Bank of England

Discussion Paper No.4

A method of quantifying companies' relative financial strength

by

D.A.J.Marais

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This paper was largely written by D.A.J.Marais of the Oxford Centre of Management Studies in the course of a short-term assignment he carried out for the Industrial Finance Unit of the Bank's Economic Intelligence Department. D.A.Reeves of the Industrial Finance Unit also played a major part in the work described in the paper.

The object of this series is to give a wider circulation to research work being undertaken in the Bank and to invite comment upon it; and any comments should be sent to the author at the address given below. The views expressed are his, and not necessarily those of the Bank of England.

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Introduction

1 This paper describes the results of an exercise in discriminant analysis, a technique which is attracting increasing interest as a tool or screening device in assessing the financial position of companies. Section 2 briefly surveys previous work in the field; Section 3 discusses methodology; Section 4 describes the performance of the model developed in the present exercise; a brief comment on the use of such models is given in Section 5.

Previous research

Univariate studies

2 The first serious attempts at company bankruptcy prediction followed the 1929-31 stock market collapse in the United States, and were based largely on an examination of the trend in mean values for certain financial ratios in the years immediately preceding failure. These studies have been fairly widely reported,[1] and it is sufficient to comment that significant differences between groups of failed and non-failed firms were evident for a number of years prior to failure. More recent work by Beaver (1966) demonstrated the predictive superiority of cash flow ratios over the short-term solvency ratios (current and quick ratios) traditionally relied upon. Unlike many of the earlier studies, Beaver realised the danger of merely relying on a simple analysis of mean ratio values and ignoring the underlying ratio distributions. The financial ratios under consideration tend to be highly skewed, and it is possible that a few extreme values may account for most of the difference in means between the groups of failed and non-failed firms. Despite these and other statistical shortcomings, the early studies established quite firmly that it was possible to identify those firms most likely to be at risk of failure. There was, however, a growing realisation that a single ratio could not reflect fully a firm's financial profile, and that a method of simultaneously combining several variables could add significantly to the effectiveness of models for predicting company failure.

Multivariate studies

3 In 1963, Tamari (1978) attempted to construct an 'index of risk' by weighting and combining several ratios on the basis of subjective and theoretical considerations. A more objective method of assigning weights and combining ratios was adopted by Altman (1968). He incorporated a statistical technique known as discriminant analysis, into a model which has generally become known as 'Z-score', and was able to demonstrate fairly conclusively the success of this approach in identifying failing companies.

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[1] See, for example, Dev (1974), Green (1978), and Lev (1974).

Altman examined twenty-two financial ratios for thirty-three American manufacturing companies failing between 1946 and 1965 and selected thirty-three non-failed firms (matched by time period, industry and asset size) as a control group with which the failed companies could be compared. The resultant model was based on the following ratios:

(i) working capital to gross total assets;

(ii) retained earnings to gross total assets;

(iii) profit before interest and tax to gross total assets;

(iv) market value of equity to book value of total debt; and

(v) sales to gross total assets.

4 The model proved to be fairly successful for the last two years before failure, but by the third year the predictive accuracy fell off quite dramatically. This work sparked off a wave of studies in the United States, and various authors were able to confirm quite conclusively that discriminant analysis could be used as an analytical tool in predicting company bankruptcy. However, all these studies were based on US data, and to date the only published work based on UK data is by Taffler (1977a and b).

Theory of failure and ratio selection

5 A large number of financial ratios have been proposed and have appeared in various combinations in different failure prediction models. This led to the situation where Taffler (1977a) was faced with the task of reducing an initial sample of 150 ratios to a meaningful sub-set of five. However, any attempt at ratio identification should be supported by some sort of conceptual framework, and not based merely on mechanistic methods such as factor analysis or stepwise regression. In the field of bankruptcy prediction the majority of studies that have appeared over the last decade have been largely empirical, emphasising the informational content of accounting statements and financial ratios, without attempting to develop a consistent theory of failure. Many of the early attempts at solvency evaluation focussed on liquidity as a major determinant of failure, and the 2:1 criterion for the current ratio (current assets to current liabilities) as a measure of liquidity had gained widespread popularity by the early 1900s. However, Fadel and Parkinson (1978) have argued that a mere comparison of the totals of current assets and current liabilities is not a direct measure of the

ability of a firm to meet its current obligations as and when they fall due, since it ignores the flow of funds into and out of the firm.

6 A recognition of the dynamic nature of the problem of evaluating solvency led Beaver (1966) to introduce the cash flow model. Beaver saw the firm as 'a reservoir of liquid assets, which is supplied by inflows and drained by outflows. The reservoir serves as a cushion or buffer against variations in the flows. The solvency of the firm can be defined in terms of the probability that the reservoir will be exhausted, at which point the firm will be unable to pay its obligations as they mature'. Within this conceptual framework the probability of failure is greater:

(i) the smaller the reservoir of liquid assets;

(ii) the smaller the inflow of resources from operations, i.e. cash flow;

(iii) the larger the claims on these resources by creditors;

(iv) the larger the outflow of resources for operations.

Blum (1974) added the following two propositions:

(v) the larger the variation in inflows (cash flow) and outflows (expenditure on operations and obligations to creditors), the greater the probability of failure; and

(vi) the more failure-prone the industry sector in which the firm operates, the greater the probability of failure.

7 Wilcox (1976) adopted a 'gambler's ruin approach' and attempted to describe a failure path in terms of a statistical process in which the basic variables were net liquidation value and the processes which cause it to change. He argued as follows:

> 'Net liquidation value is, in the language of systems dynamics, a level fed by a liquidity inflow rate and drained by a liquidity outflow rate. The inflow rate in a given period is defined as net income less dividends. It is governed by profitability and by management's dividend policy. The liquidity outflow rate is the increase each period in the book value of assets less the increase in the liquidation value of those assets. It is governed by management's capital budgeting policy and by the interaction of sales fluctuations with current asset control procedures.'

8 Turnbull and White (1975) developed a theoretical framework based on the factors they believed to be the underlying determinants of bankruptcy. In the short run, bankruptcy is the consequence

of insufficient income available to meet the firm's fixed obligations, but in the longer run the firm is able to survive this situation by borrowing additional funds. Thus they argued that the probability of bankruptcy was dependent on the firm's ability to raise sufficient funds, both internally or externally, to cover its fixed charges. And that this in turn was dependent on the firm's size, technology, future prospects, managerial ability, and the prevailing and expected economic conditions.

