Corporate Failure Prediction: An Investigation of PN4 Companies

Wan Adibah Wan Ismail
Raja Adzrin Raja Ahmad
Khairul Anuar Kamarudin
Rusliza Yahaya
Universiti Teknologi MARA

Abstract

This paper investigates twenty financial ratios to develop a local financial failures prediction model. The study covers the period of 1993-2001. We used mean and comparison of difference to the data set of five years before the failures to identify the most superlative ratios. From these ratios, we developed two prediction models by using a logistic regression. The results indicate that these models are excellent in predicting financial failures a year before failure. Both models are able to predict financial failure two years before the failures with more than 90% accuracy rate. It is hoped that this study, which is conducted using a recent data can contribute towards existing literatures on corporate failure prediction.

1.0 Introduction

Business failures and financial distresses are common in competitive business environments where market discipline ensures that the survivors would only be the toughest one. The effect of a major corporate failure could bring unbearable hardship and misery. The collapse of many Malaysian conglomerates after the 1997 financial crisis for example, has sent many corporate firms, banks and other financial institutions into financial difficulties. Losses by banks from major corporate failures during the financial turmoil exceeded the interest income earned on their lending activities. Similarly, investors have also suffered major losses on their investments.

The Kuala Lumpur Stock Exchange (KLSE) has established and implemented a number of measures to maintain an orderly and fair market for securities that are traded on the KLSE., To enhance market integrity, the KLSE has implemented its latest measures relating to Practice Note 4/2001 (PN4), which has taken into effect since February 15, 2001. Under these new Listing Requirements, all companies listed on the KLSE are required to have an adequate level of financial condition in order to warrant continued trading and listing on the Official List of Exchange. This measure is meant to alert investors and at the same time to ensure that troubled companies must take necessary action within the stipulated 12 months period or face delisting.

More than 90 companies listed on the Kuala Lumpur Stock Exchange (KLSE) are reported to be failing and they are facing the possibilities of delisting. The KLSE reveals that, as on September 1, 2002, 99 companies (out of 861 listed outfits) are categorized under PN4 category (The Edge Malaysia, 9/9/2002). These companies are plagued with mounting debts and uncertainties in the continuance of their business. Millions of ringgits in public funds and bank loans have been wiped out. The reason why these companies fall into severe financial difficulty and whether they can predict their financial distress are two interesting questions that need to be addressed and studied.

A large number of corporate failures in Malaysia since the Asian financial crisis in 1997 have provided us with an excellent opportunity for constructing and testing a business failure prediction model by using logit analysis. The logit model is used in this study because it is easier to estimate the corporate financial failure as compared with the other models. Moreover, the performance of the logit model is at least as good as that of probit or discriminant analysis (Kahya, 1997). In addition to constructing and testing the logit model, this paper will also highlights the models that could be used as the predictor of financial distress in Malaysia.

The ability to anticipate financial distress and corporate bankruptcy is considered necessary to the users of financial statements especially to those who use them in their planning process such as the managers, investors, creditors and auditors.

The findings would guide the policy-makers and financial institutions in formulating effective pre-emptive measures to mitigate corporate failures. It is also hoped that it would direct managers to take corrective measures and possible failure prevention in their own firm. The managers may use them to minimize the impact on their firm encountering the future financial difficulties. The difficulties could be avoided before it is too late. McBeth (1992) argues that financial distress research may help "in preventing a repeat of the dramatic corporate collapse of the 1980s".

This study would also be beneficial to investors and creditors as they could improve their performance if they can distinguish the trouble firms from the healthy ones. If investors or creditors were able to predict which company is on the path to financial distress or bankruptcy before anyone else, they would be able to liquidate the investment or obtain settlement of a debt. This would minimize the losses. Foster (1986) suggests that "the potential contribution of the financial distress analysis literature" to society "is substantial". Whereas, Plat and Plat (1990) points that research in financial distress is useful to the lenders, security analysts, auditors and managers. The lenders may use the research findings to help reducing the losses from the bad debts. These savings may be substantial. Meanwhile, Ferguson (1992) states that the financial distress literature might help lenders to better predict firms that will encounter financial difficulties, thus, enabling them to reduce problem loans and resultant losses.

