Identifying the Determinants of Financial Distress for Public Listed Companies in Malaysia

(Mengenalpasti Penentu Masalah Kewangan Untuk Syarikat Awam di Malaysia)

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ABSTRACT

Companies that face financial distress are always regarded as the root cause of enormous financial and economic losses for many stakeholders and at the same time, contribute to social unrest within the society. Identifying the determinants of financial distress in advance will bring many advantages to stakeholders so that they can manage their companies effectively. This study aimed to identify the determinants of financial distress for Malaysian public listed companies (PLC) by utilising financial ratios and market data. Additionally, this study focuses on finding a better distress prediction model between the traditional statistical approach that utilises a logistic regression and an artificial neural networks (ANN) model. Sixteen ratios were selected in the study and two techniques were used to assess the data of 192 Malaysian PLC. The empirical findings from this research show that current assets turnover (CAT), working capital to total assets (WCTA,) and retained earnings to total assets (RETA) display the highest ability to distinguish between financially distressed and non-distressed groups. The results also indicate that the mentioned variables possessed a high discriminant and predictive power. This study also found that the ANN model has a higher predictive accuracy compared to the logistic regression model.

Keywords: Financial distress prediction; Malaysian public listed companies; emerging market; artificial neural networks; logistic regression analysis

ABSTRAK

Syarikat-syarikat yang menghadapi tekanan kewangan lazimnya dianggap sebagai punca utama kerugian ekonomi yang besar bagi banyak pihak berkepentingan dan pada masa yang sama, menyumbang kepada pergolakan sosial dalam masyarakat. Mengenalpasti penyebab kesulitan kewangan pada peringkat awal akan membawa banyak kelebihan kepada pihak berkepentingan supaya mereka boleh mengurus syarikat mereka dengan berkesan. Kajian ini bertujuan untuk mengenal pasti penyebab kesulitan kewangan bagi syarikat-syarikat awam Malaysia dengan menggunakan nisbah kewangan dan data pasaran semasa. Selain itu, kami juga menumpukan kepada mencari model ramalan yang lebih baik antara pendekatan statistik tradisional yang menggunakan regresi logistik dan model rangkaian saraf buatan (ANN). Enam belas nisbah dipilih dalam kajian ini dan dua teknik digunakan untuk menilai 192 data syarikat-syarikat awam Malaysia. Penemuan empirikal dari kajian ini menunjukkan bahawa perolehan aset semasa (CAT)), modal kerja kepada jumlah aset (WCTA) dan pendapatan terkumpul kepada jumlah aset (RETA) menunjukkan keupayaan tertinggi untuk membezakan antara kumpulan kewangan yang bermasalah dan tidak bermasalah. Hasil kajian ini juga menunjukkan bahawa pembolehubah tersebut mempunyai kekuatan diskriminasi dan ramalan yang tinggi. Kami juga mendapati bahawa model ANN mempunyai ketepatan ramalan yang lebih tinggi berbanding dengan model regresi logistik.

Kata Kunci: Ramalan kesulitan kewangan; syarikat-syarikat awam Malaysia; pasaran baru muncul; rangkaian saraf buatan; analisis regresi logistik.

INTRODUCTION

Malaysia has faced a few financial crises since its independence in 1957. A financial crisis, when it strikes is costly at both macro and micro levels. At the macro level, the consequences of the financial crisis are a higher unemployment rate and lower real gross domestic product (GDP). At the micro-level, the financial crisis can cause companies to have tight cash flows, financial troubles, and bankruptcy due to high debts, continuous loss-making, and a deterioration of good image (Abidin & Rasiah 2009). The depth and swiftness of financial crisis may catch many by surprise. The regularity of the financial crisis highlights the need for companies' actions and decisions to be continuously monitored and overseen. The potential loss in equity value as a direct or indirect result of financial distress could cause financial losses to many stakeholders. For example, it could cause job losses to employees, reduction in equity wealth to shareholders, and default payments to bondholders. Financial distress may also lead to unrest, which in turn can have long-term consequences. Many preventive actions could be taken by stakeholders to prevent substantial financial losses if early warning signals of financial distress are identified in advance. Therefore, studies on finding pre-emptive indicators of potential financial distress are needed, particularly for developing countries, such as Malaysia since many studies on the subject have been previously focused on developed countries.

The present research aimed to contribute to the financial distress literature by studying companies located in an emerging economy that operates in a different culture, laws, and regulations in comparison to the ones in developed markets. Previous research on financial distress on companies in developed markets are abundant. Countries, such as the US, UK, and Germany have more extensive and commercial histories with more rigorous company law provisions and stronger law enforcement compared to developing countries like Malaysia (Fan, Huang & Zhu 2009). Studies on financial distress for emerging economies, such as Malaysia are rather scarce. Malaysia as an emerging market has a weaker bankruptcy law and weaker legal enforcement compared to a developed market (Degryse & Ongena 2005; Petersen & Rajan 1994). Malaysia is also known to have a loose corporate governance, smaller assets size, high bargaining power of debtors when facing financial distress, and less developed capital market (La Porta et al., 2000; Dinc 2005; Lin et al., 2009). The economics of developing countries are also more volatile compared to that of developed countries because developing countries are highly dependent on export-related activities (Fan et al., 2009). Therefore, more studies on developing countries are called for as findings of past research maybe bias as the majority of those studies focused on developed countries.

The main objective of this research was to identify the determinants of financial distress for Malaysian PLC by utilising financial ratios and market data. The financial ratios and market data can enhance the accuracy of the financial distress prediction models, and it can also gauge the financial condition of PLC. Based on the literature, these indicators have been widely used in financial distress studies. Hence, in the present study, the traditional statistical method that employs the logistic regression analysis (LRA) was utilised, which degree of accuracy was compared to that of the artificial intelligent method. The outcomes of this research are expected to assist investors and other stakeholders in making their decision on PLC in Malaysia. In summary, this study attempted to apply the ANN and LRA techniques to PLC in the Malaysian context with the purpose to present a comprehensive computational comparison of predicting financial distress determinants. The results of this research have the implications in fulfilling the strategic information needs of investors and other stakeholders who have interests in the Malaysian PLC.

