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The Classification Model for Corporate Failures in Malaysia

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Abstract

The deterioration of key financial figures could indicate early symptoms of corporate failures. The effort to classify healthy and unhealthy firms could benefit many stakeholders by minimizing their potential losses and the severity of problems. The main purpose of this paper is to develop a failure classification model for Malaysian firms using Discriminant Analysis (DA) and Logistic Regression (LR) as statistical techniques. The dataset consist of 448 total observations, selected from 32 matched-samplings of healthy and unhealthy firms in Malaysia from 1998–2004. An external validation was tested on 15 Malaysian firms for year 2005. The objective of this paper is to find the best selection of financial ratios that could discriminate between these two groups. Empirical results reveal that liquidity ratios play the most important role when determining the reasons for corporate failures in Malaysia. The results from the overall classification accuracy indicates that discriminant analysis approach produces slightly better results with 84% accuracy compared to logistic regression approach of 83%. The results also show that the probability for the sampled Malaysian firms be considered unhealthy is over 40 percent. This research contributes to the literature by identifying early symptoms to corporate failures.
Key words: Liquidity ratios, Discriminant Analysis, Logistic Regression

1. Introduction

The large number of corporate failures in recent years has proved to be costly in many ways. The late 1980s to the mid 1990s saw a collapse of big organizations such as Enron, WorldCom, Prahalad, etc. Many accounting firms are being sued for their involvement in fraud activities, with the most recent case of KPMG agreeing to pay $456 million to avoid criminal prosecution by the U.S. government over abusive tax shelters for wealthy clients. Arthur Andersen collapsed in 2002 after being accused by federal prosecutors for obstructing an investigation of Enron. This has caused massive partner and client defections at Arthur Andersen, leading to a reduction in the number of large accounting firms to four. These incidents happen not just in the United States but also around the world.

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Fraud is a big business internationally, and many large corporations have recognized this area as a major problem in business today. An extreme consequence of fraud is when the collapse of an organization affects numerous stakeholders regardless of size, location or industry. The deterioration of key financial figures could indicate early symptoms of corporate failures. Hence, the effort to classify healthy and unhealthy firms has become desirable as it could benefit such stakeholders by minimizing the potential financial losses and the severity of problems. Since financial data is quantitative in nature, it could be used objectively in statistical analysis to provide such signals.

There has been an extensive volume of research over the years in the area of predicting corporate failures. The economic costs of business failures are relatively large with direct bankruptcy costs amounting to around 1% to 5% of market value of the organization (Warner 1977, Altman 1983). More significantly, the cost comes in the form of lost management time, loss of revenue, damaged reputation, dismissal of employees, and finally the loss of tax revenue to the government. While some factors leading to corporate bankruptcy are uncontrollable, management may be able to control others. Hence, an integrated corporate strategy that creates an organizational culture for inhibiting fraud should be implemented, and appropriate actions should be taken when red flags are identified. A comprehensive investigation with review of all control processes for efficacy is essential for an effective and ethical working environment.

The need for reliable empirical models that predict corporate failures promptly and accurately is imperative, so that interested parties are able to take preventive or corrective actions. Bankruptcy prediction or corporate failure prediction has been one of the most challenging tasks in accounting. Since the study of Fitzpatrick in 1930s and during the last 60 years, there has been an impressive contribution to theoretical and empirical research concerning this area, such as Mervin (1942), Beaver (1966), Altman (1968), Deakin (1972), Edminster (1972), Blum (1974), Altman et. al (1977), Ohlson (1980), El Hennawy & Morris (1983), etc. There are also similar studies using non-U.S data including Joo-Ha-Nam et. al (2000) for Korea, Evi Neophytou et. al (2004) for United Kingdom, Shirata (1995, 1998) and Takahashi et. al (1984) for Japan, Barbro Back et. al (1996) for Finland, Muhamad Sori et. al (2001), Fauzias and Chin (2002) for Malaysia, etc[1]. The growing interest among researchers in this field is mainly due to differences between countries' underlying economic environments, business cycles, competitive nature in the markets, changes in corporate strategy, technological changes, regulatory regimes, accounting and law practices, etc. Therefore, corporate failure modeling is necessary for wide range of countries.

The Asian Crisis, however, caught many countries unexpectedly. Some of the countries predicted to be healthy and sound suffered severely from the economic downfall. As a result, the accuracy of the bankruptcy prediction model became questionable, as it failed to capture this effect beforehand. It is possible that the assumption used in most bankruptcy models that all economies operate under normal conditions needs to be revised when there are crisis symptoms. The economic miracles of

Korea, Thailand, Indonesia and Malaysia intrigued many with their average annual growth rates of more than 7 percent. But when the downturn came, none of them could endure the waves of crisis. The efforts by many researchers to uncover the forces of financial crisis have increased significantly since the Asian Crisis. An early warning system to measure vulnerability becomes complex when analysis is done based on an individual country basis, as each country has its own characteristics. The experience in Asia shows that most fiscal conditions had been quite robust and inflation was relatively moderate. A slowdown in export growth was recorded for some countries, but the most significant indicator was the deterioration of loan portfolios by financial institutions, revealing that corporate sectors were excessively in debt.

The following section provides a comprehensive literature review of various methodologies and empirical studies in chronological order. Section 3 covers the research methodology using discriminant analysis and logistic regression for the data in the study, and empirical results are presented and analyzed. Section 4 concludes the paper with a summary of findings and research limitations.

2. Literature Review

During the early 30s, given the absence of today's super computers, the most feasible way to conduct corporate failures prediction was to compare values for financial ratios between healthy and unhealthy firms. Ramser & Foster (1931), Fitzpatrick (1932), Winakor & Smith (1935) and Mervin (1942) reported an early application of comparing financial ratios of failed against non-failed firms, noting a significant difference between the two sets of comparable ratios. Fitzpatrick's study was indicative of several other studies that followed where comparisons were made between the ratios of successful and failed firms. These early studies used univariate approaches to forecasting financial failure, with the assumption that a single variable could be used for predictive purposes. Beaver (1966) also pointed out that financial ratio structures of failing firms differ from those that are successful, which enables a classification of firms as being healthy or at-risk. The significance of Beaver's work lies in two main areas. First, financial ratios could be used to predict failures. Second, it was shown that available ratios could not be used indiscriminately because some ratios could prove to be more accurate in their predictive ability than others. Generally, most studies have found that profitability, liquidity and solvency ratios as the most significant indicators but their order of importance is unclear since almost every study has produced different findings.

Univariate analysis, however, was argued to be susceptible to faulty interpretation as ratios were analyzed in isolation. Hence, an appropriate extension of this study is to build a predictive model that takes into account the interaction effects between ratios, and possibly to combine several ratios into the predictive model as found in the multivariate analysis. In doing so, one has to determine which ratio is the most important factor for detecting bankruptcy potential. Weights are then attached to the selected ratios to finally create the bankruptcy models. Altman's Z-score model (1968) was a breakthrough in bankruptcy prediction. He selected five variables using multiple discriminant analysis (MDA) and the results showed very strong predictive power exceeding 90%, and this method became the dominant approach at the time. However, since most studies done during this period used a relatively small number of firms in their samples, the generalization of the results was questionable. To find a more robust model, Altman, Haldeman and Narayanan (1977) developed the ZETA model, which can be applied to larger firms with no limitations to specific industries. Despite this effort, discriminant analysis has been criticized for its violations of multivariate normality assumption (Ohlson, 1980; Zavgren, 1983), and for the arbitrary cut-off point (Ohlson 1980). Blum (1974) however, proposed a general framework for variable selection with the probability of failure in terms of expected cash flow. Deakin (1972) tested the superiority of predictive capability between models used by Beaver (1967, 1968) and Altman (1968) by employing the same ratios used by Beaver to search for linear combinations of these ratios with the greatest predictive accuracy.