The financial analysts could also benefit from financial distress literature. Clark and Weinstein (1983) find that shares of bankrupt firm became worthless. Again better prediction may help reduce these losses. Besides this, financial distress literature may also help auditors in their going concern judgment, and hence, reduce their litigation costs and damages payouts. Lastly, since auditors need to identify the going concern of their clients' companies, they could use this study to determine their clients' ability to continue their existence.

2.0 Literature Review

Business survival is a vital element in a corporate world. Enterprises need to be aware of the'going concern' to ensure that substantial financial losses can be minimized if not eliminated. Research on corporate prediction failure is a premise to assist organizations and corporate enterprises to ring a bell about their financial condition.

The pioneer research in predicting financial distress includes the research of Beaver (1966), Altman (1968) and Altman *et al.* (1977). These researchers are then tested and extended by others to include other variables and new models to enhance the predictive ability and accuracy. Laramie (1996) extended the prior literature on bankruptcy prediction model by employing a dynamic event history methodology to distinguish between financially distressed firms that survive and those that cease. Laramie (1996) argued that the process of moving from a distressed situation to bankruptcy is a dynamic process that commences with initial conditions and incorporate other changes such as fluctuation of financial ratios over time.

Hence, the use of a dynamic or event history methodology is beneficial in identifying significant explanatory variables that differ between financially distressed and bankrupt firms and also between industry classifications. Laramie (1996) also found that accounting information and economic variables, which are external to the firms, are both crucial in elucidating the failure process.

Laitinen (1995) argued that most of the empirical effort on business failure prediction is based on the variety definitions of financial failure, which can be broadly classified as stress solidity or liquidity aspects. He further argued that the models, which are weighted by the type of failure of firms in the sample, might lead to classification errors. This occurs when the model is applied to the wrong sample. For instance, if majority of the samples consists of firms failed because of poor solidity, and a model is estimated from these samples, the consequence is that the model may not accurately predict a liquidity failure.

Therefore, Laitinen (1995) study was to present a method for identifying solidity and liquidity bankruptcy firms to avoid the frequency effect so that the accuracy of the model can be enhanced. The study was conducted for Finnish bankrupt and non-bankrupt firms and the empirical results showed that the sample mainly consisted of solidity bankruptcy firms. Consequently, the model estimated from the sample was largely contributed by this type of bankruptcy.

Kim and McLeod (1999) looked at the expert, linear and nonlinear models of expert decision-making in bankruptcy prediction. The study employed a lens model analysis where the model is used to study how well a model of expert decisions capture a valid strategy in the decision making process.

This study looked at the other side of the mirror where it analyses the human judgment and the decision making process in determining the bankruptcy prediction model as compared to other studies that looked at the relationship between financial ratios and the bankruptcy prediction model. Interestingly, their study also addresses whether a model of an expert can be more accurate than the expert.

Kim and McLeod (1999) compared the predictive accuracy of two linear models and two nonlinear models of human experts. The findings indicate that the nonlinear models can capture factors that contribute to the experts' predictive accuracy, while, the linear model cannot capture the valid nonlinear strategy as well as nonlinear models.

Pacey and Pham (1990) investigates the predictiveness of bankruptcy models in terms of its methodological problems using Multiple Discriminant Analysis (MDA) and logit/probit techniques. The three problems posed in their study include (i) the use of choice-based and equal distributed samples in model estimation and validation; (ii) the use of arbitrary cut-off probabilities; and (iii) the assumption of equal costs of errors in prediction tests. The sample consists of Australian companies over a period of twenty years.