This paper is organised in several sections. The introduction section is followed by a review of the relevant literature related to the development of the financial distress prediction models. The section that follows presents a detailed explanation of the methodology used to achieve the research objectives. Next, in the findings and interpretation section, the comprehensive data analysis and empirical outcomes are explained by comparing them to the findings of previous studies. In the concluding remarks section, the findings of this study are summarised based on the analysis of the results using plausible explications. The last section is the reference list, which are organised accordingly for readers to refer to.

LITERATURE REVIEW

Developed markets, such as the US and UK prefer to declare bankruptcy to overcome their financial distress problem. Every year in the US, there are over thirty thousand bankruptcy cases filed with the US Bankruptcy court. Meanwhile, in the UK and Europe, thousands of cases are filed each year (Davydenko & Franks 2008). Hence, a study on bankruptcy and financial distress is important to be carried out considering that many companies file for bankruptcy every year all over the world. However, compared to the extant of the literature on an effective, efficient, and sound management of a company, the literature on financial distress is relatively new (Westphal & Graebner 2010). Research on financial distress is quite complicated due to the difficulties in quantifying the problem. The complexity of financial distress originates from the diversity of the sources of financial difficulties.

Predictions of financial distress have been examined by previous researchers using different approaches from the angle of financial result, corporate governance, economic impact, and accounting standards. The Beaver's (1966) study is considered as an early contributor to the development of bankruptcy predictions utilising the univariate approach. Beaver used a sample of one hundred and fifty-eight (158) publicly-owned US companies and found that the stock price is a significant variable in predicting companies' failures.

Altman (1968) improved Beaver's study by applying a step-wise multivariate discriminant analysis (MDA) on a sample of sixty-six (66) US companies. Altman identified five significant financial ratios that can predict bankruptcy, which are (i) working capital to total assets, (ii) retained earnings to total assets, (iii) earnings before interest and taxes to total assets, (iv) market value of equity to book value of total debt, and (v) net sales to total assets. Due to its simplicity and high accuracy, the MDA approach has emerged as a popular model (Ali & Hoong 2003) and has been used by many studies, for example, Sinkey (1975) and Moyer (1977).

A comparative study on the prediction models between MDA, LRA, and Merton model had been conducted by Abdullah (2016) on a sample of one hundred and fifty eight (158) Malaysian PLC. The outcome from his study shows that LRA has the highest accuracy rate compared to that of MDA and Merton models. The study also found that the accounting-based models (LRA and MDA) outperformed the market-based (Merton) model (Abdullah 2016).

Findings from previous studies on the causes of financial distress are still inconclusive. Such inconclusiveness will be more evident if the developed market is compared against the developing market. It is widely accepted in developed economies that the enforcement of bankruptcy laws and close external monitoring by stakeholders (such as corporate bondholders and large investment institutions) play essential roles in disciplining financially distressed companies, influencing corporate financial decisions, and determining credit recovery in the event of distress. However, the situations are different in emerging markets. The widespread 'soft lending' practice in emerging markets provides an easy and cheap access to capital to some companies, prompting them to be financially irresponsible, which behaviour leads to disappointing performance and financial distress (Lin et al., 2009). Once companies are in financial distress, the weak legal enforcement and loose corporate governance in emerging markets cause the distress resolution to become complicated. Cross-country studies show that the actual use of bankruptcy law and the degree of enforcement critically depend on a country's institutional environment, such as the effectiveness of the judicial system (Claessens & Klapper 2005), the protection of investors' rights (Dahiya & Klapper 2007), and legal origin (Djankov et al., 2008). In emerging markets where institutional environments are weak, creditors often have difficulties in liquidating financially distressed companies or recovering their assets. The relationship banking strategy used as a monitoring mechanism in developed markets is unlikely to be useful in emerging markets due to the presence of multi-layer agency problems (Fan et al., 2009). Therefore, under weak legal environment and monitoring mechanisms, debtors have a higher bargaining power (Degryse & Ongena 2005) than their counterparts in the developed markets (Fan et al., 2009). Due to these differences, a study identifying the determinants of financial distress in emerging markets, such as Malaysia and comparing them with the developed markets, becomes imperative.

DATA AND METHODOLOGY

DATA

The sample for this study comprised of the Malaysian PLC that have been classified as financial distress under the Practice Note 4/2001 or 17/2005. The listing was obtained from the Bursa Malaysia website from the year 2002 to 2018. From the listing, ninety-six (96) companies were identified and matched against non-distressed companies in the same industry, asset size, and financial reporting year. This matching procedure was needed to ensure that the distress prediction model produces the lowest amount of bias results. At the same time, it can improve the reliability and consistency of the analysis (Karbhari & Zulkarnain 2004). Below is the breakdown of the selected companies according to industries.

TABLE 1. Number of selected companies according to industries

Industry	Number of financially distress companies	Number of financially non-distress companies	Total
Industrial product	38	38	76
Trading and services	21	21	42
Consumer product	10	10	20
Construction	20	20	40
Plantation	2	2	4
Hotel	2	2	4
Energy	2	2	4
Media	1	1	2
Total	**96**	**96**	**192**

DEPENDENT VARIABLE

The dependent variable in this study was bifurcated into two groups. The first group, comprising the financial distress companies, was labelled as "1". On the other hand, the second group, which represents the non-financially distress companies, was labelled as "0".

INDEPENDENT VARIABLES

The selection of the independent variables for this study was mainly based on the significance and recognition of those financial ratios as employed by previous researchers, such as Beaver (1966), Altman (1968), Deakin (1976) as well as Charitou, Neophytou and Charalambous (2004). Therefore, our financial ratios under review selected for this study were quick asset turnover (QAT), current asset turnover (CAT), asset turnover (AT), days sales in receivable (DSR), sales to fixed assets (STFA), EBIT to total assets (EBITTA), cash flow to total assets (CTA), cash flow to total debts (CTTL), debts to assets (TLTTA), debts to equity (DTE), book value of equity to total liabilities (BVETL), market value of equity to total liabilities (MVETL), current ratio (CR), working capital to total assets (WCTA), return on equity (ROE), and retained earnings to total assets (RETA).