9 In an attempt to counter various criticisms of the conventional approach to liquidity valuation, Fadel and Parkinson (1978) constructed a model adapted from the earlier work of Walter (1900), who saw the solvency of the firm as dependent on four main factors:

(i) a sufficiency of cash to cope with the short-term uncertainty inherent in a situation where the firm has incomplete control over the collection of receivables, etc.;

(ii) a net flow of funds from operations of at least nil, thus enabling it to settle its obligations as and when they arise;

(iii) the ability to generate such additional funds as are necessary to ride out the troughs of any cyclicality inherent in the trade or economy in which it operates; and

(iv) the ability to generate such additional funds as are necessary to fund any more or less permanent changes in the structure of the balance sheet.

Fadel and Parkinson (1978) argued that conventional ratio analysis may be used to measure (i) and (iii), but that (ii) and (iv) 'can best be measured by the application of the notion of cash flow, and the relation of this to the job one envisages it doing'.

10 Argenti (1976, 1977) argued that failure is a complex process which is unlikely to be modelled successfully by a single equation, such as a Z-score function. He believed that 'failure is a process that takes many years to complete and companies seem to go through three distinct stages on their way to insolvency. First, there is something wrong with them, pre-eminently with their top management or with the way they respond to change. Then they make a mistake. Finally, their finances deteriorate'. Argenti attempted to quantify a list of symptoms exhibited by a failing firm on the basis of these three stages along the

road to failure, and combine them with a number of financial ratios utilised by the quantitative analysts. Although the Argenti model has considerable merit, its practical usefulness in the current context is severely limited by its heavy reliance on subjective judgment. The objective of this project is to evaluate the susceptibility to failure of all UK-quoted industrial companies, and the nature of the project precludes specific examination of individual companies, at least initially.

General approach

11 The main purpose of the present exercise was to see to what extent a model drawing exclusively on published accounting data could, in the UK-quoted industrial sector, improve on the results of the earlier work. A specific aim was to incorporate flow of funds variables into the analysis and to compare their usefulness, in the context of failure prediction, with the more conventional balance sheet and profit and loss ratios. In what follows, earlier models for predicting company failure are evaluated, and the results as far as possible compared with those of the model developed in this study.

Sample construction

12 The following Financial Times industry classification was used in identifying the sectors considered in the current project:

> beers, wines and spirits; chemicals and plastics; drapery and stores; electrical and radio; engineering and machine tools; food and groceries; industrials (miscellaneous); motors and aircraft trades; newspapers and publishers; paper, printing and advertising; shipbuilders; shoes and leather; textiles; tobacco.

It follows that any model derived from this data is directly applicable only to the above sectors, and that the exercise would need to be repeated for those sectors (such as construction) not considered here.

The failed firm

13 Having identified the relevant sectors from which the data were to be drawn, the next stage was to construct a sample of 'failed' companies. Various definitions of failure were chosen in an attempt to identify the relevant population of failed companies:

(i) entry into receivership;

(ii) voluntary liquidation;

(iii) creditors' liquidation;

(iv) takeover of investment by the National Enterprise Board as an alternative to failure; and

(v) the need for extensive bank support to avoid failure.

14 Because of the very small number of listed companies failing in any given year, the sample was chosen from among those companies which failed during the period 1974 to 1977. This had the effect of tending to average out any underlying fluctuations in the data, such as the impact of the business cycle on company performance. Data for the three years immediately preceding the date of failure were collected. Because of the time lag between publication of accounts and actual failure, the data were variously spread over financial years ending in the calendar years 1972 to 1977.

15 The identification of a sample of firms meeting the requirements was not a straightforward task since no comprehensive source of company failures in the United Kingdom appears to exist. The search embraced a wide variety of sources, including information from the stock exchange, credit insurers, professional liquidators and receivers, commercial data services, and the London Business School. This resulted in a sample of thirty-eight firms, for two of which, however, only a two-year run of data were available.

The non-failed firms

16 After identifying the sample of failed firms, the next task was to select the non-failed companies to be included in the model. An examination of methods used in past studies, and the implications of these methods for the discriminant model, was of use in identifying the population from which to draw the sample of non-failed firms.

17 The majority of past studies have used paired sampling techniques in which a non-failed firm was matched according to certain criteria with a firm in the failed sample. Typically, industry and size have been used as pairing criteria[1] while accounting year has also been used for matching the two sets of firms.[2] Pairing in this manner ensures that inter-firm differences in industry and size do not affect the magnitude of the independent discriminant variables in the failed and non-failed groups respectively, but it precludes specific consideration of these factors in the evaluation of a firm. Taffler (1977a) did not pair

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[1] See, for example, Altman (1968), Beaver (1966), Blum (1974) Deakin (1972) and Taffler (1976b).

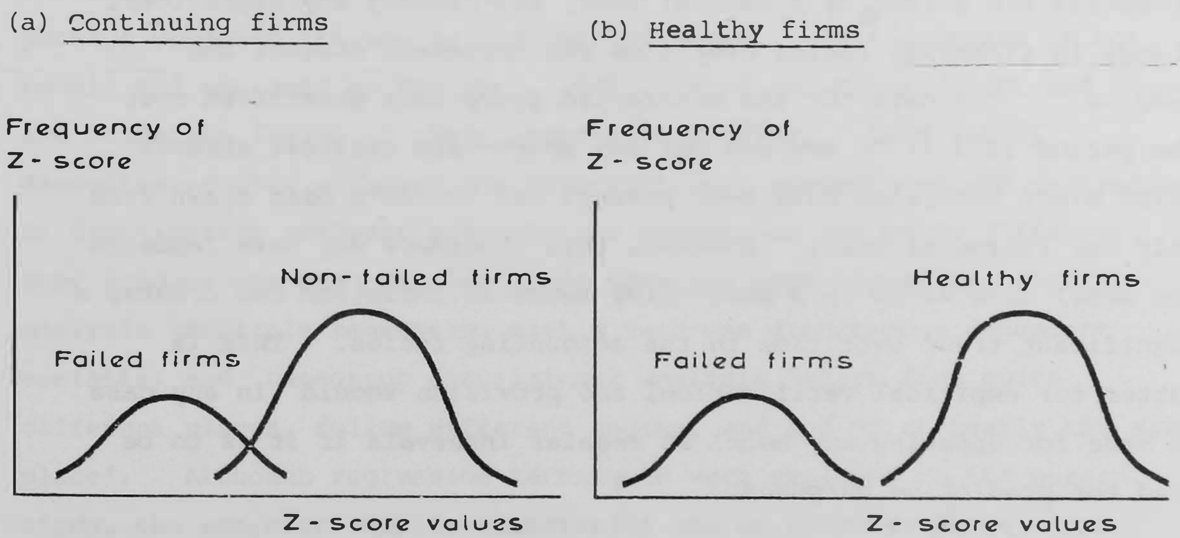
[2] See, for example, Beaver (1966), Blum (1974), Deakin (1972) and Elam (1975).

his samples by industry, size or fiscal year, and correctly observed that pairing does not improve the representativeness of the sample. The statistical methodology merely requires a sample that is representative of the population of non-failed firms.

