TESTING THE APPLICABILITY OF THE Z-SCORE: SOME EVIDENCE FROM THE UK INFORMATION TECHNOLOGY INDUSTRY

Paa Kusi Opoku
Chartered Accountant and Consultant in London
Kingsley Opoku APPIAH
Accounting and Finance Department, School of Business; Kwame Nkrumah University of Science and Technology
Joseph Arthur
Accounting and Finance Department, School of Business; Kwame Nkrumah University of Science and Technology
Corresponding Authors:
Joseph Arthur can be contacted at: jarthur1989@gmail.com
Kingsley Opoku Appiah can be contacted at: koappiah.ksb@knust.edu.gh

Abstract

Purpose – The purpose of this study is to examine the applicability of the Altman's Z-Score Model in predicting corporate failure within the UK Information Technology (Computer and Related Activities) Private Sector during the period 2000-2006.

Design/methodology/approach – The Z-Score prediction model, using the multivariate technique Multiple Discriminant Analysis (MDA) was employed to a dataset of 60 matched-paired of failed and non-failed UK Information Technology firms over the stated period. Two hypotheses were tested: 1) Failed and Non-failed companies will show differences in their financial performances as measured by accounting ratios; 2) Altman's Z-Score through MDA is able to distinguish effectively between failed and non-failed companies from the said sector.

Findings – The results support the hypotheses and are generally consistent with the existing body of empirical evidence and indicate that failure is fairly predictable with an overall correct classification accuracy of 60% one year prior to failure. However, the predictive accuracy of the model reduced significantly in the second year prior to the failure event to 38% due to a huge Type II Error.

Originality/value – This study contributes to the body of knowledge in the area of Z-Score applicability in assessing IT companies' susceptibility to failure.

Keywords – The United Kingdom, Information Technology, Z-Score
Paper type – Research paper

1. Introduction

Since the year 2000, the computer and related activities (Information Technology) industry sector has not only contributed to the global economic downturn but has suffered huge corporate collapses. Despite this, the majority of the failure prediction studies focused on the main traditional sectors such as manufacturing and banking. In Pratten (1992, 93), the personal computer industry was cited as the area where many firms eventually failed due to the nature of the business they are in. It is apparently evident that many companies that engaged in computer related activities have failed in the last few years. ''Corporate failure leads to acute financial embarrassment, which hampers the prospects of entrepreneurs and financial institutions in particular and the economy in general'' (Pai *et al*, 2006). These authors could not be much in agreement with other contemporary researchers in corporate failure that this canker continues to be one of the main challenges that face the modern day business among other issues. Consequently, corporate failure prediction continues to be of keen interest to academics and professionals in the field of accounting and finance, despite the voluminous studies done on it in the last four decades (Beaver, 1966; Altman, 1968; Deakin, 1972; Ohlson, 1980; Taffler, 1982; Neophytou and Molinero, 2000).

Following the decline in the information technology industries during the year 2000 which initiated a global downturn, there continues to be problems within this sector. In scanning through the corporate failure literature, we came across only one work done in this area; Shah (2002) worked on small and medium sized unquoted UK companies that engaged in computer related activities. The motivation for this study thus lie in the notion that this area is yet to be fully explored and for that matter the decision to test the applicability of the Altman's Z-Score model in the UK Information Technology industry sector.

Moving on, the rest of the article is set as follows: Section 2 considers briefly the relevant literature review, Section 3 examines the methodology employed for the study, Section 4 discusses the research findings and lastly, Section 5 concludes the study.

