CHAPTER 4

RESULTS OF THE STUDY

INTRODUCTION

Seventy Industrial Companies listed on the KLSE were studied. These seventy companies were classified into two groups. Group 1 comprises 35 relatively lower value companies and Group 2 comprises 35 higher value companies. The values being assesed by utilizing the Torbin Q ratio. The name of the companies in this study are given in Appendix 4-A.

RESULTS OF THE STATISTICAL ANALYSIS

THE DISCRIMINANT FUNCTION

Table 4.1 contains the standardized and unstandardized discriminant function coefficient for the analysis. The unstandardized coefficients are the multipliers of the variable when they are expressed in the original units. The standardized coefficients on the other hand are used when the variables are standardized to a mean of 0 and a standard deviation of 1.

When stepwise variable selection method was applied, using the minimization of Wilks' Lambda to the ten financial ratios, it was determined that nine out of the ten ratios were significant for selection. However subsequent tests of correlation between the variables indicate a high degree of multicollinerity between Networking capital To total assets (NWC/TA) and variables such as market value of common and prefered stock To book value of debt (MVS/BVD), retained earnings To total assets (RE/TA) and current assets To current liabilities (CA/CL). also, RE/TA manifest a high degree of collinearity with earnings before interest and tax To total assets (EBIT/TA) and net income after tax before extraordinary item To share holder's fund (NI/Shf). Another series fo tests were conducted to show the relative contribution of the variables. The tests are 'F' test, Wilks lambda test, the standardized coefficient ranking and the forward stepwise selection.. On the average NWC/TA was ranked as number six in importance and RE/TA ranked as number seven. Thus NWC/TA and RE/TA were removed from the model. A notable improvement in the problem of multicollinearity and the performance of the model was observed. This is illustrated in the subsequent sections. The variable profile finally established is shown in equation 4.1.

TABLE 4.1

Standardized and unstandardized discriminant function coefficients

VARIABLE	UNSTANDARDIZED	STANDARDIZED
X1	0.2979899	0.19858
X2	0.8330686	0.20900
X3	8.975869	0.74938
X4	0.3580427	0.31144
X5	-0.4014786	-0.33332
X6	0.3612491	0.20005
X7	-0.7366230	-0.28930
(Constant)	-1.553312	

Key of the variables:

X1 = Sales To total assets

X2 = Market value of common and prefered stock To book value of debt

X3 = Earnings before interest and tax To total assets

X4 = Current assets To current liabilities

X5 = Lomg term debt To share holder funds

X6 = Net income after tax before extraordinary item To turnover

X7 = Net income after tax before extraordinary item To share holders' fund

Equation (4.1) $Z = -1.553 + .298X1 + .833X2 + 8.976X3 + .358X4 - .401X5 + .361X6 - .737X7$

THE RELATIVE IMPORTANCE VALUES

Another issue of some interest to practitioners is the relative importance of the individual variables. It has been well accepted that statistical tests on individual variables are not conclusive in most discriminant studies due to lack of normality assumptions and the controvasial nature of the tests applied. Analysts have disputed the various tests as well. However to arrive at the final variable profile it is important to determine the interaction between the variables and the relative contribution of each variable to the total discriminating power of the function.

Discriminant function coefficients are unstable when the variables composing the model are highly correlated. If two variables composing a multivariate model are collinear, the information each adds to the model is similar, and their coefficients are assigned arbitrarily. Thus, the relative weights of the variables do not necessarily signify their relative importance.

Multicollinearity, usually found in financial data, was not as high as might be expected. Table 4.2 shows the correlation coefficients for each pair of the seven variables. From the test of multicollinearity, which was found to be moderate, we proceed to determine the individual discriminating ability of the variables. To this end the following tests are conducted:

An "F" test, which relates the difference between the average values of the ratios in each group to the variability (spread) of values of the ratios within each group is conducted. By this test the individual discriminating ability of the variable is determined; The Wilks lambda statistics in a univariate context produce lambda as the ratio of the within-groups sum of squares to the total sum of squares. Small values of lambda indicates the apparent difference in group means; The Standardized coefficients are the multiplier of the variables when they are standardized to a mean of 0 and a standard deviation of 1. The magnitude of the unstandardized coefficient is not a good index of relative importance. It could be noted in table 4.1 that the ranking order of the absolute values of the unstandardized coefficient changes, when standardized; Forward Stepwise variable selection considers the variable that has the largest acceptable value for the selection criteria to be the first variable included in the analysis. After revaluation of all variables not in the analysis, the selection procedure is repeated. By this method a ranking of the variables in the order of relatively highest contribution to the model is obtained.

