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ABSTRACT

Scaling techniques are proposed as an alternative tool for the analysis and prediction of corporate failure. This approach has the advantage of reproducing the main features of the data in the form of statistical maps that lend themselves to intuitive interpretation. The maps are further analysed by means of standard multivariate statistical tools. The methodology is demonstrated using a recent sample of UK industrial companies. A future-dated holdout sample is also employed to illustrate how the Multidimensional Scaling technique can aid practitioners when assessing the financial health of a company.

I. Introduction

Research in the corporate failure prediction area has been very popular among academics, as well as among practitioners, during the last four decades. However, as the corporate failure problem still persists in modern economies, having significant economic and social implications, and as an accurate and reliable method for predicting the failure event has not yet been found, research interest is likely to continue.

Beaver (1966) was among the first to attempt to forecast corporate failure and his study is considered a milestone in this area. Beaver's approach was 'univariate' in that each ratio was evaluated in terms of how it alone could be used to predict failure without consideration of the other ratios. Altman (1968) tried to improve Beaver's study by applying multivariate linear discriminant analysis (LDA), a method that has been proved to suffer from certain limitations[1]. Researchers, however, seemed to have ignored these limitations and continued extending Altman's model, hoping to achieve higher classification accuracy. Some examples of these attempts include among others: 1) assignment of prior probability membership classes (Deakin, 1972), 2) employment of a more appropriate 'quadratic classifier' (Altman, Haldeman and Narayanan, 1977), 3) use of cash flow based models (Gentry, Newbold and Whitford, 1987), 4) use of quarterly financial statement information (Baldwin and Glezen, 1992) and 5) investigation of the use of current cost information (Aly, Barlow and Jones, 1992; Keasy and Watson, 1986). Nevertheless, none of these attempts accomplished higher statistically significant results than Altman's earlier work and moreover, in the majority of cases, the practical application of these models presented difficulties due to their complexity.

In 1980, Ohlson used logistic regression (or logit analysis) for the prediction of failure, a method that avoids the argued limitations of the LDA technique[2]. Logit, along with probit analysis (a variation of the former), are called conditional probability models since they provide the conditional probability of an observation belonging to a certain class, given the values of the independent variables for that observation. However, Ohlson's results did not improve on the results of discriminant analysis, thus indicating that further refinements of the technique were necessary. Extensions to Ohlson's study include among others: 1) examination of the effect of industry-relative ratios in failure prediction models (Platt and Platt, 1990), 2) development of empirical models that would distinguish between failed firms and firms in financial distress (Gilbert, Menon and Schwartz, 1990), 3) development of industry specific models (Platt, Platt and Pedersen, 1994), 4) employment of multilevel logit analysis (Johnsen and Melicher, 1994) and 5) development of prediction models for the small company sector (Keasy and Watson, 1986, 1987). Conditional probability models, however, failed to offer anything more than any other technique to the user (Keasy and Watson, 1991).

Nonetheless, failure prediction researchers did not give up and continued to employ various classification techniques, always hoping for the discovery of the 'perfect' model. The most popular of these techniques are recursive partitioning, survival analysis, neural networks and the human information processing approach. A recent paper by Laitinen and Kankaanpaa (1999) empirically studied whether the results stemming from the use of these six alternative methods significantly differ from each other. Their results indicated that no superior method has been found even though the failure prediction accuracy varied depending on the prediction method applied.

This study employs an alternative technique to the corporate failure prediction problem, multidimensional scaling (MDS). Multidimensional scaling offers an intuitive representation of statistical results, thus making it possible to easily interpret results without a deep understanding of the statistical underlying principles. Also, because of the frequent instability of the results arising from standard statistical techniques, the user needs to supplement statistics with judgement. This, however, is possible in MDS and not in other approaches, which are much less transparent to the analyst.

As work by many researchers has proved that distress prediction models are fundamentally unstable, in that the coefficients of a model will vary according to the underlying health of the economy (Moyer, 1977; Mensah, 1984), hence stressing the need that the model derivation should be as close in time as possible to the period over which predictions are to be made (Keasy and Watson, 1991), a recent data set (1988-1999) of UK public industrial companies (both failed and healthy) is used.

This study proceeds as follows. Section II provides a brief description of the MDS technique; information regarding the data set is presented in section III; section IV includes the data analysis and reports the empirical findings; an illustration as to how the MDS results can be used in practical applications follows in section V and section VI provides the conclusions of the study.