During 1980s, several other methodologies attempted to improve the accuracy of the model using regression analysis by Meyer and Pifer (1970). Ohlson's (1980) logit regression framework and

Table: 2.0 Selective chronological order of the literature review

Period	Description	Contributors
1930s	Different financial characteristics between healthy and unhealthy firms	1931 — Ramser & Foster 1932 — Fitzpatrick 1935 — Winnakor & Smith 1940 — Mervin
1960s	Bankruptcy prediction models using univariate and multivariate analysis	1966 — Beaver 1968 — Altman 1970 — Meyer & Pifer 1972 — Deakin 1974 — Blum 1977 — Altman, Haydeman, Narayanan
1980s	Improvement in the prediction model using logit, probit, etc.	1980 — Ohlson 1983 — Zavgren 1984 — Zmijewski
1990s	Improvement in the prediction model and accuracy using neural network, decision tree, genetic algorithm, etc.	1993 — Serrano-Cinca 1994 — Back et al 1995 — Wilson et al 1999 — Tae, Namsik, Gunhee
Present	Revalidation of the prediction model under normal versus crisis condition	New research areas

Source: Compiled by Author

Table: 2.1 Summary of advantages and disadvantages of various techniques

Techniques	Advantages	Disadvantages
Discriminant Analysis	• Ability to conduct multiple financial ratios simultaneously • Ease of application once the model has been created • Ability to combine independent variables	• Violation of normality and independence • Reduction of dimensionality • Difficult in interpreting relative importance • Difficult in specifying classification algorithms • Difficult in interpreting time-series prediction test
Decision Tree	• Ability to generate understandable rules • Ability to perform in rule-oriented domains • Ease of calculation at classification time • Handle continuous and categorical variables • Ability to clearly indicate best fields	• Error prone with too many classes • Computationally expensive to train • Trouble with non-rectangular regions
Neural Networks	• Versatile to handle wide range of problems • Produced good results in complicated domains • Ability to handle categorical and continuous variables • Available in many off-the-shelf packages	• Require inputs in the range of (0,1) • Difficult in explaining the results • May converge on an inferior solution
Logit & Probit	• No excessive assumptions like other techniques • Results are explained in probabilities or likelihood form • The computation for Logit & Probit yields similar result except in extreme values	• Intuitively difficult to interpret • Logit is usually preferable than Probit because the former coefficients are easier to interpret (odd ratio), but if the focus is on probabilities, either method is acceptable
Genetic Algorithms	• Produce explainable results • Ease to apply the results • Ability to handle wide range of data sets • Applicable in optimization • Integrate well with neural networks	• Difficult in encoding • No guarantee of optimality • Computationally expensive • Available in few commercial packages

Source: Modified by Author from Tae, Namsik & Gunhee (1999)

Zmijewski's (1984) probit analysis were also used to quantify the log-likelihood function by comparing population frequency rate to the sample frequency rate of the individual groups to predict distress probabilities. During the 1990s, artificial neural networks produced very optimistic results with the application of artificial intelligence into classification problems for predicting bankruptcies such as Serrano-Cinca (1993), Back et. al (1994), and Wilson et. al (1995). Most neural networks studies in bankruptcy prediction have focused on the comparison of performance (prediction accuracy) between neural networks and other methodologies such as discriminant analysis, logit analysis, genetic algorithms, decision tree, etc. Some studies reported that neural networks performed slightly better than other techniques, but overall the results are inconclusive. Another innovation to the methodology was the study of genetic algorithms to find the best sets of predictors for neural networks. These algorithms have been applied successfully in several optimization problems. Genetic algorithms are stochastic techniques that can search for large or complicated spaces. Recently, hybrid studies combining neural networks and genetic algorithms have begun to emerge in the field of bankruptcy prediction.

The Asian Crisis was a significant test for all of these bankruptcy prediction models, since most of them were built under normal economic conditions. The situation in Korea for example, indicated that there was a need for prediction modeling under crisis situation. A comprehensive review of the literature shows that no study has attempted to develop models under such conditions, except Tae, Namsik and Gunhee (1999), who used dynamic modeling in a normal versus crisis situation for Korea. In short, the extensive research on corporate failures has encompassed a wide variety of methodologies and data sources. Almost all studies now rely on better statistical procedures to develop more convincing models for financial distress prediction. The above reviews suggest that further research is necessary using prediction models applied across nations within different industries for both normal and crisis economic conditions. Recent studies have greatly expanded opportunities for new contributions from researchers.

3. Research Methodology

The primary objective of this research is to find the best selection of financial accounting ratios that will accurately classify firms into healthy and unhealthy categories. Once the ratios are selected and formulated into a multivariate model, the accuracy of the model will be investigated by testing its ability to classify firms into two groups. These financial ratios can be divided into *liquidity, profitability, leverage, activity* and *operating cash flow*. This report utilizes mainly Statistical Package for Social Sciences (SPSS) Version 11.5 for Windows, and also MATLAB 7.0.1 for some minor analysis. The ratios used in this paper are shown in Table 3.0:

The *liquidity ratio* measures the extent to which a firm or other entity can quickly liquidate assets

Table: 3.0 Financial Ratios as Variables[2]

Category	Abbreviation	Description	Ratio	Cited by
Liquidity	CA/CL	Current Asset/Current Liability	R_1	M, B, D, AHN
Activity	CA/SALES	Current Asset/Sales	R_2	D
Liquidity	CA/TA	Current Asset/Total Asset	R_3	D, EM
Liquidity	CL/EQ	Current Liability/Equity	R_4	E
Activity	EQ/SALES	Equity/Sales	R_5	RF, E
Profitability	EBIT/TA	Earnings before interest and tax/Total Asset	R_6	A
Leverage	EQ/TD	Equity/Total Debt	R_7	A, AHN
Leverage	LIAB/EQ	Long Term Debt/Equity	R_8	EM
Profitability	RY/TA	Retained Earnings/Total Asset	R_9	A, AHN
Activity	S/TA	Sales/TA	R_{10}	RF, A
Leverage	TD/EQ	Total Debt/Equity	R_{11}	M
Leverage	TD/TA	Total Debt/Total Asset	R_{12}	B, D
Profitability	WC/S	Working Capital/Sales	R_{13}	E, D
Profitability	WC/EQ	Working Capital/Equity	R_{14}	Author
Profitability	WC/TA	Working Capital/Total Asset	R_{15}	A, WS, B, D
Cash Flow	OCF/TD	Net cash flow from operation/Total debt	R_{16}	BL, B, D
Cash Flow	OCF/TA	Net cash flow from operation/Total Asset	R_{17}	EM
Cash Flow	OCF/CL	Net cash flow from operation/Current Liability	R_{18}	E

Where citation was done by:
A (Altman 1968); AHN (Altman, Halderman, Narayanan 1977); B (Beaver 1966); BL (Blum 1964); D (Deakin 1972); E (Edminster 1972); EM (El Hennawy, Morris 1983); M (Mervin 1942); RF (Ramser, Foster 1931); WS (Winakor, Smith 1935).

and cover short-term liabilities, and therefore is mostly used in judging credit worthiness and is of interest to short-term creditors. *Profitability ratio* measures a firm's performance by comparing its earning to its sales, assets or equity. It is also used to compare earnings for prospective investments. *Leverage ratio* looks at how the business is utilizing borrowed funds and is an indication of long term solvency. Firms that are highly leveraged might be at risk if they are unable to make payments on their debt, therefore making it harder for them to find new lenders in the future. Having leverage is not always considered negative because it could increase the shareholders' return on their investment and often there are tax advantages associated with borrowing. *Activity ratio* measures the long-term effectiveness and short-term efficiency of management in generating sales from the firm's assets. *Operating cash flow* looks at the quality of a firm's earnings. This ratio is able to gauge a liquidity situation in the short-term. Using cash flow as opposed to income is sometimes a better indication of liquidity because cash is normally used to pay off bills.

3.1 Research Design and Procedures

The collection of data for unhealthy firms requires a definition of failure for the population sample from which these firms are chosen. The population in this study consists of all firms that are listed on the Kuala Lumpur Stock Exchange (BURSA Malaysia) during the period from 1998 until 2004. This paper will categorize any firm that is classified as Industrial Product (IP) and Consumer Product (CP) by BURSA as manufacturing. The author tries to follow the original method used by Altman (1968)[3] whenever possible, but due to scarce published data for unhealthy firms, other sectors such as Plantation, Construction, Transportation, Agriculture, Technology, Property, Trading and Finance are included within the sample. (See Table 3.1 in the *Appendix* for the list of Healthy and Unhealthy firms in the original model). In the analysis, healthy firms are coded as 0 and unhealthy as 1.

This paper therefore, defines unhealthy firms as those that have been classified into PN4 and PN17 by BURSA. A publicly listed firm that is financially distressed and makes little effort to restructure within the new time frame (about 8 months) will face de-listing from BURSA. Previously, financially distressed firms were categorized under Practice Note 4 (PN4) and there were no stringent timeframes for restructuring. There have been cases where BURSA has granted up to two years of grace period for firms to restructure. Since the Asian crisis, BURSA has de-listed only 27 companies, but it was a long and complex process. As a result, PN17, having a tighter time frame of about eight months, was introduced in order to accelerate the de-listing activity.

Once healthy and unhealthy groups have been established, data for each firm was selected from the balance sheet, income statement, statement of changes in equity, and cash flow statement. The data was collected based on a firm's performance rather than consolidated group basis. In earlier studies, there were a large number of financial ratios found to be significant in indicating corporate failures. Hence, a list of eighteen potentially helpful ratios in Table 3.0 was compiled for further evaluation. This paper also includes five significant ratios that were selected by Altman's study in 1968. Beaver (1967) concluded that cash flow to debt was the best predictor in his model. This ratio too was included together with a few more new ratios in the analysis due to its prevalence in the literature and potential relevancy to the study. A paired sampling of 32 firms between healthy and unhealthy was selected based on industry classification. In order to test the validity of the model, 15 new unhealthy firms were selected in 2005 as the validation sample (see Table 3.1 in the *Appendix* for list of unhealthy firms used for external validation). The classification accuracy for both models is compared.