The resulting "F" statistics, the Wilks lambda statistics , the standardized coefficients and ranks of variables in the failure model are presented in table 4.3. In this table we see that EBIT/Total Assets (X3) which is the profitability ratio is consistently ranked highest in relative contribution. This is not surprising if one considers that the incidence of failure in a firm that is earning a profit is almost nil. CA/CL (X4) has also been consistently ranked second highest relative contributors by three of the four tests in the table. It appears that Sales/TA (X1) has contributed the least of the seven variables. This is consistent with many past studies, especially Altman (1968), Mason and Harris (1978), Beth and Belhoul (1982 and 1983).

TABLE 4.2

CORRELATION MATRIX

VARIABLES

	1	2	3	4	5	6	7
1. X1	1.00						
2. X2	-.01	1.00					
3. X3	.20	.29	1.00				
4. X4	-.03	.33	.15	1.00			
5. X5	-.04	-.10	-.09	-.07	1.00		
6. X6	-.17	.09	.13	.06	.00	1.00	
7. X7	-.06	.11	.52	.08	-.47	-.08	1.00

Key of the variables:

X1 = Sales To total assets

X2 = Market value of common and prefered stock To book value of debt

X3 = Earnings before interest and tax To total assets

X4 = Current assets To current liabilities

X5 = Long term debt To share holder funds

X6 = Net income after tax before extraordinary item To turnover

X7 = Net income after tax before extraordinary item To share holders' fund

TABLE 4.3

Relative contribution tests and ranks of variables in the failure model

Variable	F Ratio		Wilks Lambda		Standardized Coefficient		Forward Stepwise Selection
	Amount	Rank	Amount	Rank	Amount	Rank	
X1	5.92	6	.70483	6	.19858	7	7
X2	5.84	7	.70475	7	.20900	5	3
X3	60.29	1	.77490	1	.74938	1	1
X4	14.41	2	.71578	2	.31144	3	2
X5	13.57	3	.71470	3	-.33332	2	4
X6	6.23	5	.70524	5	.20005	6	6
X7	7.43	4	.70678	4	-.28930	4	5

Key of the variables:

X1 = Sales To total assets

X2 = Market value of common and prefered stock To book value of debt

X3 = Earnings before interest and tax To total assets

X4 = Current assets To current liabilities

X5 = Lomg term debt To share holder funds

X6 = Net income after tax before extraordinary item To turnover

X7 = Net income after tax before extraordinary item To share holders' fund

CLASSIFICATION ACCURACY

In this section we attempt to determine to what extent each ratio showed differences between the two groups, by analysis of the mean and variance. Then we further investigate the accuracy of the model in predicting failure in percentage terms.

The analysis of the mean and variance of each ratio showed significant differences between the two groups that confirmed what was expected. This in particular showed that on average the non-fail firms had (see table 4.4): (I) a better activity ratio (X1: Sales/TA and X6: NI/TO) manifesting managements dynamism in dealing with competative conditions; (II) greater liquidity (X4: CA/CL) demonstrating the companys' greater ability to pay their immediate creditors from their quick source and as a consequence of the above; (III) greater profitability (X3: EBIT/TA and X7: NI/ShF). On the other hand, on average, the fail firms have a higher tendency for liverage than the nonfail firms. By observing the t values in the table, it can be seen that all the variables except X6 (NI/TO) are significant. This means that the test result reject the hypothesis that there is no difference between the groups and substantiate that the model does, infact possess discriminating power.