2. Review of relevant literature

Taffler (1982) and Deakin (1972) both noted that large firms defined failure as either creditor's compulsory or voluntary liquidation, in contrast, Pratten (1992) described corporate failure as inability of companies to meet set mission and Keasey and Watson (1988), worked within the premise of companies that had ceased trading. Fitzpatrick (1932) was the first to conduct a study using a univariate approach to identify which ratios acted as the best discriminators of failed and non-failed companies. In Beaver (1966) pioneering study, he employed univariate discriminant analysis (UDA) and concluded that Cash flow/Debt ratio was the best predictor of firms collapse on its own, and the current assets/current liabilities were the least predictor. Beaver (1968), in a follow up study noted that changes in the market prices of stock were a decent indicator for financial distress and collapse. Neophythou *et al* (2000) used UDA and concluded that financial leverage ratios such as Retained Earning to Total Assets (RETA) indicated very high classification accuracy. The UDA models have been criticised due to the issue of single ratio's ability to determine the survivability and it is argued that UDA provides inconsistent signals with variables giving conflicting forecasting results. These defects led to the pursuits of a more robust technique that avoids the problems mentioned above and this brings us to the use of Multivariate Models.

To overcome the setbacks of the Univariate models, the Multivariate Models were developed which considers the simultaneous interactions of various financial variables and assesses their predictive powers in terms of corporate failure. Multiple Regression Analysis and Multiple Discriminant Analysis (MDA) are the two original multivariate models developed to be used in corporate failure studies. More recently Linear Probability Model (LPM), Logit, Neural Networks, and Probit models have all been applied as statistical techniques to determined failure prediction, and Altman (1968); Deakin (1972); Moyer (1977); and Taffler (1984) have all employed MDA and according to Charitou *et al* (2004), it is the most popular statistical technique among the failure prediction models.

Altman (1968) was the first researcher to develop a multivariate model, tried to improve upon Beaver's pioneering work and although his works were not devoid of criticisms by other researchers, this study recognises that it still stands as the leading authority in the corporate failure prediction literature. According to Platt & Platt (1991), Altman's model considered only manufacturing firms and there is the need for re-estimation of coefficients for other industry sectors. Examples of studies that made such attempts as cited by Neophytou and Molinero (2001) are: assignment of prior probability membership classes (Deakin, 1972); consideration of more appropriate 'quadratic classifier' (Altman *et al*, 1977); the use of cash flow based models (Gentry *et al,* 1987); the use of quarterly financial statement information (Baldwin and Glazen, 1992) and, investigation of the use of current cost information (Aly *et al,* 1992; Kasey and Watson, 1986).

Moyer (1977) critically assessed some core aspects of the Altman's model by testing the applicability of it to failed and surviving companies and asserted that to achieve a better explanatory power, the market value of equity/book value of debt and sales/total assets ratios be excluded from the model. This assertion throws in a huge departure from the position held by Altman who claimed the sales/total ratio is the second most important variable in the model in terms of discriminating power. Taffler (1974) was the first major study conducted in the UK using the MDA technique and he was motivated by the fact that, up to the early 1970s, the major studies in corporate failure have all come out of the United States of America. He applied MDA technique and used principal component analysis in the selection of variables for the Z-score model. Similar approach had been applied by Altman (1968), but distinctively, Taffler did not consider matching firms by industry and size as of any real significance. The model provided a good classification accuracy in a year prior to failure but not so much could be said of its results for two and three years to the failure, but was a significant step in failure prediction development in the UK and the most widely quoted studies to date in the UK.

In the ensuing decade, Taffler (1982, 1983) refined his model; employed sample from the UK manufacturing sector and this time samples were matched by industry and size and were all quoted on the London Stock Exchange. Taffler (1984), realising that the previous study models could not be applied universally across sectors subsequently developed a separate model for companies in the distribution sector. According to Morris (1997), the best-known multiple discriminant analysis application in the UK is the models developed by Taffler. He is regarded as a major contributor in the sense that he used a different approach, and also introduced modification into the definition of non-failed companies with the purpose of improving the predictive power of the model. Taffler's model suffers from lack of evidence of ex-ante prediction capability of financial ratios, just like the Altman's model. This study agrees that there are a couple of limitations to the use of MDA and thus, not wholly reliable in predicting corporate failure. Also, researchers such as Grice and Ingram (2001) are of the view that one cannot assume the models hold firmly across economic conditions and over time. Notwithstanding, MDA is still undeniably the most popular statistical technique in the corporate failure prediction business according to Aziz and Humayon (2006), despite its much publicised limitations. That is a fact not lost on the writer and thus being his preferred technique to apply in this study.