3.2 Research Techniques

Multiple discriminant analysis and logit analysis have very different assumptions concerning the relationship between independent variables. The former analysis is based on linear combination of independent variables while the latter uses the logistic cumulative probability function to determine the bankruptcy prediction model. The aim of this analysis is to see whether there is an essential difference between methods which may lead to significant differences in classification accuracy.

3.2.1 Multiple Discriminant Analysis (MDA)

MDA was first applied during the 1930s and was used mainly in biological and behavioral sciences. Pioneering work using this approach was applied successfully to financial problems in consumer credit evaluation and investment classification, as cited by Durand (1941) and by Myers and Forgy (1963) in evaluating good and bad installment loans.

The purposes of discriminant analysis are:

- To test for mean group differences and describe overlapping among groups.
- To construct classification schemes based on a set of variables and assign the unclassified observation into the appropriate groups.
- To assess the relative importance of the independent variables in classifying the dependent variables.

MDA tries to derive the best linear combination of two or more independent variables that will discriminate between a priori defined groups, healthy and unhealthy firms, and the equation takes the following form:

$$Z=W_1R_1+W_2R_2+\ldots.+W_n R_n \tag{1}$$

Where

Z	= Discriminant scores
Wi (i = 1, 2, …, n)	= Discriminant weights
Ri (i = 1, 2, …., n)	= Independent variables (financial ratios)

Once each firm receives a single composite discriminant score, it is compared to a cut-off value that establishes which group the firm belongs to. If a particular firm has characteristics (financial ratios) that can be quantified for all firms in the analysis, MDA will produce a set of discriminant coefficients. When these coefficients are applied to the actual ratio, there exists a basis for classification into one of the mutually exclusive groups[4].

The advantage of MDA lies in its capability to simultaneously analyze the entire profile of characteristics which are common to these firms, as well as the interaction effects between them. MDA is usually used for dependents having more than two categories, but in this case, the technique is called discriminant analysis because there are only two groups under study. However, this technique imposes two main conditions. First, variables in every group must follow a multivariate normal distribution, and secondly the covariance matrices for every group must be equal. Many empirical studies have shown that normality conditions of the firms are often violated, especially for unhealthy firms. Multicollinearity among independent variables and equal group variances are also another problem especially when stepwise procedures are used (Hair et al. 1992). However, empirical studies have demonstrated that the violation of normality assumption does not diminish classification capability but rather its predictive ability.

Discriminant analysis utilizes the stepwise procedure with F values for entry criteria at 1.25, and removal at 1.0 was applied in selecting critical variables. This procedure was chosen because no priori beliefs were attached to the eighteen independent variables. The selection rule was used to minimize Wilks' Lambda (λ) at each step[5].

3.2.2 Logistic Regression Analysis (Logit)

Binomial (or binary) logistic regression is a form of regression used when the dependent is a dichotomy. Logistic regression analysis has been used to investigate the relationship between binary and ordinal response probability and explanatory variables with the method of maximum likelihood. This is achieved by transforming the dependent into a logit variable, which is the natural log of the odds of the dependent occurring or not. Hence, logit produces estimates on the probability of a certain event occurring. Unlike discriminant analysis, this method weights the independent variables and assigns a Z-score in probability form. The advantages of logit include no assumptions of multivariate normality, equal covariance matrices, homoscedasticity, etc. Logit's lesser stringent requirements allow it to avoid all the problems inherent in discriminant analysis. Logit analysis also incorporates non-linear effects and uses logistical cumulative function in predicting bankruptcy (Ohlson 1980).

In logistic regression, the dependent variables may have only two values such as healthy or unhealthy and produce predicted values from 0 to 1. The logistic function can be written as follows:

$$Z_n = a + B_1R_1 + B_2R_2 + \ldots B_nR_n \qquad (2)$$

Where

Z_n = Healthy or Unhealthy

a = Constant

Bi (i = 1, 2, …n) = Coefficients

Ri (i = 1, 2, …., n) = Independent variables (financial ratios)

The logarithm of the likelihood of any outcome between healthy and unhealthy is then given by:

$$\mathrm{Ln}\left(\frac{\text{Probability of unhealthy}}{\text{Probability of healthy}}\right) = a + B_1R_1 + B_2R_2 + \ldots B_nR_n \qquad (3)$$

In this equation, the log of unhealthy is a function of a constant, plus a series of weighted averages of financial ratios. Or more specifically,

$$\text{Probability of unhealthy}\left(\frac{1}{1+e^{-Z}}\right) = \frac{1}{1+e^{-(a+B_1X_1+B_2X_2+\ldots B_nX_n)}} \qquad (4)$$

3.3 Empirical Results Using Discriminant Analysis

One basic step for the analysis is the identification of any significant differences between the two groups of firms. Table: 3.2 shows the basic preliminary univariate information for the means of two groups and the overall mean of the eighteen financial ratios. Wilks' Lamba, F and significant values contribute bivariate information about the differences between means of each ratio. Inspection of the group means reveals a substantial difference between healthy and unhealthy firms. In the ANOVA table below, the smaller the Wilks' lambda, the more important the independent variable is to the discriminant function. Wilks' lambda is significant by the F test for *R_2, R_6, R_9, R_{14}, and R_{17}*. We can see that these five ratios indicate higher values for the unhealthy group.

Table: 3.2 Variable Means and Test of Significance

Variable Means By Group				Tests of Equality of Group Means			
Ratio	No	Healthy	Unhealthy	Total Mean	Wilks' Lambda	F	Sig.
R_1	64	4.235	3.753	3.994	0.999	0.080	0.779
R_2	64	3.431	23.005	13.218	0.807	14.823	0.000
R_3	64	0.317	0.441	0.379	0.920	5.387	0.024
R_4	64	0.552	-4.609	-2.028	0.979	1.305	0.258
R_5	64	18.778	-3.569	7.604	0.964	2.297	0.135
R_6	64	-0.004	-0.673	-0.338	0.896	7.178	0.009
R_7	64	43.764	11.393	27.578	0.952	3.115	0.082
R_8	64	0.091	0.122	0.107	0.994	0.372	0.544
R_9	64	-0.049	-3.032	-1.541	0.849	11.020	0.002
R_{10}	64	0.247	0.161	0.204	0.974	1.664	0.202
R_{11}	64	0.644	-4.475	-1.916	0.980	1.280	0.262
R_{12}	64	0.271	5.294	2.783	0.922	5.241	0.025
R_{13}	64	-1.302	-27.672	-14.487	0.951	3.162	0.080
R_{14}	64	0.070	0.565	0.318	0.889	7.763	0.007
R_{15}	64	0.075	-4.811	-2.368	0.926	4.956	0.030
R_{16}	64	0.615	-0.183	0.216	0.920	5.378	0.024
R_{17}	64	0.026	-0.060	-0.017	0.895	7.294	0.009
R_{18}	64	0.222	-0.029	0.096	0.989	0.676	0.414

In checking for multivariate normality, the larger the log determinant in the table below, the more the group's covariance matrix differs. A total of seven independent variables have been identified in the analysis, and the log determinant is expected to be relatively equal due to the assumption of homogeneity covariance matrices. Discriminant function analysis is still robust even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers. This test significantly concludes that the groups do differ in their covariance matrices, therefore violating an assumption of multivariate normality.

Table: 3.3 Test of Equality of Group Covariance Matrices using Box's M

CATEGORY	Rank	Log Determinant	Box's M	Approx.	df1	df2	Sig.
Healthy	7	-14.008					
Unhealthy	7	-2.675					
Pooled within-groups	7	-4.212	256.01	8.036	28	13394.7	2.3931E−32

Note: Tests null hypothesis of equal population covariance matrices

Next is the determination of the eigenvalues[6] for the two-group discriminant analysis. Table 3.4 shows the summary for canonical discriminant functions. When the canonical correlation is large, there is a high correlation between the discriminant functions and the groups. The value of 0.692 indicates that the function discriminates between the groups quite significantly.

Table: 3.4 Canonical Discriminant Functions

Eigenvalues					Wilks' Lambda				
Function	Eigen-Value	% of Variance	Cum %	Canonical Correlation	Test of Function	Wilks' λ	Chi-Sq	df	Sig.
1	0.917	100	100	0.692	1	0.522	38.058	7	2.95E−06

First 1 canonical discriminant functions were used in the analysis.

