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DETECTING FINANCIAL DISTRESS

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ABSTRACT

This paper examines two types of statistical tests, which are multiple discriminant analysis (MDA) and the logit model to detect financially distressed companies. Comparison between the two statistical tests is implemented to identify factors that could differentiate financially distressed companies from the healthy company. Among the fifteen explanators, MDA shows that current ratios, net income to total asset, and sales to current asset, are the indicators of financially distressed companies. Other than net income to total asset, the logit model provides two different ratios which are shareholders' fund to total liabilities, and cash flow from financing to total liabilities, to identify financially distressed companies. It was found that the logit model could accurately predict 91.5% of the estimation sample and 90% of the holdout sample whereas the discriminant model shows an overall accuracy rate of 84.5% and 80% for the estimation and the holdout sample respectively.

ABSTRAK

Kajian ini menguji dua jenis ujian statistik iaitu analisis diskriminan dan model logit bagi mengenal pasti syarikat yang berada di dalam kesulitan kewangan. Perbandingan di antara kedua-dua jenis ujian statistik dibuat untuk mengenal pasti petunjuk yang dapat membezakan syarikat yang berada di dalam kesulitan kewangan dengan syarikat yang sihat. Di antara lima belas nisbah kewangan yang dimasukkan dalam kajian ini, analisis diskriminan menunjukkan bahawa nisbah semasa, pendapatan bersih kepada jumlah aset dan jualan kepada aset semasa merupakan petunjuk kepada kesulitan kewangan. Selain daripada nisbah pendapatan bersih kepada jumlah aset, model logit pula memberikan dua nisbah yang berbeza iaitu ekuiti pemegang saham kepada jumlah liabiliti dan aliran tunai daripada aktiviti pembiayaan kepada jumlah liabiliti untuk mengesan syarikat yang mengalami kesulitan kewangan. Hasil daripada kajian ini menunjukkan bahawa model logit dapat *memberikan ketepatan klasifikasi sebanyak 91.5% dalam keseluruhan sampel dan 90% dalam sampel kawalan manakala model diskriminan memberikan kadar ketepatan keseluruhan sebanyak 84.5% untuk keseluruhan sampel dan 80% untuk sampel kawalan.*

INTRODUCTION

At the end of 2002, there were 21 companies able to restructure their financial conditions whereas 16 companies failed to formulate its restructuring plans and were delisted from the Bursa Malaysia (The Star, January 11, 2003). These are companies that fall under Practice Note 4 (PN4) classification of distressed companies. Financial distress is a situation where a company's cash flow is inadequate to cover its current obligations. The obligations include unpaid debts to suppliers and employees, actual or potential damages from litigation, and missed principal or interest payments under borrowing agreements or default (Wruck, 1990; Altman, 1993; Ward & Foster, 1997; Soo, Fauzias & Puan Yatim, 2001).

According to the Securities Commission, a listed company can be defined as distressed if it is classified under Practice Note No.4/2001 (PN4) issued by the Bursa Malaysia. A listed company that meet any of the following criteria is classified as PN4 companies:

a) deficit in the adjusted shareholders' equity on a consolidated basis.

b) receivers and/or managers have been appointed over the company's property, or property of its major subsidiary or major associated company.

c) auditors have expressed adverse or disclaimer opinion in respect of the company's going concerns in its latest audited accounts.

d) special administrators have been appointed over the company, its major subsidiary or major associated company, pursuant to the provisions of the Pengurusan Danaharta Nasional Bhd Act 1998.

Previous bankruptcy studies emphasised that several financial ratios could be used to differentiate between healthy and financially troubled companies. However, Gilbert, Menon and Schwartz (1990) found that among the group of financially troubled companies, these ratios were unable to differentiate companies that have actually failed from other financially troubled companies. As a result, it is difficult to assess the likelihood of bankruptcy for the troubled companies. Rationally, most companies tend to be financially distressed before reaching the bankruptcy state. Ward and Foster (1997) emphasised that a financial distress model could provide better information to various claimholders of a company as it could identify various symptoms of financially distressed companies at the early stages so as to provide ample time for the management to formulate their action plan.

Consequently, the main objective of this paper is to identify those factors that could differentiate financially distressed companies from the healthy companies by using the Practice Note 4 (PN4) classification of distressed companies introduced by the Bursa Malaysia in February 2001. The remaining part of this paper is organised as follows. Section 2 provides the literature on the variables used for this study, whereas Section 3 describes the methodology. The results would then be covered in Section 4 and finally Section 5 concludes the paper.