II. Multidimensional Scaling

Existing models for the prediction of corporate failure represent finer and finer refinements within a standard methodology. Normally, two samples are selected, one of failed companies and one of continuing companies, a particular statistical analysis is performed and an assessment is made of the classification ability of the model on the basis of observed results. As each model makes demands on the statistical properties of the data and as these are never totally met, more and more refined models are required to try to avoid the shortcomings of previously established analyses. Nevertheless, despite the refinements introduced at the various stages, there are not great differences between the models, from which it follows that very similar results are obtained irrespective of the technique applied. This is clearly the situation described by Kuhn (1970), who argues that this always takes place when researchers are locked into an existing paradigm. The similarity of the results is also due to the close mathematical relationships that exist between the various approaches: if the methodologies have much in common, then the fact that the results are fundamentally the same should not be a surprise.

Here we propose the use of Multidimensional Scaling techniques (MDS) as a paradigm shift. MDS is a multivariate statistical analysis tool that attempts to produce graphical representations of the main characteristics of the data. MDS has a close connection with Principal Components Analysis-see Mar Molinero (1991) or Chatfield and Collins (1980), although it is more general in outlook, as it can work with orderings and does not require the data to be measured on a ratio or interval scale, Stevens (1951). MDS represents a break with existing tradition in the sense that the evaluation of the problem takes place at two different levels, at the technical level and at the intuitive level. Pictorial representations highlight the most salient features of the data, help in the interpretation and guide the use of other statistical tools. A good introduction to MDS can be found in Kruskal and Wish (1978). MDS has been used before in the accounting and finance area; Mar Molinero and Serrano Cinca (2000) give a review of the literature.

MDS has various advantages over other approaches. First, there is often a problem with extreme observations in financial data. Outlier detection and treatment should always be contemplated as a first step in any multivariate analysis that uses company data, as this kind of observations can influence the results. The detection and treatment of extreme observations is delicate and important and certainly not straightforward, as discussed by Ezzamel and Mar Molinero (1990). MDS, which relies on relationships of order, does not suffer so much from the extreme observation problem, as outliers are incorporated as peripheral points in MDS maps. These maps, though, are more visually attractive and less cluttered if outliers are removed.

Second, MDS maps do not make distributional assumptions on the data. This is in contrast with Linear Discriminant Analysis, which requires normality and assumes equal variance-covariance matrices. Neither assumption holds in the context of failure prediction; see Ezzamel and Mar Molinero (1990) for a discussion of the normality hypothesis and Richardson and Davison (1983 and 1984) for a discussion of equality of variance-covariance matrices. Logit provides a more general model, which does not require multivariate normality, although it is closely related to linear discriminant analysis-see Haggstrom (1983). Many studies have found little difference between the two approaches in terms of classification success (e.g. Casey and Bartczak, 1985; Laitinen and Kankaanpaa, 1999).

The third issue to be addressed is variable selection. Standard statistical models require an initial analysis in data reduction, normally some kind of factor analysis. Data reduction is not necessary under the MDS approach, as estimation takes automatic care of this part of the modelling process.

Summarising, MDS does not make distributional assumptions on the data, does not require the removal of extreme observations, does not call for an initial exercise in data reduction, has a strong theoretical basis and produces easily accessible pictorial representations of the main characteristics of the data, which are amenable to the exercise of judgement in the interpretation of the results. In what follows, the MDS modelling process will be described in detail.

III. The data

As mentioned in the introduction, this study employs financial statement data of 50 UK public industrial companies that failed between the years 1988 to 1999, as well as data from the financial statements of 50 healthy companies[3]. As the matching of the failed and healthy companies in terms of fiscal year, industry and total asset size is now a common practice when conducting failure prediction studies, this approach was also adopted in our study[4]. Table 1 of the appendix lists the sample companies, along with their standard industrial classification (SIC) codes and the year and nature of failure for the insolvent companies. As it can been seen, data were collected for the three most common types of failure, i.e. receivership, administration and liquidation[5].

The financial statement information was collected from the following sources: a) Datastream, b) Compustat (Global), c) Worldscope European Disclosure and d) Silverplatter: UK Corporations. Failure dates were found in the Wall Street Journal Index (Europe) and in the UK Insolvency database.

The final sample of companies was divided into two sets: the first set includes companies that failed between 1988 and 1997 and the respective healthy ones and it was used for training the model (90 companies); the second set includes companies covering the two-year period 1998 and 1999 and it was retained in order to test the model (10 companies)[6].