The paper presented results of the estimation of a number of popular financial distress model and address the issue of methodological errors to try to reassess their predictiveness accuracy. Pacey and Pham (1990) found that models based upon publicly available financial information possess insignificant predictive ability.

Barnes (1998) offers another multivariate model in a similar manner in which bankruptcy prediction model is applied. His study examines whether it is possible to forecast takeover targets by using publicly available information.

The findings indicate that takeover targets cannot be predicted solely by utilizing publicly available accounting information. As such, Barnes (1998) examines the possibility of combining anticipatory share price changes into the model yet it did not improve the predictive accuracy of the model. Thus, this suggests that the market may not be efficient in its strong form of the Efficient Capital Market Hypothesis (ECMH).

Mossman *et.al* (1998) study is based on the UK setting over a period of two decades. They tested four types of bankruptcy prediction models based on financial statement ratios, cash flows, stock returns and return standard deviations of which some of these important ratios have been neglected in the prior literature.

The results shows that no single model proposed in the literature as during that date is entirely satisfactory in differentiating between bankrupt and non-bankrupt firms. They further suggested that new research should be undertaken to incorporate and make full use of all readily available data to come out with a better prediction model.

Flagg and Giroux (1991) took a different approach in which they predict which 'failing firms' will eventually go bankrupt. As opposed to prior studies that employed matched pairs design of bankrupt vs. non-bankrupt firms to predict bankruptcy, this research proposed a model based on failure events and financial ratios that employed ex ante logistical regression model. Flagg and Giroux (1991) findings suggest that non-financial ratios indicators can be used to increase understanding of the failure process and improve bankruptcy prediction.

Poston and Harmon (1994) evaluate the effectiveness and accuracy of financial ratios in determining the failure or turnaround of the financially distressed firms. This research captured the turnaround phenomenon, which has largely been ignored in the prior literatures.

Whittred and Zimmer (1984) examine a sample of Australian companies in terms financial distress with regards to the timeliness of the financial reporting. They found that firms entering financial distress experience longer auditor's signature lag (as a proxy for the timeliness of financial reporting). Unfortunately, they discover that the reporting lag do not contribute to the ability to predict distress.

All in all, it can be said that the ample literature on corporate failure prediction provide a fine background for this research. It is hoped that result of this research will shed additional light on the corporate prediction model and can caution the corporate enterprises about their financial situations.

3.0 Research Methodology

A sample of financially distressed companies was taken from the companies listed on the Kuala Lumpur Stock Exchange, under the PN4 sector. This research covers time period of 1993-2001. Fifty-four companies constitutes the original sample selected randomly, consisting of 27 PN4 companies and 27 healthy companies. The original sample was used to develop the local financial distress prediction models. We then collected another 54 companies comprising 27 PN4 companies and 27 healthy companies as a second sample. The second sample was used to measure the effectiveness of the models developed from the original sample. The choice of variables or financial ratios that we identified to provide early indication of financial distress are based on data available from the balance sheets and income statements for up to five years prior to financial distress. According to Kahya (1997), there is no single accepted "theory of business failure" that can be used to guide the selection of variables in business failure prediction models. The majority of the previous researchers have used a stepwise procedure in their studies because of the large number of independent variables included in the model without any compelling theory. The variables to be included in this study are based on the variables found to be significant explanatory variables in past financial distress models, as selected by Altman, et al. (1995). Table 1 lists 20 variables, which measure profitability (1,2,6,7); activity/turnover (3, 4, 5); size (8); fixed charge coverage (9,10,11); liquidity (12,13,14,17); solvency; leverage (15, 16,19, 20); and earnings stability (18). Some of the variables are expressed as logarithmic transformations in order to mitigate the effect of outliers.