3. The research question and methodology

Despite the voluminous studies done over the last four decades (Beaver, 1966; Altman, 1968; Deakin, 1972; Ohlson, 1980; Taffler, 1982; Neophytou and Molinero, 2000), a single universally acclaimed model of determining how and why corporate entities fail is not in sight. Consequently, it is not surprising that corporate failure prediction continues to be of keen interest to academics and professionals in the field of accounting and finance, due to the huge financial and human cost associated with corporate failure. The study contributes to the existing body of literature on corporate failure prediction by addressing the following research hypothesis:

RH1: The potential failed and non-failed companies will show differences in their financial performance as measured by accounting ratios.

RH2: MDA and the intended Z-Score is able to distinguish effectively between failed and non-failed companies in the computer and related activities private sector.

3.1 Data set required

The definition of failure in most corporate failure prediction studies is legalistically inclined; this allows for easy and objective dating of the event and also assists in the classification of the population under examination (Neophytou *et al*, 2000). This approach is adopted here due to the benefits expected to be accrued in the data collection process and the final sampled data set consists of companies that have failed under the spectrum of liquidation, receivership and/or dissolution. In deciding the data set required, the researcher took into account the objectives of the study and thus the data gathering process was designed to produce data on two main fronts – failed and non-failed companies.

The data set one consist of companies from the private sector engaged in computer and related activities that had failed during the period 1 January 2000 – 31 December 2006. Data set two is made up of companies from the same sector but that have existed throughout the period concerned. Each data set is made up of thirty companies and for a company to make it for inclusion in this data set; it must among other things satisfy the following requirements:

- The company's shares must not have been traded publicly, i.e. must be unquoted entity.
- The company must have been classified as operating in the IT sector (SIC code 7260).
- For failed companies, the company must have been classified as inactive by FAME (Financial Analysis Made Easy) due to liquidation process, receivership and/or dissolved between the period of 1st of January 2000 and 31st December 2006.
- The sampled firms must have had at least three years of trading data prior to their respective failure dates. The merits of this criteria is in two folds: a) to avoid the selection of companies failing in the very first years of their lives; b) to provide enough years of financial data needed for the exercise usually 2-3 consecutive years.
- The company must have a turnover of at least £10 million to avoid picking companies that have failed primarily due to its size in terms of turnover than otherwise. Also, to avoid dealing with too large companies, sampled companies' turnover should not be more than £500 million.

3.2 The Sample Selection and Data collection

The paired sample approach was applied in the sample selection process; a number of failed and non-failed companies were matched against each other in terms of size denoted by the turnover value, Platt and Platt (1990); Barnes (1990); and Ginoglou *et al* (2002) applied this method. This method was criticised by other researchers but, Barnes (1990) disagrees and argued that pure random sampling has its own deficiencies. A list of private registered companies and their failure status obtained from the Company House and the required data were extracted which contains among other things; information on trade classification (SIC code), financial year, date of last filed accounts, company status and company type. With the help of FAME database available at the London South Bank University (LSBU) Library system, the required data were assembled. The estimation sample was refined to 30 companies with regard to the financial variables needed for the data analysis.

