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FORECASTING CORPORATE FAILURE IN MALAYSIAN INDUSTRIAL SECTOR FIRMS

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ABSTRACT

Financial ratios have long been used as predictor of important events in financial markets of developed economies. Formulating business failure prediction models utilising financial ratios is no exception. However, there is hardly any evidence on failure prediction in developing markets such as Malaysia. This study develops a failure prediction model for industrial sector listed firms that discriminates between 24 failed and non-failed for the period 1980 to 1996. The findings show that the model correctly and significantly classified 91.1% and 89.3% of the failed and non-failed firms respectively. An alternative prediction model developed based solely on accounting information showed similar results. These models predict failure up to 4 years before the actual event. The variables in the final model implies that profits, cash flows, working capital and net worth are important determinants of failures of firms listed in the Kuala Lumpur Stock Exchange.

INTRODUCTION

Corporate failures are a common phenomenon of developing and developed economies (Altman, Baidya, and Dias, 1979). Despite the immense amount of research into this issue in developed economies, the phenomenon of failure predictions is far from resolve as the findings are not universal in nature. Findings from developed economies cannot be generally applied to developing economic environments due to differences in market structure, provisions and implementation of law and accounting standards.

The ability to predict impending failures using common identifiable attributes of failed firms can help pre-empt failures. This would avoid financial distress to all stakeholders, reduce the substantial costs of bankruptcy and contribute to a more stable business and financial environment[1]. Predicting corporate failure is based on the premise that failure is a gradual process, and a consequence of problems developed over many years and the symptoms of the problems are identifiable. These common symptoms are a decline in profits, working capital, liquidity, asset quality, arrears interest and loan repayment, delay in payment to suppliers, staffs and all other creditors, and implementation of some form of austerity measures.

The consistency of the symptoms allow formulation of corporate prediction models to identify and avoid potential failures or implement measures to avoid and/or minimise the cost of failures in cases where failures are inevitable.

The number of corporate failures in Malaysia has increased over the last few years. Firms are considered failed when they apply to the court or relevant authorities for restructuring or reorganisation scheme based on a scheme of arrangement pursuant to section 176 of the Malaysian Companies Act 1965. These firms have to formulate survival options strategies for corporate rescues and reconstruction. However, highly leveraged corporations with severe financial problems might resort to outright liquidation. The objective of this study is to develop a model that identifies significant accounting and market based attributes of firms that can discriminate between failed and non-failed firms. These attributes will provide important insights to policy makers and financial institutions to guide them formulate effective pre-emptive measures to mitigate corporate failures.

REVIEW OF LITERATURE

The earliest study using multivariate data analysis on failure prediction was conducted by Altman (1968) using a set of financial and economic ratios as possible determinants of corporate failures. The study used sixty-six corporations from manufacturing industries comprising of bankrupt and non-bankrupt firms and 22 ratios from five categories, namely, liquidity, profitability, leverage, solvency and activity. Five ratios were finally selected for their performance in the prediction of corporate bankruptcy and the derived model correctly classified 95 percent of the total sample (correctly classifying 94 percent as bankrupt firms and 97 percent as non-bankrupt firms) one-year prior to bankruptcy. The percentage of the accuracy declined with increasing number of years before bankruptcy.

Altman, Marco and Varetto (1994) reported the use of neural network in identification of distressed business by the Italian central bank. Using over 1,000 sampled firms with 10 financial ratios as independent variables, they found that the classification of neural networks was very close to that achieved by discriminant analysis. They concluded that the neural network is not a clearly dominant mathematical technique compared to traditional statistical techniques.

Begley, Ming and Watts (1995) incorporated the time "bias" factor into the classic business failure prediction model. Using Altman (1968) and Ohlson's (1980) models to a matched sample of failed and non-failed firms from 1980's, they found that the predictive accuracy of Altman's model declined when applied against the 1980's data. The findings explained the importance of incorporating the time factor in the traditional failure prediction models.

Campbell (1996) constructed a multivariate prediction model that estimates the probability of bankruptcy reorganisation for closely held firms. Six variables were used in developing the hypotheses and five were significant in distinguishing closely held firms that reorganise from those that liquidate. The five factors were firm size, asset profitability, the number of secured creditors, the presence of free assets, and the number of under-secured secured creditors. The prediction model correctly classified 78.5% of the sampled firms. This model is used as a decision aid when forming an expert opinion regarding a debtor's likelihood of rehabilitation.