METHODOLOGY – LOGISTIC REGRESSION ANALYSIS (LRA)

The first methodology that was used in this research was the LRA. It is a suitable regression analysis to be used when the dependent variable is binary. There are many advantages in utilising LRA for the discriminant analysis and the most prominent one is that the model is relatively robust. Compared to MDA, the model is stringently relevant only when the underlying variables are jointly normal with equal covariance matrices (Press & Wilson 1978). LRA can overcome the restriction of the MDA model, such as the requirement of multivariate normality and equality in dispersion matrices among groups (Laitinen & Kankaanpaa 1999).

The dependent variable is binary where Y_i can be a financially distressed company (classified as 1) or Y_i can be a non-distressed company (classified as 0). In the linear regression model, the dependent variable Y_i is continuous, whereas in logistic regression, it is binary. There are three approaches to developing a probability model for a binary response variable, such as (1) linear probability model (LPM), (2) logistic regression analysis model, and (3) probit model. This paper would only address the LPM and LRA models.

The application of the linear regression model for a model that has a binary dependent variable, which is termed as LPM, renders the meaning of the expected value of the dependent variable to be a probability. Probability is a linear function and the application of the linear regression estimation to the model with a binary dependent variable results in what is termed as LPM. The probability of the occurrence being in a financial distress is a linear function and the probability can be either 0 or 1. Based on these principles, a suggestion has been made to specify the probability as a logistic function.

The study of qualitative response variable by considering the LPM regression model can be explained further as follows:

$$Y_i = \beta_1 + \beta_2 X_i + \mu_i \qquad \text{(Equation 1)}$$

Where;
X = explanatory variables (such as financial ratios and market data)
Y = 1 if the company is financially distressed and 0 if the company is financially non-distressed

The conditional expectation of Y_i given X_i, $E(Y_i \mid X_i)$, can be interpreted as the conditional probability that the event will occur given X_i, that is, $\Pr(Y_i = 1 \mid X_i)$. Therefore, $E(Y_i \mid X_i)$ provides the probability that a company is financially distressed and whose explanatory variable is the given amount of X_i. Assuming $E(\mu_i) = 0$, (to obtain unbiased estimators), the following equation was obtained:

$$E(Y_i \mid X_i) = \beta_1 + \beta_2 X_i \qquad \text{(Equation 2)}$$

If P_i= probability that Y_i = 1 (the event occurs) and (1 - P_i) = probability that $Y_i = 0$ (the event does not occur), the variable Y_i has the following (probability) distribution:

The definition of mathematical expectation can be written as follows:

$$E(Y_i) = 0(1 - P_i) + 1(P_i) = P_i \qquad \text{(Equation 3)}$$

By comparing Equation 2 with Equation 3, the connection can be expressed in the following equation:

$$E(Y_i \mid X_i) = \beta_1 + \beta_2 X_i = P_i \qquad \text{(Equation 4)}$$

The conditional expectation of the model in Equation 1 can be construed as the conditional probability of Y_i. In this model, there is a constraint where the probability of P_i must lie between 0 and 1. Therefore, the conditional expectation (or conditional probability) must lie between 0 and 1 as follows:

$$0 \leq E(Y_i \mid X_i) \leq 1 \qquad \text{(Equation 5)}$$

LPM is afflicted by several issues, such as (1) non-normality of μ_i, (2) heteroscedasticity of μ_i, (3) likelihood of Y_i lying outside the 0 – 1 range, and (4) the usually lower R^2 values. Due to the limitations of

LPM, we chose logistic regression because it can overcome those limitations. In explaining the probability of companies whether financially distressed or non-distressed in relation to the explanatory variable in Equation 4, the LPM was:

$$P_i = \beta_1 + \beta_2 X_i \qquad \text{(Equation 4)}$$

Where X is the explanatory variable (such as financial ratios and market data) and $P_i = E(Y_i = 1 \mid X_i)$ means the company is financially distressed. The expected response variable for logistic regression can be written as $(Y_i \mid X_{1i} \ldots . X_{ni}) = Pr(Y_i = 1) = \frac{1}{1+e^{-Z_i}}$. If we fit this relationship with a linear regression model, the predicted values for $E = (Y_i)$ can be below 0 or above 1.

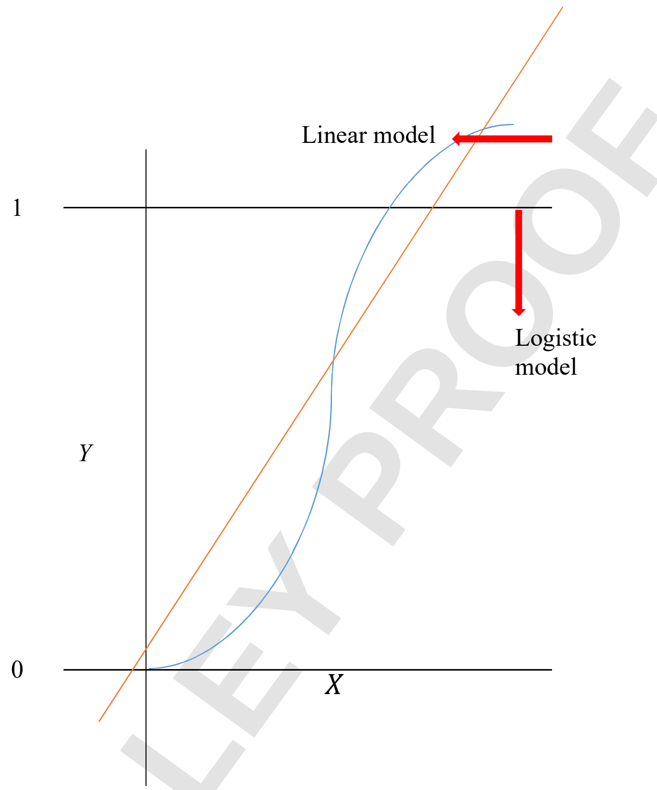

FIGURE 1. Comparing logistic regression with linear regression model

For logistic regression, P_i can be written as follows:

$$P_i = \frac{1}{1+e^{-(\beta_1+\beta_2 X_i)}} \qquad \text{(Equation 6)}$$

For the simplicity of explanation, Equation 6 can be written as follows:

$$P_i = \frac{1}{1+e^{-Z_i}} = \frac{e^Z}{1+e^Z} \qquad \text{(Equation 7)}$$

where $Z_i = \beta_1 + \beta_2 X_i$. Equation 7 signifies what is known as the (cumulative) logistic distribution function. Z_i ranges from -∞ to +∞ and P_i ranges between 0 and 1. P_i is nonlinearly related to Z_i. If P_i is the probability of a financially distressed company, then (1 - P_i) is the probability of a financially non-distressed company (Gujarati 1995) as follows:

$$1 - P_i = \frac{1}{1+e^{Z_i}} \qquad \text{(Equation 8)}$$

A company is classified as distressed if the calculated probability from the logistic regression model is more than 0.5. Otherwise, it would be non-distressed (Tinoco & Wilson 2013). It is necessary to find the significant explanatory financial ratios that can discriminate between the two groups to get reliable results from the LRA model. The stepwise procedure is applied to finalise the appropriate explanatory variables to be used in the maximum likelihood estimate (Nam & Jinn 2000).

METHODOLOGY – ARTIFICIAL NEURAL NETWORK (ANN)

There are a few limitations with the conventional statistical techniques. For example, MDA has some restrictive assumptions that require the variables to be linear, normal, and independent. These assumptions have always been violated, and therefore, the outcome from MDA is not robust. ANN performs better than a regression in the treatment of missing data, outliers, and multicolinearity (Kumar & Bhattacharya 2006). Elliot and Kennedy (1988) explained in detail the drawbacks of MDA, which led to the development of ANN.

ANN mimicks the way human brains work and moulds it into a form of soft computing methods. As it is trained, the network learns by adjusting the weights in positive ways when it gets a correct outcome, and in negative ways when it receives an incorrect outcome. ANN has gained popularity in the early 1990. For example, Odom and Sharda (1990) built a neural network model to predict financial distress and compared its outcome with MDA.

This study utilised the ANN model with sixteen inputs of the ratios under review and two outputs that signify the two different categories of companies' condition, which is financially distressed and non-financially distressed. The inputs were divided into training and testing samples. The training sample was used to build the model, while the testing sample was used to validate the model as propagated by Kwon, Han, and Lee (1997). In this study, the ANN model had selected 135 data points for the training sample and 57 data points for the testing sample. The model is a fully-connected, back-propagation model with three layers of neurons. The first layer is for input data, and the second layer is for the additional hidden layer. The reason the multiple hidden layers were not chosen was because the complexity level of this model was relatively low with just sixteen inputs, which require a relatively small number of neuron connections. The third layer represents the output/result after regression. The details of the layers are described in Figure 2 below.

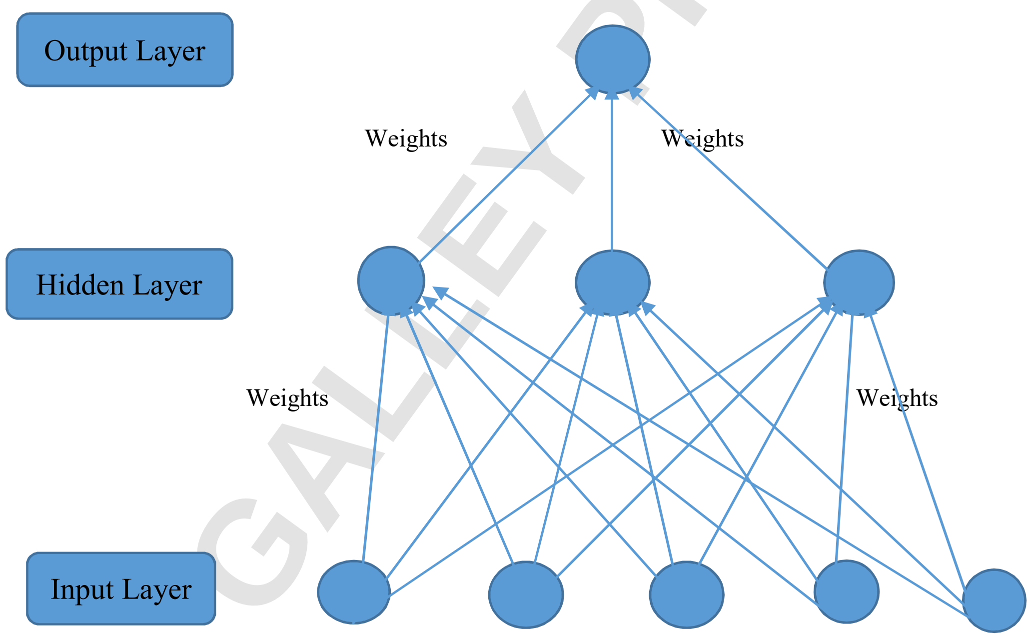

FIGURE 2. Architecture of a Layered Neural Networks

EMPIRICAL FINDINGS AND INTERPRETATIONS

DATA DESCRIPTION

This study employed a sample of 192 publicly listed companies comprising financially distressed and non-distressed companies over the period 2002 to 2018. Table 2 presents the descriptive statistics of the variables. As expected, the ratios of non-distressed companies reflect a better financial strength compared to those of distressed companies. The financially healthy companies have higher asset turnover (AT) ratio (0.731) as compared to distressed companies (0.533). The asset turnover ratio measures a company's ability to generate sales from its assets and the ratio indicates that non-distressed companies perform better in generating sales from their assets compared to financially distressed companies.

This study also looked at the current assets turnover (CAT) ratio that measures a company‘s ability to generate sales through its current assets. The finding shows that the mean of current assets turnover (CAT) ratio is also higher for financially healthy companies (1.580) than for distressed companies (1.456), which finding implies that non-distressed companies manage to generate higher sales from its current assets. The average days' sales in receivables (DSR) for distressed companies is 1,308 days, which is significantly higher than the DSR of the financially healthy companies, which has a mean DSR of 164 days. This finding indicates that financially distressed companies take a longer period to collect money from their debtors and this affects their cash flows. The ratio also indicates that financially healthy companies are more efficient in turning account receivables into cash.