A sample of non-failed firms to match the sampled failed ones was drawn using the same criteria albeit non-failed paired sample. A control sample of non-failed firms (stratified by size in terms of turnover) was drawn from the FAME database to match the failed companies obtained already. The surviving statuses of these companies were confirmed via the Companies House online status check service. The mean turnovers for the failed and non-failed groups were £40.215 and £40.327 million respectively. This method is simple to understand and thus manageable by the researchers and despite Palepu (1986) criticisms, this approach is consistent with other major studies by: Altman (1968); Platt and Platt (1990); Taffler (1995); and Neophytou *et al* (2000). Matching the samples by size in terms of turnover and by fiscal year would in turn help eliminate other factors as possible explanation for corporate failure (Morris, 1997). Subsequent to the above considerations, 30 companies classified as active in the FAME electronic database were selected as the matched pairs of the failed companies. No validation sample was considered as often done in failure prediction studies because this study aims to test the applicability of an already developed model thus such validation sample not required.

3.3 Selection of predictor variables

Altman Z-Score model combines five common financial ratios and using a weighting system it is used to determine the likelihood that a company would collapse. Although it was derived based on data from manufacturing firms, it has proven to be also effective in determining the risk that a Private General Firm (Services included) will fail. The discriminant function is a regression model and the variables employed are from four areas of accounting information; working capital, gearing, profitability and asset turnover or performance (see Table 3.1 below).

Table 3.1: Elements of the Altman's Model

Ratio	Measurement Mode
X1: Working Capital/Total Assets (WC/TA)	Working Capital (Liquidity)
X2: Retained Earnings/Total Assets (RE/TA)	Gearing (Leverage)
X3: Earnings Before Interest and Tax/Total Assets (EBIT/TA)	Profitability
X4: Market Value of Equity/Total Liabilities (MVE/TL)	Leverage (Gearing)
X5: Sales/Total Assets (S/TA)	Asset turnover or Performance

The model was reviewed to suit the needs of private entities following the demands and request requests by interested parties. There were further revisions to the model and this time purposely developed for non-manufacturing entities with variables made up of four elements instead five for the earlier two developed models. This latter revision excluded the 'sales/total assets' (S/TA) variable and Altman acknowledged that, it was to mitigate the potential industry effect which may arise due to industry sensitivity of the S/TA variable. A case in point is the IT industry where total assets are significantly smaller relative to the turnover of the companies. The book value of equity was used for the gearing component instead of the market value in adapting the 4-variable model for private sector but the classification results are reckoned to be similar to the revised five-component model. The new Z-Score model is presented as: $Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$. In line with the discussion above, this model is to be applied in the study as the tool for the statistical analysis and as this study is about unquoted companies, the market value of equity is replaced with the book value of equity to reflect the status of the sampled companies as Altman advocated.

4. Empirical analysis and results

In this section we consider the analysis and results of the data and would be considered under the following headings: 4.1 Results 1-Year Prior to Failure; 4.2 Results 2-Years Prior to Failure; 4.3 Assessment of Type I and Type II Errors; 4.4 Comparison with the 5-Variable Model and conclusion.

4.1 Analysis and results1-Year prior to failure

As depicted in Table 4.1, the study recorded a classification success rate of 77% for the failed group (G1) and 43% for the non-failed group (G2). These results indicate an encouraging scenario for the failed group but not all that for the surviving group; as a result the model is modestly accurate with the overall classification accuracy rate of 60%. The Z-Scores values for the failed group (G 1) ranges from -15.66 for the least successful company to 4.01 for the most successful company, with the mean score of -1.28. On the other hand, the Z-Scores values of the non-failed group's (G2) range from -0.50 for the least successful to 12.74 for the most successful with 2.45 as the mean score. Not surprisingly, the G2 has a higher mean score than its counterpart in the G1, a score of 2.4 as against -1.28. The results indicate Type I error of 23% and Type II error of 57% and as the study aims to test the predictability accuracy of the adopted model, a lower Type I error is desirable. And as such it is felt that the model has demonstrated enough discriminating powers in the relevant sector considered thereby it is encouraging to pursue further study.