Although the financial statements of the sample companies were obtained for at least three years, only the most recent year was used in the analysis (i.e. the first year before failure for the failed companies and the respective fiscal year for the healthy). Forty financial ratios were constructed, thus ensuring that an adequate number of ratios represents each of the five major ratio categories: financial leverage, operating cash flow, liquidity, profitability and activity. These ratios and their definitions can be found in table 2 of the appendix.

When applying any traditional multivariate statistical method, before proceeding to the actual data analysis, the variables must be subjected to a preliminary analysis in order to check for multicollinearity, to remove redundant information and consequently to increase degrees of freedom in the estimation. MDS, on the other hand, can cope with highly correlated data and with redundant information and thus this kind of analysis was skipped.

Another problem faced when dealing with financial ratios is that each ratio is measured in different units. Hence, to enable comparisons between companies and to make the results insensitive to the measurement units, the ratios were standardised to zero mean and unit variance.

A number of ways exist that can be used to compare individual companies, depending on the measure of dissimilarity (or similarity) used, although in the majority of cases the results are robust to the choice of this measure. The most common (and the simplest) dissimilarity measure employed in the MDS literature is the Euclidean distance[7]. This is closely related to the correlation coefficient between companies using ratios as variables, a measure that is at the basis of Linear Discriminant Analysis and Logit. Thus, the dissimilarity matrix, on which the MDS analysis is based, is a square matrix of distances between companies and will have as many rows and as many columns as there are companies in the analysis. Each company will be represented by means of a point in the space. What we would like to know is if there are areas of the space in which failed companies concentrate and areas where non-failed companies concentrate.

IV. Analysis of data and empirical findings

Dimensionality

An MDS analysis produces statistical representations that have the form of maps. The number of dimensions in which the MDS map is to be drawn is an important decision that has to be taken prior to any further analysis. However, there is no standard statistical procedure that yields to the 'correct' or 'true' dimensionality, but several procedures do exist that can guide the researcher as to approximately how many dimensions are necessary for that particular data set. Nonetheless, as MDS is used as a descriptive model for representing and understanding the data, other considerations enter into decisions about the appropriate dimensionality, i.e. interpretability, ease of use and stability (Kruskal and Wish, 1978).

Given the close connection between MDS and Principal Component Analysis (PCA) (Chatfield and Collins, 1980), it is appropriate to analyse the dimensionality of the data by means of PCA. This was done in the present case. It was found that the first ten principal components accounted for 89.5% of the total variance[8] (see table 3). However, producing a MDS map in ten dimensions was not possible for two main reasons: 1) it would have been extremely difficult (if not impossible) to interpret all ten dimensions; experience also suggests that not all the dimensions are relevant to the interpretation of failure, and 2) the computer program ALSCAL[9] used for all the MDS calculations permitted the use of no more than six dimensions.

An alternative way that provides indications for the dimensionality of the map is the examination of how a unit change in dimensionality affects a particular goodness-of-fit measure. A number of goodness-of-fit measures exist in the MDS area; Kruskal's stress formula 1 (i.e. the so-called 'elbow test') was chosen for this study. The results are given below:

Table 4
Change in Stress 1 values in respect to a unit increase in dimensionality