18 Of interest in the Taffler studies (1977a and b) was the attempt to identify a population of 'healthy' firms for use in the discriminant model. This contrasted with the use of 'continuing' or non-failed firms in virtually all the previous studies, although Altman and Loris (1976) also used the concept of 'healthy' firms. The argument for using 'healthy' firms is that a random sample of 'continuing' firms may well include firms with financial characteristics no different from those of firms in the failed set, resulting in a corresponding decrease in the discriminatory power of the model and an increase in the type 2 errors (misclassification of a non-failed firm as failed). Taffler (1977a) suggested that 'the group of continuing enterprises should consist of financially sound and consequently distinct companies for correct application of the (statistical) methodology'. However, this approach needs to be examined more closely in order to see what bias it may generate. The argument may be illustrated graphically as follows:

Chart A

Distribution of discriminant scores with non-failed firms sampled from the population of continuing firms and from the population of healthy firms



19 By restricting the sample to firms in the 'healthy' population, the distribution of discriminant (Z) values for firms in the healthy sample is merely shifted along the X axis away from the distribution of Z values for the failed firms. The result for the sample of firms used to construct the discriminant model, and this cannot be over-emphasised, must be a higher efficiency in classification irrespective of the merits of the underlying discriminant model. However, accuracy in classification under these ideal conditions cannot be extrapolated with certainty to the total population of continuing firms to which the discriminant function will typically be applied. In addition, there is the practical problem of defining the population of 'healthy' companies, by deciding what criteria are to be applied to the total population of continuing firms to identify this subsector. There must also be a very real danger of merely prejudging the results of the very function that it is hoped to construct. It is for these reasons that in the present exercise a method of sampling from the total population of non-failed companies was preferred, and the Financial Times listing of quoted companies was used to define the population. A systematic sampling procedure was used to select the fifty-three firms which constitute the sample of non-failed or continuing companies.

20 A further issue was the identification of the time periods from which the data for non-failed firms were to be drawn. This problem does not arise in studies where failed and non-failed companies are paired by financial year, but clearly any significant change in financial ratios over time may seriously distort the results. The data for the non-failed group were stratified over the period 1973-77 to average out any short-term cyclical effects which might otherwise have been present had the data been drawn from only one financial year. However, this procedure may have rendered the model less valid in a predictive sense if inflation has created a significant trend over time in the accounting ratios. This is matter for empirical verification, and provision should in any case be made for updating any model at regular intervals if it is to be used for predictive purposes.

The financial ratios used

21 The financial ratios analysed were all constructed from published accounting data, and no attempt was made to incorporate any stock

market variables. As the data were collected for only three accounting periods, it was not possible to consider any trend variables. In addition to forty-seven ratios calculated from balance sheet and profit and loss statements, a further twelve ratios were constructed from sources and uses of funds tables. These ratios are listed in the appendix. Broadly, the ratios fall into the following categories:

liquidity gearing profitability turnover	ratios calculated from balance sheet and profit and loss data
cash flow funds flow	ratios calculated from sources and uses of funds data.

The ratios were selected on the basis of success in past failure prediction studies and popularity in the published material. The use of funds flow ratios, although advocated in the literature for at least a decade, has not been widespread, and no known study of company failure has explicitly incorporated these ratios into its analysis. An attempt was made to construct the funds flow ratios within the 'cash flow' framework described earlier, with the specific intention of use in a failure prediction context.

Statistical methodology

22 Although the exercise this far has been described as one in discriminant analysis, the ready availability of a multiple regression package prompted its use in the current study. This approach is not novel, and was used by Edmister (1972), Meyer and Pifer (1970) and Pogue and Soldofsky (1969) in their respective studies. Ladd (1966) demonstrated that although the distributional assumptions and derivations of discriminant analysis and multiple regression are quite different, they produce the same results. He observed that linear probability analysis (multiple regression with a zero-one dichotomous dependent variable) and two-group discriminant analysis 'start from quite different places, follow different routes, and end up at nearly the same place'. Although regression techniques were employed in the present study, the exercise remains essentially one of discrimination.

23 To confirm the equivalence of two-group discriminant analysis and multiple regression, the data were transferred to the Oxford University Computer Centre and run on the SPSS discriminant analysis package.

Five different models were compared, and, in terms of accuracy of classification, four of the five models produced identical results for each of the three years before failure. For the fifth model, the number of non-failed firms misclassified in the third year before failure was slightly different, but otherwise the results were identical. Consequently, it was felt that for all practical purposes the multiple regression model would suffice, and consequently the results reported in Section 4 all refer to the regression model.

Failure prediction models evaluated

24 The models that were subjected to empirical evaluation fall into two distinct classes, i.e. the simpler univariate models and the more sophisticated multivariate models. The single ratio models which were examined were the ratio of cash flow to total debt suggested by Beaver (1966), and the ratio of cash flow to current liabilities (found to be the best single ratio in the present project), as well as the quick ratio (quick assets to current liabilities) and current ratio (current assets to current liabilities) popularly used in solvency analysis. Two multi-ratio models were tested, i.e. those by Deakin (1977) and by Taffler (1977b) The Deakin model, developed in the United States, incorporated the following ratios:

X_1 = profit before tax to gross total assets;

X_2 = cash to gross total assets;

X_3 = current assets to gross total assets;

X_4 = quick assets to current liabilities; and

X_5 = current assets to total sales.

The Taffler model was developed on UK data, and should provide a more meaningful comparison with the model developed here. The proprietary nature of this model prohibited Taffler from revealing the exact definition of these ratios, and they were consequently approximated by the following:

X_1 = current assets to total debt;

X_2 = profit before tax to current liabilities;

X_3 = current liabilities to total capital employed; and

X_4 = quick assets minus current liabilities to total sales minus pre-tax profits as an approximation of the no-credit interval.

It is important to stress that, with regard to the testing of the two multivariate models, the ideal situation would have been simply to apply the original models as developed by the respective authors to the data used in the present analysis. The proprietary nature of the Taffler model meant that this clearly was not possible, and as the Deakin model was developed on US data it meant that in this case too the discriminant weights had to be estimated. The procedure adopted here was to fit both a regression and a discriminant function to the financial ratios used in the respective models, and then to test the classification efficiency of these models on the data used in the present study. Thus any results reported here can only be regarded as an approximation of the accuracy of the original models, and this is particularly true for the Taffler model where, in addition to estimating discriminant weights, several approximations were made to the original specifications of the model.