Table 4.1: Classification Results – One Year Prior to Failure

Actual Group		Predicted Group		Total
		G1	**G2**	
Count	**G1**	23	7	30
	G2	17	13	30
%	**G1**	77	23	100
	G2	57	43	100

4.2 Analysis and results 2-years prior to failure

With the results from 2-years prior to failure, the model achieved 55% predictive accuracy for identifying successfully failed companies and 26% for non-failed companies. The model thereby, showed extremely poor classification success rate with overall predictive accuracy of rate of 38.3%. The Z-Scores values of the G1 ranges from -26.22 to 4.71, with a mean of -0.67 while in G2, the Z-Scores ranges from 12.86 to -2.94 respectively, and 2.10 being the mean score. In line with the researchers expectations, the non-failed group has a higher mean score (2.10) than the failed group (-0.67). The reduction in the classification accuracy compared to one year prior to failure is understandable and expected; because impending failure is more distant and indications are less clear (Altman, 2000). Table 4.2 below shows the classification matrix for these results.

Table 4.2: Classification Results – Two Years Prior to Failure

Actual Group		Predicted Group		Total
		G1	G2	
Count	G1	11	9	20
	G2	20	7	27
%	G1	55	45	100
	G2	74	26	100

Although, the Type I error is smaller than the Type II (45% against 74%), it is still high in relation to the Altman's benchmark. Notwithstanding this, 55% correct classification is encouraging evidence that failure signals could be picked two years before. Further test is necessary to determine the level of applicability and the predictive accuracy of this model in the considered industry sector.

4.3 Assessment of Type I and II and Errors

It is imperative in corporate failure prediction studies, to investigate the potential factors which could have contributed to the misclassification of failed companies as non-failed and vice versa. This is to ascertain whether valid conclusions could be drawn after logical inquiry into the profiles of the misclassified companies. It is observed that, 5 out of the 7 misclassified companies have turnover less than the mean turnovers of both groups of £40.215m and £40.327m and only 7 out of the 30 sample had greater mean turnovers than that of the failed group. Critical analysis of the Type II error reveals that, companies have failed with both lower and higher than average turnovers and thus contrary to Altman *et al* (1977) views which supports others like Beaver (1966), an indication that a company's turnover size is not primarily a discriminating factor in terms of company's propensity to fail.

With the exception of Lexar Media (Europe) Ltd, all the misclassified companies have positive profitability related ratios (RE/TA and EBIT/TA) as compared to the negative mean ratios for G1. In comparison with G2, only Hyder Services Ltd out of the 7 misclassified failed companies have better

EBIT/TA than the average non-failed group mean. In line with the above analysis, all the seven misclassified companies seem to be profitable as opposed to the loss making mean failed group, and this could be one of the reasons why these seven companies were misclassified. On the financial leverage (risk) of the companies measured by the SF/TL, all the misclassified companies have a better financial leverage position compared to the failed group average of 0.0865 except Lexar Media (Europe) Ltd. It has a worse financial risk position than the average failed company and that seems to have something to do with its negative profitability related ratios and it is the only misclassified company that had a negative profitability related ratios as described above. From the above analysis, companies with less favourable financial leverage appear to be susceptible to failure, and there is the likelihood that these companies were misclassified due to their relatively better financial leverage position.

On liquidity front, all the seven misclassified companies have significantly higher working capital ratio than both the failed and non-failed groups' average of 0.1289 and 0.1676 respectively. From the Type II Error, it is observed that majority of the misclassified companies have lower working capital ratio compared to the average surviving company. From this individual ratio, it is posited that companies with relatively smaller working capital in relation to the total assets, are prone to failure and the possibility exists that these companies were misclassified due to their relatively better working capital relative to total assets. The WC/TA ratio could be said to be the most creditable indicator of the misclassification as all the seven misclassified companies have significantly better ratios than both the failed and non-failed companies.