LITERATURE REVIEW

Financial ratios are commonly used as a prediction of failure/ bankruptcy, bond ratings (Beaver, 1966; Altman, 1968; Houghton & Woodliff, 1987; Shirata, 1998), information for loan officers in decision-making (Libby, 1975), and detect distributional characteristics of financial ratios in business failure prediction (Deakin, 1976). Mears (1966) stated that preparation of financial ratios is merely the first step in the overall process of reaching a business decision. Normally, factors that influence the success and failure of a company are reflected in its financial statements (Lincoln, 1984). For example, poor management will be reflected in the profit and loss statement, in the same way that economic downturns will be shown in the company's declining cash flow.

There has been a considerable debate in the literature as to which ratios are most useful to assess the likelihood of failure (Scott, 1981). In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators on predicting bankruptcy. However, the priorities are not clear as most studies cited different ratios being the most effective indicator of bankruptcy. Furthermore, most of these studies did not have an absolute test for the importance of variables (Barnes, 1987; Altman, 1993; Mohamed, Ang & Ahmadu, 2001).

According to Scott (1981), although there are huge numbers of possible financial variables available to predict bankruptcy, researchers were neither guided nor constrained by the theory in their selection process. Chen and Shimerda (1981) and Soo *et al.* (2001) pointed out that there has been no acceptable theoretical foundation for the selection of ratios.

Since there is no theory that has been developed in selecting the most relevant ratios, the important criterion would be to choose ratios based on their simplicity and relevancy to the local environment (Chen & Shimerda, 1981; Mohamed *et al.*, 2001). An early contribution to the development of a quantitative model in predicting bankruptcy was carried out by William Beaver (Beaver, 1966), who studied predicting bankruptcy through stock market prices. Altman (1968) improved Beaver's univariate analysis by introducing the multivariate approach. He used a step-wise Multiple discriminant Analysis (MDA) to develop a prediction model with a higher degree of accuracy. By using a sample of 66 US manufacturing companies, which consisted of 33 companies in each of the bankrupt and successful groups respectively, five financial ratios were found to be significant. The ratios were working capital to total assets (A), retained earnings to total assets (B), earnings before interest and taxes to total assets (C), market value of equity to book value of total debt (D), and net sales to total assets (E). The model gave a Z-score or discriminant score that would indicate a healthy or a likely bankrupt company. He found that all firms with an index of 2.99 or above were in the non-bankrupt group and those with an index of 1.81 or below were in the bankrupt group. The cutoff index that made the most accurate prediction of bankruptcy one year before filing for bankruptcy was 2.675. Using this index, 94 % of the companies in a matched-pairs sample were correctly classified in their bankrupt or non-bankrupt groups. No probability of failure is derived from the calculation. The coefficients in the equation are calculated to minimise the Z-score from overlapping between the two populations, probable bankrupts and healthy companies. He ended up with a model in the following form $Z = 1.2A + 1.4B + 3.3C + 0.6D + .999E$.

Altman, Haldeman and Narayanan (1977) then developed and marketed a *'second-generation'* model called "ZETA analysis", which could predict better than Altman's earlier model. Their sample consisted of 53 bankrupt companies and a matched sample of 58 non-bankrupt companies in the US. The researchers concluded that the ZETA model was far more accurate in classifying bankrupt firms two to five years before bankruptcy. The classification accuracy of bankrupt firms five years before failure was 69.8% using the ZETA analysis and 36% using the 1968 model.

Recently, Heine (2000) revisited the study on predicting financially distressed companies in the US using Altman's Z-score model and ZETA credit risk model. 86 distressed companies from 1969 to 1975, 110 bankrupt companies from 1976 to 1995, and 120 companies which have defaulted on their publicly held debt were taken as the sample.

In addition, he extended the study to unlisted firms, non-manufacturing entities, and new bond rating equivalent model for emerging markets corporate bonds. Heine (2000) found that both models produce an accuracy of 96.2% (ZETA) and 93.9% (Z-Score model) for a one-year prior to bankruptcy model. However, the accuracy is consistently higher for the ZETA model in 2-5 years prior to the distress date. For the fifth year, the ZETA model is still about 70% accurate but the Z-score's accuracy fell to 36%. Heine (2000) concluded that the ZETA model for assessing bankruptcy risk of corporations had demonstrated improved accuracy over the Z-Score model. Moreover, he also stressed that the study was based on data more relevant to current conditions and to a larger number of industrial companies which showed the applicability and the robustness of the ZETA model.

Other studies in predicting bankruptcy have also been covered in other countries. Shirata (1998) proposed a generalised bankruptcy prediction model based on 686 Japanese companies that went bankrupt and 300 non-bankrupt companies. By using MDA, which is independent of industry and size, he found that the model could classify Japanese bankrupt firms with more than 86.14 % accuracy.