Mossman, Bell, Swartz and Turtle (1998) conducted a study to compare four types of bankruptcy prediction models that are based on financial statement ratios, cash flows, stock returns', and returns standard deviations. They tested four bankruptcy models: Altman's (1968) Z-score model based on financial ratios; Aziz, Emanuel, and Lawson's (1988) model comprised of cash flows; Clark and Weinstein's (1983) market return model, and Aharony, Jones, and Swary's (1980) market return variation model. They found that in the year prior to bankruptcy, the ratio model is the most effective in explaining the likelihood of bankruptcy. In the three years preceding bankruptcy, the cash flow model most consistently discriminates between bankrupt and on-bankrupt firms. The findings suggest different uses for the models, as stakeholders might be particularly interested in cash flow variables as an "early warning" indicators of failure. Alternatively, a large negative shift in accounting ratio variables could be a useful indicator of imminent financial collapse.

RESEARCH METHODOLOGY

The data used in this study is a set of financial ratios derived from financial statements (balance sheets and income statements) of sampled failed listed companies (Appendix 1). For each failed firm, a non-failed "match" was identified for the period from 1980 to 1996. The used of a matched sample of failed and non-failed firms (one-to-one match) might introduce a potential firm failure bias (Palepu, 1986). It is claimed that the potential for failure is overstated using this technique. However, it is stressed that the bias may or may not be important depending on the usage of the model. If the model is used to rank the firms for the potential failure in order to perform a more detailed analysis, then the bias is not important. However, if the model is used to identify investment portfolio selection, then the bias is significant. Furthermore, Zmijewski (1984) reviewed 17 financial distressed studies that used this controversial method and found that although a choice based sample bias was present, the results do not indicate significant changes in overall classification and classification rates. Finally, Platt & Platt (1990, 1991) urged that one-to-one sampling technique is still an acceptable method in failure prediction studies.

Listed firms were defined as failed firms, when they resort protection under section 176 of the Companies Act 1965. Twenty-four failed firms were sampled with a matching sample of 24 non-failed firms (Appendix 2). Firms in the matched sample were selected based on the following criteria:

1. Same industry
2. Same failure year
3. Closest asset size
4. Same age since incorporation

The above criteria were set as control factors to ensure that, with minimum bias, suitable firms were used in the development of the failure prediction model. Furthermore, the use of the one-to-one matched procedure is consistent with previous studies documented in Beaver (1966), Altman (1968), Blum (1974) and others.

The failed firms were identified from information contained in the KLSE daily diary. Financial statement data of the failed and non-failed firms were sourced from annual reports for five years prior to failure.

To determine the variables that can explain failures, discriminant analysis was used with a dichotomous dependent variable of failure or non-failure. The independent variables are the 65 financial ratios used by Beaver (1966), Altman (1968) and Ou and Penmen (1989).

RESULTS

A forward stepwise multivariate discriminant analysis was used to determine the discriminating variables. In stepwise estimation, normalised independent variables were entered into the discriminant function one at a time on the basis of their discriminating
power[2]. The following prediction model was specified:

$$Z = -0.82231+1.558828X1-0.96348X2-0.18368X3+0.138034X4 \quad (1)$$

where,

Z	= Overall Index
X1	= Log V12 (Total Liabilities Percent)
X2	= Square Root V25 (Current Asset Turnover)
X3	= Log V65 (Market Value to Debts)
X4	= Log V17 (Cash to Current Liabilities)

The results of analysis indicate that the failed group centroid (DV=0) is at -1.1856 and the non-failed group (DV=1) centroid at 1.1856. The cutting score of the function equals to zero calculated on the average values of both centroids. The assessment of the predictive accuracy of the discriminant function using classification matrices is summarised in Table 1.

The accuracy rate of the original sample is 90.2 percent (average of correct classification of DV=0 at 91.1 percent and DV=1 at 89.3 percent). This classification accuracy is relatively high compared to the priori chanceclassifying individuals correctly without the discriminant function i.e. 50 percent. The Press Q statistic was 160.4, [the critical value (the Chi-square value for 1 degree of freedom at the 1% confidence level) is 6.63], implying that the predictions were significantly better than chance.

Table 1: Classification Results

		Dependent Variable	Predicted Group Membership 0	1	Total
Original	%	0	91.1	8.9	100
		1	10.7	89.3	100
U-Validation	%	0	91.1	8.9	100
		1	11.6	88.4	100

Interpretation of the Results

This section examines the relative importance of each independent variable in discriminating between the failed and non-failed group using: (1) standardised discriminant weights, (2) discriminant loadings (structure correlations), and (3) partial F values. Table 2 summarise the results and the significant variables.