Table 3.5 is the standardized discriminant function coefficients derived from the stepwise analysis on the eighteen financial ratios. These coefficients serve the same purpose as beta weights in multiple regressions, i.e. they show the relative importance of the independent variables in predicting the dependent. The standardized coefficients with the largest absolute size indicate that the ratios have the greatest contribution towards discrimination. The values could have positive or negative effects on the discriminant function. The optimal function for the model included seven ratios with the greatest contribution from R_2 (CA/Sales), followed by R_3 (CA/TA), R_6 (EBIT/TA) and so forth. In creating the model, the unstandardized discriminant coefficients are used for making classifications in discriminant analysis. The constant plus the sum of products of the unstandardized coefficients with the observations yields the discriminant scores. Therefore, the final discriminant analysis model for Malaysian firms in the sample is:

Table: 3.5 Canonical Discriminant Function Coefficients and Relative Contribution

Ratio	Variable	Category	Unstandardized	Standardized	Sign	Relative Contribution (Ranking)
R_1	CA/CL	Liquidity	0.060	0.409	+	5th
R_2	CA/Sales	Activity	-0.037	-0.756	-	1st
R_3	CA/TA	Liquidity	-2.795	-0.594	-	2nd
R_6	EBIT/TA	Profitability	0.554	0.554	+	3rd
R_8	LIAB/EQ	Leverage	-1.652	-0.334	-	6th
R_{10}	S/TA	Activity	1.743	0.466	+	4th
R_{17}	OCF/TA	Cash Flow	2.487	0.314	+	7th
		(Constant)	1.364			

$$Z = 1.36 - 2.8R_3 + 2.49R_{17} + 1.74R_{10} - 1.65R_8 + 0.55R_6 + 0.06R_1 - 0.04R_2 \qquad (5)$$

Where:

Z = Overall Discriminant Scores

R_3 = Current Asset/Total Asset (CA/TA): Liquidity

R_{17} = Net cash flow from operation/Total Asset (OCF/TA): Cash flow

R_{10} = Sales/Total Asset (S/TA): Activity

R_8 = Long Term Debt/Equity (LIAB/EQ): Leverage

R_6 = Earnings before interest and tax/Total Asset (EBIT/TA): Profitability

R_1 = Current Asset/Current Liability (CA/CL): Liquidity

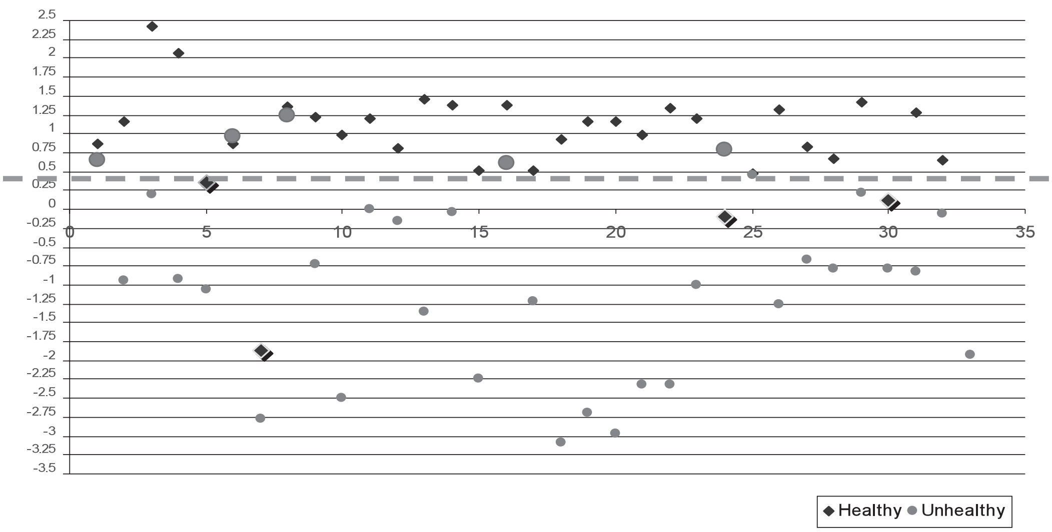
R_2 = Current Asset/Sales (CA/S): Activity

These seven ratios derived from the discriminant function reveal that *liquidity* is the major problem facing Malaysian firms in the analysis. The result is also consistent with the World Bank Report[7] on Asian Crisis suggesting that Malaysian firms suffered more from the liquidity crisis rather than from financial insolvency. For firms that are in difficulty, we would expect liquid business assets to slowly decline to compensate for poor sales performance as in R_3, R_{10}, R_1, and R_2. This can be seen in the current asset ratio in relation to total assets, current liability and sales, and sales ratio in relation to total assets. Given the relative contribution of the variables for group discrimination, R_2 and R_3 are critical to the model. In order to absorb the shock to the economy, liquid assets are the main source of short-term funds to assist firms in their operational needs. A firm that continues to have consistent operating losses has a much lower chance of profitability and survival. With the demolishing position in the competitive environment, this could eventually drive them out from the business.

The inclusion of R_6 and R_{10} in the Malaysian model is also consistent with Altman's 1968 study which selected S/TA and EBIT/TA as the critical indicators of failure. Likewise, no organization could survive without generating enough cash flow from their normal operation, making R_{17} one of the most significant factors in predicting corporate failures in Malaysia. Finally, solvency ratio also plays a role in determining corporate sustainability.

A cut-off score can be used to categorize observations. If the discriminant score of the function is less than or equal to the cut-off, the case is classified as 0, or if above it is classified as 1. When group sizes are equal, the cutoff is the mean of the two centroids. If the groups are unequal, the cutoff would be the weighted mean. A good discriminant function requires the means of the two groups to differ significantly for good discrimination. The closer the means, the more errors of classification there are likely to be. In general, a high occurrence of Type 1 error i.e. misclassifying unhealthy as healthy is undesirable because it could lead to real non-reversible financial losses to stakeholders. Type 2 error, on the other hand, would create some negative perceptions and uncertainties when healthy firms are misclassified as unhealthy, but the impact is much lesser than Type 1 error. Therefore, in order to minimize these errors, the author has selected a cut-off point of 0.45 as it produces the lowest Type 1 error of 15.6%. Figure 1.0 indicates that firms with Z values less than 0.45 would be best classified as unhealthy.

Figure: 1.0　Scatter plot for Healthy and Unhealthy (1998–2004)



In determining classification accuracy, the percentage between the total numbers of correctly classified observations to the total number of observations is compared. This accuracy matrix is a measure of goodness of fit for the classification model. It measures how well the model is discriminating between the two groups. Table 3.7 shows that the model correctly identifies 30 out of 32 healthy firms (94% accuracy) and 24 out of 32 unhealthy firms (75% accuracy). Overall, the model correctly classifies over 84 percent of the sample firms with Type 2 error of approximately 6 percent and Type 1 error of 25 percent.

Table: 3.7 Classification Results[8]

		CATEGORY	Predicted Group Membership Healthy	Unhealthy	Total
Original	Count	Healthy	30	2	32
		Unhealthy	8	24	32
	%	**Healthy**	**93.75**	**6.25**	100
		Unhealthy	**25**	**75**	100

84.4% of original grouped cases correctly classified.

Table: 3.7 summarizes the results from analyzing the Casewise results below. The summary provides information about the actual group, the predicted group based on the assigned discriminant function with asterisk indicating misclassification, the Mahalanobis distance to the group centroid, and the discriminant scores.

Casewise Statistics				**Highest Group**			**Second Highest Group**			
	Case Number	Actual Group	Predicted Group	P(D>d |G=g)	P(G=g |D=d)	Squared Mahalanobis	Group	P(G=g |D=d)	Squared Mahalanobis	Discriminant Scores
Original	1	0	0	0.945	0.838	0.005	1	0.162	3.298	0.874
	2	0	0	0.822	0.900	0.050	1	0.100	4.448	1.167
	3	0	0	0.140	0.990	2.178	1	0.010	11.293	2.418
	4	0	0	0.260	0.980	1.271	1	0.020	9.072	2.070
	5	0	0	0.558	0.662	0.342	1	0.338	1.688	0.357
	6	0	0	0.947	0.839	0.004	1	0.161	3.308	0.876
	7	0	*1**	0.358	0.971	0.845	0	0.029	7.860	-1.861
	8	0	0	0.681	0.928	0.169	1	0.072	5.270	1.353
	9	0	0	0.782	0.909	0.077	1	0.091	4.671	1.219
	10	0	0	0.972	0.863	0.001	1	0.137	3.683	0.977
	11	0	0	0.800	0.905	0.064	1	0.095	4.572	1.196
	12	0	0	0.891	0.820	0.019	1	0.180	3.053	0.805
	13	0	0	0.611	0.939	0.259	1	0.061	5.727	1.451
	14	0	0	0.668	0.930	0.184	1	0.070	5.351	1.371
	15	0	0	0.673	0.727	0.178	1	0.273	2.139	0.520
	16	0	0	0.664	0.931	0.189	1	0.069	5.381	1.377
	17	0	0	0.670	0.726	0.182	1	0.274	2.127	0.516

