Apply Logit analysis in Bankruptcy Prediction

YING ZHOU and TAHA M.S. ELHAG
Department of Management of Projects
The University of Manchester
G floor, Pariser Building, School of Mechanical, Aerospace and Civil Engineering, The University of Manchester, PO Box 88, Manchester M60 1QD,
United Kingdom

Abstract: -Signs of a potential business bankruptcy are evident well before actual bankruptcy occurs. For managers, creditors, and all other concerned parties this lag allows time to take remedial action. Therefore, building models, which signal approaching financial failure, have been an important part of corporate finance literature, in order to help management refocus their energy, revaluate their corporate strategy and eliminate losses. This paper reviews the literature of bankruptcy prediction and the decision process of Logit analysis. Setting the optimized cut-off point process is employed in this study; and in-sample t test is chosen to examine the selected predictors. A four-variable Logit model, resulting from a forward-stepwise selection procedure, were built up in this study, it correctly predicted 81% with 92% type I error, 70% type II error from 100 matched-samples 1 year prior to bankruptcy.

Key-Words: - Logit Analysis, Bankruptcy Prediction, Financial Distress Analysis, Business failure, Statistical Analysis

1 Introduction

Concerns about business failures tend to accelerate at a greater proportion during turbulent economy period. In the 1970's, the two giant corporate failures of economic prominence were: the wake of Penn Central Transportation bankruptcy which was approximately $5 billion in assets; and the WT Grant company which was succeeded in 1980 by Chrysler Corporation with a bankruptcy price tag of $12 billion in assets; and most recently, the subject of bankruptcy has had significant publicity with the Enron and WorldCom business practice irregularities (Charles, 2003). All these failure events have heightened everyone's attention on the significant ripple effect that bankruptcy could have on the economy with severe damage to other's economic well being such as investors, lenders, and the general consumer as well as the business itself thus creating a highly vulnerable atmosphere for the industry that is impacted.

Because of the rising number of business failures, a large number of researchers and practitioners have worked on the prediction of business failure. According to Aziz and Dan (2006), there are mainly three groups of approaches, statistical models, artificially intelligent expert system and theoretical models. Each method has its own assumptions and different contributions in the field of financial distress prediction.

This paper reviews the literature of bankruptcy prediction and the decision process of Logit analysis. Setting the optimized cut-off point process is employed in this study; and in-sample t test is chosen to examine the selected predictors. A four-variable Logit model, resulting from a forward-stepwise selection procedure, correctly predicted 81% with 92% type I error, 70% type II error from 100 matched-samples 1 year prior to bankruptcy.

2 Bankruptcy Prediction

The definition of business failure has been adopted by Dun & Bradstreet (D&B), a leading supplier of relevant statistics on unsuccessful business, failure includes businesses that ceased operations following assignment or bankruptcy, with loss to creditors, and voluntarily withdraw, leaving unpaid obligation, or were involved in court actions such as receivership, reorganization, or arrangement.

According to the report of Insolvency service by UK government, there were 3,113 liquidations in England and Wales in the first quarter of 2007 on a seasonally adjusted basis, with a decrease of 2.8% on the previous quarter and a decrease of 11.6% on the same period a year ago. Figure 1 shows the number of company liquidations in England and Wales from 1998 to 2006. The average number of liquidation is above 20,000 per year.

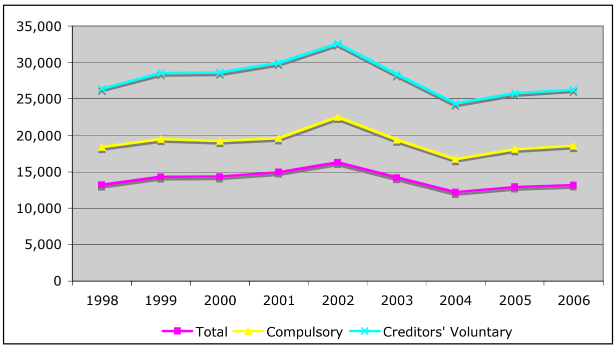

Figure 1 illustrates the number of company liquidations in England and Wales from 1998 to 2006 (*Source; The insolvency service, last update, 29th, January, 2007*)