25 The Altman (1968) model, which inspired so much of the later work on company failure prediction, would seem to be the obvious model to be subjected to further evaluation, but the nature of Altman's ratios made its application in the United Kingdom impractical. Altman regarded the ratio of retained earnings to total assets as the single most important ratio in his model, but the derivation of a figure for retained earnings in the United Kingdom is complicated by the UK system of corporate taxation. Retained earnings is the residual from pre-tax profits after allowing for corporation tax and dividend payments, but the tax charge reported in the profit and loss statement often bears no resemblance to the actual tax paid. This figure would be reported in the statement of sources and uses of funds, but as this was not available for many of the firms under consideration, the actual tax liability could not be ascertained. The retained earnings figure would consequently be distorted. It was considered that any approximation might so distort the original model as to render any further analysis meaningless, and regrettably this meant that no empirical analysis was possible.

Results

26 The first stage of the analysis was the evaluation of the four single-ratio models described in paragraph 24. The trend in mean values for these four ratios is illustrated in Chart B opposite, and the separation of mean values is clearly evident as much as three years before failure. The results in terms of the number of firms misclassified in each of the three years before failure is given in Table A below, and these tended to confirm Beaver's (1966) results. In the last two years before failure the two cash flow ratios comfortably outperformed the current and quick ratios traditionally relied upon as solvency indicators,but their use as discriminators was clearly limited because of the large number of non-failed firms that were misclassified. As already noted,the two multivariate

Table A

Number of failed (F) and non-failed (NF) firms misclassified by various models

Model	One year before failure		Two years before failure		Three years before failure	
	F	NF	F	NF	F	NF
Current ratio	7	20	10	18	13	15
Quick ratio	4	20	9	19	15	13
Beaver model	2	13	5	11	14	11
Best single ratio	2	12	4	9	15	8
Deakin model[a]	2	10	5	10	19	7
Taffler model[a]	3	10	5	7	18	8
Model A	1	4	5	7	12	4
Model B	1	5	3	8	9[b]	2
Number of observations	38	53	38	45	36	34

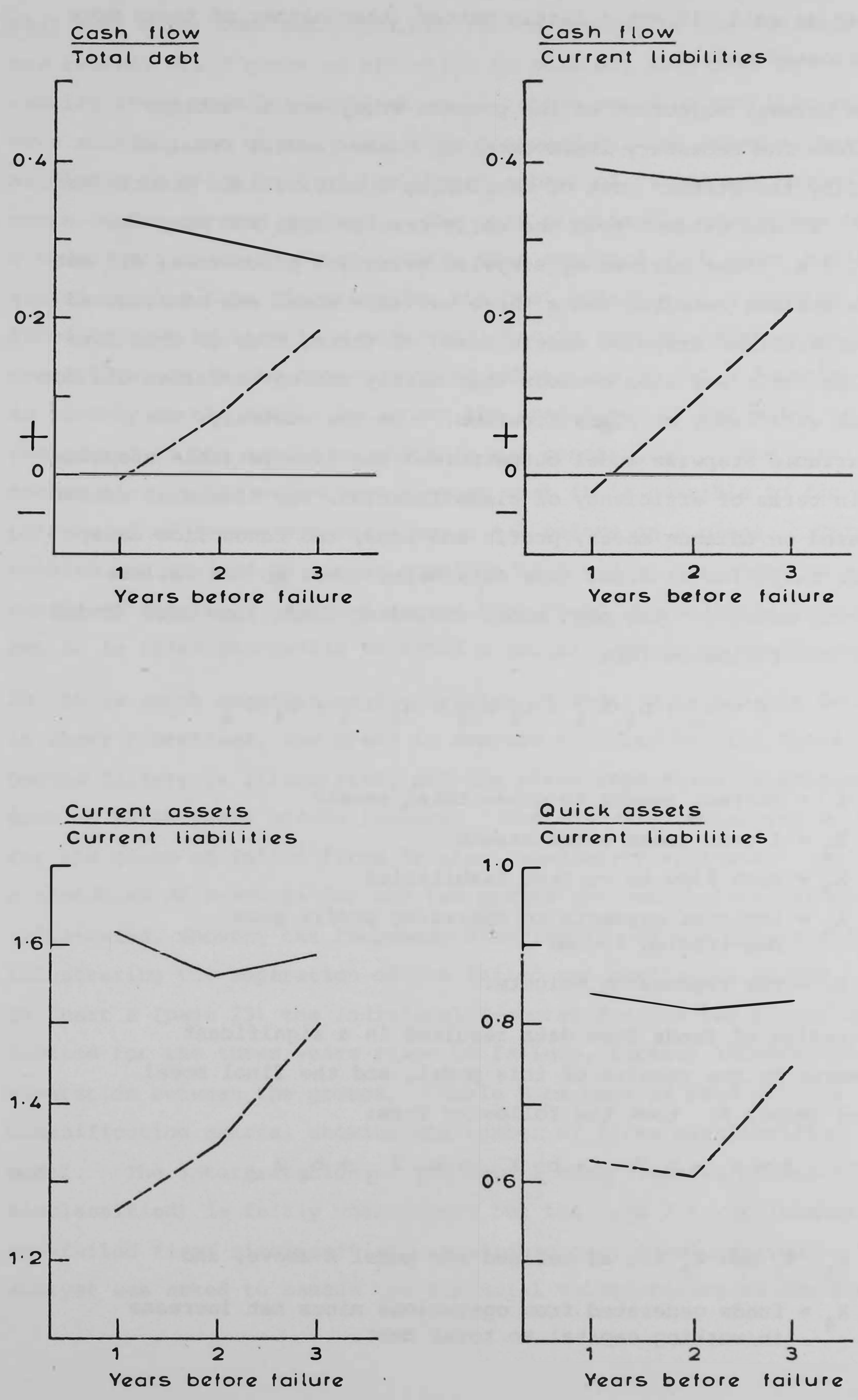
[a] Note that the results reported here can only be considered an approximation of the true classification efficiency of the original model. This is discussed in greater detail in paragraph 24.

[b] Funds flow data are derived from a comparison of two successive accounting periods, and missing data for one firm in the fourth year before failure meant that, for Model B only, this period contained thirty-five failed firms.

Chart B

Trend in average ratio values for the three years prior to failure

- Non-failed firms
- Failed firms



models tested were those by Taffler (1977b) and Deakin (1977), and the results are reported in Table A on page 18. There seems to be little to choose between them, but it is disturbing to note that the best single ratio (cash flow to current liabilities) seems to perform at least as well, if not a little better, than either of these more sophisticated models.