The better financial health of non-distressed companies is also reflected in their higher quick asset turnover (QAT) ratio and sales to fixed assets (STFA) ratio. The mean of QAT for non-distressed companies (2.804 times) is higher than the mean for distressed companies (2.793 times), which suggest that the distressed companies had poor collecting processes, a lousy credit policy, or bad customers. A higher mean for non-distressed companies implies that these companies operated on a cash basis, their collection of account receivables were efficient, or they had high-quality customers who paid off their debts quickly. Another finding is related to the STFA ratio. The STFA ratio measures how a company can generate sales from fixed assets. The finding shows that the STFA mean for non-distressed companies (5.999 times) is higher than the mean for distressed companies (3.769 times), which indicates that non-distressed companies managed to generate more sales from their fixed assets compared to distressed companies.

The cash flow to assets (CTA) ratio for financially healthy companies and distressed companies are 0.066 and -0.266, respectively. This show that financially healthy companies are more efficient in using their assets to produce earnings before paying for their contractual obligations, tax expense, and depreciation expense. Another cash flow ratio in our study is cash flow to total debt (CTTD). CTTD mean ratio for the non-distressed companies is 5361 and for the distressed companies is -5.687. CTTD measures the period the company would take to repay its debt if it dedicates all of its cash to debt repayment. The high ratio for the non-distressed companies implies that they were in a better financial position to pay back their debt.

The financially distressed companies are high in debt, with a mean of total liabilities to total assets (TLTTA) of 0.684. The same mean ratio for the financially healthy companies was recorded at 0.294 only. The high debt of the distressed companies also reflects the debt to equity (DTE) ratio, of which the result shows that the distressed companies' mean ratio is -1.587. Meanwhile, the non-distressed companies only recorded 0.368 mean ratio. The high debt of financially distressed companies indicates that they undertook a massive debt to finance their growth, which led to a higher risk of financial distress because these companies were incurring high-interest expense and had to pay a scheduled debt obligation on time to avoid bankruptcy.

Further, the average current ratio (CR) of the distressed companies is 0.896, while it is 2.769 for the non-distressed companies, which means that for every RM1.00 of current liabilities of financially healthy companies, there are RM2.769 of the current assets. The amount decreases to RM0.896 for the distressed companies. The ratio is an indication that the distressed companies would probably have difficulties to meet their short-term credit obligations. The results in Table 4 also show that the financially healthy companies were more liquid than the financially distressed companies. The mean of working capital to total assets (WCTA) ratio for the financially healthy companies (0.795) is higher than the WCTA of the distressed companies (-0.369). The negative ratio of the distressed companies indicates that they were in financial difficulties to meet the working capital requirement because the financially distressed companies were high in debt and possessed many idle assets that were not generating revenue to the maximum.

The distressed companies also have a higher return on equity (ROE) ratio of 2.547 compared to the ROE of the non-distressed companies (-0.004). This indicates that return on equity for the non-distressed companies was higher because these companies were making profits, while the distressed companies were making a loss or minimal profits. The negative mean ratio for RETA and EBITTA for the distressed companies (-0.600 and -0.308 respectively) indicate that these companies were in loss-making. The good companies, by contrast, were making a profit as reflected by the positive mean of RETA and EBITTA (0.042 and 0.039 respectively).

The non-distressed companies also have higher means of the book value of equity to total liabilities (BVETL) ratio and market value of equity to total liabilities (MVETL) ratio than those of the distressed companies. The higher mean of MVETL (29,026) ratio suggests that the non-distressed companies were valued more by the market participants compared to the distressed companies (2.264). Meanwhile, the higher mean of BVETL ratio indicates that the accounting record for the non-distressed companies (30,185) shows a higher value of equity to total liabilities. Both ratios also imply that the non-distressed companies were more stable and resilient when facing financial difficulties because their equities were higher than their liabilities.

Table 2 also identifies the variables that have the highest ability to discriminate between the two groups. The results indicate a significant mean difference at 5 % level in all variables except CAT, DSR, QAT, STFA, DTE, ROE, and MVETL. Hence, it can be concluded that all independent variables are significantly different except CAT, DSR, QAT, STFA, DTE, ROE, and MVETL.

TABLE 2. Mean difference for selected companies one year before financial distress event

Variable	Group	Mean	Standard Deviation	Min	Max	t-statistic	
CAT	Distress	1.456	1.380	0.002	9.443	0.630	
	Non-distress	1.580	1.348	0.114	11.953		
AT	Distress	0.533	0.451	0.001	2.138	2.738	*
	Non-distress	0.731	0.544	0.029	3.448		
DSR	Distress	1308	8584	12	84189	-1.306	
	Non-distress	164	201	24	1588		
CTTD	Distress	-5.687	52.729	-517	1	2.152	*
	Non-distress	5361	24437	-825	172590		
TLTTA	Distress	0.684	0.618	0.004	6	-5.257	*
	Non-distress	0.294	0.382	0.000001	3		
QAT	Distress	2.793	3.373	0.004	21	0.250	
	Non-distress	2.804	2.255	0.001	15		
STFA	Distress	3.769	10.313	0.006	84	1.109	
	Non-distress	5.999	16.788	0.163	133		
CTA	Distress	-0.266	0.944	-8.781	0.532	3.406	*
	Non-distress	0.066	0.144	-0.509	0.812		
DTE	Distress	-1.587	22.366	-147.096	58.028	0.856	
	Non-distress	0.368	0.593	-2.626	3.318		
CR	Distress	0.896	1.511	0.030	4	5.614	*
	Non-distress	2.769	2.897	0.200	14		
ROE	Distress	2.547	21.460	-15.408	154	-1.16	
	Non-distress	-0.004	0.287	-2.252	0.749		
WCTA	Distress	-0.369	0.662	-4.763	0.715	7.308	*
	Non-distress	0.179	0.319	-1.441	0.893		
RETA	Distress	-0.600	0.941	-7.538	0.707	6.199	*
	Non-distress	0.042	0.383	-1.417	0.771		
EBITTA	Distress	-0.308	0.986	-9.253	0.310	3.411	*
	Non-distress	0.039	0.145	-0.605	0.758		
BVETL	Distress	4.110	27.148	-0.821	266	2.746	*
	Non-distress	30185	107685	-0.381	710961		
MVETL	Distress	2.264	16.242	0.004	157	1.787	
	Non-distress	29026	159136	0.014	1497600		

* significance at $\alpha = 0.05$

Next, we proceed with a correlation analysis on the variables under review. The result of the pair-wise correlation coefficients that are significant at 5 % is shown in Table 3. The outcome of the correlation analysis test indicates that some of the selected variables in this study are highly correlated with one another. For example, the correlation between CTA against EBITTA is 0.998, DTE against ROE is -0.970, TLTTA against WCTA is -0.788, and CTTD against BVETL is 0.834. The results suggest that there is a high correlation for some of the variables under review.