The health of a bank in a highly competitive business environment is dependent upon:

- How financially solvent it is at the inception
- Its ability, relative flexibility and efficiency in creating cash from its continuous operations
- Its access to capital markets
- Its financial capacity and staying power when faced with unplanned cash short-falls

As a bank or film becomes more and more insolvent, it gradually enters a danger zone. Then, changes to its operations and capital structure must be made in order to keep it solvent (insolvency website).
With regarding to Dun & Bradstreet statistics (1987), the causes of business failures were attributed to five factors: (1) economic, (2) management experience, (3) declining sales, (4) increase in expenses, and (5) other miscellaneous factors, which are shown in Figure 2 below. As information illustrated in Figure 2, economic factors are the leading cause of business failures with management experience as the second.

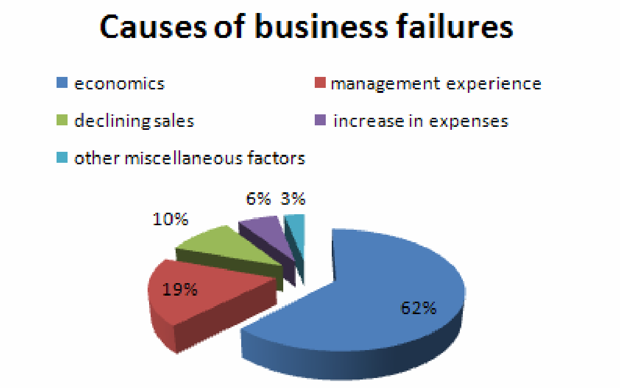

Figure 2 Causes of business failures

Business failure studies have concentrated on various methods or predictors of the occurrence of bankruptcy incorporation. The statistical technique attempts to understand why a group of firms failed in the past and why another group of matched firms survived. Moreover, the objective of the statistical technique is to find indictors that can always correctly identify an upcoming failure. A number of statistical techniques have been used to develop bankruptcy prediction models. The more generally utilized are univariate analysis (Beaver, 1966), multiple discriminant analysis (Altman, 1968), Logit (Ohlson, 1980) and Probit analysis (Zavgren, 1985), recursive partitioning (Fryman, Altman and Kao, 1985) and neural networks (Coats and Fant, 1993). These techniques attempt to find a group of financial ratios that can be reviewed to judge how likely a firm is to fail. Furthermore, most statistical studies attempt to accurately predict failure that their predictive accuracy tends to fall off dramatically more than two years before failure.

3 Overview of Logit Analysis

Logit analysis, which is a widely used technique in the situation of the probability of a dichotomous outcome, is based on a cumulative probability function, provides the conditional probability of an observation belonging to a certain class without requires independent variables to be normal, and it considers all the perspective factors in a problem solved simultaneously. The feature of this type model is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis does (Chi and Tang, 2006).
Figure 3 represents the decision process of Logit analysis, which is mainly divided into 6 stages. The Logit Loglinear Analysis procedure analyzes the relationship between dependent (or response) variables and independent (or explanatory) variables. The dependent variables are always categorical, while the independent variables can be categorical (factors). The weighted covariate mean for a cell is applied to that cell. The logarithm of the odds of the dependent variables is expressed as a linear combination of parameters. A multinomial distribution is automatically assumed; these models are sometimes called multinomial logit models. This procedure estimates parameters of logit loglinear models using the Newton-Raphson algorithm.