Some of the published works in Malaysia adopting discriminant analysis to predict corporate failure are by Shamser, Zulkarnain and Mohamad Ali (2001), Zulkarnain, Mohamad Ali, Annuar, and Zainal Abidin (2001), and the most recent study is by Zulkarnain, Shamser, Mohamad Ali and Annuar (2002). Shamser *et al.* (2001) tried to identify the general characteristics of failed firms that were listed on the Bursa Malaysia. They found that the liquidity, profitability and cash flows of the failed firms showed a gradual deterioration, while the leverage of the companies showed a gradual increase. The most significant deterioration in these ratios occurred one year before failure and in the failure year. They concluded that a consistent trend in the changes of the selected financial ratios would provide an early warning on potential failures and these ratios could be used to construct prediction models in Malaysia.

Zulkarnain *et al.* (2001) focused their study on Malaysian industrial sector companies. Similar to the study by Shamser *et al.* (2001), their sample was the listed companies that requested protection under Section 176 of the Companies Act 1965. A sample of 24 failed companies were matched with 24 non-failed companies for the period 1980 to 1996. They used forward stepwise MDA to determine the discriminating variables. The findings show that the model accurately and significantly classified 91.1% and 89.3% of the failed and non-failed companies respectively. The model could predict failure up to four years before the actual events. There were four variables that could significantly discriminate between failed and non-failed companies. The variables were percentage of total liabilities, current asset turnover, market value to debts, and cash to current liabilities. Based on their discriminating power, the most important variable was percentage of total liabilities whereas the least important variable was cash to current liabilities.

Following their work in 2001, Zulkarnain *et al.* (2002) continued their study by adding a market value of share variable, which they then classified as the market-based model. By comparing the accounting versus market-based models, they found six significant determinants of corporate success and failure: total liabilities to total assets, asset turnover, inventory to total assets, sales to inventory, market value to debts, and cash to total assets ratios. Total liabilities to total assets discriminated the most and cash to total assets discriminated the least among the six variables. It appears the market-based model accurately classified 86.2% of the companies while the accounting based-model accurately classified 88.1% of the companies tested. When a new sample of failed firms in the year 1998 was taken, both models could correctly classify failed firms up to four years before the failure occured.

An alternative to discriminant analysis is to use a conditional probability model, usually using logit to estimate the probability of occurrence of a particular outcome (Ohlson, 1980; Ward & Foster, 1997; Mohamed *et al.*, 2001; Soo *et al.*, 2001). Ohlson (1980) employed conditional logit analysis in his study on the business failure prediction model. He used 105 bankrupt companies and 2058 non-bankrupt companies in his study for the period 1970 until 1976. According to him, the prediction error rate is larger if the predictors are derived from the financial statements. In his analysis, four variables were found to be statistically significant in affecting the probability of failure within one year: size of the company, total liabilities to total assets, funds provided by operations to total liabilities, and the percentage change in net income.

Joo and Jinn (2000) also employ a logit maximum likelihood estimator in their study by using 46 non-financial listed companies in Korea that went bankrupt in 1997 and 1998. The researchers constructed a matched sample according to industry and total asset. They argued that the matching of sample in terms of size is very important because of the "too big to fail" problem prevalent in Korea. Their findings show that among the 33 financial ratios, asset turnover, retained earning to total asset and leverage are the key variables to predict corporate bankruptcy. The model could predict financially sound companies with 73.9% accuracy and insolvent companies with 80.4% accuracy. In order to validate their result, Joo and Jinn (2000) used an independent holdout sample, which consisted of bankrupt as well as non-bankrupt companies. The findings showed that the model could predict with 74.07% accuracy of bankrupt companies, and 78.26% accuracy of non-bankrupt companies. In addition, they found most companies that went bankrupt during the economic crisis from 1997 to 1998 had shown signs of financial distress long before the crisis. Hence, the researchers conclude that the crisis of 1997 and 1998 was not just a temporary foreign exchange crisis, but reflected on the poor performances of Korean companies before the economic crisis.

In Malaysia, there are limited number of researchers adopting a logit model in their study (Mohamed *et al.*, 2001; Soo *et al.*, 2001). Mohamed *et al.* (2001) discussed the application of a logit model in predicting corporate failures using different variables other than cash flows. Based on a sample that includes companies that seek or did not seek court protection under Section 176 of the Malaysian Companies Act 1965, they found that debt ratio, interest coverage and total asset turnover to have significant discriminating power. The logit model was able to classify accurately 80.7% of the companies in the estimation sample and 74.4% of the holdout sample. When Soo *et al.* (2001) conducted a similar study with an addition of cash flow ratios, they also found three variables to be significant, but the ratios are different from those found by Mohamed *et al.* (2001), except for asset turnover. Nevertheless, the proxy used to represent asset differs for both studies where Mohamed *et al.* (2001) used total asset whereas Soo *et al.* (2001) used current asset.