27 The primary objective of the present study was to attempt to achieve the necessary improvement on these results required to justify the greater cost of developing a multivariate discriminant model. It was evident from the early results that the stepwise models, i.e. those derived by stepwise selection procedures, did not provide optimal results, and a three-variable model was constructed that outperformed stepwise models based on three, four or even five variables. It was also obvious that merely adding variables did not increase efficiency of classification. On the contrary, the four-variable stepwise model outperformed the five-variable stepwise model in terms of efficiency of classification. The financial ratios were based on balance sheet, profit and loss, and funds flow data, with the inclusion of funds flow data being novel to the failure prediction models. The best model excluding funds flow data (Model A) took the following form:

$$Z = b_o + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4$$

where

X_1 = current assets to gross total assets

X_2 = 1 over gross total assets

X_3 = cash flow to current liabilities

X_4 = interest payments to operating profit plus non-trading income

b_j = the regression weights.

The inclusion of funds flow data resulted in a significant improvement on the results of this model, and the final model selected (Model B) took the following form:

$$Z = b_o + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4$$

where

X_1, X_2 and X_3 are as defined for Model A above, and

X_4 = funds generated from operations minus net increase in working capital to total debt.

The results in terms of classification efficiency are reported in Table A, and the superiority of this second model is clearly illustrated, particularly in the second and third years before failure. However, there can be no claim that this model is optimal, and it is possible that some other combination of the ratios tested, or the inclusion of new ratios, could prove as effective or possibly even more so. To examine every possible combination of ratios would be prohibitive, and even adopting one of the algorithms proposed by, for example, Beale et al (1967) in order to find the 'best' subset of ratios was beyond the scope of the current project. The only practicable course was to adopt a model that appeared satisfactory, when compared with other models tested, rather than to search for the best possible. A problem faced by most multivariate model builders is that of 'statistical overfit' which is the consequence of attempting to fit a function so closely to the sample data that the usefulness of the model is restricted to the sample on which it was constructed. The parallel in mathematics is the well-known theorem that it is possible to fit a polynomial of degree n through any n + 1 points on a plane. This problem was avoided as far as possible by limiting the model to a small number of carefully selected ratios that could be logically justified, but it is often impossible to avoid a certain amount of sample bias.

28 It is worth considering the results of Model B in greater detail. In Chart C overleaf, the trend in average Z-scores for the three years before failure is illustrated, and the clear separation is evident as much as three years before failure. The downward trajectory in Z-scores for the group of failed firms is also immediately apparent. In Chart D a histogram of Z-scores for the two groups one year before failure is illustrated, showing the frequency distribution of Z-scores and clearly illustrating the separation of the failed and non-failed groups. In Chart E (page 23) the individual Z-scores for the two groups are plotted for the three years prior to failure, further illustrating the separation between the groups. Table B on page 24 sets out the classification matrix, showing the number of firms misclassified by this model. The interpretation of the type 1 error (number of failed firms misclassified) is fairly unambiguous but the type 2 error (number of non-failed firms misclassified) requires closer consideration. An analyst was asked to assess the financial vulnerability of the five

Chart C

Trend in average Z-score values for the three years before failure

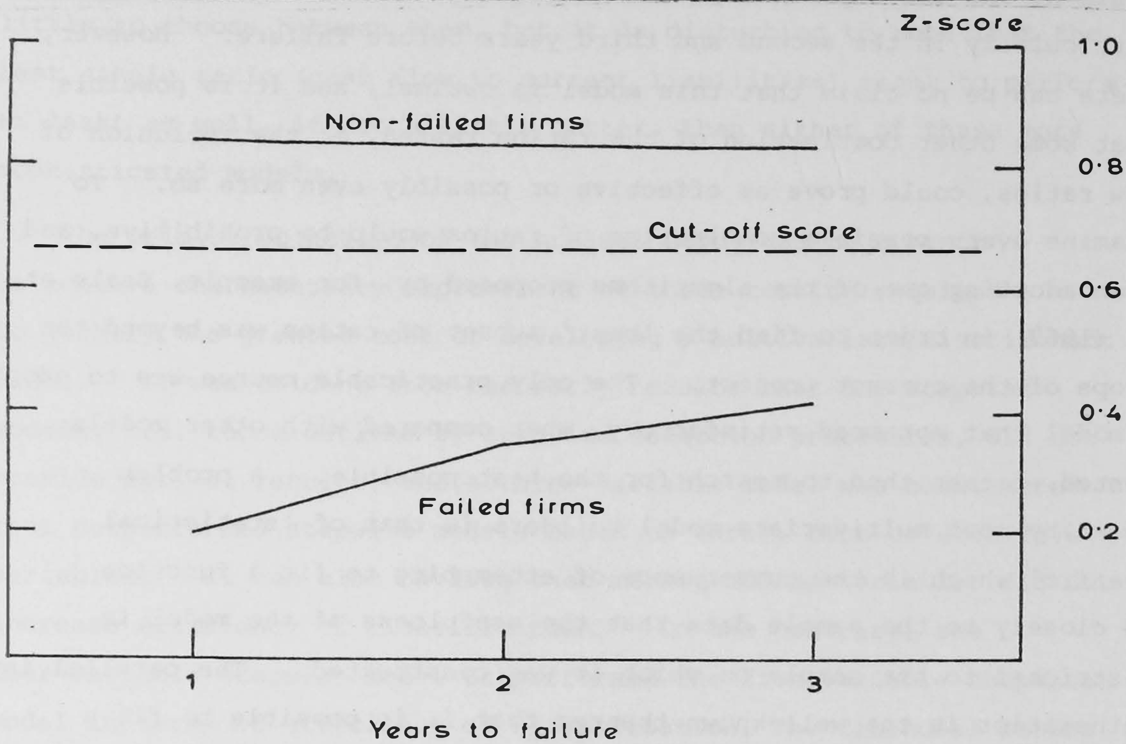
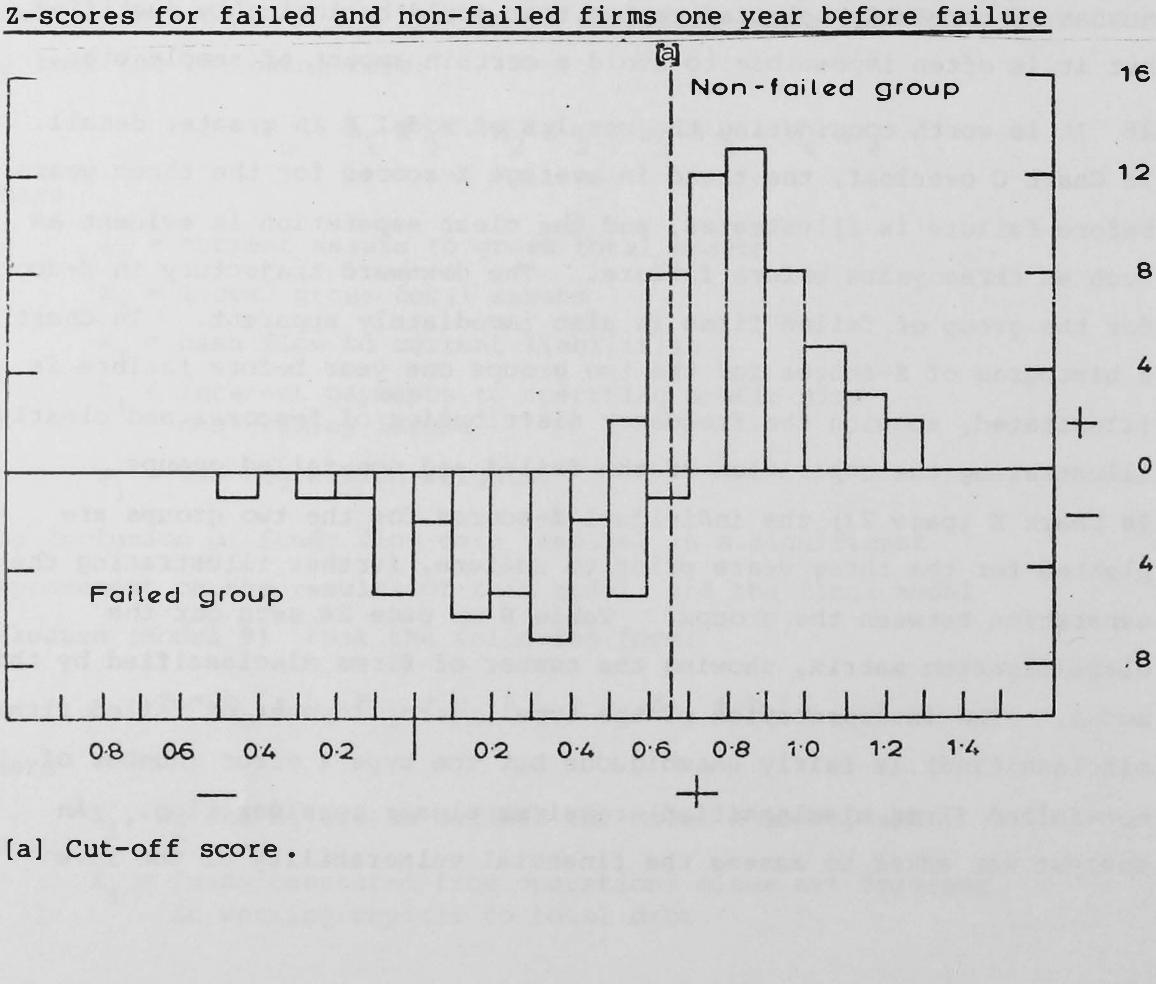