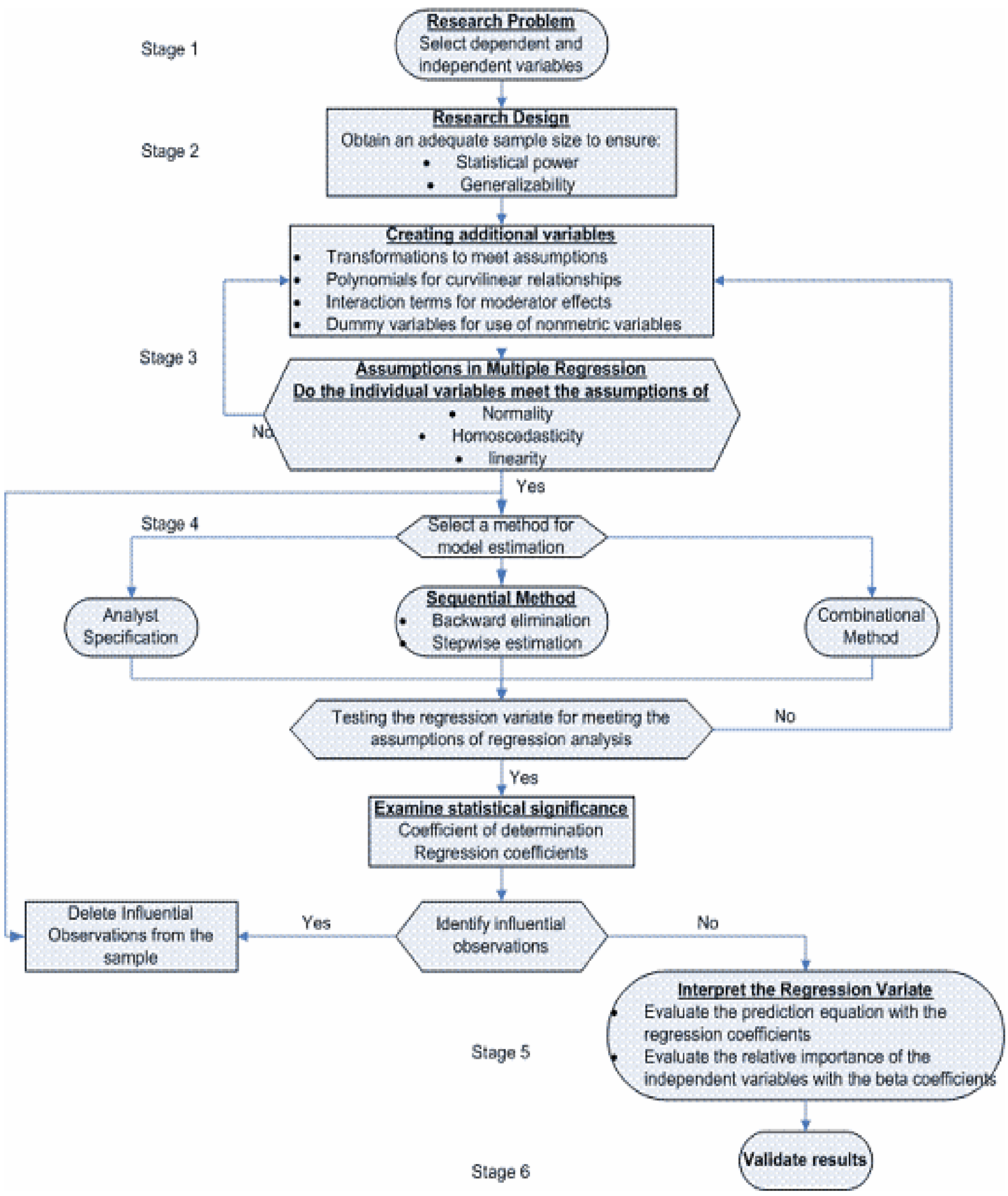

Figure 3 Decision process of Logit Analysis

The selection of predictors for bankruptcy prediction model is the most burdensome aspect due to financial theory does not indicate which invariable should be involved in (Theodossiou, 1991). According to Hair et al (1998), the forward stepwise procedure, the most popular search method for development of bankruptcy prediction model, is useful when researcher attempts to consider a relationship between large numbers of independent variables for inclusion in the function. In this procedure, the significance of the score statistics and the probability of a likelihood-ratio statistic based on the maximum partial likelihood estimates are used to determine which variables to enter or drop from the model (SPSS, 2003).