Two more ratios that were found significant by Soo *et al.* (2001) are current assets to current liabilities and the percentage change in net income of the company. These ratios were used to measure the liquidity and profitability of a company. The researchers argued that high ratio of the two measures do not necessarily mean that the company has sufficient money to pay off its obligations. In addition, they also found that the probability of financial distress is inversely related between the ratio of cash and marketable securities to total assets. Therefore, the researchers concluded that the cash position of a company provides a better signal of financial deterioration and should be highlighted in order to detect financially distressed companies. This is because there is a higher likelihood of corporate failure for companies that have less cash. The study by Soo *et al.* (2001) had a higher accuracy than the on done by Mohamed *et al.* (2001). The overall accuracy rate for the estimation and holdout sample is 82.4% and 90% respectively. As we can see, most of the studies done in Malaysia concentrated on either MDA or logit model to predict corporate failures. There was no comparison made between the two models to identify factors that could differentiate financially distressed companies from the healthy companies.

METHODOLOGY

We have used the Practice Note 4/2001 (PN4 thereafter) to select our sample. Out of the broad classification of PN4, we only concentrated on companies that have a deficit in the adjusted shareholders' equity on a consolidated basis through a list that was presented by the investment advisory firm, Surf88, dated 23 August 2000. There were 54 companies identified with negative shareholders' funds. In order to validate the list of companies, it was compared against a company database at www.klse-ris.com.my. Out of 54 companies, two companies (Menang and Idris Hydraulic) were excluded as they do not fall under the classification of having negative shareholders' fund. Hence, only 52 companies were used in this study.

The non-distressed and distressed companies are matched on a one-to-one basis based on the stock exchange industry group and size (measured by total asset) in order to control for possible confounding influences. This is in accordance to Gilbert *et al.* (1990) and Platt and Platt (1990). The use of one-to-one matched procedure is also consistent to the work by Beaver (1966), Altman (1968), Laitinen (1994), Gadenne and Iselin (2000), and Zulkarnain *et al.* (2001). To check on the accuracy of the prediction model, a new holdout sample was used. From the total of 52 distressed companies, 10 were selected randomly as a holdout sample. The remaining 42 companies were used for model building.

Another criterion that was that was used in selecting the sample was companies must have a complete set of financial data for a period of two years prior to the event year. A database at www.klse-ris.com.my and annual reports which were obtained from the Bursa Malaysia library were the main source of financial information.

For model building, multiple discriminant analysis (MDA) which takes the form of $Z = \beta_1 V_a + \beta_2 V_b + ... + \beta_n V_n$ based on a stepwise approach is adopted to select the best discriminating variables that could predict distressed and non-distressed companies. This model would then be compared to the logit analysis to examine which model could provide a higher accuracy in predicting financially distressed companies. The logit prediction model was adopted from Ohlson (1980), Joo and Jinn (2000) and Gujarati (1995: 554).

$$Z_i = \beta' x_i + u_i \tag{1}$$

Where:

Z_i = non-distressed if $Z_i > 0$
Z_i = distressed, otherwise
x_i = companies financial ratios
u_i = error term
Z_i ranges from $-\infty$ to $+\infty$

The probability and likelihood function for the non-distressed companies can be defined as follows:

$$P_i = E(Y=2 \mid x_i) = \frac{1}{1 + e^{-(\beta' x_i + u_i)}} \tag{2}$$

For ease of exposition, it is written as

$$P_i = \frac{1}{1 + e^{-z_i}}$$

$$\text{where } Z_i = \beta' x_i + u_i$$

Equation (2) represents what is known as the (cumulative) logistic distribution function.

In order to apply the prediction model, the weights of the financial ratios are estimated in equation (1) using the financial ratios of listed companies. If P_i represents the probability of non-distressed companies which is given in equation (2), then $(1-P_i)$, would be the probability of distressed companies. Hence,

$$1 - P_i = \frac{1}{1 + e^{z_i}} \tag{3}$$

Optimal β (weights) can be estimated where the likelihood value is maximised. The probability of the distressed is obtained by substituting β into the cumulative probability function. A company is classified as distressed if the calculated probability from the logit model is more than 0.5, otherwise it would be non-distressed.

Similar to the discriminant analysis, a forward stepwise method is adopted in logistic regression. This procedure would enable the predictor variables to be entered based upon their contribution to the likelihood ratio statistics. Therefore, variables that do not contribute significantly to the statistics are not entered by the procedures. Soo *et al.* (2001) stressed that the lack of theoretical basis in selecting the independent variables was the main reason why a stepwise procedure is needed. A similar argument was made by Menard (1995) as he stated that stepwise methods are used when neither the theory nor knowledge correlates to the phenomenon. In addition, the used of a stepwise procedure would at least reduce multicollinearity problems which make it difficult to make any statistical inferences and to build an unquestionable model.