Table 2: Summary of Interpretative Measures

		Discriminant Loading		Univariate F Ratio	
Variable	Standard Weights Value	Value	Rank	Value	Rank
Total Liabilities Percent	0.902043	0.777272	1	112.4141	1
Current Asset Turnover	-0.4487	-0.45092	2	29.14781	2
Market Value to Debts	-0.3417	-0.43081	3	15.50468	3
Inventory Percent	NI	-0.28145	4	NI	NI
Current Assets Percent	NI	-0.27677	5	NI	NI
Cash to Current Liabilities	0.358284	-0.14141	6	12.58273	4
Long Term Liabilities Percent	NI	0.053519	7	NI	NI

Note: NI = Not Included

From the discriminant loadings and univariate F values, the ranking of discriminating power of variable is identified. Among the four variables identified, Total Liabilities Percent discriminate the most and Cash to Current Liabilities discriminate the least.

Validation of the Discriminant Results

This section examines the validity of the discriminant function. The validity was determined using the leave-one-out classification or known as the U validation method. This method tested the validity of the model by removing items one at a time and classifying them into the discriminant groups using a model developed from the remaining sample items. The validation results are summarised in Table 1. The model is accurate up to 89.7 percent (average of correct classification of DV=0 at 91.1 percent and DV=1 at 88.4 percent) using U validation method. This results show that the model has good potential for application.

Exclusion of Market Based Variable

The model developed in the previous section utilised both market and non-market (accounting information) based variables. The market-based model had one variable that required market based information, namely market value of share (V65). Users might want to make a choice between market-based and accounting based model to predict failure. The result shows that the same sets of significant variables under this option except the coefficients and the centroid are different.

The alternative prediction model is as follows,

$$Z = 2.34744+1.751301X1-0.981019X2+0.141036X3 \quad (2)$$

Where,
Z = Overall Index
X1 = Log V12 (Total Liabilities Percent)
X2 = Square Root V25 (Current Asset Turnover)
X3 = Log V17 (Cash to Current Liabilities)

The centroid of this new function for the non-failed firms (DV=0) at –1.116776 and the failed firms at 1.116776. The cutting score is equal to zero and the procedure for classifying firms is as follows:

1. Classify a firm as failed firms if its discriminant score is positive in value.
2. Classify a firm as non-failed firms if its discriminant score is negative value.

The revised model's classification accuracy was 87.9 percent (average of correct classification of DV=0 at 92.9 percent and DV=1 at 83.0 percent) in both the analysis and cross-validated sample. The performance comparison of original and alternative models, summarised in Table 3, suggests that the original model was superior.

The above finding was supported by the superior performance of the original model in the cross-validated procedures (U Method). The original model correctly classified 89.7% as compared to 87.9% of the alternative model. The original model consistently outperformed the alternative model in U method and external validation procedures. In external validation, the original model correctly classified 92.2% compared to the alternative model at 91.2% as shown in Table 3. These findings suggest that the original model is marginally superior for failure prediction of Malaysian listed companies.

External Validation

Before making any generalisations, the models developed were tested for external validity on new samples of failed firms in the year 1998. Fifteen failed firms in 1998 were introduced to test the validity of the model.

Table 3: A Comparison of Classification Accuracy

Panel A: Analysis Sample					
Model Develop From Market Based Variables			Model Develop From Non-Market Based Variables		
Group	Correct Classification (%)	Mis-classification (%)	Group	Correct Classification (%)	Mis-classification (%)
0	91.1	8.9	0	92.9	7.1
1	89.3	10.7	1	83	17
Avg.	90.2	9.8	Avg.	87.9	12.1
Panel B: Cross-Validated Procedures					
Group	Correct Classification (%)	Mis-classification (%)	Group	Correct Classification (%)	Mis-classification (%)
0	91.1	8.9	0	92.9	7.1
1	88.4	11.6	1	83	17
Avg.	89.7	10.3	Avg.	87.9	12.1
Panel C: External Validation Procedures					
Year	Correct Classification (%)	Grey Area (%)	Group	Correct Classification (%)	Grey Area (%)
0	100	0	0	100	0
1	100	0	1	100	0
2	87	13	2	80	20
3	73	20	3	74	13
4	53	34	4	47	40
5	20	53	5	20	53
Avg	72.17	20	Avg	70.17	21

Note: Avg = Average

The original model accurately classified more than 50 percent of failed firms four years before failure (Table 3). The model perfectly predicts failure event up to 2 years before failure after taking into consideration the grey area (zero misclassification). The alternative model was similarly accurate as the original model and showed accurate identification of failed firms up to two years before failure.