Logit analysis with forward stepwise regression in employed to construct predictive models in this study. In application of bankruptcy prediction, the dependent variable *status* has two outputs: 0 is denoted as bankrupt firms, 1 is denoted as healthy firms (Liao, 1994). Thus, a Logit model used for bankruptcy prediction is related to a set of potential predictor variables in the form below (Hosmer and Lemeshow, 1989; Pampel, 2000):

$$\log\left[\frac{P(E)}{1-P(E)}\right] = \beta_0 + \beta_1 \times x_{i1} + \beta_2 \times x_{i2} + \cdots + \beta_n \times x_{in} \qquad (1)$$

where,

P(E):probability of nonbankruptcy in the ith firm

‰an intercept

X_1LX_n: input variables

%L‰ coefficients of the nth input variables

Thus, when expressed in Logit form,

odds ratios of bankruptcy are defined as;

$$\frac{\text{P(E)}}{\text{(1-P(E))}}$$

where P(E) is the probability of healthy (nonbankruptcy)

By solving P (E) through Equation (1), the predicted probability of healthy firms can be described as;

$$P(E) = \frac{e^{y}}{1+e^{y}} \qquad (2)$$

where,

e: the base of nature logarithm

y=‰+‰x_{i1}+L+‰x_{in}

To classify sample firms into two sub-groups, the logit(y) value of each sample firm can be computed based on the estimate model and then apply to the probability function (2).

4 Research Design

4.1 Data source & Sample selection

Selection of 100 samples from database AMADEUS (Analyse Major Database for European Sources), there are all from European countries from 2000 to 2005.In order to detect the maximal difference between bankrupt and healthy firms, the sample design is based on the Beaver-Altman matched-pairs sample criteria in terms of total asset in Manufactory Industry (NAICS, 31+32+33).

4.2 Research variables

A total of 26 variables are selected for bankruptcy prediction. Three of them are ignored since too few available data. Thus, there are 23 variable chosen from financial statement of each sample firm in four groups shown in table 1, which include liquidity, operational efficiency, profitability, capital structure, and growth ability, etc. A table in Appendix I present all the financial ratios in this study.

Ratio Name	Ratio ID
Profitability	R1-R7
Operational efficiency	R8-R12
Management Structure	R13-R17
Human Resource management	R18-R23

Table 1 Four Groups of Financial ratios

4.3 Misclassification costs& Cut-off points

Two types of classification error are employed to examine the predictive ability of estimated model. Type I error indicates the proportion of classifying bankruptcy firm as healthy one, while Type II error indicates the proportion of classifying healthy firm as bankrupt one. In the former case, the costs of misclassification can include principal, interest, collection fee, and legal fee, whereas in the second situation, it includes the costs of foregone business sales. Since reducing the occurrences of one type error will lead to the increases the occurrences of the other type error, the optimal cut-off point depends one the relative costs of two types of error. Concluded by Trade experts, Type I error is 2-20 times more serious than Type II error, with a most likely value of 15 times more serious, i.e., misclassification costs of Type I error is far more expensive than Type II error (Lee et al., 2002; Thomas, Edelman and Cook, 2002).

Various criteria of setting cut-off point in prior studies have been used for measuring misclassification costs and prediction model performance. Forth, Altman (1968) and Deakin (1972) use cut-off point which minimize misclassification accuracy; Ohlson (1980) and Palepu (1986) use the cut-off points where the distributions of two groups intersect; and Frydman, Altman and Kao (1985) and Barniv, Agarwal and Leach (2002) use cut-off points that minimize the number of misclassifications. Cut-off point ranged from 0.1 to 0.9 is employed in this study, in order to obtain a reasonable classification rate as the optimal cut-off by decreasing Type I error so that fewer bankrupt firms go undetected (Chi and Tang, 2006).