Chart D

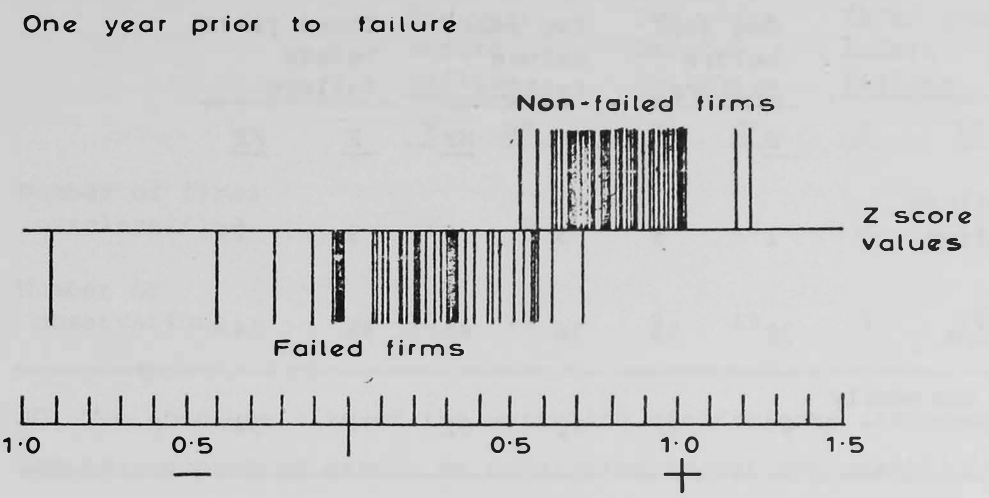
Z-scores for failed and non-failed firms one year before failure

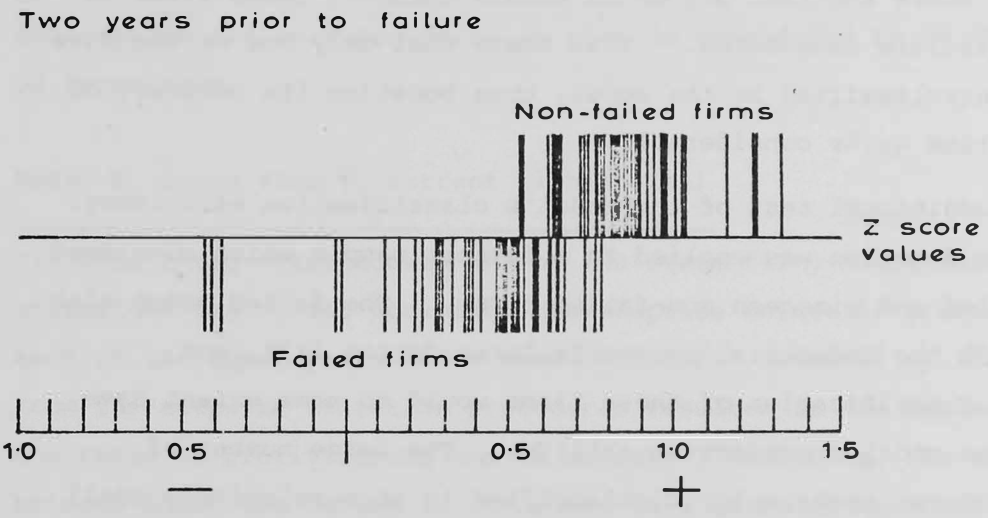


[a] Cut-off score.