4.4 Comparison with modified 4-Variable Model

Quite a number of writers advocated against the measurement of the profitability ratio as ‘‘EBIT to Total Assets’’ and argued that, profit has a profound link with Turnover more than Total Assets and as such the profitability ratio should ideally be measures by ‘‘ EBIT to Turnover’’. In here, the results of the failed and non-failed companies' from both the original model and the modified model are examined. The most significant observation made from this result is that, the Z-Score values from the failed companies did not change. On the part of the non-failed companies, with exception of EPICOR

SOFTWARE (UK) LTD. all other companies Z-Score value changed. Nonetheless, there were no changes in classification, which is being classed as failed by the original Model and classed subsequently as non-failed by the Modified Model and vice versa, despite the recording of 18 positive and 11 negative changes to the Z-Score values.

4.5 Comparison with the 5-Variable Model

The comparison was extended to the 5-Variable model although, Altman (2000) has argued for the exclusion of the performance ratio of Sales to Total Assets due to its potential industry sensitivity effect. It is noted that, this is more the case in the computer and related activities sector where turnover are significantly higher than the total assets employed. The classified success rates of the model incorporating the sales to total assets (5-Variable Model) differ remarkably from the 4-Variable Model. For the failed group, the recommended model (4-Variable) achieved a classification success rate of 77% but with the inclusion of the performance ratio the rate has fallen to 63%. In the case of the non-failed, the 4-Variable model achieved a success rate of 43% which reduced to 37% with the inclusion of the performance ratio. This gives an indication that the performance ratio has got an impact on the Z-Score Model's predictive accuracy thus confirming the industry sensitivity impact noted earlier.

The sensitiveness of the sector under consideration is remarkably felt in the final Z-Score if the Sales/Total Assets ratio is significantly high. Two companies from the failed group Newhalt Ltd. and Lexar Media (Europe) Ltd. are considered here. Newhalt Ltd. with the performance ratio of 59.31 times had a change in score from 2.47 to 60.44 with application of the 5-Variable model. On the other hand, Lexar Media (Europe) Ltd. with performance ratio of 1.2 times had its score fallen from 3.97 to 0.79. Also, Galmarley Ltd. and Aveva Solutions Ltd. from the non-failed group with the performance ratio of 8.76 times had resulted in a change in score from 0.55 to 8.99. In the case of Aveva Solutions Ltd; with 0.73 times performance ratio, its score fell from 3.88 to 2.11. This analysis gives an indication that the performance ratio measured by the Sales/Total Assets has the ability to influence the predictive accuracy of the Z-Score model. This therein confirms why Altman (2000) asserts that the performance ratio is sensitive to the general private sector (Computer and related activities in this study) companies thereby its exclusion from the adopted Z-Score Model in the study.

5. Summary and conclusions

The primary objective of this study was to test the applicability of the Altman's Z-Score model (developed for the Private General Firm) in predicting corporate failure with evidence from the UK Information Technology Industry. It also aimed to assess if any the main differences in the financial characteristics of failed and non-failed companies within the concerned industry. Several prior studies in the UK over the last four decades had been conducted but hardly had the IT industry been explored, thereby the justification for the study through the researchers desire to probe into the aforementioned sector.

The Z-Score model tested in the study proved to be fairly successful in predicting corporate failure in the computer and related activities sector. The study considered two sets of tests by employing data gathered from one and two years prior to failure. In the first test, it was observed from the analysed results that the model proved to be significantly accurate in predicting failure correctly in 77% of the failed group in one year to failure. But not the same could be said of the classification accuracy of the non-failed group with a disappointing 43% accuracy. As a result, the overall predictive accuracy of the model's application in the study stood at a modest 60% as compared to the 95% recorded by Altman (2000). The second year test observes the discriminating accuracy of the model from using data gathered two years prior to failure and the overall accuracy stood at a poor 38.3% resulting from 55% and 26% accuracy from the failed and non-failed group respectively. Although, this classification accuracy is miles below the amount recorded during the original model development success rate of 70%, this study agrees with Altman (2000) assertion that the reduction in accuracy from the one year to two years prior to failure is expected.