5 Experiment results analysis

5.1 Independent-sample t-test

Analysis of variance examines the relationship between an independent variable and a dependent variable, correlation and regression examine the relationship between two independent variables, and the chi-square (x^2) test of independence is used to examine the relationship between two independent variables.

Table 2 (see in Appendix) presents the mean values of all variables of healthy group and bankrupt group of the model estimation sample. Their independent sample t-test statistics and related p values of the two groups are presented in the table. According to Pallant (2005), differences of groups can be assessed by p-value (2-tailed);

- If the p-value (2-tailed) is equal or less than 0.05, then there is a significant difference in the mean scores on categorical variable for each of the two groups.
- If the p-value (2-tailed) is above 0.05, there is no significant difference between the two groups.

Therefore, the two groups are distinct in six ratios- R1 (return on shareholders fund), R3 (Return on total assets), R4 (Cash Flow/ Turnover), R5 (Profit Margin), R7 (EBIT Margin) and R12 (Credit Period). A comparison of the two groups' means of profitability ratios shows that the bankrupt group had lower profit generation ability before failure. The t-tests also suggest that there is a significant difference in operating efficiency ratio. Also, as t-test show, there are no remarkable differences between two groups in terms of management structure ratios and human resource ratios.

As guidelines, proposed by Cohen (1988), for interpreting the effect size for independent-samples t-test;

- If effect size = 0.01, small effect
- If effect size = 0.06, moderate effect
- If effect size= 0.14, large effect

So forth, the major differences of two groups in terms of the magnitude of six ratios, R1, R4, R5, R7, R9, R11, whose effect size value around 0.06 or even more higher, are relatively evident. Also, these evidences support the results of t-test for disparities of the two groups.

5.2 Setting Cut-off points

Table 3 presents the classification ability of the Logit models applied at cut-off point range from 0.1 to 0.9 in terms of classification rate, Type I and Type II error, and also the wrong classified cases for each group firms.

Cut-off.	C.R.	Type I	Type II e	0->1	1->0
0.1	65%	68%	2%	34	1
0.2	72%	50%	6%	25	3
0.3	77%	36%	10%	18	5
0.4	80%	26%	14%	13	7
0.5	77%	22%	24%	11	12
0.6	79%	14%	28%	14	7
0.7	81%	8%	30%	4	15
0.8	75%	4%	46%	2	22
0.9	67%	0%	68%	0	33

Table 3 Cut-offs, Classification Accuracy and Error Rates for Logit Models

The classification accuracy ranges from 65% to 81%, and Type I error is up to 0, Type II error is up to 2%. In order to detect the highest classification rate with minimum number of misclassification cases, cut-off point is set as 0.7 to optimize the Logit model performance.

5.3 Overall Performance of Logit Model

The results of the Logit Model with cut-off point 0.7 are presented in Table 4. The Overall Model Fit table shows the usefulness of the model, the Cox & Snell R square and Nagelkerke R values provide an indication of the amount of variation in dependent variable explained by the model. As shown in Table 4, 42.7% and 56.9% of the variability is explained by this set of variables.

The Omnibus Tests of Model Coefficients presents an overall indication of how well the model performs, which refers to as a goodness-of-fit test, all sig. in this table are less than 0.05, which reveals that the estimated Logit model provide a good fit to data and the estimated of the variables' parameters are meaningful. The Hosmer & Lemeshow's goodness-of-fit value also supports the model as being worthwhile, sig. is 0.407 in this study with chi-square value 8.272 with 8 degrees of freedom, indicates that the final four-predictor model fits the data well since there is no significant discrepancy between the observed and predicted classifications.

The Variable (in this equation) table shows the information about the contribution or importance of each predictor. Wald test, is commonly used to test the significance of the individual coefficient for each predictor in Logit model (Hair, et al., 1998), shows the first four predictors with the most important effects of dependent variable.

With significance level sets at p-value=0.01, the Logit forward stepwise procedure selected and retained four predictors from 23 candidate variables, which could best differentiate the healthy firms from the bankrupt firms.