Fifteen financial ratios that are used as the independent variables for the MDA and logit analyses are as follows: net income over total assets, current assets turnover, current ratio, shareholders' fund over total liabilities, current assets over total assets, cash and marketable securities over total assets, company size (represented by total assets), cash from operating activities over total liabilities, cash from investing over total liabilities, cash from financing over total liabilities, change in net income (CHIN), net profit margin, gross profit margin, quick ratio, and profit before tax over interest expense.[1]

ANALYSIS OF RESULTS

Table 1 shows the univariate analysis to identify ratios that have the highest ability to discriminate between financially distressed and non-distressed companies. The results show that variables with a mean difference that is significant at the 5% level are net income to total assets, current assets to current liabilities, shareholders' fund to total liabilities, cash and marketable securities to total assets, cash flow from operating activities to total liabilities, cash flow from financing to total liabilities, net profit margin, gross profit margin, and quick ratio.

Table 1
Means Difference between Distressed and Non-Distressed Companies

Variable	t-statistic	Sig.
Net Income/Total Assets	-4.599	0.000*
Sales/Current Assets	-0.497	0.621
Current Assets/Current Liabilities	-6.375	0.000*
Shareholders' Fund/Total Liabilities	-6.533	0.000*
Current Assets/Total Assets	-0.936	0.352
Cash and Marketable Securities/Total Assets	-2.768	0.007*
Size	0.756	0.452
Cash From Operating /Total Liabilities	-3.855	0.000*
Cash From Investing/Total Liabilities	0.228	0.820
Cash From Financing/Total Liabilities	2.929	0.004*
Net Profit Margin	-3.577	0.001*
Gross Profit Margin	-3.638	0.001*
Quick Ratio	-5.787	0.000*
Profit Before Tax/Interest	-1.020	0.311
CHIN	-1.797	0.076

* *significant at* $\alpha = 0.05$

When a correlation analysis was executed (refer to Table 2), there were 23 pair-wise correlation coefficients that were found to be significant at the 5% level. Some of the independent variables were highly correlated, such as shown by the value of 0.883 for current assets to current liabilities against shareholders' fund to total liabilities, 0.911 for current assets to current liabilities against quick ratio, 0.732 for shareholders' fund to total liabilities against quick ratio, and 0.770 for cash and marketable securities to total assets against quick ratio. The evidence shows that some of the variables used are highly collinear with one another.

Furthermore, a tolerance statistic is also analysed for the independent variables. According to Menard (1995: 66), if the tolerance statistic is greater than 0.2, there is no serious collinearity problem. If we were to refer to Table 3, all the independent variables have a tolerance statistic above 0.2, except for size, cash from operating activities to total liabilities and cash from financing to total liabilities. As such, it is confirmed that multicollinearity problems probably exist in our study. Hence, a stepwise procedure is needed to ensure any statistical inferences made from the models will not be questionable.

Table 2

Pearson Correlation Coefficients

	NI/TA	S/CA	CA/CL	SF/TL	CA/TA	CMS/TA	SIZE	COA/TL	CFI/TL	CFF/TL	CHIN	NPM	GPM	QUICK RA	PBT/INTE
NI/TA	1	-.699(**)	.252(**)	.247(*)	0.181	0.099	.265(**)	0.142	-0.04	-0.097	0.165	.285(**)	.287(**)	.227(*)	0.039
		0	0.008	0.01	0.061	0.308	0.006	0.143	0.679	0.32	0.089	0.003	0.003	0.018	0.692
S/CA		1	-.212(*)	-0.107	-.424(**)	-0.157	-.352(**)	-0.072	-0.016	-0.009	0.019	-0.038	-0.038	-0.183	-0.037
			0.027	0.272	0	0.104	0	0.458	0.867	0.925	0.845	0.698	0.692	0.059	0.705
CA/CL			1	.883(**)	.343(**)	.646(**)	-0.002	.479(**)	-0.141	-0.063	0.134	.218(*)	.223(*)	.911(**)	.330(**)
				0	0	0	0.986	0	0.147	0.514	0.167	0.024	0.02	0	0.001
SF/TL				1	0.051	.449(**)	-0.051	.449(**)	-.233(*)	-0.096	.216(*)	0.172	0.175	.732(**)	.322(**)
					0.602	0	0.597	0	0.015	0.324	0.025	0.075	0.069	0	0.001
CA/TA					1	.341(**)	0.158	0.154	0.036	-0.074	-0.134	.193(*)	.195(*)	.374(**)	0.06
						0	0.103	0.111	0.713	0.445	0.167	0.046	0.043	0	0.543
CMS/TA						1	0.1	.556(**)	-0.029	-0.061	0.178	0.14	0.146	.770(**)	.357(**)
							0.305	0	0.766	0.528	0.066	0.15	0.133	0	0
SIZE							1	0.075	0.136	-0.039	-0.113	0.047	0.047	-0.012	0.066
								0.443	0.162	0.692	0.244	0.632	0.628	0.905	0.502
COA/TL								1	-.302(**)	-.346(**)	.224(*)	0.132	0.135	.528(**)	0.189
									0.001	0	0.02	0.172	0.162	0	0.053
CFI/TL									1	-.231(*)	0.079	-0.137	-0.137	-0.134	-0.144
										0.016	0.415	0.157	0.156	0.166	0.141
CFF/TL										1	-.202(*)	-0.05	-0.05	-0.038	-0.105
											0.036	0.61	0.605	0.697	0.284
CHIN											1	0.06	0.063	0.122	0.065
												0.537	0.519	0.207	0.51
NPM												1	1.000(**)	.235(*)	0.041
													0	0.014	0.678
GPM													1	.241(*)	0.043
														0.012	0.661
QUICK RA														1	.359(**)
															0
PBT/INTE															1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 3
Tolerance Statistics