Tests of Relationship Between the Final Variables in the Model, and Profit and Cash Flow Variables

In the model development process, prime variables such as assets, liabilities, equity, sales and expenses were considered for inclusion in the model. Whereas variables that have potential negative values like profit, cash flow and working capital were omitted due to the requirement of the transformation techniques to include variables with positive values only. To ensure fair treatment on all classes of financial ratios and to avoid misconception among users of accounting information who often use cash flow, profit, working capital and net worth variables in their analysis, an additional analysis was performed to investigate whether the selected determinants in the prediction model have any relationship with the above mentioned variables (i.e. cash flows, profits, working capital and net worth). A Pearson correlation test was employed to investigate this relationship and the results are summarised in Table 4.

The findings show a strong relationship among the final variables and cash flow, profit, working capital and net worth variables. For example, total liabilities percent (V12) has a significant relationship with cash flow to assets (V02), return on sales (V05), return on assets (V07), working capital percent (V16), net worth to sales (V28), profit before depreciation to sales (V47), pre-tax income to sales (V49), operating income to asset (V56) and earning power (V64).

In summary, V12 is the image and considered representatives of the variables mentioned above. The other selected variables in the final model also had a significant relationship with the cash flow, profit, working capital and net worth variables.

This significant correlation suggests that the variables selected in the final models are good proxies for the commonly used variables by investors to predict financial health of firms.

Table 4: Pearson Correlation Test

Pearson Correlation - Industrial Sector					
		Final Variable In Prediction Model			
P	Variables	V12	V17	V25	V65
r	V02	0.720	-0.045	-0.137	0.029
o	V03	-0.011	-0.026	0.010	-0.023
f	V04	-0.096	0.613	0.061	0.229
i	V05	0.561	-0.033	-0.194	-0.032
t	V06	0.026	-0.022	-0.030	-0.017
&	V07	0.717	-0.046	-0.151	0.032
C	V09	-0.079	0.634	-0.004	0.258
a	V16	0.998	-0.046	-0.191	-0.032
s	V26	-0.116	-0.138	0.377	-0.031
h	V27	0.121	-0.050	-0.047	-0.049
	V28	0.640	-0.031	-0.182	-0.032
F	V37	-0.072	0.036	0.199	0.096
l	V38	-0.017	-0.002	0.034	-0.005
o	V47	0.581	-0.031	-0.190	-0.031
w	V48	0.113	-0.018	-0.164	-0.023
	V49	0.561	-0.033	-0.194	-0.032
V	V50	0.026	-0.022	-0.030	-0.017
a	V56	0.191	-0.019	-0.056	0.070
r	V57	0.077	0.082	-0.132	0.051
i	V59	-0.099	0.116	0.184	0.029
a	V60	-0.003	-0.036	-0.009	-0.016
b	V61	0.061	0.053	-0.218	0.032
l	V62	-0.068	-0.045	0.084	0.011
e	V63	-0.012	-0.028	0.013	-0.025
s	V64	0.695	0.126	-0.238	0.113

Note: The shaded cell showed the correlation is significant at the 1% level

CONCLUSION AND IMPLICATIONS

The findings showed that the original prediction model (accounting and market-based variables) was superior to the accounting based (i.e. alternative) model. This could be due to first one factor difference (market value of shares) between the models. Both models showed exceptional performance with high correct classification accuracy rate (more than 80 percent) in both internal and external validity. The findings suggest that the models are reliable and have good pratical use for making decisions in real markets as the validation tests showed better than chance prediction i.e. the percentage of correct classification of failed and non-failed firms was at 53% as far as 4 years before failure. This implies a great potential to use these models to accurately identify failures. Finally, there was a strong relationship between the final variables in the prediction models with commonly used investor yardstick of cash flow, profit, working capital and net worth.