TABLE 3. Correlation matrix of variables under review one year before financial distress event

	CAT	AT	DSR	CTTD	TLTTA	QAT	STFA	CTA	DTE	CR	ROE	WCTA	RETA	EBITTA	BVETL	MVETL
CAT	1															
AT	.404**	1														
DSR	-.098	-.119	1													
CTTD	.036	.193**	-.017	1												
TLTTA	.052	-.143*	.025	-.137	1											
QAT	.619**	.280**	-.097	-.015	.048	1										
STFA	.036	.419**	-.032	.067	-.089	-.014	1									
CTA	-.006	.058	-.003	.080	-.721**	-.022	.026	1								
DTE	.060	.041	-.003	.006	-.084	.072	-.094	.135	1							
CR	-.161*	.048	-.022	.114	-.220**	-.151*	.184*	.139	.022	1						
ROE	-.076	-.057	.003	-.011	.098	-.079	.088	-.138	-.970**	-.039	1					
WCTA	-.191**	.204**	.028	.129	-.788**	-.125	.170*	.706**	.098	.506**	-.106	1				
RETA	-.106	.005	-.120	.137	-.720**	-.098	.044	.751**	.124	.333**	-.132	.751**	1			
EBITTA	-.026	.054	.001	.079	-.724**	-.035	.032	.998**	.132	.143*	-.134	.711**	.757**	1		
BVETL	-.017	.107	-.017	.834**	-.175*	-.061	.037	.078	.008	.211**	-.014	.155*	.182*	.078	1	
MVETL	.044	.214**	-.014	.789**	-.115	.000	.037	.071	.005	.103	-.009	.118	.121	.069	.607**	1

**. Correlation is significant at the 0.01 level (2-tailed).

To further analyse the issue of multicollinearity problem, we computed the variance inflation factor (VIF), i.e., VIF = $1/(1 - R_j^2)$ where R_j^2 is the determination coefficient for regression of the ith regressor on all the other regressors. Commonly, VIF > 10 is used as a cut off value to indicate multicollinearity problem (Tinoco & Wilson 2013). Referring to Table 4, we can see that CTA, DTE, ROE, and EBITTA have the VIF value that is more than the cut-off value. Therefore, it can be concluded that multicollinearity problem exists in our study. Hence, the four variables were eliminated from our regression. A stepwise procedure needed to be performed in the implementation of the LRA to ensure that any statistical inference made from the models is reliable. The stepwise method was also used to select the best discriminating variables at each step and the variables that are not useful in discriminating between groups were eliminated.

TABLE 4. Variance inflation factors one year before financial distress event

Variables	R^2	$VIF = 1/(1 - R_j^2)$
CAT	0.547	2.21
AT	0.486	1.95
DSR	0.101	1.11
CTTD	0.829	5.85
TLTTA	0.718	3.55
QAT	0.397	1.66
STFA	0.245	1.32
CTA	0.996	250
DTE	0.943	17.54
CR	0.458	1.85
ROE	0.943	17.54
WCTA	0.839	6.21
RETA	0.722	3.60
EBITTA	0.996	250
BVETL	0.729	3.69
MVETL	0.64	2.78

RESULT FOR LOGISTIC REGRESSION ANALYSIS (LRA)

Table 5 exhibits the results after employing the stepwise LRA procedure to the selected variables. Nagelkerke R^2 (also known as the coefficient of determination) is 0.50, indicating that the variables in this analysis can explain 50 percent of the variance in the dependent variable; financially distressed and financially non-distressed categories.

TABLE 5. Logistic regression analysis of predictor variables

Variable	LRA
CAT	-0.356*
	(1.924)
WCTA	-3.070*
	(4.644)
RETA	-1.766*
	(3.532)
Constant	0.091*
	(0.275)
Log-likelihood	175.823
Nagelkerke R^2	0.500

Notes: The absolute value of Z-statistics is reported in parenthesis
* significance at $\alpha = 0.05$
** significance at $\alpha = 0.10$

From Table 5, it shows that the significant variables after employing LRA are CAT, followed by WCTA and RETA. The coefficient of CAT is negative as hypothesised. The CAT coefficient is -0.356 and the estimated odds ratio is 0.7005 ($e^{-0.356}$). Hence, it can be assumed that an increase in 1 unit of CAT, causes the estimated change in odds for the companies to be in financial distress, to decrease by a multiplicative factor of 0.7005 with the condition that the other variables remain constant. CAT measures the company's ability to generate sales from its current assets. Thus, a higher CAT suggests a better performance of the company and the lower its probability of being in financial distress. The result implies that companies need to consistently generate high revenue from its current assets to avoid financial difficulties. We can summarise that financially distressed companies have less ability to generate revenue from their current assets to the maximum compared to the non-distressed companies.

The next variable found to be significant in the LRA model is RETA. RETA also carries the expected negative sign, where an increase in cumulative earnings over total assets lowers the company's financial distress likelihood. RETA is a measure of cumulative earnings over time as a proportion of total assets. It implicitly quantifies the age of a company. The RETA ratio for a young company may be lower than the RETA of an older company because the older company has more time to build up its cumulative profits. We can also quantify the leverage level of a company through the RETA ratio because RETA indirectly informs whether a company has financed its assets through its retained earnings or debts. A high scoring value of RETA indicates that the company finances its assets by utilising its retained earnings. A negative coefficient of RETA suggests that the company has a low proportion of retained earnings to total assets. This can lead to an increase in the likelihood of the company to fall into financial distress. The RETA coefficient is -1.766 and the estimated odds ratio is 0.171 ($e^{-1.766}$), which means, for each increase in 1 unit of RETA, it is expected that the odds of those companies to be in financial distress will decrease by a multiplicative factor of 0.171, with the condition that the other variables remain constant. Retained earnings ensures the financial stability and growth of a company when the earnings are reinvested in profitable projects. Therefore, to decrease the financial distress probability, companies should find ways to increase their profits by investing in the right projects and retaining the profits as much as possible. RETA is also found to be significant in predicting financial distress in many empirical studies, including Altman (1968), Altman, Haldeman and Narayanan (1977) as well as Lincoln (1984).