- R7 (EBIT Margin)
- R9 (Interest Cover)
- R12 (Credit Period)
- R19 (Costs of employee/operation profit)

The B. values in first column are used to calculate the probability of a case failing into a specific category of output, in this study, either healthy or bankrupt. Thus, the Logit model for predicting bankruptcy can be written in terms of logit y as follow;

$$Logit(y) = 0.948 + 0.319R_7 - 0.014R_{12} - 0.04R_{17} - 0.77R_9 \quad (3)$$

Overall Model Fit								Value
-2 log likelihood (-2LL)								82.990
Cox & Snell R2								0.427
Nagelkerke R2								0.569
Omnibus Test of Model Coefficients						X2	df	Sig.
Step						5.361	1	0.021
Block						55.64	4	0.000
Model						55.64	4	0.000
Hosmer & Lemeshow's goodness-of-fit test						8.272	8	0.407
Variables	b.	S.E.	Wald	*df*	Sig.	Exp(B)	95.0%C.I.EXP(B)	
							Lower	Upper
R7	0.319	0.072	19.838	1	0.000	1.376	1.196	1.583
R12	-0.014	0.004	12.024	1	0.001	0.986	0.978	0.994
R17	-0.040	0.016	6.296	1	0.012	0.961	0.931	0.991
R19	-0.77	0035	4.814	1	0.028	0.926	0.865	0.992
constant	0.948	0.885	1.148	1	0.284	2.580		

Table 4 Results of Logit Analysis

The values in Exp (B) column are the odds ratios for each selected predictor. According to Tabachnick and Fidell (2001), the odds ratio is the increase (or decrease if the ratio is less than one) in odds of being in one outcome category when the value of the predictor increases by one unit. In this study, the odds ratio of healthy firms, assigned as 1, the EBIT margin is 1.376 times higher than the one with bankrupt firms, and all other predictors are being equal. For each of the odds ratios Exp (B) shown in the last column is 95 percent confidence interval (95% CI for Exp (B)), giving a lower and upper boundaries.

The selection of set of predictors by forward stepwise procedure are different from the set of independent-sample t-test, from which totally six variables are obtained, this does not mean bankrupt firms differs from healthy firms in just these four predictors, it simply means that these four ratios together can best distinguish the two groups.

The significant financial ratios, employed in this model, are in the areas of profitability, operational efficiency, and Human resources management. These information imply that reasons of firms in manufactory industry went bankrupt would be (1) decrease of profit generation ability; (2) insufficient operating capital and loss its ability to pay interest, which leads to further financial distress; (3) lack of managing relationship with customers, which indicated by the longer time for a firm's customer to grant credit; (4) relatively lower human resource quality, compared with generating operation revenue, unreasonable cost per employee will result in less profit in future.

6 Conclusions

This study developed a four-variable Logit model to predict bankruptcy, the overall prediction accuracy is 81% with cut-off point 0.7, while type I error is 92% and type II error is 70%. As the information shown by the in-sample t test, the bankrupt group had lower profit generation ability before failure, and there is a significant difference in operating efficiency ratio. Although the selected set of predictors by forward stepwise procedure is different from the set selected by in-sample t test, the overall performance of logit model indicates the predictors, which stands for firm's profitability, operational efficiency, and human resources management, can distinct the healthy and bankrupt firms evidently. According to the experiment results, it can be concluded that, causes of firms in manufactory industry went bankruptcy could be (1) decrease of profit generation ability; (2) insufficient operating capital and loss its ability to pay interest, (3) lack of managing relationship with customers, (4) relatively lower human resource quality, which support the statistical report by Dun & Bradstreet (1987).

This study is not without its limitations. In the first place, due to limited data from failed company, out-of-sample test is unused in this study. In additional to that, the up-to-date literature shows the great significance of non-financial ratio information in bankruptcy prediction, such as the firm specific characteristics (size, maturity, R&D expenses, and depreciation) and country risk measures, this study only sampled firms' financial ratios as predictors. The authors believe the prediction ability of Logit analysis in bankruptcy prediction can be improved by involving the non-financial ratio information from sample firm in further study.