Dimensions	Stress1
1	0.20828
2	0.12478
3	0.08671
4	0.07070
5	0.05287
6	0.04127

Figure 1

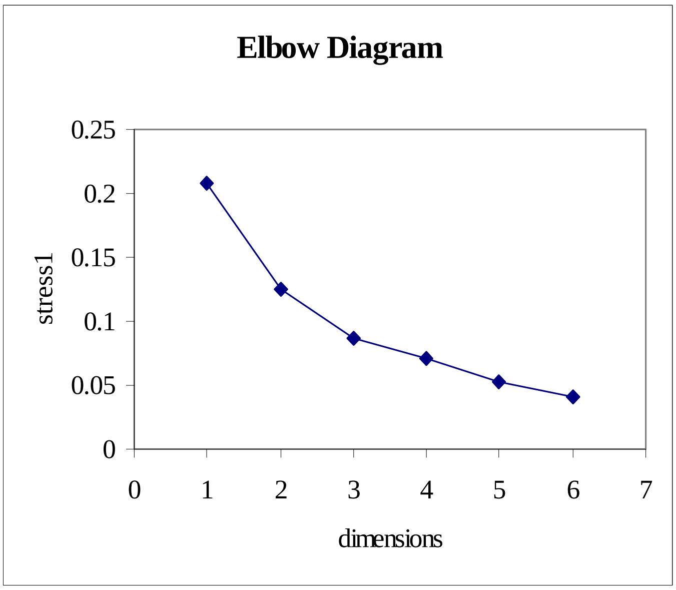

Figure 1 shows the way in which stress varies with dimensionality and suggests that a solution in three dimensions gives a satisfactory representation of the data. $Stress_1$ takes the value of 0.0867 which, according to Kruskal (1964a), is regarded as “good”. However, for the purposes of this paper, the MDS map was obtained in a six dimensional space but only three dimensions are reported. Analyses were conducted in a six dimensional representation and the last three dimensions were found not to be related to the failure problem, therefore they were treated as residual variation.

A map in six dimensions is only a mathematical construct. We describe as a map a set of points in a six-dimensional space. Each company is a point in this space, whose position is given by a set of six co-ordinates. An MDS analysis is conducted because there is a strong suspicion that the points that represent non-failed companies are grouped in one part of the space, while the points that represent failed companies are in another part of the six-dimensional space. There is also a suspicion that such points are in a sub-space and that not all the dimensions are involved.

The position of each company, i, in the space is given by a set of six co-ordinates. Let these co-ordinates be $d_{i1}, d_{i2}, \dots, d_{i6}$. The conjecture that failed companies will concentrate in an area of the space and non-failed companies will occupy a different region, can be formalised in the following way. Let F_i be a binary variable such that takes the value 1 if company i survives and the value of 0 if it fails (or the other way round). Then,

$$F_i = f\,(d_{i1}, d_{i2}, \dots, d_{i6}, \text{error}) \qquad (1)$$

indicates a relationship between location and failure. If a linear discriminant model is appropriate, then a logit discriminant formulation is valid. In this case,

$$\ln\,(F_i/1\text{-}F_i) = \beta_0 + \beta_1 d_{i1} + \dots + \beta_6 d_{i6} + e_i \qquad (2)$$

If it is the case that some dimensions have nothing to offer in the failure/success dichotomy, it will then be found that the corresponding β coefficients will take near zero values.

Dimensions one and four yielded p-values of 0.0000, thus suggesting that they play a major role in judging the solvency position of a firm. It was also proved that the third dimension, which had a p-value of 0.0093, also makes a contribution to the prediction of company failure. Hence, the above results suggest that a map drawn only in the first, third and fourth dimension may provide an adequate representation of the salient features in the data. It is normally possible to attach meaning to the dimensions found important. This will be explored below.

Interactions and non-linearities were also explored by using the squares and some cross products of the co-ordinates in equation 2 as regressors. The results, however, indicated that the only non-linear term that can significantly add to the prediction of failure was the square of the first co-ordinate. This finding is of great importance as it suggests that some dimensions can act in a non-linear way, thus proving that multivariate techniques that assume linearity, e.g. linear discriminant analysis or the forms of logit traditionally used in this kind of research, fail to capture the richness of a data set. Similar results were also reported by Mar Molinero and Serrano Cinca (2000). The representation of the companies in dimensions 1 and 4 is shown in Figure 2.

Figure 2

Multidimensional Scaling representation of UK companies (1988-1997)