Chart E

Distribution of Z-scores for failed and non-failed firms





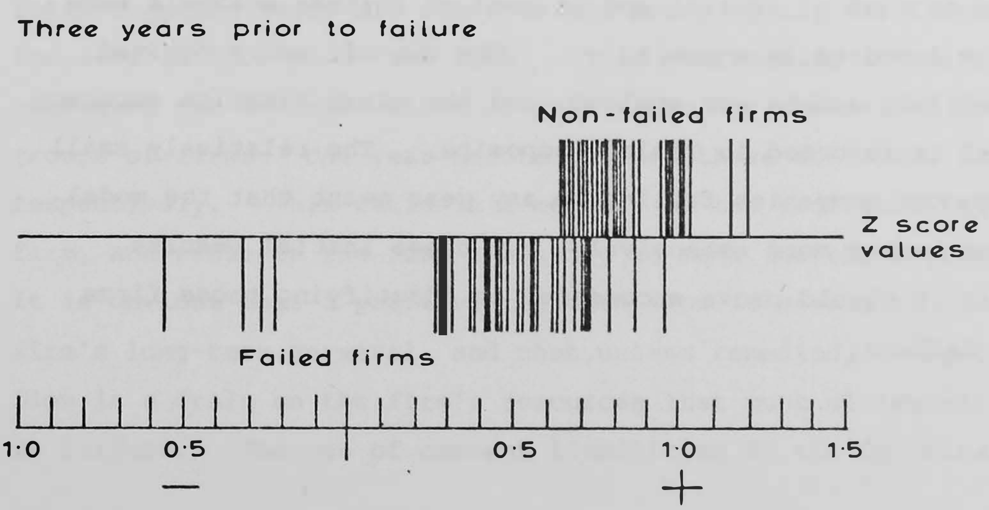


Table B

Number of failed (F) and non-failed (NF) firms misclassified by Model B

	One year before failure		Two years before failure		Three years before failure	
	F	NF	F	NF	F	NF
Number of firms misclassified	1	5	3	8	9	2
Number of observations	38	53	38	45	35	34
Percentage correctly classified	97	91	92	82	74	94

non-failed firms misclassified by the model one year before failure, and the observation was that four of the firms were in a fairly precarious state and that any model should identify these firms as potential failure candidates. This means that only one of the five firms was misclassified by the model, thus boosting its accuracy of classification quite considerably.

29 As an additional test of the model's classification efficiency, the Z-score function was applied to a further sample which consisted of ten failed and nineteen non-failed firms. The failed group also included all the industrial sector failures during 1978, and successful classification of these firms would to some extent have verified the model's predictive ability. The large number of non-failed firms technically misclassified in this relatively small sample is due to the fact that the sample deliberately included a number of firms known to be experiencing financial difficulty. That these firms at risk of failure and in need of further analysis were assigned low Z-scores is encouraging. The cut-off score derived from the original sample was applied, and the classification accuracy of the model is reported in Table C opposite. The relatively small number of quoted companies failing in any year meant that the model could not be tested more extensively, but these initial results suggest that it should prove successful in identifying those firms at risk of failure.

Table C

Number of failed (F) and non-failed (NF) firms misclassified by Model B

	One year before failure		Two years before failure		Three years before failure	
	F	NF	F	NF	F	NF
Number of firms misclassified	1	9	1	12	2	11
Number of observations	10	19	9	19	7	19

30 The absolute size of the weighting coefficients assigned by the regression program cannot be considered to reflect unambiguously the relative importance of the respective ratios. However, the results of numerous discriminant runs, univariate tests and stepwise regressions do provide an indication of the relative importance of the ratios, and the four ratios are examined below in what is considered to be their order of importance.

Ratio X_3 (cash flow to current liabilities)

31 This ratio overshadowed any of the other fifty-eight ratios in univariate tests, and dominated the stepwise selection procedures in each of the three years under consideration. Removal of this ratio from the stepwise selection procedures resulted in its replacement by the ratio of profit before tax to current liabilities. The similarity between these two ratios is reflected in a correlation coefficient of 0.99, but the use of ratio X_3 improved the classification efficiency of the model as a whole. The positive regression coefficient for this ratio suggests that, all other things being equal, the larger the ratio, the less failure-prone the firm. This observation is confirmed by examining the average values of this ratio for the failed and non-failed groups of firms: one year before failure these are -0.02 and 0.39 respectively. This ratio is a measure of the profitability of the firm, and reflects the firm's ability to meet its short-term commitments. It is obvious that a positive net cash flow is essential for the firm's long-term survival, and that,unless remedied, a negative cash flow is a drain on the firm's resources that must ultimately result in failure. The use of current liabilities in the denominator of

this ratio becomes more meaningful when it is noted that bank overdrafts are a major component of this term. A comparison of the ratio of bank overdrafts to gross total assets for the failed and non-failed groups presented in Table D below suggests that the failed group tends to have a much greater proportion of bank overdrafts relative to the size of the company.

Table D

Mean values for gearing ratio one year before failure

	Failed firms	Non-failed firms
Overdrafts / Gross total assets	0.22	0.08

Weaver (1971) suggested that larger firms have ready access to the market for fixed-interest securities, and this could imply that the failed firms, which are on average significantly smaller than the non-failed firms, of necessity place greater reliance on short-term finance. Ratio X_3 measures the ability of the firm to generate sufficient cash to meet these short-term commitments, and its inclusion in the model is of even greater appeal when the 'cash flow' model described in paragraph 24 is considered. It measures both the inflow of resources from operations (the greater this inflow, the lower the probability of failure) as well as the claims on these resources by creditors (the higher these claims, the greater the probability of failure).

Ratio X_2 (1 over gross total assets)

32 This ratio is merely a measure of the firm's size measured in terms of its gross total assets, and the negative regression coefficient suggests that the probability of failure is inversely related to company size. The average values for this ratio one year before failure are 0.41 for the failed group and 0.10 for the non-failed group, illustrating quite clearly the smaller size on average of the failed firms. Along with ratio X_3, this ratio was consistently selected during various stepwise procedures for each of the three time periods, and removal of this ratio resulted in a significant reduction in discriminating ability in the models examined. The inclusion of this ratio is intuitively appealing when the following

factors are taken into consideration. The very size of a company may often act as a buffer against external turbulence. Thus, a large firm is often better able to weather cyclical fluctuations in the demand for its products, or to ride out major economic depressions. The same applies to internal turbulence, for a greater depth in management might be expected in a larger organisation, making a problem of succession in top management, for example, less crucial to the survival of the firm. Prais (1976) examined the growth of firms in the UK manufacturing sector during the period 1909-70, and argued that the risk-bearing advantages of large firms was a major incentive for growth. The 'size equals security' syndrome means that large firms enjoy a significant advantage in terms of lower finance costs as well as greater availability of capital. Of course, despite these and other advantages of size, the pursuit of growth at all costs in no way guarantees survival in an increasingly competitive environment, but clearly size can be a key factor in determining the probability of survival.