References:

[1]. Altman, E (1968), 'Financial ratios, discriminant analysis and prediction of corporate bankruptcy', *Journal of Finance,* 23, 589-609.

[2]. Aziz, M. A. and Dar, H. A. (2006), 'Predicting corporate bankruptcy: where we stand?' *Corporate Governance,* 6 (1), 18-34.

[3]. Barniv, R, Agarwal, A and Leach, R (2002), 'Prediction bankruptcy resolution', *Journal of Business Finance & Accounting,* 29 (3), 497-520.

[4]. Beaver, W. (1966), 'Financial ratios as predictors of failure. Empirical Research in Accounting: Selected Studies 1966', *Journal of Accounting Research,* 62 (2), 179-92.

[5]. Charles, T. (2003), 'A Comparative Examination of Bankruptcy Prediction: Altman MDA Study versus Luther ANN study: A Test of predictive strength between the two techniques.' (Nova Southeastern University).

[6]. Chi, L C and Tang, T C (2006), 'Bankruptcy Prediction: Application of Logit Analysis in Export Credit Risks', *Australian Journal Of Management,* 31 (1), 17-27.

[7]. Coats, P. K. and Fant, F.L. (1993), 'Recognizing financial distress patterns using a neural network tool', *Financial Management*.

[8]. Cohen, J (1988), *Statistical power analysis for the behavioral sciences* (Hillsdale, NJ: Erlbaum).

[9]. Deakin, E. B. (1972), 'A discriminant analysis of predictors of business failures.' *Journal of Accounting Research,* 10 (1), 167-79.

[10]. Frydman, H, Altman, E I and Kao, D (1985), 'Introducing recursive partitioning for financial classification: the case of financial distress', *Journal of Finance,* 40 (March), 269-91.

[11]. Hair, J F, Anderson, R E, Tatham, R L and Black, W C (1998), *Multivariate Data Analysis with readings* (4th ed; New Jersey: Prentice Hall, Englewood Cliffs).

[12]. Hosmer, D N and Lemeshow, S (1989), *Applied Logistic Regression* (New York: Wiley).

[13]. Insolvency.com <www.insolvency.com>.

[14]. Lee, T. S., Chiu, C. C., Lu, C. J. and Chen, I. F. (2002), 'Credit scoring using the hybrid neural discriminant technique', *Expert Systems with Applications,* 23, 245-54.

[15]. Liao, K. F. (1994), *Interpreting probability models: Logit, Probit, and other generalized linear models* (CA: Sage, Thousand Oaks).

[16]. Ohlson, J A (1980), 'Financial ratios and the probabilistic prediction of bankruptcy', *Journal of Accounting Research,* 18 (1), 109-31.

[17]. Palepu, K G (1986), 'Predicting takeover targets: a methodological and empirical analysis', *Journal of Accounting and Economics,* 8 (1), 3-35.

[18]. Pallant, J (2005), *SPSS survival manual: a step by step guide to data analysis using SPSS for windows (Version 12)* (2nd ed. ed.: Open University Press).

[19]. Pampel, F C (2000), *Logistic Regression: A Premier, Sage* (CA: Thousand Oaks).

[20]. Insolvency service, Insolvency (2007), (updated 29/01/2007) <www.insolvency.gov.uk>, accessed 02/06.

[21]. SPSS, Inc. (2003), *SPSS regression models 12.* (Englewood Cliffs, NJ: Prentice Hall).

[22]. Theodossiou, P (1991), 'Alternative models for assessing the financial condition of business in Greece', *Journal of Business and Accounting,* 18 (5), 697-720.

[23]. Thomas, L. C., Edelman, D. B. and Cook, J. N. (2002), *Credit Scoring and its Applications* (Philadelphia: Society for Industrial and Applied Mathematics).