Variable	Tolerance
Net Income/Total Assets	0.846
Sales/Current Assets	0.943
Current Assets/Current Liabilities	0.813
Shareholders' Fund/Total Liabilities	0.484
Current Assets/Total Assets	0.939
Cash and Marketable Securities/Total Assets	0.745
Size	0.110
Cash From Operating Activities/Total Liabilities	0.186
Cash From Investing/Total Liabilities	0.852
Cash From Financing/Total Liabilities	0.061
Net Profit Margin	0.595
Gross Profit Margin	0.610
Quick Ratio	0.239
Profit Before Tax/Interest	0.315
CHIN	0.311

Table 4 reports the results of the MDA. It appears that current ratio (V_c) is more important than net income to total asset (V_a) in predicting financially distressed companies. Among the three variables that enter the discriminant model, the sales to current assets (V_b) has the least discriminating power. Panel B of Table 4 shows that 90.48% of distressed companies and 78.57% of non-distressed companies were correctly predicted in the estimation sample. This implies an overall prediction accuracy of 84.52% in the estimation sample. The model was then used to predict distress in the holdout sample. The result is almost similar to the estimation sample, where the model could correctly classify 90.00% of distressed companies and 70.00 % of non-distressed companies for the holdout sample. This resulted an overall classification accuracy rate of 80.00% in the holdout sample.

The discriminant analysis model prediction accuracy is slightly higher than the model by Ganesalingam and Kumar (2001), which was conducted in Australia. With regard to the Malaysian study, the predictive accuracy is lower than the predictive accuracy of the Zulkarnain *et al.* (2001) model. This would probably be due to the smaller sample size utilised by Zulkarnain *et al.* (2001) which comprised of 24 failed and 24 non-failed companies as compared to 42 failed and 42 non-failed companies in our study. Moreover, Zulkarnain *et al.* (2001) were focussing on the industrial sector whereas this study covered seven different industrial sectors in Malaysia. In comparison to a recent study by Zulkarnain *et al.* (2002), the predictive accuracy of this study is slightly lower than their study. The Zulkarnain *et al.* (2002) model could accurately classify 88.10% whereas the predictive accuracy of the discriminant model in this study was 84.52%.

Table 4
Discriminant Analysis

Panel A

Variable	Wilks' Lambda	Significant
Current Asset/Current Liabilities (V_c)	0.6410	.000*
Net Income / Total Assets (V_a)	0.588	.000*
Sales / Current Assets (V_b)	0.545	.000*

* *significant at* $\alpha = 0.05$

Panel B

Percentage correctly predicted	Estimation Sample	Holdout Sample
Distressed	90.48	90.00
Non-Distressed	78.57	70.00
Overall	84.52	80.00

The results of the stepwise logistic regression are presented in Panel A and Panel B of Table 5. The –2 Log Likelihood statistic tests the null hypothesis where the coefficients of independent variables in the model are zero. Panel A shows that among the variables, only two ratios are found to be significant based on the Wald Statistic (Shareholders' fund to total liabilities and cash flow from financing to total liabilities). However, according to Menard (1995: 38) a likelihood ratio (LR) test is more accurate in evaluating the statistical significance of the contribution of an independent variable to the explanation of a dependent variable. The Wald Statistic normally gives an inflated standard error, which could result in failure to reject the null hypothesis when the null hypothesis is false. Hence, when a likelihood ratio test is executed, it is observed that three variables are found to be significant (net income over total assets, shareholders' fund to total liabilities and cash flow from financing to total liabilities). Panel B of Table 5 shows that the p-values are less than 0.05, which indicate that these variables are significant in contributing to the model and in predicting financial distress. In comparison to the MDA, only net income to total assets entered the logistic regression.