In addition, four out of 65 financial ratios significantly discriminated between failed and non-failed firms. These variables are ranked in descending order of their discriminating power:

1. Total Liabilities Percent (V12)
2. Current Asset Turnover (V25)
3. Market Value to Debts (V65)
4. Cash to Current Liabilities (V17)

These variables could guide the policy makers to formulate an early warning system to either evade or mitigate impeding failures. For example, bankers or creditors could use the model to assess the potential borrowers' credit risk and continuously assess the borrower's financial condition in making decisions to renew or extend the loan. Managers could use the findings in their financial planning i.e. if failure can be predicted three to four years earlier, management could take remedial action such as exercising merger or restructuring to avoid the potential bankruptcy costs. Regulating agencies such as the Securities Commission and Kuala Lumpur Stock Exchange might want to assess a firm's going-concern status, solvency and compliance of certain important requirements. This is important to pre-empt any systematic financial failures and bailouts using public funds. Auditors could use the findings in expressing a fair opinion of the overall financial condition and the status of the firm as a going concern. This relates to corporate governance issues as findings in this study also showed that more than 60% of the failed firms had unqualified auditor report even one year before the actual failure. Finally, investors could use the findings to help them make better selection decision in their portfolio investment.

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Appendix 1: List of Ratios Examined

Code	Ratio Name	Ratio Formula
V01	Cash flow to Sales	(Income + Depreciation)/Sales
V02	Cash flow to Assets	(Income + Depreciation)/Total Assets
V03	Cash flow to Net Worth	(Income + Depreciation)/(Total Assets-Total Liabilities)
V04	Cash flow to Total Debt	(Income + Depreciation)/Total Liabilities
V05	Return on Sales (ROS)	Net Income/Sales
V06	% Change in ROS	(ROS % CY - ROS % PY)/ROS % PY
V07	Return on Assets (ROA)	Net Income/Total Assets
V08	Return on Equity (ROE)	Net Income/(Total Assets - Total Liabilities)
V09	Net Income to Total Debt	Net Income/Total Liabilities
V10	Current Liabilities Percent	Current Liabilities/Total Assets
V11	Long Term Liabilities %	Long Term Liabilities/Total Assets
V12	Total Liabilities Percent	Total Liabilities/Total Assets
V13	Cash Percent	Cash/Total Assets
V14	Quick Assets Percent	(Cash + Accounts Receivable)/Total Assets
V15	Current Assets Percent	Current Assets/Total Assets
V16	Working Capital Percent	(Current Assets - Current Liabilities)/Total Assets
V17	Cash to Current Liabilities	Cash/Current Liabilities
V18	Quick Ratio	(Cash + Accts Receivable)/Current Liabilities
V19	% Change in Quick Ratio	(Quick Ratio CY- Quick Ratio PY)/Quick Ratio PY
V20	Current Ratio	Current Assets/Current Liabilities
V21	% Change in Current Ratio	(Current Ratio CY -Current Ratio PY)/Current Ratio PY
V22	Cash Turnover	Sales/Cash
V23	Receivable Turnover	Sales/Account Receivable
V24	Quick Asset Turnover	Sales/Quick Assets
V25	Current Asset Turnover	Sales/Current Assets
V26	Working Capital Turnover	Sales/(Current Assets -Current Liabilities)

V27	% Change in Sales/WC	(Sale/WC% CY – Sale/WC % PY)/ Sale/WC % PY
V28	Net Worth to Sales	(Total Assets – Total Liabilities)/Sales
V29	Asset Turnover	Sales/Total Assets
V30	% Change in Sales to Total Assets	(Sales to TA % CY – Sales to TA % PY)/ Sales to TA % PY
V31	Days Sales in Receivable	Account Receivables/(Sales/365)
V32	Inventory Percent	Inventory/Total Assets
V33	Inventory Growth	(Inventory CY – Inventory PY)/ Inventory PY
V34	Sales Growth	(Sales CY – Sales PY)/Sales PY
V35	Depreciation Growth	(Depreciation CY – Depreciation PY)/Depreciation PY
V36	Dividend Growth	(Dividend CY – Dividend PY)/ Dividend PY
V37	Return on Opening Equity (ROOE)	(Net Income/Beginning Owners Equity
V38	% Change in ROOE	(ROOE CY – ROOE PY)/ROOE PY
V39	Equity to Debt	(Total Assets – Total Liabilities)/ Total Liabilities
V40	% Change in Equity to Debt	(Equity/Debt CY – Equity/Debt PY)/(Equity/Debt) PY
V41	Equity to LT Debt	(Total Assets – Total Liabilities)/LT Liabilities
V42	% Change in Equity to LTD	(Equity LTD% CY – Equity LTD% PY)/Equity LTD % PY
V43	Equity to Fixed Assets	(Total Assets – Total Liabilities)/Net Fixed Asset
V44	% Change in Equity to Fixed Assets	(Equity FA % CY – Equity FA % PY)/Equity FA % PY
V45	Times Interest Earned	Income Before Interest and Taxes/ Total Interest
V46	% Change in Times Interest Earned	(Times Interest % CY – Times Interest % PY)/ Times Interest % PY
V47	Profit Before Depreciation to Sales	(Profit + Tax + Depreciation)/Sales
V48	% Change in Profit Before Depreciation to Sales	PrB4 Depreciation % CY – PrB4 Depreciation % PY)/ PrB4 Depreciation % PY
V49	Pretax Income to Sales	(Profit + Tax)/Sales
V50	% Change in Pretax Income to Sales	(PrB4 Tax % CY – PrB4 Tax % PY)/ PrB4 Tax % PY
V51	Sales To Inventory	Sales/Inventory
V52	% Change in Sales to Inventory	(Sale/Inventory % CY – Sale/Inventory % PY)/ (Sale/Inventory % PY)
V53	Sales to Fixed Assets	Sales/Fixed Assets