WCTA was also found to be significant under the LRA model. It reflects the liquidity of the company. An increasing WCTA ratio is a positive indication because it shows that the company is highly liquidated and the cash flow is in good condition. If the ratio is in negative or of low value, it indicates that the company is in an unstable condition due to either high debts and high current liabilities, or low working capital, or both. A low fraction of working capital to total assets that produces a negative coefficient indicates that the probability of the company to face financial distress is high. This is due to the incapability of the company to pay its short-term debt obligation. The estimated odds ratio for WCTA is 0.046 ($e^{-3.07}$) and the coefficient is -3.07. We can deduce that for each increase in 1 unit of WCTA, the estimated odds for the companies to be in financial distress decrease by a multiplicative factor of 0.046 with the condition that the other variables remain constant. Looking at the difference in WCTA for both distressed and non-distressed companies as presented in Table 2, it can be noted that it is significant, which indicates that the extent of liquidity carried by the non-distressed companies is significantly greater than those of the failed companies. The results reveal that most of the failed companies were unable to generate sufficient liquidity for their companies by utilising existing assets in the organisation. This finding is consistent with the study by Deakin (1972) who found that liquidity as measured by WCTA to be the best predictor of potential distress classification.

Based on the results in Table 5, a predictive model was generated as follows:

0.091 – 3.07X1 – 1.766X2 – 0.356X3 = Z
Where;
X1 = Working capital to total assets (WCTA)
X2 = Retained earnings to total assets (RETA)
X3 = Current assets turnover (CAT)
Z = Overall score

The probability of financial distress can be computed based on the Z score result as follows:

$$P = \frac{1}{1 + e^{-Z}} \qquad \text{(Equation 7)}$$

As clarified earlier, the equation represents what is known as the (cumulative) logistic distribution function. The weights of the variables were estimated in equation (1) and applied to the prediction model. The parameter or optimal β (weights) can be projected where the probability value is maximised. The probability of distressed can be quantified by substituting β in the cumulative probability function. If the result from the probability function is less than 0.5, a company can be classified in the non-financially distressed group, or otherwise, it would be classified in the financially distressed group.

This research also employed the ANN method besides the LRA method. We used a back-propagation network (BPN) with the Multi-Layer Perceptron (MLP) architecture. This structure is the most frequently used for the ANN technique to predict financial distress (Odom & Sharda 1990). In the current study, the sixteen input neurons in the structure were the variables under review as highlighted in the earlier section. Meanwhile, for the output layer, it produces a single neuron that can have a value of "1" (that indicates the company is in a financial distress condition) or "0" (that represents non-financial distress classification).

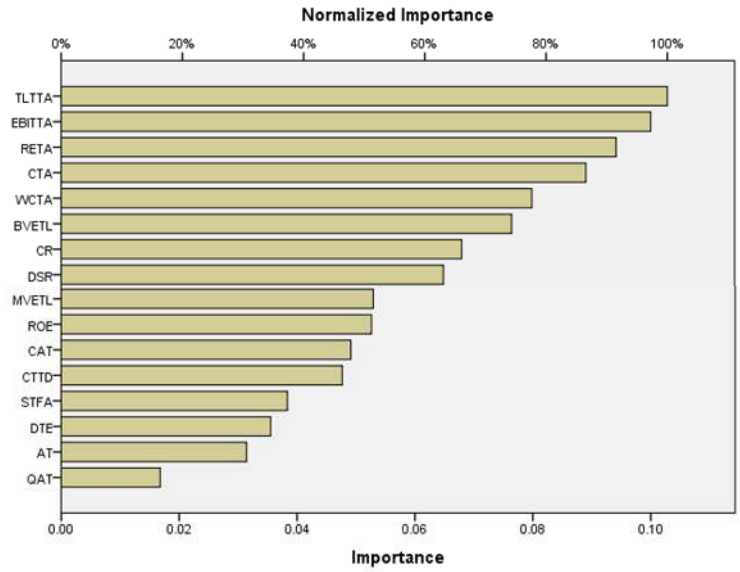

FIGURE 3. Normalised importance of selected variables one year before financial distress event

The rank of importance for the ratios used in the ANN method is presented in the form of a bar graph in Figure 3. Among the financial ratios that have been identified as critical by the the ANN method are TLTTA, EBITTA, RETA, CTA, and WCTA. Based on Table 5, the LRA method also identifies RETA and WCTA as significant variables. Therefore, it can be concluded that ANN and LRA have identified almost similar financial ratios for predicting financial distress. Hence, interested stakeholders should evaluate RETA and WCTA carefully from time to time to predict financial distress.

CLASSIFICATION ACCURACY AND INTERPRETATIONS

The next assessment is classification accuracy, which examines the result from each model to determine whether a model can do well in reality. The classification accuracy was divided into two groups and the first group was categorised as Type I accuracy. Type I accuracy identifies financially distressed companies in the financial distress zone, while Type II accuracy identifies non-financially distress companies in the safe zone. Caouette, Altman, and Narayanan (1998) state that Type I accuracy is more significant than Type II accuracy. They explained that it would cost more to stakeholders if they are unable to recognise a deteriorating company (Type I error) than the opportunity loss of declining investment in a high potential company (which is classified as Type II error).

The ANN accurately predicts 91.2 %, with 3.1 % Type I error and 16.0 % Type II error as shown in Table 6. The ANN accuracy rate performs better than the LRA by 8.4 % in predicting financial distress. Fletcher and Gross (1993), Salchenkerger et al. (1992), and Zhang et al. (1999) also found that ANN with a Multi-Layer Perceptron (MLP) architecture has a higher accuracy rate compared to the LRA model. This finding indicates that the ANN model is a robust technique for forecasting financial distress. The accuracy rate from the present study is better than that of Sulaiman et al. (2001) and Low, Nor, and Yatim (2001) who only managed to produce an accuracy rate of 80.7 % and 82.4 %, respectively.