18	0	0	0.982	0.850	0.001	1	0.150	3.466	0.919
19	0	0	0.819	0.901	0.052	1	0.099	4.466	1.171
20	0	0	0.828	0.899	0.047	1	0.101	4.416	1.159
21	0	0	0.970	0.864	0.001	1	0.136	3.695	0.980
22	0	0	0.684	0.927	0.165	1	0.073	5.251	1.349
23	0	0	0.794	0.906	0.068	1	0.094	4.606	1.204
24	0	*1**	0.395	0.543	0.724	0	0.457	1.068	-0.091
25	0	0	0.643	0.711	0.215	1	0.289	2.020	0.479
26	0	0	0.703	0.924	0.145	1	0.076	5.135	1.324
27	0	0	0.903	0.824	0.015	1	0.176	3.107	0.820
28	0	0	0.783	0.779	0.076	1	0.221	2.591	0.667
29	0	0	0.630	0.936	0.232	1	0.064	5.602	1.424
30	0	0	0.414	0.559	0.668	1	0.441	1.139	0.125
31	0	0	0.733	0.918	0.117	1	0.082	4.956	1.284
32	0	0	0.773	0.774	0.083	1	0.226	2.547	0.654
33	1	1	0.999	0.855	0.000	0	0.145	3.549	-0.942
34	1	*0**	0.455	0.591	0.557	1	0.409	1.295	0.196
35	1	1	0.985	0.851	0.000	0	0.149	3.481	-0.923
36	1	1	0.907	0.880	0.014	0	0.120	4.006	-1.059
37	1	*0**	0.984	0.860	0.000	1	0.140	3.627	0.962
38	1	1	0.069	0.995	3.314	0	0.005	13.729	-2.763
39	1	*0**	0.768	0.911	0.087	1	0.089	4.751	1.237
40	1	1	0.829	0.797	0.046	0	0.203	2.786	-0.727
41	1	1	0.122	0.991	2.393	0	0.009	11.775	-2.489
42	1	*0**	0.347	0.501	0.885	1	0.499	0.891	0.001
43	1	1	0.428	0.570	0.628	0	0.430	1.193	-0.150
44	1	1	0.673	0.929	0.178	0	0.071	5.319	-1.364
45	1	1	0.365	0.517	0.821	0	0.483	0.957	-0.036
46	1	1	0.196	0.985	1.672	0	0.015	10.098	-2.235
47	1	*0**	0.746	0.763	0.105	1	0.237	2.438	0.619
48	1	1	0.790	0.907	0.071	0	0.093	4.627	-1.209
49	1	1	0.032	0.997	4.617	0	0.003	16.268	-3.091
50	1	1	0.080	0.994	3.059	0	0.006	13.204	-2.691
51	1	1	0.043	0.996	4.101	0	0.004	15.285	-2.967

	52	1	1	0.166	0.988	1.923	0	0.012	10.702	-2.329
	53	1	1	0.166	0.988	1.921	0	0.012	10.698	-2.328
	54	1	1	0.955	0.868	0.003	0	0.132	3.768	-0.999
	55	1	*0**	0.878	0.816	0.024	1	0.184	2.997	0.789
	56	1	*0**	0.621	0.699	0.244	1	0.301	1.933	0.448
	57	1	1	0.757	0.914	0.096	0	0.086	4.815	-1.252
	58	1	1	0.785	0.780	0.074	0	0.220	2.600	-0.670
	59	1	1	0.875	0.814	0.025	0	0.186	2.982	-0.784
	60	1	*0**	0.467	0.600	0.530	1	0.400	1.338	0.214
	61	1	1	0.879	0.816	0.023	0	0.184	3.002	-0.790
	62	1	1	0.905	0.825	0.014	0	0.175	3.117	-0.823
	63	1	1	0.380	0.531	0.769	0	0.469	1.015	-0.065
	64	1	1	0.322	0.974	0.980	0	0.026	8.263	-1.932

** Misclassified cases*

3.4 Empirical Result Using Logistic Regression

The dependent variables encoded Healthy as 0 and Unhealthy as 1, and the selection of the significant predictors was made using forward LR method. The chi-square goodness-of-fit tests the null hypothesis of whether the steps and variables are justified, provided that the significance of the step is less than 0.05. In step 1, when the first variable is added to the model, it has significant impact

Table: 4.0 Model Summary

Omnibus Tests of Model Coefficients

	Chi-square	Sig.		
Step	5.921	0.014962	-2 Log likelihood	49.635
Block	39.088	1.66E-08	Cox & Snell R Square	0.457
Model	39.088	1.66E-08	Nagelkerke R Square	0.609

Table: 4.1 Model if Term Removed

Variable	Model Log Likelihood	Change in -2 Log Likelihood	Sig. of the Change
R_2	-29.474	9.314	0.002275
R_9	-28.299	6.964	0.008317
R_{17}	-27.778	5.921	0.014962

on the dependent variables. The step is then repeated by adding a second variable, and so on until the adding no longer improves the model. Table 4.0 and Table 4.1 show how well the model fits the data. From Nagelkerke R Square, about 61 percent of the variation in the model can be explained by the logistic regression model.

A small -2 Log likelihood value would indicate that the model fits the data well. If the change in -2 Log likelihood is larger than the probability for stepwise removal (i.e. in the default case 0.1 for removal criteria), then the variables can be removed from the model. For these results, however, the significance of changes are all below 0.1, hence no variables selected above should be removed from the model. Therefore R_2, R_9, and R_{17} are found to have a high degree of explanatory power in identifying corporate failures based on logistic regression analysis. The result is also consistent with discriminant analysis in section 3.3, where R_2 and R_{17} are also part of the significantly selected variables in the model. The summary of variables included in the equation is displayed in Table 4.2 below.

Table: 4.2 Variables in the equation

	B	S.E.	Wald	Sig.	Exp(B)	
R_2	0.077	0.044	3.148	0.076	1.080	Variable(s) entered on step 1: R2.
R_9	-0.836	0.491	2.901	0.089	0.433	Variable(s) entered on step 2: R9.
R_{17}	-17.358	9.699	3.203	0.074	0.000	Variable(s) entered on step 3: R17.
Constant	-1.123	0.444	6.389	0.011	0.325	

The Hosmer and Lemeshow Goodness-of-Fit Test divides subjects into deciles based on predicted probabilities, and includes chi-square computed from observed and expected frequencies. If Hosmer and Lemeshow Goodness-of-Fit test statistic is .05 or less, we would reject the null hypothesis, but this is not the case here. The results show that we would accept the null hypothesis i.e. there is a difference between the observed and predicted values of the dependent ($p = 0.138$, chi-square 8 degrees of freedom). Hence, we can conclude that the logistic model fits quite well with the data at an acceptable level. The contingency table below represents a full model with the independents as well as the constant. It compares the predicted values for the dependent variable based on the regression model with the actual observed values in the data. If the probability is less than 0.5, it will classify the firms into the healthy group and if it exceeds 0.5, it will go into the second group, i.e. unhealthy group. In short, the model produces excellent results by correctly predicting the two groups at overall classification accuracy of 83 percent.

In order to predict the probability of a firm being unhealthy, it is possible to substitute the three selected variables R_2, R_9, and R_{17} into equation (2). The Malaysian Logit model is given by:

Table: 4.3 Contingency Table for Hosmer and Lemeshow Test

	CATEGORY = Healthy		CATEGORY = Unhealthy		
	Observed	Expected	Observed	Expected	Total
1	6	5.550	0	0.450	6
2	6	5.220	0	0.780	6
3	2	4.946	4	1.054	6
4	5	4.581	1	1.419	6
5	5	4.328	1	1.672	6
6	4	3.627	2	2.373	6
7	3	2.503	3	3.497	6
8	1	1.127	5	4.873	6
9	0	0.103	6	5.897	6
10	0	0.016	10	9.984	10

Classification Table

PREDICTED

Category	Healthy	Unhealthy	Percentage Correct
Healthy	29	3	90.625
Unhealthy	8	24	75
Overall Percentage			**82.8125**

The cut value is .500

$$Z = -1.12 - 17.3R_{17} - 0.84\, R_9 + 0.08\, R_2 \tag{6}$$

Then,

$$\text{Probability of being Unhealthy} = \frac{1}{1+e^{-Z}} = 1/\left(1+e^{-1.12-17.3R17-0.84\,R9+0.08\,R2}\right) \tag{7}$$

Table 4.4 shows the probabilities of being unhealthy and contains the predicted values from the original group sample using data from 1998 until 2004 with logit model above.

It is worth noting that the probability of a firm being unhealthy is rather low. We can generally conclude that there is nearly 40 percent chance that the sample firms would be predicted as unhealthy. This table also indicates that Malaysian firms did not show high probabilities of failure before the crisis. In the external validation, both models correctly classified 80% of the new sample (2005) as unhealthy.