Now then we investigate the classification accuracy of the model. In this process, the initial sample of 35 firms in each of the two groups is examined. Recall that the sample data was collected for the period 1984 to 1992 both inclusive. Thus to predict failure one year in advance, we start by using the data for the model in 1984 to predict for 1985 which is then compared with the actual data (from the Torbin Q ratio) for 1985. This one year predictive ability of the model is generated in percentage terms. The same procedure is repeated , next using the data for the model in 1985 to predict for 1986 and then similarly using data for 1986 to predict for 1987 until we finally used the 1991 model data to predict for 1992. Thus the average of the predictive ability of the model generated above represent the one year percentage predictive accuracy of the model. A similar procedure is repeated in determining the classification accuracy of the model two years in advance. This time the model data for 1984 is used to predict for 1986 and similarly , data for 1985 is used to predict for 1987. This procedure is repeated over and over for predicting up to five years in advance. Since the discriminant coefficients are derived from this sample, a high degree of classification accuracy is anticipated. The classification matrix for the initial sample is given in table 4.5. The results are indeed encouraging.

It can be seen that the model is most efficient in predicting the first year to failure, manifesting a predictive ability of 82.19%. The model tested with data for predicting two and three years to failure showed an accuracy of 81.77% and 80.13% respectively. This shows a sign of deterrioration of the predictive ability of the model as the years to failure become remote. The model, however seem to improve in its predictive ability for the fifth year prior to failure. This shows a reversal in trend which is not what was expected. The most logical conclusion therefore would be that the model becomes very much more unreliable after four years to failure. It must be borne in mind that the fail sample was selected at random from a group of 40 low valued firms. As the sample was too small, the distinction of firm size differ quite considerably and this may have had some effect upon the efficiency of the function. It has also been proved in past studies that the efficiency of the model deterriorates in its predictive ability as the years of failure become more and more remote. Again it must be borne in mind that, in this specific study no information was available indicating the failure of the firms in the fail group. They were merely seen to indicate lower relative values to the non-fail groups. Since the Companies in the fail group did not in fact fail, it is impossible to determin the predictive ability of the model relative to the year of failure.

TABLE 4.4

CLASSIFICATION EFFICIENCY

	MEANS		VARIANCE		t
RATIOS	Fail	Non-fail	Fail	Non-fail	Value
X1	.85011	1.11348	.59097	.73157	-4.73
X2	1.70385	3.53584	1.72120	3.08128	-9.18
X3	.02022	.06537	.09829	.06623	-11.34
X4	1.24108	1.81528	.75361	.96845	-8.47
X5	.44959	.10282	1.18218	.09469	4.86
X6	-.01771	1.8291	.17434	.75634	-1.39
X7	-.06518	.10739	.55637	.07123	-5.24

Key of the variables:

X1 = Sales To total assets

X2 = Market value of common and prefered stock To book value of debt

X3 = Earnings before interest and tax To total assets

X4 = Current assets To current liabilities

X5 = Lomg term debt To share holder funds

X6 = Net income after tax before extraordinary item To turnover

X7 = Net income after tax before extraordinary item To share holders' fund

TABLE 4.5

CLASSIFICATION ACCURACY

	FAILED SAMPLE	NON-FAILED SAMPLE	TOTAL SAMPLE
YEAR	PERCENT CORRECT	PERCENT CORRECT	PERCENT CORRECT
1	79.96	84.70	82.19
2	79.78	82.75	81.77
3	78.76	80.50	80.13
4	75.83	76.02	75.92
5	76.04	76.40	77.27

APPLICATIONS

This is an attempt to extend the model for more general application, for the benefit of executives, credit managers and investors in working environments where they do not have access to computer procedures such as the multiple discriminant analysis. In order to achieve this aim, a "cut-off" point, or optimal Z value is determined. This is the criterion (score) against which a firm's discriminant score is judged to determine into which group it should be classified. This should enable prediction without computer support possible.

In this study, since the groups sample size are equal, the optimal cutting score (or critical Z value) will be halfway between the two group centroids. The cutting score is therefore defined as

$$Zct = \frac{Za + Zb}{2}$$

where

Zct = Critical cutting score value for equal group size

Za = Centroid for failed firms

Zb = Centroid for nonfail firms

From the analysis it is noted that Za = -.67112 and Zb = .64476 thus substituting in the above equation we have Zct = -0.013 which could be estimated to be Zct $\cong$ 0.00. Therefore firms with a Z value less than 0.00 will be classified into the fail group and those with Z value greater than 0.00 will be classified into the nonfail group.