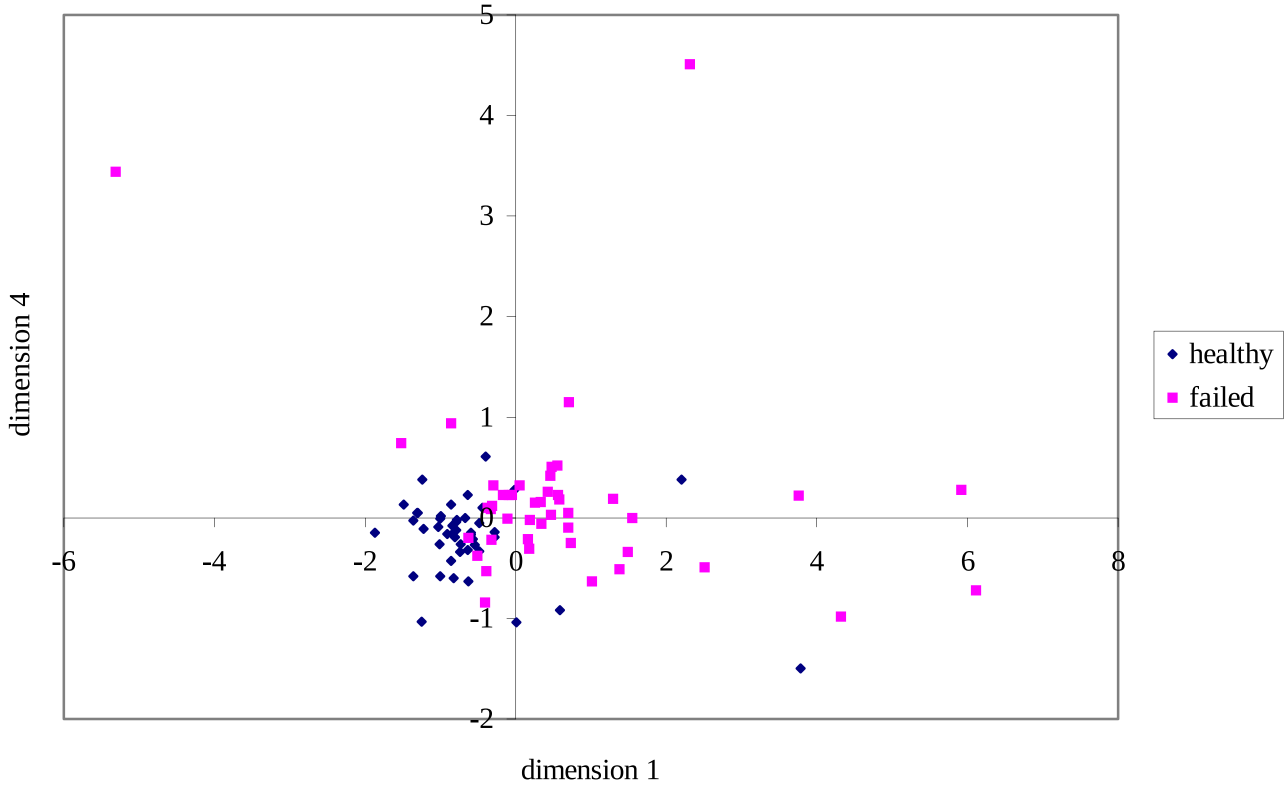

Figure 2 above, is of crucial importance. It is the projection of the six dimensional map in the first and fourth dimension. Each point of the map represents a company, either failed or healthy. This is shown by means of points with different shapes in the representation. It can clearly be seen that failed companies fall towards the right-hand side of the map, while healthy firms are clustered on the left-hand side. This observation suggests that the first dimension is a powerful failure indicator[10]. Moreover, it is clear that an imaginary curved line exists that leaves the majority of the failed companies on the right-hand side and most of the continuing companies on the left-hand side of the map. This finding also enforces the argument that linear discriminant analysis is inappropriate for these kinds of analyses.

Figure 4 of the appendix plots the companies in the same way as Figure 2 with the only difference that instead of distinguishing between failed and healthy companies, it gives the estimated probability of failure for each company, as calculated from a simplified logit model, which included only the dimensions found important in explaining corporate failure, i.e. dimensions one, three and four.

ProFit Analysis

ProFit analysis, which stands for Property Fitting, is a technique used to interpret the maps. It attempts to explain up to what point the value that a particular ratio takes for a given company is associated with the position in the space of the point that represents that company. ProFit analysis is regression based. It summarises the results of a linear multiple regression analysis using the financial ratio as the dependent variable and the co-ordinates in the configuration for each company as the independent variables. According to Kruskal and Wish (1978), by performing ProFit analysis "we seek some weighted combination of the co-ordinates of the configuration which agrees with or "explains" the variable as well as possible". The R^2 of the regression is one measure of how well this can be done[11]. Graphical representation of regression results does not take place if R^2 falls below a certain cut-off value. In this case, the cut-off value was taken to be 70% and resulted in ten ratios not being represented in the map. This suggests that those ratios are not relevant to the classification problem.

Hence, forty multiple regressions were run using each financial ratio in turn as dependent variable and the six co-ordinates of the points in the space as explanatory variables. Table 5 of the appendix reports the results of this analysis: note that in half of the cases the R^2 value exceeds 80% and in 30 out of the forty cases it exceeds 70%, thus indicating a sufficient fit. The table also presents the regression coefficients of the dimensions[12] along with their respective level of significance.