Table: 4.4 Probability of Being Unhealthy from Logit

NO	1998P		1999P		2000P		2001P		2002P		2003P		2004P		**AveP**	
1	0.74	1	0.36	0	0.40	0	0.62	1	0.58	1	0.58	1	0.56	1	**0.03**	**0**
2	0.19	0	0.30	0	0.39	0	0.44	0	0.43	0	0.43	0	0.39	0	**0.16**	**0**
3	0.38	0	0.31	0	0.39	0	0.34	0	0.36	0	0.36	0	0.25	0	**0.00**	**0**
4	0.19	0	0.34	0	0.39	0	0.42	0	0.43	0	0.43	0	0.54	1	**0.05**	**0**
5	0.24	0	0.30	0	0.40	0	0.57	1	0.53	1	0.53	1	0.25	0	**0.09**	**0**
6	0.49	0	0.32	0	0.40	0	0.45	0	0.45	0	0.45	0	0.58	1	**0.31**	**0**
7	0.50	1	0.31	0	0.59	1	0.47	0	0.49	0	0.49	0	0.63	1	**0.35**	**0**
8	0.37	0	0.33	0	0.41	0	0.25	0	0.28	0	0.28	0	0.26	0	**0.05**	**0**
9	0.23	0	0.30	0	0.41	0	0.33	0	0.34	0	0.34	0	0.31	0	**0.11**	**0**
10	0.12	0	0.58	1	0.39	0	0.33	0	0.35	0	0.35	0	0.25	0	**0.00**	**0**
11	0.75	1	0.35	0	0.40	0	0.35	0	0.37	0	0.37	0	0.35	0	**0.02**	**0**
12	0.54	1	0.31	0	0.40	0	0.44	0	0.42	0	0.42	0	0.28	0	**0.41**	**0**
13	0.24	0	0.33	0	0.39	0	0.36	0	0.38	0	0.38	0	0.27	0	**0.00**	**0**
14	0.24	0	0.36	0	0.40	0	0.54	1	0.53	1	0.53	1	0.46	0	**0.01**	**0**
15	0.28	0	0.51	1	0.41	0	0.49	0	0.50	0	0.50	0	0.57	1	**0.31**	**0**
16	0.45	0	0.43	0	0.44	0	0.44	0	0.43	0	0.43	0	0.60	1	**0.02**	**0**
17	0.31	0	0.46	0	0.61	1	0.21	0	0.35	0	0.35	0	0.25	0	**0.15**	**0**
18	0.17	0	0.35	0	0.44	0	0.52	1	0.50	0	0.50	0	0.53	1	**0.00**	**0**
19	0.65	1	0.45	0	0.40	0	0.57	1	0.52	1	0.52	1	0.63	1	**0.07**	**0**
20	0.38	0	0.34	0	0.44	0	0.43	0	0.44	0	0.44	0	0.43	0	**0.00**	**0**
21	0.71	1	0.30	0	0.40	0	0.60	1	0.53	1	0.53	1	0.66	1	**0.06**	**0**
22	0.17	0	0.30	0	0.47	0	0.42	0	0.42	0	0.42	0	0.40	0	**0.00**	**0**
23	0.80	1	0.79	1	0.87	1	0.50	0	0.48	0	0.48	0	0.45	0	**0.01**	**0**
24	0.91	1	0.44	0	0.40	0	0.35	0	0.36	0	0.36	0	0.31	0	**0.51**	**1**
25	0.84	1	0.32	0	0.40	0	0.00	0	0.04	0	0.04	0	0.55	1	**0.00**	**0**
26	0.38	0	0.41	0	0.40	0	0.34	0	0.39	0	0.39	0	0.33	0	**0.01**	**0**
27	0.56	1	0.72	1	0.40	0	0.00	0	0.76	1	0.76	1	0.26	0	**0.59**	**1**
28	0.60	1	0.30	0	0.43	0	0.33	0	0.29	0	0.29	0	0.34	0	**0.29**	**0**
29	0.69	1	0.85	1	0.39	0	0.02	0	0.01	0	0.01	0	0.27	0	**0.07**	**0**
30	0.82	1	0.40	0	0.49	0	0.37	0	0.37	0	0.37	0	0.34	0	**0.80**	**1**
31	0.52	1	0.37	0	0.40	0	0.44	0	0.41	0	0.41	0	0.52	1	**0.26**	**0**
32	0.43	0	0.98	1	0.40	0	0.52	1	0.51	1	0.51	1	0.56	1	**0.14**	**0**
33	0.65	1	0.61	1	0.74	1	0.43	0	0.43	0	0.43	0	0.28	0	**1.00**	**1**
34	0.97	1	0.42	0	0.41	0	0.59	1	0.50	1	0.50	1	0.53	1	**0.96**	**1**
35	0.30	0	0.35	0	0.91	1	0.47	0	0.51	1	0.51	1	0.43	0	**1.00**	**1**
36	0.96	1	0.71	1	0.41	0	0.55	1	0.25	0	0.25	0	0.74	1	**0.85**	**1**
37	0.34	0	0.30	0	0.41	0	0.21	0	0.76	1	0.76	1	0.27	0	**0.33**	**0**
38	0.22	0	0.58	1	0.42	0	0.86	1	0.21	0	0.21	0	0.59	1	**1.00**	**1**
39	0.69	1	0.57	1	0.39	0	0.23	0	0.73	1	0.73	1	0.38	0	**0.24**	**0**
40	0.46	18	0.30	0	0.42	0	0.84	1	0.36	0	0.36	0	0.63	1	**1.00**	**1**
41			0.32	0	0.43	0	0.34	0	0.42	0	0.42	0	0.31	0	**1.00**	**1**
42			0.54	1	0.40	0	0.43	0	0.65	1	0.65	1	0.50	1	**1.00**	**1**
43			0.87	1	0.83	1	0.72	1	0.82	1	0.82	1	0.72	1	**0.99**	**1**
44			0.90	1	0.45	0	0.96	1	0.66	1	0.66	1	0.76	1	**1.00**	**1**
45			1.00	1	0.42	0	0.75	1	0.52	1	0.52	1	0.63	1	**0.99**	**1**
46			0.32	0	0.81	1	0.55	1	0.58	1	0.58	1	0.51	1	**1.00**	**1**
47			0.33	0	0.40	0	0.63	1	0.98	1	0.98	1	0.44	0	**0.29**	**0**
48			0.41	0	0.40	0	1.00	1	0.96	1	0.96	1	0.53	1	**0.60**	**1**
49			0.39	0	1.00	1	0.96	1	0.63	1	0.63	1	0.76	1	**1.00**	**1**
50			1.00	1	0.41	0	0.71	1	0.86	1	0.86	1	0.48	0	**1.00**	**1**
51			0.63	1	0.93	1	0.97	1	0.63	1	0.63	1	0.46	0	**1.00**	**1**
52			0.30	0	0.80	1	0.69	1	0.48	0	0.48	0	0.38	0	**1.00**	**1**
53			0.53	1	1.00	1	1.00	1	0.76	1	0.76	1	0.25	0	**1.00**	**1**
54			0.54	1	0.49	0	0.91	1	0.42	0	0.42	0	0.38	0	**1.00**	**1**
55			0.65	1	0.41	0	0.40	0	0.22	0	0.22	0	0.69	1	**0.31**	**0**
56			0.99	1	0.46	0	0.54	1	0.57	1	0.57	1	0.25	0	**0.17**	**0**
57			0.60	1	0.82	1	0.40	0	0.83	1	0.83	1	0.76	1	**1.00**	**1**
58			0.57	1	0.40	0	0.42	0	0.13	0	0.13	0	0.45	0	**0.86**	**1**
59			0.78	1	0.93	1	0.43	0	0.36	0	0.36	0	0.76	1	**0.93**	**1**
60			0.30	0	0.39	0	0.33	0	0.77	1	0.77	1	0.76	1	**0.62**	**1**
61			0.98	1	0.39	0	0.85	1	0.48	0	0.48	0	0.45	27	**1.00**	**1**
62			0.96	1	0.56	1	0.52	1	0.63	1	0.63	1			**0.99**	**1**
63			0.71	1	0.40	0	0.77	1	0.63	1	0.63	1			**1.00**	**1**
64			0.41	26	0.39	0	0.12	0	0.43	27	0.43	27			**0.99**	**1**
					0.22	14	0.42	27							**0.47**	**30**

In short, we could summarize the findings as follows:

- R_1, R_2, R_3, R_6, R_8, R_{10}, and R_{17} are significant predictors selected by discriminant analysis to provide insights into corporate failures in Malaysia.
- In contrast, R_2, R_9, and R_{17} are selected by logit model.
- Liquidity appears to be a critical factor to corporate sustainability.
- There is at least 40 percent chance of the sampled Malaysian firms being predicted unhealthy with logit model.
- Ultimately, when the two methodologies are compared, discriminant analysis performs slightly better than logistic regression with an overall classification accuracy of 84.4% and 82.8% respectively.
- In the validation sample, both models correctly classify 80% of the unhealthy firms as being unhealthy.

4. Conclusion

The primary objective of this study was the development of a corporate failure classification model for Malaysian firms. Many empirical studies have used data for US firms, and few researchers have attempted to develop models based on country-level data. Research on corporate failure prediction has evolved from a very simple univariate analysis to more complex and sophisticated statistical techniques such as using neural networks and algorithms to increase the prediction accuracy. Efforts in this area however, were put into a real test during the Asian Crisis of the late 90s. The traditional model which rated many corporations as healthy and sound suddenly became invalid. This highlighted the important issue of whether there is a need for different prediction models under normal versus crisis conditions. The crisis in 1997 affected many Asian countries and resulted in currency depreciation and the overnight collapse economies. The degree of the problem is beyond the capacity of the legal infrastructure, which prompted Malaysia to change its approach from formal insolvency proceedings towards a restructuring-based approach.