[24]. Zavgren, C.V. (1983), 'The prediction of corporate failure: the state of the art', *Journal of Accounting Literature,* 2, 1-38.

Appendix I Financial Ratios of healthy firms and bankruptcy firm

Ratio		Healthy	Bankrupt	T		p-value	effect
ID	Name	mean	mean	statistic	p-value	2-tailed	size
R1	Return on shareholders fund	35.39	2.68	2.319	0.020	0.024	0.05
R2	Return on capital employed	21.04	6.81	1.296	0.095	0.198	0.02
R3	Return on total assets	11.13	6.14	2.185	0.102	0.031	0.05
R4	Cash flow/ turnover	12.05	6.00	4.043	0.407	0.000	0.14
R5	Profit margin	10.25	3.93	4.014	0.568	0.000	0.14
R6	EBIDA Margin	31.41	7.82	1.465	0.076	0.146	0.02
R7	EBIT Margin	10.68	4.22	4.835	0.970	0.000	0.19
R8	Net asset turnover	2.23	11.04	-1.524	0.026	0.134	0.02
R9	Interest cover	18.71	63.64	-1.898	0.000	0.063	0.04
R10	Stock turnover	11.75	15.53	-1.292	0.034	0.200	0.02
R11	Collection period	51.42	64.28	-1.841	0.909	0.069	0.03
R12	Credit period	33.96	44.98	-2.916	0.837	0.004	0.08
R13	Current ratio	1.54	1.46	0.537	0.376	0.592	0.00
R14	Liquidity ratio	1.11	1.07	0.276	0.255	0.783	0.00
R15	Shareholders liquidity ratio	1.62	18.96	-1.390	0.028	0.171	0.02
R16	Solvency ratio	35.45	31.00	1.270	0.002	0.208	0.02
R17	Gearing ratio	144.96	355.29	-1.488	0.006	0.143	0.02
R18	Operating profit per employee	1199.36	1104.96	0.178	0.875	0.859	0.00
R19	Costs of employee/ operating profit	13.50	15.92	-1.449	0.874	0.150	0.02
R20	Aver. Cost of employee/ year	65.10	72.70	-0.473	0.555	0.638	0.00
R21	Share funds per employee	230.12	180.50	0.719	0.800	0.474	0.01
R22	Working capital per employee	143.90	131.94	0.258	0.566	0.797	0.00
R23	Total asset per employee	685.56	573.04	0.609	0.759	0.544	0.00

Appendix II Formulas of financial ratios

Profitability ratios		
R1	Return on shareholders fund	(PLBT/SHFD)*100
R2	Return on capital employed	((PLBT+INTE)/(SHFD+NCLI)*100
R3	Return on total assets	(PLBT/TOAS)*100
R4	Cash flow/ turnover	(CF/OPRE)*100
R5	Profit margin	(PLBT/OPRE)*100
R6	EBIDA Margin	((EBIT+DEPR)/OPRE)*100
R7	EBIT Margin	(EBIT/OPRE)*100
Operational efficiency		
R8	Net asset turnover	OPRE/(SHFD+NCLI)
R9	Interest cover	OPPL/INTE
R10	Stock turnover	OPRE/STOK
R11	Collection period	(DEBT/OPRE)*360
R12	Credit period	(CRED/OPRE)*360
Management Structure ratios		
R13	Current ratio	CUAS/CULI
R14	Liquidity ratio	(CUAS-STOK)/CULI
R15	Shareholders liquidity ratio	SHFD/NCLI
R16	Solvency ratio	(SHFD/TOAS)*100
R17	Gearing ratio	((NCLI+LOAN)/SHFD)*100
Human Resource Management		
R18	Operating profit per employee	OPRE/EMPL
R19	Costs of employee/ operating profit	(STAF/OPRE)*100
R20	Aver. Cost of employee/ year	STAF/EMPL
R21	Share funds per employee	SHFD/EMPL
R22	Working capital per employee	WKCA/EMPL
R23	Total asset per employee	WKCA/EMPL