The results of ProFit analysis are represented as lines through the six-dimensional space. The lines are drawn through the centre of the MDS configuration. They can only be seen in projection and their slope and orientation cannot be assessed unless made explicit. To help with the interpretation, a unit dimensional vector is associated with each line. All directional vectors start from the origin of co-ordinates and their ending is projected. Thus, if a vector is wholly contained in the subspace formed by, for example, dimensions 1 and 4, it will appear in the representation as being unit length. If the vector is orthogonal to this subspace, it will project in the centre of coordinates. The nearer to the centre of coordinates the ending of the vector is, the lower the emphasis to be placed on this vector for interpretation purposes, within the projected space being studied.

In this particular case, each ratio is represented in the form of a small marker, which represents the end point of the respective vector, in dimensions 1 and 4 (figure 5) and in dimensions 1 and 3 (figure 6)[13]. To further facilitate interpretation, Hierarchical Cluster

Analysis (HCA) was performed (Johnson, 1967). The Euclidean distance between the end point of the vectors in the six-dimensional space was calculated and used for clustering purposes, by applying the 'between-groups linkage' cluster method provided by SPSS v.9.0 package. The resulting points and the cluster outlines in dimensions 1 and 4 and in dimensions 1 and 3 can be seen in figures 5 and 6, respectively.

A quick examination of the figures 5 and 6 reveals that financial ratios tend to group around distinct clusters, thus indicating that not all of these neighbouring ratios are necessary to describe a given aspect of the financial position of a firm. Instead, the most representative ratio from every cluster can be used, e.g. the most central ratio. Two major distinct clusters appear in both figures; a cluster that falls on the far left-hand side of the graph, which contains ratios belonging to the profitability and operating cash flow categories, and a rather bigger cluster falling towards the middle/right-hand side, which groups ratios mainly from the financial leverage and liquidity categories.

The fact that profitability and operating cash flow ratios are grouped together comes to no surprise since the two concepts are closely related: net cash flow from operating activities differs from net income for three reasons: "noncash" expenses, timing differences and "nonoperating" gains and losses. In the short-run, profitability is usually overshadowed by apparently more important liquidity considerations, e.g. operating cash flows, but in the long-run an entity that is not profitable cannot remain in the business because it will not generate profits that will enable it to meet its obligations.

Similarly, a company's liquidity and financial leverage position are also closely related: liquidity refers to the firm's ability to generate sufficient funds (working capital) to meet current operating needs and to repay current (short-term) debts promptly; financial leverage ratios indicate the firm's dependence on borrowed money, hence they are used to assess the firm's solvency position, i.e. its ability to meet the required interest and principal payments of its long-term debts (high leverage is usually associated with lower solvency capacity). If a company possesses insufficient liquidity to meet its due short-term obligations, then its ability to obtain long-term commercial credit is reduced.

The cluster analysis results, along with the results of ProFit analysis (table 5) can facilitate now the interpretation of the three dimensions found to be associated to the failure event. Dimensions 1 and 4 seem quite straightforward to interpret: dimension 1 appears to be related with the profitability/operating cash flow position of a firm and dimension 4 with its financial leverage/liquidity position. The interpretation of dimension 3, however, requires some extra time and a closer look at table 5 and the two figures. A small cluster seems to be directly related to this dimension: it groups three profitability ratios (ebitseq, wcfonw & roe) and is located in the middle/lower part of figure 6. These three ratios are of great importance to the ordinary shareholders, as they represent different variations of the return they earned for their investment in the company. Therefore, dimension 3 relates to the shareholders' return and it complements dimension 1. It is also worth noting that after spending some time examining the results of ProFit analysis, we concluded that dimension 2 is associated to the activity-ratio category. But as dimension 2 was not found to be related to the failure event, it is reasonable to deduce that activity ratios cannot discriminate failed from healthy companies. This conclusion was also drawn by many insolvency prediction researches (e.g. Beaver, 1966; Ohlson, 1980).

To summarise, it can be stated that the most important determinants of corporate failure are the profitability/operating cash flow and financial leverage/liquidity positions of the companies. Here it should be noted that these findings are in agreement with the empirical results of Charitou, Neophytou and Charalambous (1999) who applied logit analysis and

Neural Networks to corporate failure prediction using the same data set. In specific, their final insolvency prediction models, which yielded in high training and testing classification results, consisted of the following three variables: total liabilities to total assets (tlat), earnings before interest and taxes to total liabilities (ebittl) and cash flows from operations to total liabilities (cffotl). This agreement of results further supports the claimed superiority of MDS, which offers intuitive representations of statistical results, while, at the same time, it yields the same results that would be generated by the use of more traditional statistical approaches.