Table 1 : List of variables and Descriptions

No.	Variable Name	Description
1	EBIT/TA	Earnings before interest and taxes over total assets
2	NI/TC	Net income over total capital
3	SALES/TA	Sales over total assets
4	LOG(SALES/TA)	Natural logarithm of ratio of sales over total assets
5	SALES/TC	Sales over total cost
6	EBIT/SALES	Earnings before interest and taxes over total sales
7	NI/SALES	Net income over total sales
8	LOG(TA)	Natural logarithm of total assets
9	EBIT/INT	Earnings before interest and taxes over interest
10	LOG(EBIT/INT)	Natural logarithm of earnings over interest
11	CF/TL	Cash flow over total liabilities
12	WC/LTD	Working capital over long term liabilities
13	CURRENT RATIO	Current asset over current liabilities
14	WC/TA	Working capital over total assets
15	RET/TA	Retained earnings over total assets
16	BEQ/TC	Book value of equity over total capital
17	NORMALISED QUICK RATIO	(Current assets – current liabilities— inventory) / total assets
18	EBIT/SIGMA EBIT	Earnings before interest and taxes over standards deviation of three years
19	BEQ/TL	Book value of equity over total liabilities
20	MEQ/TL	Market value of equity over total liabilities

The Logit Model

Logit analysis is employed in this study since it does not impose any distribution on the explanatory variable and it can directly provide the probability of bankruptcy (Field, 2000). In logistic regression, instead of predicting the value of a variable Y from a predictor variable X_1 or several predictor variables (X_s), we predict the probability of Y occurring given known values of X_1 (or X_s). In many instances probabilities are stated as odds. In general:

$$Ln[odds(Y \backslash X_1, X_2, \ldots X_n)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad (1)$$

Or

$$Ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad (2)$$

Where

$$\frac{p}{1-p} = [odds(Y \backslash X_1, X_2, \ldots X_s)]$$

and p is the probability of Y occurring given the independent variables X_1, X_2, ... X_s. Eq. (2) models the log of the odds as a linear function of the independent variables, and is equivalent to multiple regression equation with log of the odds as the dependent variable. In its simplest form, when there is only one predictor variable X_1 the logistic regression equation from which the probability of Y is predicted is given as:

$$P(Y) = \frac{1}{1+e^{-(\beta_0+\beta_i X_i + e)}} \qquad (3)$$

in which P(Y) is the probability of Y occurring. When several predictors are included in the equation, the equation becomes:

$$P(Y) = \frac{1}{1+e^{-z}} \qquad (4)$$

$$Z = \beta_0 + \beta_1 X_1 + \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots \beta_n X_n \qquad (5)$$

In this study, P(Y) is the probability that the firm will fall under PN4 condition, the X_i are the measured firm attributes and the b are the parameters to be estimated. Logistic regression equation described above expresses the multiple linear regression equation in logarithmic terms and thus overcomes the problem of violating the assumption of linearity (Field, 2000). The equation presented above expresses the equation in terms of the probability of Y occurring (i.e. the probability that a case belongs in a certain category). As such, the resulting value from the equation is a probability value that varies between 0 and 1. A value close to zero means that Y is very unlikely to occur, and a value close to 1 means that Y is very likely to occur. Just like linear regression, each predictor variable in the logistic regression equation has its own coefficient.

When running the analysis, value of these coefficients need to be estimated in order to solve the equation. These parameters are estimated by fitting models, based on the available predictors, to the observed data. Specifically, the values of the parameters are estimated using the maximum-likelihood method, which selects coefficients that make the observed values most likely to have occurred.

4.0 Results

Univariate Result

Table 2 shows the mean and median of twenty ratios of distressed firms and healthy firms in the original sample. The table also provides results from the test of differences between the two groups. This procedure was carried out to eliminate ratios that have less probability to predict financial distress. The results of test of differences show that six ratios cannot be used to differentiate between financially distressed firms and healthy firms. These six ratios are EBIT/TA, LOG(SALES/TA), SALES/TC, EBIT/SALES, NI/SALES and WC/LTD. Therefore, these six variables are excluded from further analysis in searching for the best variables to predict financial distress.