Table 5
Stepwise Logistic Regression:
Analysis of Maximum Likelihood Estimates

Panel A: Variables entering the model: Wald Statistic

Variable	Coefficient	Wald	Significant
Net Income/Total Assets	2.311	0.301	0.583
Shareholders' Fund/ Total Liabilities	9.634	8.503	0.004*
Cash Flow From Financing/ Total Liabilities	-8.606	4.920	0.027*
Constant	-2.507	4.361	0.037

* *significant at* $\alpha = 0.05$

Panel B: Variables entering the model: Likelihood Ratio Test

Variable	Coefficient	Change in –2 Log Likelihood	Significant
Net Income/Total Assets	2.311	5.900	0.015*
Shareholders' Fund/ Total Liabilities	9.634	38.083	0.000*
Cash Flow From Financing/ Total Liabilities	-8.606	9.375	0.002*
Constant	-2.507	4.361	0.037

Model statistics
-2 Log Likelihood 83.317 with 4 degree of freedom (p=0.000)
* *significant at* $\alpha = 0.05$

Panel C: Classification results

Percentage correctly predicted	Estimation sample	Holdout Sample
Distressed	90.50	100.00
Non-Distressed	92.50	80.00
Overall	91.50	90.00

A significant positive coefficient for the variable net income to total assets suggests that companies with higher proportion of net income to total assets are less likely to experience financial distress. Companies that are unable to generate income are prone to have problems, as they may not be able to fulfill their debt obligations. This finding appears to support Ohlson (1980) and Ward and Foster (1997) whom reported net income to total assets had significant predictive ability for US companies. The second variable, shareholders' fund to total liabilities also has a significant positive coefficient. This shows that the lower the proportion of shareholders' funds to total liabilities, the higher the likelihood of the companies to experience financial distress. This result is consistent with Gilbert *et al.* (1990) who found a similar ratio to have a significant ability to predict financial distress for both the bankrupt and distressed estimation sample, and the bankrupt and random sample.

The third variable that is found to be significant is cash flow from financing to total liabilities. Its negative coefficient shows that the higher the amount borrowed, the greater is the likelihood that a company would not be able to meet its obligations. The importance of cash flow from financing to total liabilities in predicting financial distress collaborates with the findings of Ward and Foster (1997), whom found the ratio to have a significant predictive ability two years prior to bankruptcy.

Panel C of Table 5 shows the classification results. 90.50% of distressed companies and 92.50% of the non-distressed companies were correctly classified in the estimation sample. When the coefficients of the estimated model were used to classify the holdout sample, 100% of the distressed and 80.00% of the non-distressed companies were correctly classified. The overall accuracy rate for the estimation and the holdout sample is 91.50% and 90.00% respectively.

The predictive accuracy of the logistic regression model in this study is slightly better when compared to Mohamed *et al.* (2001) and Soo *et al.* (2001). The findings of Mohamed *et al.* (2001) show 80.7% accuracy in their estimation sample and 74.4% in the holdout sample. Soo *et al.* (2001) reported 82.4% accuracy for the estimation sample and 90% accuracy for the holdout sample.

The finding in this study shows that the discriminant analysis model came up with three variables that could distinguish between distressed and non-distressed companies: current ratio, net income to total assets and sales to current assets. In comparison to the stepwise logistic regression based on the likelihood ratio, other than net income to total assets, shareholders' fund to total liabilities and cash flow from financing to total liabilities, were found to be significant in identifying distressed and non-distressed companies. It could be observed that the MDA model put a lot of emphasis on how current assets are being utilised to cover the short term obligations and how these assets contribute to the sales figure; whereas the logistic regression concentrates a lot more on the proportion of shareholders' funds to total liabilities where the lower the proportion, the higher is the likelihood of companies experiencing financial distress. Furthermore, the logistic regression also stresses the importance of companies' cash flows in covering their total liabilities.

CONCLUSION

By using 84 observations, it was found that the logistic regression analysis could accurately predict 91.50% and 90.00% of the respective estimation and holdout sample; whereas the MDA model gives an overall accuracy rate of 84.50% and 80.00% for the estimation and the holdout sample respectively. For the logistic regression, the probability of financial distress is directly related to the ratio of cash flow from financing to total liabilities, net income to total assets, and shareholders' fund to total liabilities ratios. The positive coefficient for the last two ratios indicate that a company is considered healthy or non-distressed if it has a higher net income to total assets and shareholders' fund to total liabilities. There is a lower likelihood of corporate failure if a company can generate income from its investments. Except for net income to total assets, the MDA model shows that current ratio and sales to current assets are important factors in discriminating between the financially distressed and healthy companies.

END NOTES

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1 Most of the variables were selected from the studies implemented by McKibben (1972), Mohamed *et al.* (2001), Ohlson (1980), Soo *et al.* (2001) and Zulkarnain *et al.* (2001).

REFERENCES

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*, 589-609.

Altman, E. I. (1993). *Corporate Financial Distress and Bankruptcy* (2nd ed.). New York: John Wiley.

Altman, E. I., Haldeman, R. G. & Narayanan, P. (1977). Zeta Analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, *1*, 9-24.