The goal of this paper was to find which financial ratios best discriminate between healthy and unhealthy firms, employing discriminant analysis and logistic regression as statistical techniques. The majority of samples were manufacturing firms listed in BURSA, and relevant data was collected from 1998 to 2004. An external validation covering unhealthy firms for 2005 was also used to test the accuracy of the model. Liquidity ratios were found to be the most significant predictor for corporate failures in Malaysia. This is also consistent with the World Bank's Report findings on Malaysia during the crisis. Furthermore, the results also indicate that operating cash flows could play an important role in predicting failures. The two methodologies reported only a slightly better result for discriminant analysis compared to logistic regression with an overall classification accuracy of 84.4% and 82.8%

respectively. Both models reported 25% of Type 1 error while discriminant analysis produced slightly lower Type 2 error at 6.25% compared to logistic regression at 9.375%.

There are a number of limitations of this study such as small sample size, and therefore the results cannot be generalized to the whole country of Malaysia. Another limitation is the use of financial ratios as predictors. There may be many other important key quantitative variables such as share prices, macroeconomic indicators, and qualitative variables such as type of ownership, management style, etc. that are not considered in the model but are known to have significant influence on a firm's performance. Ultimately, misclassification errors are based on predictive accuracy and do not have monetary implications. Therefore, more quantitative and qualitative variables should be incorporated to achieve a more responsive model in relation to the real economy.

Notes

1 According to Moyer (1977) and Mensah (1984), the coefficients of a model vary according to the underlying health of the economy, and stress the importance of being close to the time of prediction (Keasey and Watson, 1991).

2 Some of these definitions were adopted from Neophytou and Molinero, 2004.

3 Due to Altman's pioneer research utilizing multivariate approach in corporate failure prediction and dominant benchmark method against other statistical methods.

4 See Altman (1968).

5 Wilks' Lambda is the ratio of the within-groups sum of squares to the total sum of squares. This is the proportion of the total variance in the discriminant scores not explained by differences among groups. A λ of 1.00 occurs when the observed group means are equal, while a small λ indicates that the group means is different. A small λ shows that within group variability is small compared to total variability.

6 Eigenvalue is also known as the characteristic root of each discriminant function, and reflects the ratio of importance of the dimensions, which classify cases of the dependent variable (between group sums of squares divided by within group sum of squares).

7 See Pomerleano (1998).

8 The Casewise result is based on the default cut-off point at zero from SPSS. At this cut-off point, the Type 1 error is 25%.

References

Altman, E. I., 1968. Financial Ratio, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*. Vol. 23, No. 4, September 1968: 589–610.

Altman, E., Haldeman, R., and Narayanan, P., 1977. ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance*. Vol. 1, No. 1, January 1977: 29–54.

Altman, E. I., 2000. Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models, Unpublished manuscript. July 2000: 1–54.

Altman, E. I., 1983. Corporate financial distress: A complete guide to predicting, avoiding and dealing with bankruptcy. John Wiley & Sons, New York.

Allmon, A., 2004. Simple Regression and Financial Statement Analysis. UNC Greensboro *Journal of Student Research in Accounting*. Issue 1: 39–56.

Beaver, W. H., 1966. Financial Ratio as Predictors of Failure, Empirical Research in Accounting: Selected Studies 1966, *Journal of Accounting Research*. Supplement to Vol. 5: 71–111.

Beaver, W. H., 1968. Alternative Accounting Measures as Predictors of Failure. *Accounting Review,* Vol. 43, No. 1, January 1968: 113–122.

Back, B., Laitinen, T., Sere, K., and Wezel, M., 1996. Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms. *Turku Centre for Computer Science*, Technical Report No. 40, September 1996: 1–18.

Blum, M. P., 1974a. The Failing Company Doctrine. Boston *College Industrial and Commercial Review,* 16: 13–31.

Blum, M. P., 1974b. Failing Company Discriminant Analysis. *Journal of Accounting Research.* Vol. 12, No. 1: 1–25.

Deakin, E. B., 1972. A Discriminant Analysis of Predictors of Business Failure. *Journal of Accounting Research*. Vol. 10, No. 1, Spring 1972: 167–179.

Durand, D. D., 1941. Risk Elements in Consumer Installment Financing. Studies In Consumer Installment Financing. *National Bureau of Economic Research*, New York: 105–142.

Edminster, R., 1972. An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. *Journal of Finance and Quantitative Analysis.* Vol. 7, No. 2, March 1972: 1477–1493.

El Hennawy, R., and Morris, R., 1983. The Significance of Base Year in Developing Failure Prediction Models. *Journal of Business Finance and Accounting*. Vol. 10, No. 2, Summer 1983: 209–223.

Ezzamel, M., Mar-Molinero, C., and Beecher, A., 1987. On the Distributional Properties of Financial Ratios. *Journal of Business & Accounting*, Vol. 14, No. 4, Winter 1987: 463–481.

Forsyth, T. B., 1991. A Study of the Ability of Financial Ratio to Predict Corporate Failure and the Relationship between Bankruptcy Model Probability, The University of Alabama, Ph.D.Thesis 1991: 1–163.

Fauzias, MN., and Chin, F., 2002. Z-Score Revisited: Its Applicability in Predicting Bankruptcy in the Malaysian Environment. Banker's Journal: *The Journal of the Institute of Bankers*, *Malaysia,* No. 120, 2002: 20–28.

Fitzpatrick, P. J., 1932. A Comparison of Ratios of Successful Industrial Enterprises with Those of Failed Firms. *Certified Public Accountant.* October, November and December 1932: 598–605, 656–662, 727–731.

Hair, Jr. et. al, 1984. Multivariate Data Analysis with Readings (4th edition 1995). Prentice-Hall, Englewood Cliffs, NJ.

Hair, J., Anderson, R., Tatham, R., and Black, W., 1992. Multivariate Data Analysis. Macmillan Publishing Company. New York.

Joo-Ha, N., and Taehong, J., 2000. Bankruptcy Prediction: Evidence from Korean Listed Companies during the IMF Crisis. *Journal of International Financial Management and Accounting*. Vol. 11, No. 3: 178–197.

KPMG Malaysia Fraud Survey 2004 Report: 1–27.

KPMG Malaysia Fraud Survey 2000 Report: 1–22.

Keasey, K., and Watson, R., 1991. Financial Distress Prediction Models: A Review of Their Usefulness. *British Journal of Management*, July 1991: 89–102.

Merwin, C. L., 1942. Financing Small Corporations: In Five Manufacturing Industries, 1926–36. *National Bureau of Economic Research.*

Meyer, P. A., and Pifer, H. W., 1970. Prediction of Bank Failures. *Journal of Finance.* Vol. 25, No. 4, September 1970: 853–868.

Mensah, Y. M., 1984. An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study. *Journal of Accounting Research*, Vol. 22, No. 1, Spring 1984: 380–395.

Moyer, R. C., 1977. Forecasting Financial Failure: A Re-Examination. *Financial Management*, Vol. 6, No. 1: 11–17.

Muhamad Sori, Z., Mohamad, S., and Abdul Hamid, M. A., 2001. Why Companies Fail? An Analysis of Corporate Failures, Akauntan Nasional: *Journal of Malaysian Institute of Accountants*, Vol. 14, No. 8, August 2001: 5–8.

Muhamad Sori, Z., Abu Kasim, N., and Karbhari, Y., 2006. Assessing Corporate Financial Distress in an Emerging Capital Market, *The Accounting Journal*, Vol. 6, Issue 1, Winter 2006: 1–12. (http://www.theaccountingjournal.org/21st_files/new_page_4.htm)

Myers, J. H. and Forgy, E. W., 1963. The Development of Numerical Credit Evaluation Systems. *Journal of the American Statistical Association*. Vol. 58, No. 303. 1963: 779–806.

Neophytou, E., and Mar-Molinero, C., 2004. Predicting Corporate Failure in the UK: A Multidimensional Scaling Approach. *Journal of Business Finance & Accounting*, Vol. 31, No. 5 & 6, June/July 2004: 677–710.

Neophytou, E., Charitou, A., and Charalambous, C., 2004. Predicting Corporate Failure: Empirical Evidence for the UK. *European Accounting Review*, Vol. 13, No. 3, September 2004: 465–497.

Ohlson, J. A., 1980. Financial Ratio and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research,* Vol. 18, No. 1, Spring 1980: 109–131.

Pomerleano, M., 1998. Corporate Finance Lessons from the East Asian Crisis. Public Policy for the Private Sector, Note No. 155, October 1998: 1–8.