Table 2 : Mean and Median of Ratios Between Groups
(Test of Mean of Differences Between Groups Included)

	Distressed (N=27)		NonBankrupt (N=27)		
	Mean	***Median***	***Mean***	***Median***	**T-Value**
EBIT/TA	0.0151	-0.2000	0.0926	0.0900	-0.3380
NI/TC	2.1203	0.0300	0.0752	0.0800	1.6150 **
SALES/TA	0.4594	0.3600	0.6460	0.4700	-4.7400 *
LOG(SALES/TA)*	-0.4857	-0.4150	0.3818	0.3200	-2.1820
SALES/TC	-0.7551	0.6200	1.0300	0.6900	-1.5240
EBIT/SALES*	23.6393	-0.0500	-2.2767	0.1700	0.9800
NI/SALES*	22.6137	-0.2000	-2.7980	0.1000	0.9580
LOG(TA)	8.6462	8.7900	9.1700	9.1200	-8.1980 **
EBIT/INT	-69.5120	-0.2600	59.8906	8.6500	-3.2870 **
LOG(EBIT/INT)*	0.4798	0.3700	1.1638	0.9700	-5.5870 **
CF/TL	0.2640	0.1300	0.3821	0.1800	-2.9240 **
WC/LTD*	-57.1400	-1.1000	34.7767	0.6400	-1.3070
CURRENT RATIO	0.8444	0.6500	1.6158	1.3000	-9.6000 **
WC/TA	-0.5901	-0.2000	0.0827	0.0700	-5.1100 **
RET/TA	-1.6440	-0.2100	0.2109	0.2100	-4.3560 **
BEQ/TC	0.9782	0.7900	0.1163	0.1100	5.2370 **
NORMALISED	-0.7824	-0.3900	0.0272	-0.0300	-5.6970 **
EBIT/SIGMA	0.9184	-0.1800	5.6391	4.0400	-11.7450 **
BEQ/TL	0.3241	0.1300	2.3965	1.3000	-14.0060 **
MEQ/TL	1.5253	0.4100	4.6510	2.3500	-7.6880 **

* denotes 5% significance level, ** denotes 1% significance level

Table 3 lists the trend of 14 financial ratios for distressed group from fifth year to the first year prior to the classification of the companies into PN4 by the KLSE. We search for the consistent and correct sign of ratios between the periods. The ratios are LOG(TA), CURRENT RATIO, RET/TA, EBIT/SIGMA and BEQ/TL. Five ratios are identified to be the most significant ratios in predicting the corporate failures.

Table 3: Mean Ratios of Distressed Group (Five Years Prior to Distress)

Ratio	***T-1*** **(N= 27)**	***T-2*** **(N= 27)**	***T-3*** **(N= 27)**	***T-4*** **(N= 27)**	***T-5*** **(N= 27)**
NI/TC	4.2619	6.0154	0.1646	-0.1115	0.1888
SALES/TA	0.3519	0.4608	0.4300	0.5415	0.5169
LOG(TA)	8.4970	8.6704	8.7142	8.7169	8.6381
EBIT/INT	8.1804	-4.5092	0.3727	3.3308	7.2308
LOG(EBIT/INT)*	0.6300	0.1663	0.4380	0.5171	0.5618
CF/TL	0.1859	0.2369	0.3142	0.2492	0.3365
CURRENT RATIO	0.5778	0.6650	0.8092	1.0185	1.1619
WC/TA	-1.3315	-0.6642	-0.2735	-0.5058	-0.1469
RET/TA	-4.1159	-1.4169	-1.0423	-0.9977	-0.5519
BEQ/TC	1.3033	1.0942	1.0012	0.7035	0.7762
NORMALISED	-1.5222	-0.8673	-0.4627	-0.6969	-0.3342
EBIT/SIGMA	-1.0822	-0.2742	1.0992	1.5492	3.3769
BEQ/TL	-0.1407	0.2462	0.2915	0.5719	0.6696
MEQ/TL	1.0207	1.4176	1.1820	1.3708	2.6820

Development of Malaysian's Financial Distress Model.