V. Using multidimensional scaling in practice

MDS diagrams can help practitioners assess the financial health of a company that was not included in the original analysis. The company in question can be superimposed as a new point on the MDS map, which was previously derived from a training data set. Thus, if this new point falls amongst the healthy companies, then the probability of this company failing in the near future is minimal. However, if the ratio structure of the new company is similar to the ratio structure of other companies that failed in the past, then the new point would fall amongst the failed companies, hence raising serious doubts as to the ability of this entity to remain as a 'going-concern'.

Two alternative ways exist in which new companies can be added to the data set: re-estimation and reverse use of profit analysis. When applying the latter method, each profit line is calibrated by adding a scale of measurement. These scales can then be used to approximately locate any new company on the configuration. Although this method may not be exact, it is simple and effective. Having in mind that an exact result is not really necessary, this method can be easily applied by practitioners seeking to evaluate a company's financial position.

Several ways currently exist in which re-estimation can be performed. One possibility is to fix in the space the points that represent previously studied companies and estimate the optimal position for the new company with a restricted version of the MDS algorithm. However, this option was not available in the version of SPSS that was used for this study. Another possibility is to add each new company in question to the original data set (one at a time) and repeat the analysis. This approach was followed in order to assess the financial health of the ten companies that were held as a holdout sample.

As already mentioned, five of these companies failed during the two-year period 1998/99 and the other five are the respective healthy ones (in terms of financial year, industry and asset size). The final configuration of the companies, according to our MDS model, can be viewed in the following figure. For convenience, the points representing the holdout companies are numbered from 91 to 100 and the respective company names can be found in table 1.

Figure 7
Multidimensional Scaling representation of the holdout companies

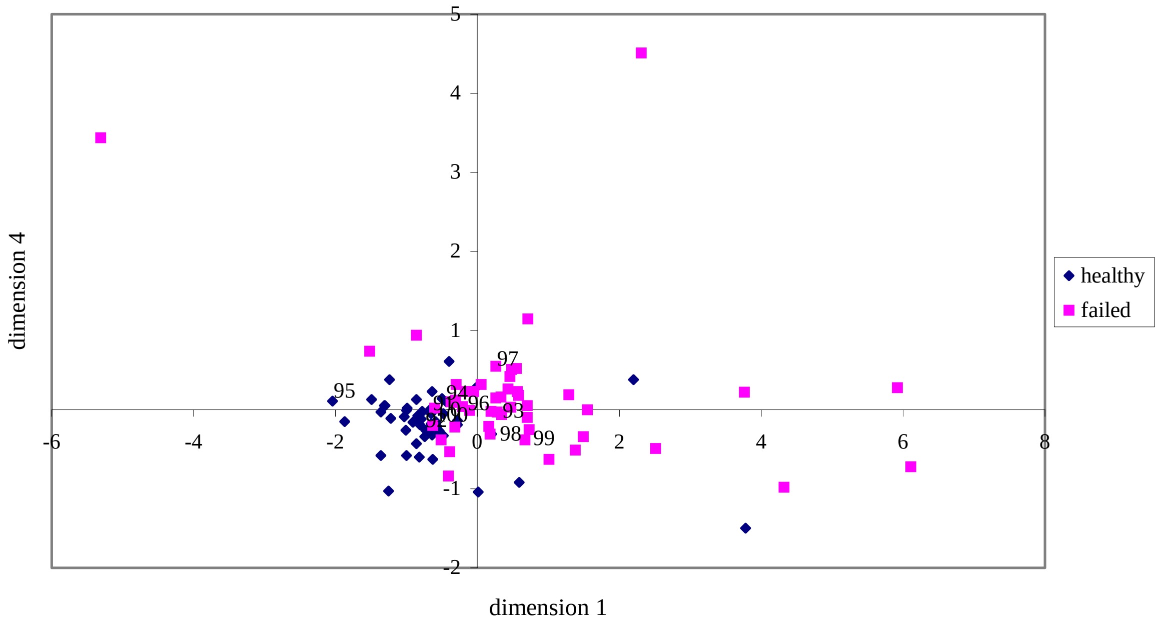

Figure 7 reveals that eight out of the ten companies in question fell within the ‘correct’ group of companies, i.e. the four healthy new companies fell amongst the healthy original companies and the insolvent ones amongst the failed. However, two companies were ‘misclassified’: Waste Management International plc (no. 91; failed company) and Stoddard International plc (no. 98; healthy company).