Ratio X_1 (current assets to gross total assets)

33 This ratio could be interpreted as a measure of company liquidity in that it measures the size of the reservoir of liquid assets relative to the size of the company, with the positive regression coefficient suggesting that the less liquid the firm, the greater its probability of failure. However, the exceptionally low correlation coefficients between this ratio and the other liquidity ratios (for example,for the current ratio, $r = 0.12$, and for the quick ratio, $r = -0.07$), as well as the results of the principal components analysis,suggest that this interpretation is inappropriate. A possible interpretation is to view it as the complement of the ratio of fixed assets to total assets (this ratio was not calculated). Firth (1975) suggested that too high a figure for this latter ratio implies that a company may be expanding too rapidly, with consequent pressure upon liquidity. This will mean a lower ratio of current or total assets, with a consequent greater probability of failure. It is interesting to note that the average values for this ratio one year before failure are 0.64 and 0.63 for the failed and non-failed groups respectively, suggesting that, examined singly, this ratio would not discriminate between the two groups of firms. However, the correlation coefficient between this and the other ratios in the model is virtually zero, suggesting that

ratio X_1 is measuring a quite distinct dimension of company performance. This is further confirmation of the fact that in any multivariate model the variables cannot be isolated and evaluated singly, but must be evaluated in conjunction with the other variables, and it is on this basis that ratio X_1 warrants inclusion in the model.

Ratio X_4 (funds generated by operations minus net movement in working capital to total debt)

34 This was the only ratio in the model that made use of funds flow data, and its inclusion seemed to add a further dimension to the analysis in that it significantly improved upon the classification efficiency of any of the other models. The numerator of this ratio provided a more accurate indication of the total amount of cash generated during a particular year in that it considered the net movement in working capital in addition to the profits generated. For example, a reduction in debtors means a corresponding increase in the cash balance over which management has discretion, and this is a source of funds which is available to meet the company's financing requirements. The ratio measures the ability of the firm to generate sufficient funds to meet both its long and short-term commitments, and is fairly similar to ratio X_3, thus raising the question of why two relatively similar ratios should be included in one model.

35 The observation has already been made that small firms seem to have heavier overdraft commitments relative to their size, and that ratio X_3 seems to measure the ability of the firm to cover its short-term obligations. Larger firms, because of their ready access to the fixed-interest securities market, and the cheaper cost of finance associated with the lower risk, tend to finance their borrowing requirements by issuing long-term debt, and this ratio could be measuring the ability of these firms to meet their longer-term financing commitments. An examination of the firms correctly classified as a result of including ratio X_4 in the model shows that they are all significantly larger than the average failed firm, thus tending to lend support to the above argument. However, these are only tentative conclusions, and further research into the use of funds flow ratios in general is called for.

Comment

36 In conclusion, some comment on the interpretation of the Z-score is called for. The Z-score has been used as an index of financial vulnerability, but this figure should be interpreted with the utmost caution. A low Z-score does not imply that a firm will fail, merely that it is exhibiting characteristics similar to those of past failures, and consequently no decision as to the future viability of the firm can be taken without a closer analysis. A useful addition to a more detailed company investigation would be to examine the trend in Z-scores over the last few accounting periods, and a steady decline in Z-scores would certainly suggest a higher probability of failure.

37 A further, and potentially more confusing, problem is the interpretation of Z-scores when a large number of firms are ranked according to this figure. For example, given two firms with Z-scores of 0.25 and 0.50 respectively, does this mean that the firm with the lower Z-score is more likely to fail? What interpretation would be placed on Z-scores of 0.50 and 0.55 respectively? An examination of the Z-score formula would certainly seem to indicate, for example, that the less profitable the firm, the lower its Z-score, and consequently the higher its probability of failure. But certain firms have the potential to sustain a period of losses and still survive, so that this confuses the interpretation of the Z-score even further.

38 Thus it would seem unwise to place too great an emphasis on rankings, and a more sensible interpretation would be as follows. All firms with Z-scores less than the cut-off point should be regarded as possible future problem cases and require further examination. In addition, a declining Z-score would seem to indicate a deteriorating financial position, thus demanding urgent attention. But this is ultimately a decision for the analyst. There is no suggestion that multivariate statistical models such as Z-score should replace existing solvency evaluation procedures, which generally require the services of a skilled accountant or analyst. All that Z-scores can hope to do is act as a sophisticated screening device and so direct attention to those firms most urgently in need of analysis.

<u>Appendix</u>

<u>Financial ratios</u>

<u>Liquidity</u>

1 C/GTA
2 QA/GTA
3 CA/GTA
4 WC/GTA
5 C/CL
6 CA/CL
7 QA/CL
8 STK/CA
9 (QA - CL)/(S - PBT)
10 CA/TD
11 QAA/CL
12 CL/TCE
13 1/GTA

<u>Gearing</u>

14 CL/GTA
15 LTD/GTA
16 (LTD + OVD)/GTA
17 TD/GTA
18 (TD + PREF)/GTA
19 CL/NW
20 (LTD + OVD + STB)/NW
21 TD/NW
22 (LTD + OVD + STB)/TCE
23 (LTD + OVD + PREF + STB)/TCE
24 (LTD + OVD + STB)/TCE
25 (LTD + PREF)/EQ
26 LTD/EQ
27 INT/(OP + NTI)

<u>Profitability</u>

28 TP/S
29 OP/S
30 PBIT/TCE
31 PBT/GTA
32 PBT/TD
33 PBT/CL

<u>Turnover</u>

34 C/S
35 D/S
36 STK/S
37 QA/S
38 CA/S
39 GTA/S
40 WC/S
41 STK/WC

<u>Cash flow</u>

42 CF/S
43 CF/GTA
44 CF/(TD + PREF)
45 CF/CL
46 INT/CL
47 CF/NW

<u>Funds flow</u>

48 FPO/TCG
49 MLF/TCG
50 CFA/DEP
51 CFA/TCG
52 (CIBO + CIC)/TCG
53 (LOAN + CIBO + CIC)/TCG
54 FPO/CFA
55 DVD/FPO
56 (FPO - MWC)/TD
57 FPO/TU - T2 - T3)/TCE
58 MWC/FPO
59 (TS - T1 - T2 - T3)/TCE

Key to financial ratio definitions

C = cash + marketable securities

CA = current assets

QA = quick assets

QAA = quick assets + market value of investments

WC = working capital

STK = stock + work in progress

S = sales

D = debtors

CL = current liabilities

LTD = long-term debt

OVD = bank overdrafts

TD = total debt (= LTD + CL)

PREF = preference capital

STB = short-term borrowings

INT = total interest charges

TP = trading profit

OP = operating profit

NTI = non-trading income

PBIT = profit before interest and tax

PBT = profit before tax

GTA = gross total assets (= net total assets + current liabilities

TCE = total capital employed

NW = net worth

EQ = equity capital + reserves

CF = cash flow (= TP + NTI - INT)

FPO = funds generated by operations

TCG = total cash generated (= TS + CIC + CIBO)

MLF = net movement in liquid funds

CFA = change in fixed assets

DEP = depreciation

CIBO = change in bank overdrafts

CIC = change in creditors

LOAN = loan capital

DVD = dividends

MWC = net movement in working capital

TU = total uses of funds

TS = total sources

T1 = externally generated funds

T2 = essential cash payments

T3 = change in working capital

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