We plan to develop two prediction models based on these ratios. The ratios to be used as predictor are LOG(TA), CURRENT RATIO, RET/TA, EBIT/SIGMA and BEQ/TL. Before developing the local model, we run the correlation tests to check the multicollinearity between the variables. Table 4 shows the correlation matrix between the variables.

Table 4 : Correlation Matrix

	LOG(TA)	CURRENT RATIO	RET/TA	RET/TA	BEQ/TL
LOG(TA)	-				
CURRENT RATIO	0.152*		-		
RET/TA	0.379*	0.101	-		
EBIT/SIGMA	0.149*	0.181*	0.177*	-	
BEQ/TL	0.065	0.593*	0.150*	0.150*	-

* significant at the 0.01 level

Based on the correlation matrix, we found a high and significant correlation between CURRENT RATIO and BEQ/TL. Therefore, in developing the model, we do not include both ratios together. Apart from that, the high univariate significance (see table 2) and a correct sign of all coefficients in the model (see table 3) have been considered in developing this model. We run the logit regression and developed two models from the selected variables. The models are: -

Model A

$$A = -19.44 + 2.07\ LOG(TA) + 5.94 RET/TA + 0.11\ EBIT/SIGMA + 0.60\ CURRENT\ RATIO$$

Model B

$$B = -25.4 + 2.68\ LOG(TA) + 3.92\ RET/TA + 0.11\ EBIT/SIGMA + 1.21\ BEQ/TL$$

Distressed Firm Classification

Panel A of Table 4 lists the classification accuracy of model A based on data from financial statements of firms, one to five years prior to distressed classification for the two different samples. When we test model A with the second sample, it is found that the prediction accuracy is very good in the first year prior to distressed classification with about 92% of the companies are correctly classified (only two misclassification out of 27). The accuracy remains excellent in the second year prior to distressed classification (89%) and it decreases to 74% in year 3 (t-3).

Table 4 : Five-Year Predictive Accuracy of Distressed Group

Panel A. Model A:

A = -19.44 + 2.07 LOG(TA) + 5.94RET/TA + 0.11 EBIT/SIGMA + 0.60 CURRENT RATIO

T	Original Sample					Second Sample				
	Total	Hits	Misses	% Correct	% Error	Total	Hits	Misses	% Correct	% Error
t – 1	27	26	1	96.30	3.70	27	25	2	92.59	7.41
t – 2	27	25	2	92.59	7.41	27	24	3	88.89	11.11
t – 3	27	21	6	77.78	22.22	27	20	7	74.07	25.93
t – 4	27	20	7	74.07	25.93	27	20	7	74.07	25.93
t – 5	27	19	8	70.37	29.63	27	19	8	70.37	29.63

Panel B. Model B:

B = -25.4 + 2..68 LOG(TA) + 3.92 RET/TA + 0.11 EBIT/SIGMA + 1.21 BEQ/TL

T	Original Sample					Second Sample				
	Total	Hits	Misses	% Correct	% Error	Total	Hits	Misses	% Correct	% Error
t – 1	27	27	0	100.00	0.00	27	26	1	96.30	3.70
t – 2	27	25	2	92.59	7.41	27	25	2	92.59	7.41
t – 3	27	21	6	77.78	22.22	27	22	5	81.48	18.52
t – 4	27	18	9	66.67	33.33	27	20	7	74.07	25.93
t – 5	27	19	8	70.37	29.63	27	19	8	70.37	29.63

Panel B of Table 5 shows the classification accuracy of model B. Model B accurately predicts distressed companies at the rate of 96% in one year before the distressed classification in the second sample. The prediction accuracy in the second year is about 92%, which is higher than model A. model B can predict the financial distress at more than 80% accuracy rate in year t-3. The result shows that model B is more superior to predict financial distress than model A. If compared to the Korean models, they are better than our model in the t-1 with an accuracy rate of 97% for both models. However, the predictive accuracy of model B in t-2 and t-3 are better compared to the Korean models which only able to predicts financial distress at the accuracy rate of 86% in t-2 and 71% in t-3.