Furthermore, it was also observed that the failed and non-failed group have remarkable differences in terms of financial performance. In general the non-failed group performed as expected better than their failed group counterparts as measured by the financial ratios. The mean, maximum, and minimum values of all the considered variables of the non-failed group were better than that of the failed group. The study acknowledges and concludes that, the results are encouraging and quite accurate, more importantly with respect to a year prior to failure. However, the outcome could be said to be inconclusive in supporting the hypothesis the study sought to test. The researchers belief that the model would have classification success differences depending on the sector considered as there are variations in the financial characteristics of the sectors that broadly comes under the general private firm of which the model was developed for. The application of the model should therefore take into consideration some other factors depending on the peculiarity of the sector concerned.

A number of issues were identified in the course of the study which may have impacted on the outcome and considering the moderate outcome of the study in terms of the classification accuracy success rate, a follow-up study incorporating the issues concerned is appropriate. Although, the study's sample of 30 paired companies is in line with the minimum number recommended by Diamantopoulos and Shclegelmilch (1997), an increase to a minimum of 40 is suggested. It is expected that this would give the study a wider coverage and thus increase generalisation validity in terms of the final results. It was observed in the analysis that the turnover size of the sampled companies have no direct impact on the survivability or otherwise of a company. It is suggested therefore that, the restriction of turnover size considered in the selection process be excluded in subsequent studies. The benefit of this it is felt would be accrued in increasing the number of qualifying companies to achieve the increase in sample required as suggested above.

Although the results are moderate with an overall classification accuracy of 60% and 40% for one and two years prior to failure respectively, the model demonstrates predictive capabilities. The effect of the peculiar characteristics of the computer and related activities sector coupled with the limitations noted could be a catalyst of this low performance of the model. Nonetheless, the researchers recognises the potential benefits of the study are in tune with other prior studies and these include: credit worthiness assessment by bankers and lenders, risks assessment of investment portfolios by investors and corporate managing bodies and going concern considerations by both internal and external auditor.

References

Altman, E.I. (1968) 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *Journal of Finance,* Vol. 23, No.4, (September) pp. 589-609.

Altman, E. I., Haldeman, R. G. and Narayanan, P. (1977) 'Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations', *Journal of Banking and Finance,* Vol. 1, No. 1, pp. 29-54.

Altman, E.I. (2000) 'Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA® Models'**,** *Stern School of Business, New York University,* July 2000 (Adapted and Updated version of Altman 1968 and 1977).

Anyane-Ntow, K. (1991) 'Accounting Information and its Relationship to Corporate Financial Distress Process', *The Journal of Applied Business Research,* Vol.7, No.3.

Argenti, J. (1976) *Corporate Collapse: The Causes and the Symptoms,* McGraw-Hill, Maidenhead, Berks.

Beaver, W.H (1966) 'Financial Ratios as Predictors of Failure, Empirical Research in Accounting', *Supplement to Journal of Accounting Research,* pp.71-111.

Casey, C.J. and Bartczak, N.J (1984) 'Cash Flow –It's Not the Bottom Line', *Harvard Business Review,* July-August, pp. 61-66.

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

Collins, J. and Hussey, R. (2003) *Business Research*, 2nd ed, Palgrave Macmillan, Houndmills, Basingstoke.

Deakin, E.B. (1972) 'A Discriminant Analysis of Predictors of Business Failure', *Journal of Accounting Research,* March, pp. 167-179.

Fitzgerald, T. (2006) 'Predicting and Pre-empting the Corporate Heart Attack', *Business Credit,* June.

Gentry, J. A., Newbold, P. and Whitford, D. T. (1987) 'Funds flow components, financial ratios and bankruptcy', *Journal of Business Finance and Accounting,* Vol.14, No.4.

