	Deutsche Bank	F	5.63	5.22	8.23	6.95	10	36.03	72.06	3727	0.49
7	CIMB	L	6.61	7.58	5.92	6.16	9.05	35.33	70.65	73783	9.51
8	Public Bank	L	6.21	8.38	7.86	6.23	6.19	34.86	69.71	78505	9.98
9	Hong Leong	L	5.44	6.83	5.61	6.98	10	34.85	69.71	49471	6.29
10	Bangkok Bank	F	9.93	5.5	6.88	7.07	4.87	34.25	68.5	852	0.11
11	Alliance Bank	L	6.48	7.59	4.36	6.24	9.55	34.22	68.43	12898	1.61
12	OCBC	F	6.23	7.65	5.28	6.76	7.08	32.99	65.98	20271	2.44
13	Citibank	F	5.97	9	4.89	3.03	10	32.88	65.76	13991	1.68
14	Bank of Nova Scotia	F	8.59	8.77	6.71	6.68	2.08	32.82	65.65	1560	0.19
15	Bank of America	F	10	6.51	6.22	0	10	32.73	65.46	491	0.06
16	RHB	L	6.33	7.46	5.26	6.12	7.24	32.42	64.83	45006	5.32
17	Affin	L	4.66	6.76	5.84	6.28	8.78	32.32	64.64	15501	1.83
18	Maybank	L	6.02	7.61	4.72	6.52	7.01	31.87	63.75	136388	15.86
19	United Overseas Bank	F	5.9	7.81	3.87	6.39	6.3	30.27	60.53	21648	2.39
20	AmBank	L	5.62	7.61	2.12	5.78	4.52	25.65	51.3	26896	2.52
	Industry Component Score		6.77	7.38	5.91	6.27	8.07	Industry Health Score			66.69

Note: F denotes foreign bank; L denotes domestic bank. Health score is each bank's total score indexed to100. Weighted score is the health score multiplied by the bank's total assets divided by the total assets in the entire banking industry. Industry Health Score is the summation of the weighted health scores for each bank. Scores of 100 indicate excellent health, 0 otherwise.

Table 12 presents the health scores for the 20 foreign and domestic commercial banks in

Malaysia for the year 2011. We can see that the top 3 banks in Malaysia in terms of health are Bank of Tokyo-Mitsubishi, JP Morgan Chase and the Royal Bank of Scotland while the bottom 3 are Maybank, United Overseas Bank and AmBank. We can also see that on average, banks in Malaysia are in a sound position in terms of liquidity and management efficiency but still have a long way to go in terms of capitalisation, asset quality and earnings. Eight banks had a perfect liquidity score while three had liquidity scores below 5. In terms of management efficiency, only seven banks scored below the industry average although all 20 banks scored above 5 – an acceptable level but could still be further improved. Only 2 banks had a perfect capitalisation score while only one bank scored below 5. Although most banks had capitalisation scores above 5, some caution must be noted as only five banks recorded scores that were significantly greater than 5. The other 14 banks only managed scores no greater than 6.7. With regards to earnings, only two banks scored below 5. The other 18 banks recorded earnings scores that were comparable to one another and the industry average with the exception of the Royal Bank of Scotland which scored the highest (9.56). The asset quality of commercial banks in Malaysia warrants the most attention. Ten banks recorded asset quality scores below the industry average while five banks scored below 5, placing them in the critical category.

As a whole, it is reasonable to say that the Malaysian banking industry is in a state of moderate health, with a health score of 66.69 – a C or C+ at best. As a result, precautionary measures should be put in place to address these concerns, the first being the asset quality of Malaysian banks since 55.61% of the total loans in the banking sector are driven by household borrowings (BNM, 2011) where 26% of it is for residential mortgages. Banks are essentially exposing themselves to high level of concentration risk in sectors that might not be as stable as once thought. The drop in property prices as a result of the AFC and the crash in the property and mortgage market as a result of the sub-prime crisis are two prime examples of the dangers inherent in the property sector.

5. Conclusion

Over the last decade, we have witnessed major financial institutions collapse due to poor lending practices. Given their importance in the economy, bank failures send shockwaves across the country and the region as well – something that economies recovering from the recession can scarcely afford. Burdened with the task of steering the economy into recovery, regulators find it difficult to dedicate more resources into overseeing bank practices. Consequently, regulators need a bank health framework that makes their oversight task simpler, yet effective. Our model meets this purpose with a much higher degree of accuracy as compared to others. We also develop a Bank Health Index that allows for time-progressive monitoring of bank health, as opposed to the conventional point-in-time assessments. Progressive monitoring provides regulators with timely information allowing them to take precautionary measures in advance whenever any bank breaches a pre-determined lower threshold. The Bank Health Index also serves observers, investors and potential clients by providing information on the bank's soundness vis-à-vis other banks, allowing them to make a more informed when choosing their bank, besides keeping banks in check.

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Notes

Note 1. In the t-test, the hypothesis is stated as follows: H_0: the difference between the two group means is zero, H_1: the difference between the two group means is significantly different from zero.

Note 2. In this study, the failure-prediction model is not to predict failure *per se*, but to identify which variables have the power to predict failure in advance. It is thus necessary that the variables in the model here do show a statistically significant difference between the two samples. In previous studies of bank failure prediction, this had not been a strict requirement (Espahbodi, 1991).

Note 3. Due to space constraints, we did not report these figures here. They are however, available from us upon request.

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