Based from the table, we found that the prediction accuracy of financial distress in the second sample is lower compared to the original sample. However, the prediction accuracy rates are still high and this means that the model can be used in Malaysian environment.

Healthy firms Classification

Panel A and B of table 5 list the classification accuracy of model A and B in determining healthy firms for a nine-year period for the two samples. Results in panel A show that model A is able to predict correctly the healthy firms of the second sample at the minimum accuracy rate of 78%. The classification error percentage fell from 3.7% to 22.2%. Model B is also excellent in predicting healthy firms. The model perfectly and accurately predicts healthy firms of the second sample for the year 1996. The classification errors of this model ranges between 0% to 18%.

Table 5 : Classification Accuracy of Healthy Firms

Panel A. Model A :

A = -19.44 + 2.07 LOG(TA) + 5.94RET/TA + 0.11 EBIT/SIGMA + 0.60 CURRENT RATIO

YEAR	Original Sample					Second Sample				
	Total	Hits	Misses	% Correct	% Error	Total	Hits	Misses	% Correct	% Error
1993	27	22	5	81.48	18.52	27	21	6	77.78	22.22
1994	27	25	2	92.59	7.41	27	24	3	88.89	11.11
1995	27	24	3	88.89	11.11	27	25	2	92.59	7.41
1996	27	25	2	92.59	7.41	27	25	2	92.59	7.41
1997	27	26	1	96.30	3.70	27	26	1	96.30	3.70
1998	27	25	2	92.59	7.41	27	25	2	92.59	7.41
1999	27	23	4	85.19	14.81	27	23	4	85.19	14.81
2000	27	24	3	88.89	11.11	27	24	3	88.89	11.11
2001	27	25	2	92.59	7.41	27	24	3	88.89	11.11

Panel B. Model B :

B = -25.4 + 2..68 LOG(TA) + 3.92 RET/TA + 0.11 EBIT/SIGMA + 1.21 BEQ/TL

YEAR	Original Sample					Second Sample				
	Total	Hits	Misses	% Correct	% Error	Total	Hits	Misses	% Correct	% Error
1993	27	21	6	77.78	22.22	27	22	5	81.48	18.52
1994	27	23	4	85.19	14.81	27	23	4	85.19	14.81
1995	27	27	0	100.00	0.00	27	26	1	96.30	3.70
1996	27	27	0	100.00	0.00	27	27	0	100.00	0.00
1997	27	26	1	96.30	3.70	27	25	2	92.59	7.41
1998	27	25	2	92.59	7.41	27	24	3	88.89	11.11
1999	27	22	5	81.48	18.52	27	23	4	85.19	14.81
2000	27	23	4	85.19	14.81	27	22	5	81.48	18.52
2001	27	24	3	88.89	11.11	27	23	4	85.19	14.81

Both Malaysian models are as good as the Korean's K1 and K2 models. The K1 classification errors for financially distressed firm for five accounting period ranges between 6% to 22% whereas the K2 model records classification errors of 6% to 25%. Therefore, we strongly believe that our models are fit to be used in discriminating between financially distressed firms and healthy firms.

5.0 Conclusion

The purpose of this research is to identify ratios than can be used by users especially investors in forecasting the probability of the companies before they are classified as financial distressed. We have successfully developed two models to discriminate between financially distressed and healthy firms. Both models recorded excellent predictive accuracy rate for both groups in the original and second sample. We believed that these two models are superior or at par with the recent Korean models. We do expect that our results will have several beneficial applications, particularly in Malaysian environment. Early warning models are potentially useful, even if it is not totally accurate.

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