Barnes, P. (1987). The analysis and use of financial ratios: A review article. *Journal of Business Finance and Accounting*, *14*(4), 449-461.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Supplement to Journal of Accounting Research*, *4* (3), 71-111.

Chen, K. & Shimerda, T. (1981). An empirical analysis of useful financial ratios. *Financial Management*, *10*, 167-179.

Deakin, E. B. (1976). Distributions of financial accounting ratios: some empirical evidence. *The Accounting Review, 90-96*.

Gadenne, D. & Iselin, E. R. (2000). Properties of accounting and finance information and their effects on the performance of bankers and models in predicting company failure. *Journal of Business Finance and Accounting*, *27* (1) & (2), 155-193.

Ganesalingam, S. & Kumar, K. (2001). Detection of financial distress via multivariate statistical analysis. *Managerial Finance*, *27* (4), 45-55.

Gilbert, L. R., Menon, K. & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business Finance and Accounting*, *17*, 161-171.

Gujarati, D. N. (1995). *Basic Econometrics* (3rd ed.). Singapore: McGraw-Hill International Editions.

Heine, M. L. (2000). *Predicting financial distress of companies: revisiting the Z-Score and Zeta Model*. Retrieve January 2, 2003, from http://pages.stern.nyu.edu/~ealtman/Zscore.pdf.

Houghton, K. A. & Woodliff, D. R. (1987). Financial ratios: The prediction of corporate 'success' and failure. *Journal of Business Finance and Accounting*, *14* (4), 537-554

Joo, H. N. & Jinn, T. (2000). Bankruptcy prediction: evidence from Korea listed companies during the IMF crisis. *Journal of International Financial Management and Accounting*, *11*(3), 178-197.

Laitinen, E. K. (1994). Traditional versus operating cash flow in failure prediction. *Journal of Business Finance and Accounting*, *21* (2), 195-217.

Libby, R. (1975). Accounting ratios and the prediction of failure: some behavioral evidence. *Journal of Accounting Research*, Spring, 150-161.

Lincoln, M. (1984). An empirical study of the usefulness of accounting ratios to describe levels of insolvency risk. *Journal of Banking and Finance*, *8*, 321-340.

Lo, A. (1986). Logit versus discriminant analysis: A specification test and application to corporate bankruptcies. *Journal of Econometric*, *31*, 151-178.

McFadden, D. (1976). A comment on discriminant analysis 'versus' logit analysis. *Annals of Economic and Social Measurement, 5*, 511-523.

McKibben, W. (1972). Econometric forecasting of common stock investment returns: A new methodology using fundamental operating data. *Journal of Finance, 27* (2), 371-381.

Mears, P. K. (1966). Discussion of financial ratios as predictors of failure. *Supplement to Journal of Accounting Research, 4* (3), 119-122.

Menard, S. (1995). *Applied Logistic Regression Analysis*. Thousand Oaks, CA: Sage.

Mohamed, S., Ang, J. & Ahmadu, U. S. (2001). Predicting corporate failure in Malaysia: An application of the logit model to financial ratio analysis. *Asian Academy of Management Journal, 6* (1), 99-118.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*, 109-131.

Platt, H. D. & Platt M. B. (1990) Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance and Accounting, 17*, 31-51.

Scott, J. (1981) The probability of bankruptcy: A comparison of empirical predictions and theoretical models. *Journal of Banking and Finance, 5*, 317-344.

Shamsher, M., Zulkarnain, M. S. & Mohamad Ali, A. H. (2001). Why companies fail? An analysis of corporate failures. *Akauntan Nasional*, 5-8.

Shirata, C. Y. (1998). *Financial ratios as predictors of bankruptcy in Japan: An empirical research*. Retrieve February 25, 2003, from http://www3.bus.osaka.cu.ac.jp/apira98/archives/pdfs/31.pdf.

Soo, W. L., Fauzias, M. N. & Puan Yatim. (2001). Predicting Corporate Financial distress using the logit model: The case of Malaysia. *Asian Academy of Management Journal, 6* (1), 49-61.

The Star, 11 January 2003.

Ward, T. J. & Foster, B. P. (1997). A note on selecting a response measure for financial distress. *Journal of Business Finance and Accounting, 24*, 869-879.

Wruck, K. H. (1990). Financial distress, reorganization, and organizational efficiency. *Journal of Financial Economics, 27*, 419-444.

Zulkarnain, M. S., Mohamad Ali, A. H., Annuar, M. N. & Zainal Abidin, M. (2001). Forecasting corporate failure in Malaysian industrial sector firms. *Asian Academy of Management Journal*, 6(1), 15-30.

Zulkarnain, M. S., Shamsher, M., Mohamad Ali, A. H. & Annuar, M. N. (2002). Determinants of corporate success and failure: The Malaysian case. *Akauntan Nasional*, 23.