TABLE 6. Validity test for LRA and ANN one year before financial distress event

	Observed state		Predicted state - %		Overall Correctly (incorrectly) classified - %
			1	0	
LRA Model	Financially distress companies	1	81.2	18.8	82.8 (17.2)
	Non-financial distress companies	0	15.6	84.4	
ANN Model	Financially distress companies	1	96.9	3.1	91.2 (8.8)
	Non-distress companies	0	16.0	84.0	

CONCLUDING REMARKS

This study aimed to identify the determinants of financial distress for Malaysian PLC. We also tested the accuracy of the ANN model in predicting financial distress based on an appropriately selected set of ratios and compared it with the LRA model. The current study applied the models to a sample of 192 PLC in Malaysia that were categorised in six different business sectors.

From the result of this study, it shows that the determinants that differentiate between non-distressed companies and distressed companies were CAT (activity ratio) and RETA (profitability ratio), which findings imply that the financial distress prediction concentrates more on assets generating income. In other words, financially healthy companies significantly rely on the ability of its assets to generate income. The company's assets will deteriorate without proper maintenance if they are unable to generate income as planned. Such a condition will lead to high capital expenditure and low income-generating assets that will soon cause financial difficulties to the companies.

In this study, RETA and WCTA were also found to be significant variables for the two methods employed. WCTA represents the liquidity of companies and it indicates that the ability of companies to remain liquid is an essential element for a healthy company. Therefore, it can be concluded that WCTA is a significant variable among the financial ratios in predicting financial distress. Interested parties should pay more attention to the WCTA ratio if they want to identify distress or non-distress companies.

From the research, the finding also shows that ANN outperformed LRA by 8.4 %. The result also suggests that the ANN model has a lower Type I error compared to LRA. It is more critical for stakeholders to be able to identify Type I error compared to Type II error because it is very costly to investors and other stakeholders to invest in financially distressing companies that are wrongly predicted as healthy. We also noticed that LRA and ANN identified almost identical determinants of financial distress, and the margin of difference for the accuracy rate between the two methods is minimal, indicating that LRA and ANN are efficient predictors for financial distress forecast.

This study also found that the market information variable, such as MVETL is insignificant in the two distress prediction models that were employed in the study. The main reason is that the market value of the share price for the financially distressed companies was stagnant one year before the financial distress event. The result implies that investors already abandoned the share of these companies long before it was classified under financial distress.

Based on the findings, the individual determinant, such as WCTA and RETA that were found to be significant for Malaysian PLC were also found to be significant in the developed markets. However, the group significant determinants (that consists of CAT, WCTA, and RETA) and their weights are different from the studies in the developed markets. Therefore, it is more appropriate for developing countries to utilise findings from studies in countries that have quite a similar culture, laws, and regulations.

This research has implications for professionals, including investors, bankers, and other stakeholders. By using the model built from the analysis in this study, investors would be able to assess companies' financial conditions in advance and to take steps to avoid damages if businesses are highly likely to suffer financial distress. On the other hand, banks may evaluate the prospective borrower's credit risk prior to acceptance, using the model established in this study. In addition, they can continually monitor the financial health of the borrowers, from year to year, until the loans are fully settled.

Financial instability has significant repercussions for creditors, managers, and employees as well as regulatory bodies. Regulatory bodies can utilise the model developed in this study as an internal tool to improve the risk assessment procedures, pricing strategies, and provisioning levels as required in Basel II. During an economic crisis, regulatory bodies, such as the Ministry of Finance that owns government-linked companies

(GLCs) can utilise the findings from this research to determine the best candidates for financial bailouts. Additionally, regulatory bodies could perform reform by including a few elements, such as strengthening supervision and enforcing sensible rules, especially in the area of debt level, that should be tightened. Regulators may consider issuing standards on reducing the level of excessive debt for all public listed companies because of the negative impact of excessive debt on business feasibility. Regulatory bodies could also ensure that the regulatory framework is enhanced, rather than allowing it to deteriorate. Therefore, incentives must be given to owners and managers of companies for prudent management. In addition, reforms should aim to protect the regulators from political interference, especially in making operational decisions to avoid ineffective regulation.

As other scholars have done in previous empirical studies, our work also has some limitations. However, these limitations serve as an opportunity to expand this study in the future. We would like to recommend that future research expands the current study to a larger sample size and a longer duration. We also suggest that future research employs modern methods of forecasting the likelihood of financial distress, such as the hazard model and the recursive partitioning algorithm. These models could provide better prediction because they are viewed as stable, sensitive to changes, and more robust. We would also like to propose that future studies on financial distress to be applied to non-public listed companies and small medium enterprise (SME). Banks need to assess all loan applications, including the occurrence of failure for SME, which are more common than PLC. Therefore, it contributes significantly to the literature if similar studies can be applied to SME. However, there might be a problem in gaining access to the financial data since SME data are not publicly available. This research is limited to Malaysian public listed companies only. Therefore, future research can include other developing countries such as Indonesia, Thailand, and Philippine (so that we can compare the results from those on South-East Asian countries with Malaysia) to investigate whether the different economic environment criteria has any impact on financial distress. More studies in developing countries are necessary since the analysis is more applicable to all parties in those countries than research findings in developed countries. Future research can also add more dependent and independent variables related to financial distress prediction. For dependent variables, researchers can try to use rating categories (especially for studies that involve bonds) rather than general classification categories (financially distressed and non-financially distressed groups) as used in this study. Rating categories are more accurate to predict bonds condition because bonds have a few rating classifications, such as AAA, BBB, CCC, and Aaa. For independent variables, researchers can improve the model by adding more relevant independent variables to get more robust results. Examples of independent variables that can be assessed in the future are stock market return, inflation, and GDP. Research can also be conducted on the theoretical aspect of financial distress prediction since it is still lacking in the literature. To conclude, financial distress prediction is still a developing theoretical and empirical research field. Therefore, it is desirable for academicians and practitioners to continue their research in this challenging and exciting area of modern finance.

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