A brief further investigation has then been carried out in order to identify any particular problems that these two companies might have experienced during that period. Waste Management International plc 1998 liquidation appears to be a voluntary one as its US parent company, Waste Management Inc., decided to buy back the roughly 20% of shares not owned by the Waste Management group and make it a wholly-owned business unit[14]. Therefore, the ratio structure of this company is far from similar to the ratio structure of previously failed firms, consequently making it impossible for the MDS model to identify it as a potential failure. The same problem would have been faced by any other classification technique and suggests that voluntary liquidation can be very different from more usual forms of failure. In fact, MDS can be used to assess the extent of this difference and arrive at conclusions beyond the statistics.

As far as Stoddard International plc (previously named Stoddard Sekers plc) is concerned, investigation revealed that the company had very serious difficulties during the financial year 1997/98, with its shares sinking 60% in a single day in the anticipation of a huge trading loss and of no final dividend[15]. However, the company managed to survive after disposing a loss-making subsidiary and getting a completely new management team, which proved to be extremely competent. Thus, it could be argued that the model has correctly classified this company as a failed one and that a totally new company rose out of the failure.

VI. Conclusions

It has been argued that Multidimensional Scaling offers an alternative to existing models for the prediction of company failure. MDS has advantages over standard approaches in the sense that the results of the analysis are much more accessible to the non-initiated. MDS relies on relations of order and does not suffer from extreme observations problems, although the representation is much more attractive when extreme observations are removed.

The use of the technique has been demonstrated with respect to a previously analysed data set, which includes both failed and non-failed companies. MDS maps have been produced and it has been shown that failed and non-failed companies fall in clearly distinct areas within the maps. Further interpretation of the maps was performed using standard multivariate statistical approaches: cluster analysis, linear regression and logit. A holdout sample was used to test the classification accuracy of the model. The history of the companies that the model failed to classify properly was studied and shown to conform to modelling expectations.

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[1] The multiple linear discriminant approach (LDA) is based on the following assumptions that are frequently violated: a) the independent variables are multivariate normal and b) the covariance matrices of the two groups (failed and nonfailed) are equivalent.

[2] For the advantages of logistic regression over LDA see Ohlson (1980) and Mensah (1984).

[3] It should be noted that the training data set, which includes companies that failed between 1988 to 1997 and their respective healthy ones, was also employed by Charitou, Neophytou and Charalambous (1999).

[4] For a discussion of the advantages of matched samples refer to Zavgren (1983) and Jones (1987).

[5] The Insolvency Act of 1986 provides five courses of action for insolvent companies: Administration, Company Voluntary Arrangement (CVA), Receivership, Liquidation and Dissolution.

[6] The advantages of using an out of sample period ex-ante test are discussed by Jones (1987).

[7] All statistical results reported in this paper were obtained by means of the SPSS 9.0 statistical package. SPSS provides several other alternative measures of dissimilarity, e.g. Squared Euclidean Distance, Chebychev, Block, Minkowski.

[8] The cut-off limit for eigenvalue extraction was set at 0.8 in line with Jolliffe's (1972) recommendation.

[9] ALSCAL was originally designed and programmed by Young, Takane and Lewyckyj and it is incorporated into SPSS 9.0 statistical package.

[10] Figure 3 of the appendix, which plots the companies against the first and third dimension, further supports the discriminating power of the first dimension.

[11] A good description of ProFit analysis can be found in Shiffman, Reynolds and Young (1981).

[12] In order to enable the graphical representation of the ratios (Figures 5 & 6), the coefficient weights were standardised so that their sums of squares equal to 1 for every scale.

[13] The reason of representing only the end point of the vectors involved and not their projected lines, is mainly aesthetical; the use of lines would have resulted in an overloaded figure from which it would have been difficult to draw conclusions.

[14] Information Access Company, a Thomson Corporation Company; IAC (SM) Newsletter Database (TM), Copyright 1999 Profitastral Ltd; Haznews, January 1,1999.

[15] Global News Wire, Copyright 1998 The Herald (United Kingdom), February 27,1998.