V54	% Change in Total Assets	(Total Assets CY – Total Assets PY)/ Total Assets PY
V55	% Change in WC%	(WC % CY - WC % PY)/WC % PY
V56	Operating Income to Assets	(Profit + Tax + Interest)/Assets
V57	% Change in Operating Income to Asset	(OI/Asst CY - OI/Asst PY)/ (OI/Assets PY)
V58	% Change in LTD	(LTD CY - LTD PY)/LTD PY
V59	Dividends to Cash Flows	Dividends/(Profit + Depreciation)
V60	Net Income to Cash Flow	Profit/(Profit + Depreciation)
V61	Operating Profit %	(Profit + Tax + Interest)/Sales
V62	Return on Owners Equity	(Profit + Tax + Interest)/(Stock +Retained Earnings)
V63	Total Assets to Net Worth	Total Assets/(Total Assets - Total liabilities)
V64	Earning Power	Profit/ (Fixed Assets + Inventory)
V65	Market Value To Debts	Market Value Equity/Book Value of Total Liabilities

Note:

CY	=	Current Year
PY	=	Prior Year
%	=	Percentage
WC	=	Working Capital
TA	=	Total Assets
LT	=	Long Term
LTD	=	Long Term Debt
FA	=	Fixed Asset
PrB4	=	Profit Before
OI	=	Operating Income

Appendix 2: List of Sampled Firms

No.	Failed Firms	Non-Failed Firms
1	United Engineers (Malaysia) Bhd	Malaysian Mosaics Bhd
2	Innovest Bhd	Sanyo Industries (M) Bhd
3	Insas Bhd	South Johore Amalgamated Holdings Bhd
4	UMW Holdings Bhd	Amalgamated Steel Mills Bhd
5	RJ Reynolds Bhd	Dreamland Holdings Bhd
6	Lien Hoe Corporation Bhd	Khong Guan Holdings Malaysia Bhd
7	Lion Land Bhd	George Kent Malaysia Bhd
8	Damansara Realty Bhd	United Malayan Flour Mills Bhd
9	Uniphoenix Corporation Bhd	Linatex Process Rubber Bhd
10	Grand United Holdings Bhd	FCW Holdings Bhd
11	Mega First Corporation Bhd	Malex Industries Bhd
12	Gula Perak Bhd	Malaya Glass Bhd
13	Menang Corporation (M) Bhd	Loytape Bhd
14	MBf Land Bhd	Berjaya Kawat Bhd
15	George Town Holdings Bhd	Kamunting Corporation Bhd
16	Diversified Resources Bhd	DNP Holdings Bhd
17	Berjaya Capital Bhd	Ajinomoto (Malaysia) Bhd
18	FACB Bhd	Cement Manufacturers Sarawak Bhd
19	Promet Bhd	Shell Refining Co (F.O.M.) Bhd
20	Larut Consolidated Bhd	MMC Engineering Group Bhd
21	Olympia Industries Bhd	Pacific Chemical Bhd
22	Leader Universal Holdings Bhd	Cement Industries of Malaysia Bhd
23	Worldwide Holdings Bhd	Dutch Baby Milk Industries (M) Bhd
24	Berjaya Sports Toto Bhd	Roxy Electric Industries (Malaysia) Bhd

ENDNOTES

[1] Altman (1984) showed that firms incur bankruptcy costs in the range of 11 to 17% of the firm value three years prior to bankruptcy in developed economies.

[2] Before discriminant analysis is implemented, normality test was carried out on all independent variables. One variable was found normal, eighteen variables was found to be lognormal and seven variables' square root was found to be normal. However, the variables that potentially could have negative values were excluded from the analysis due to problem in transforming the data.