Ginoglou, D., Agorastos, K. and Hatzigagios, T. (2002) 'Predicting Corporate Failure of Problematic Firms in Greece with LPM, Logit, Probit, and Discriminant Analysis Models', *Journal of Financial Management and Analysis,* Vol.15, No.1

Kim, K.S. (2005) 'Examining Corporate Bankruptcy: An Artificial Intelligence Approach', *Business Performance Management,* Vol.7, No.3.

Laitinen, T. and Kankaanpaa, M. (1999) 'Comparative Analysis of Failure Prediction Methods: the Finnish Case', *European Accounting Review,* Vol.8, No.1.

Leedy, P. D. and Ormrod, J. E. (2005) *Practical Research Planning and Design*, 8th ed, Pearson Education, New Jersey.

Lin, L. and Piesse, J. (2004) 'Identification of Corporate Distress in UK Industries: a Conditional Probability Analysis Approach', *Applied Financial Economics,* Vol.14.

Liu, J. (2004) 'Macroeconomic Determinants of Corporate Failures: Evidence from the UK', *Applied Economics,* Vol. 36.

Mar-Molinero, C. and Ezzamel, M. (1991) 'Multidimensional Scaling Approach to Corporate Failure', *Omega,* Pp.259-274.

Morris, R. (1997) *Early Warning Indicators of Corporate Failure: A Critical Review of Previous Research and Further Empirical Evidence,* Ashgate Publishing Ltd, Brookfield, VT.

Morse, G. (2007) 'Set Up to Fail', *Harvard Business Review,* Vol. 62, No.6, June.

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

Neophytou, E. and Mar Molinero, C. (2001) 'Predicting Corporate Failure in the UK: A Multidimensional Scaling Approach', *Discussion Papers in Accounting and Management Science, University of Southampton,* February

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

Ohlson, J.A. (1980) 'Financial Ratios and the Probabilistic Prediction of Bankruptcy', *Journal of Accounting Research,* Vol.18, No.1, Spring.

Pai, G. A. R., Annapoorani, R. and Pai, G. A. V. (2006), 'A Principal Component Analysis – Multiple Discriminant Analysis Model for Prediction of Corporate Failure in India', *Finance India*, Vol. 20 No. 4, December, pp. 1413-1428.

Pratten, C. (1992) 'Corporate Failure', *The Institute of Chartered Accountants in England and Wales,* London.

Sharma, D.S. (2001) 'The Role of Cash Flow Information in Predicting Corporate Failure: The State of the Literature', *Managerial Finance,* Vol. 27, No. 4.

Taffler, R.J. (1977) Finding Those Companies in Danger Using Discriminant Analysis and Financial Ratio Data: A Comparative Based Study, *City Business School Working Paper,* No. 3.

Taffler, R. J. (1982) 'Forecasting Company Failure in the UK using Discriminant Analysis and Financial Ratio Data', *Journal of the Royal Statistical Society*, Vol.145, No.3, pp. 342-358.

Taffler, R.J. (1983) 'The Assessment of Company Solvency and Performance Using a Statistical Model: A Comparative UK Based Study', *Accounting and Business Research,* Autumn, pp. 296-307.

Taffler, R.J. (1985) 'The Use of the Z-Score in Practice', *City Business School Centre for Empirical Research in Finance and Accounting Working Paper,* June.

Trieschmann, J.S. and Pinches, G.E. (1973) 'A Multivariate Model for Predicting Financially Distressed P-L Insurers', *Journal of Risk and Insurance,* Vol.40, pp. 327-338.

Turetsky, H., McEwen, R.A. (2001) 'An empirical investigation of firm longevity: a model of ex ante predictors of financial distress', *Review of Quantitative Finance and Accounting*, Vol. 16 No.4

Turner, I. (2005) 'Corporate Failure', *Henley Manager Update,* Vol.17, No.2, Winter.

Wu, W., Lee, V.C.S. and Tan, T.Y. (2006) 'Data Preprocessing and Data Parsimony in Corporate Failure Forecast Models: Evidence from Australia Materials Industry', *Accounting and Finance,* Vol. 46.