Pomerleano, M., 1998. The East Asia Crisis and Corporate Finances: The Untold Microstory. *Worldbank Policy Research Working Paper*, WPS 1990.

Platt, H. D. and Platt, M. B., 1991. A Note on the Use of Industry-Relative Ratios in Bankruptcy Prediction*. Journal of Banking & Finance*. Vol. 15, No. 6, 1991: 1183–1194.

Ramser, J., and Foster, L., 1931. A demonstration of ratio analysis. Bulletin No. 40, Urbana, 1ll. University of Illinois, *Bureau of Business Research.*

Richard, E. V., 1988. The Selection of Financial Accounting Ratios to Measure Highly Successful Manufacturing Firms: A Discriminant Analysis, *Yushodo Current Research Series,* Unpublished Thesis on Financial Accounting, No. 26: 1–178.

Richardson, F., and Davidson, L., 1983. An Exploration into Bankruptcy Discriminant Model Sensitivity. *Journal of Business Finance & Accounting*. Vol. 10, No. 2: 195–207.

Ryan, A. H., 1996: The Use of Financial Ratios As Measures of Risk in the Determination of the Bid-Ask Spread. *Journal of Financial & Strategic Decisions*, Vol. 9, No. 2, Summer 1996: 33–40.

Serrano Cinca, C., Martin, B., and Gallizo, J. 1993. Artificial Neural Networks in Financial Statement Analysis: Ratios versus Accounting Data, paper presented at the 16th Annual Congress of the European Accounting Association, Turku, Finland, April 28–30, 1993.

Scott, J., 1981. The Probability of Bankruptcy: A Comparison on Empirical Predictions and Theoretical Models. *Journal of Banking & Finance*. Vol. 5, No. 3: 317–344.

Shirata, C. Y., 1995. Read the Sign of Business Failure. *Journal of Risk and Management*. Vol. 23: 117–138.

Shirata, C. Y., 1998. Financial Ratios as Predictors of Bankruptcy in Japan: An Empirical Research, paper #31. Proceedings of The Second Asian Pacific Interdisciplinary Research in Accounting Conference, *APIRA,* August 98: 437–445.

Sprengers, M. A, 2005. Bankruptcy Prediction Using Classification and Regression Trees. Bachelor Thesis, Erasmus University Rotterdam: 1–87.

Takahashi, K., Kurokawa, Y., and Watase, K., 1984. Corporate Bankruptcy Prediction in Japan. *Journal of Banking and Finance*. Vol. 8, No. 2: 229–247.

Tae, K. S., Namsik, C., and Gunhee, L., 1999. Dynamics of Modeling in Data Mining: Interpretive Approach to Bankruptcy Prediction. *Journal of Management Information Systems*, Vol. 16, No. 1, Summer 1999: 63–85.

Wai, L., 2001. Corporate Debt Restructuring Committee, Kuala Lumpur, "Forum for Asian Insolvency Reform: An Assessment of the Recent Development and the Role of Judiciary, Bali-Indonesia, Feb 7 & 8, 2001, Relationship between Informal Workouts and the Courts": 1–4.

Warner, J. B., 1977. "Bankruptcy costs: some evidence". *The Journal of Finance*. Vol. 32, No. 2: 337–347.

Winnakor, A. H., and Smith, R. F., 1935. Changes in financial structure of unsuccessful industrial corporations. *Bull, Bureau of Business Research,* University of Illinois, Urbana., 1935.

Wilson, R. L., and Sharda, R., 1994. Bankruptcy Prediction Using Neural Networks, *Decision Support Systems.* Vol. 11, No. 5: 545–557.

Zmijewski, M. E., 1984. Methodological Issues Related to the Estimation of Financial Distress Prediction Models. Studies on Current Econometric Issues in Accounting Research. *Journal of Accounting Research*. Supplement 1984, Vol. 22: 59–82.

Zavgren, C. V., 1983. The prediction of corporate failures: The state of the art*. Journal of Accounting Literature*, Vol. 2,

No. 1: 1–38.
Zavgren, C. V., 1985. "Assessing the Vulnerability to Failure of American Industrial firms: A Logistic Analysis", *Journal of Business Finance and Accounting*. Vol. 12, No. 1, Spring 1985: 19–45.

Appendix

Table: 3.1 (a) List of firms in the original model

Code	Sector	Healthy Firms	Status	Code	Sector	Unhealthy Firms	Status
H1	IP	Adv Packaging Technology	Active	U1	TRD	Aktif Lifestyle Corp. Bhd	PN4
H2	IP	Aikbee Resources Bhd	Active	U2	CN	Avangarde Resources Bhd	PN17
H3	IP	Ajiya Bhd	Active	U3	PROP	Ayer Hitam Tin Dredging	PN4
H4	IP	Aluminium Co. (M) Bhd	Active	U4	IP	Bell & Order Bhd	PN17
H5	IP	Amalgamated Containers Bhd	Active	U5	PLANT	Bukit Katil Resources Bhd	PN4
H6	IP	Amalgamated Industrial Steel Bhd	Active	U6	IP	CHG Industries Bhd	PN4
H7	IP	Amsteel Corp. Bhd	Active	U7	AGRIC	Consolidated Farms Bhd	PN4
H8	IP	Ancom Bhd	Active	U8	CN	Cygal Bhd	PN4
H9	IP	Ann Joo Resources Bhd	Active	U9	IP	Jin Lin Wood Industries Bhd	PN4
H10	IP	APL Industries Bhd	Active	U10	IP	K.P. Keningau Bhd	PN4
H11	IP	APM Automotive Holdings Bhd	Active	U11	PROP	Kemayan Corp. Bhd	PN4
H12	IP	Astral Supreme Bhd	Active	U12	IP	Kilang Papan Seribu Daya Bhd	PN4
H13	IP	Atlan Holdings Bhd	Active	U13	CN	Jasatera	PN4
H14	IP	Box-Pack (M) Bhd	Active	U14	TECH	Lityan Holdings Bhd	PN17
H15	IP	Bright Packaging	Active	U15	IP	Mega Pascal Bhd	PN17
H16	IP	BTM Resources Bhd	Active	U16	IP	Mentiga Corp. Bhd	PN4
H17	IP	Camerlin Group Bhd	Active	U17	TRD	Mycom Bhd	PN4
H18	IP	CB Industrial Product Bhd	Active	U18	TRANS	Nauticalink Bhd	PN4
H19	IP	Central Industrial Corp. Bhd	Active	U19	PROP	Olympia Industries Bhd	PN4
H20	IP	Chinwell Holdings Bhd	Active	U20	FIN	Omega Holdings Bhd	PN4
H21	IP	Choo Bee Metal Industries Bhd	Active	U21	PROP	Petaling Tin Bhd	PN17
H22	IP	Chuan Huat Resources Bhd	Active	U22	FIN	Pica (M) Corp. Bhd	PN4
H23	IP	CN Asia Corp. Bhd	Active	U23	IP	Poly Glass Fibre (M) Bhd	PN17
H24	IP	CNLT (Far East) Bhd	Active	U24	CP	Pohmay Holdings Bhd	PN17
H25	IP	Concrete Engineering Products Bhd	Active	U25	PROP	Sateras Resources (M) Bhd	PN4
H26	IP	Delloyd Ventures Bhd	Active	U26	CN	Setegap Bhd	PN17
H27	IP	Denko Industrial Corp. Bhd	Active	U27	IP	Sinora Industries Bhd	PN17
H28	IP	DRB-Hicom	Active	U28	PROP	Tanco Holdings Bhd	PN17
H29	IP	Seal Incorporated	Active	U29	PLANT	The North Borneo Corp	PN4
H30	IP	YTL Cement Bhd	Active	U30	IP	Trutech Holdings Bhd	PN4
H31	IP	Yung Kong Galvanising Inds. Bhd	Active	U31	IP	United Chemical Inds. Bhd	PN4
H32	IP	HIL Inds. Bhd	Active	U32	IP	Wembley Inds. Holdings Bhd	PN4

Table: 3.1 (b) List of firms in the validation procedures

Code	Sector	Name	Status
V1	CP	Comsa Farms Bhd	PN17
V2	CP	Elba Holdings Bhd	PN17a
V3	CP	FA Peninsular Bhd	PN17a
V4	IP	FCW Holdings Bhd	PN17a
V5	CP	Federal Furniture Holdings (M) Bhd	PN17
V6	CP	Foremost Holdings Bhd	PN17a
V7	IP	Harvest Court Industries Bhd	PN17a
V8	IP	Kumpulan Belton Bhd	PN17a
V9	IP	Paracorp Bhd	PN17a
V10	CP	Putra Capital Bhd	PN17a
V11	CP	Setron (Malaysia) Bhd	PN17a
V12	CP	Silverstone Corporation Bhd	PN17a
V13	IP	Syarikat Kayu Wangi Bhd	PN17a
V14	IP	Techventure Bhd	PN17a
V15	IP	Tenggara Oil Bhd	PN17a

Note: PN17a is the amended list from BURSA as at May 25, 2006.