Bank failure: a multidimensional scaling approach

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Mathematical models for the prediction of company failure are by now well established. Most of the work on multivariate modelling of distress prediction attempts to obtain a score that gives the failure probability of a company. A data set of 66 Spanish banks, 29 of which failed, is used to show that multidimensional scaling (MDS) techniques can be of use to produce simple tools for the analysis of financial health. MDS has the advantage of producing pictorial representations that are easy to interpret and use. This is done without loss of statistical rigour given the very close links between MDS and other multivariate statistical techniques that are normally used in the analysis of failure. As an example, the technique is used to trace the financial path of an ailing bank.

Keywords: bankruptcy prediction, financial ratios, multidimensional scaling, box and whiskers diagrams, Spanish banking system

1. INTRODUCTION

Mathematical models for the prediction of failure are by now well established. Two of them are prevalent in the literature: logit and discriminant analysis. In recent times there has been an interest in the use of neural networks in this context.

Discriminant analysis makes unrealistic demands on the structure of the data. The statistical issues have been studied by Eisenbeis (1977). Linear Discriminant Analysis (LDA) starts from the premise that two different populations coexist in the data set, one of failed and one of continuing firms. For LDA to be appropriate, both populations need to be described by multivariate normal distributions with the same variance-covariance matrices, although their means are presumed to be different. Richardson and Davidson (1983 and 1984) survey the financial ratio literature for evidence of model validity and also perform their own empirical investigations; they conclude that, within this area of knowledge, the assumptions underlying LDA are not satisfied. Eisenbeis suggests the use of Quadratic Discriminant (QDA) models, which are less demanding in terms of assumptions, although there is a severe price to pay: models become much more difficult to estimate and implement. Nevertheless,
Richardson and Davidson (1984) warn against the use of QDA and suggest that logit or probit should be used in practice.

Logit analysis shares the same mathematical basis with LDA (Haggstrom, 1983), but is slightly less demanding in terms of assumptions. In particular, logit does not require multivariate normality (Lo, 1986). Logit uses the logistic function as a discriminant device, although this function is only chosen because of its mathematical properties. It is just a convenient tool. The logit model, by transformation, can be linearized, and in this form it has an attractive interpretation. It explains the odds that an observation has of belonging to either population: failed or healthy. There are alternatives to the logistic function that have similar mathematical properties but these cannot be linearized and do not have simple interpretations.

Both logit and discriminant analysis require, before implementation, a selection of the variables that enter the model. The selection of the final set of variables is complex, delicate and important, see Davidson and MacKinnon (1984) for a discussion of specification issues in the logit model. It is difficult to discard the fear that an important variable has been missed or that a spurious one has been included. Furthermore, both models are sensitive to discordant observations (Pregibon, 1981). Modelling must always start by addressing the problem of outliers, not an easy task as discussed in Ezzamel and Mar-Molinero (1987 and 1990). Landwehr et al. (1984) suggest some graphical methods that could be used to assess the validity of logit models.

Neural networks models, such as the multilayer perceptron (MLP) may also solve classification problems. MLP has been used in studies on company failure, such as the one carried out by Altman et al. (1994). Trigueiros and Taffler (1996) offered a precise reflection on the situation of research into neural networks dealing with accounting information.

From the point of view of the practitioner, the methodologies described above share the common characteristic of requiring a strong knowledge of statistics in order to understand and use the models. Practitioners may be obliged to use results in a 'black box' mode and may find it difficult to combine statistical results with the exercise of judgement.

An alternative model for the analysis of company failure, multidimensional scaling (MDS), which bypasses many of the above shortcomings was suggested by Mar-Molinero and Ezzamel (1991). Their study was, however, concerned with explaining the process that a company follows on its path to failure rather than with prediction.

In this paper we extend that work and suggest a way in which MDS models can be used as an alternative to discriminant analysis or logit in order to classify companies as failed or continuing. The use of MDS type of techniques has the further advantage that the results of the analysis can be presented in the form of maps which have intuitive interpretation. Implementation does not make any sophisticated statistical demand on those who will have to live with the model. This is done without loss of rigour since MDS can be shown to be equivalent to other more traditional techniques when certain restrictive assumptions apply. What MDS offers is a different paradigm, a different way to look at the problem. The power of MDS lies in its accessibility. The results of MDS analysis can be
interpreted without a deep understanding of the statistical underlying principles. MDS makes calls on the intuition of the user rather than on his/her knowledge of statistics. It is also the case that MDS is robust to the presence of outliers in the data.

The paper starts with a brief description of MDS and a summary review of applications of MDS in the accounting and finance area. The technique is then used to analyse the financial ratios of a sample of Spanish banks, and it is shown that there were clear differences between healthy banks and those that had financial difficulties. The MDS representations that were obtained are used to trace the evolution of a bank that failed after the crisis was over. It is argued that this last bank could have been identified as being at risk long before failure took place.

2. MULTIDIMENSIONAL SCALING MODELS

Multidimensional scaling models are well established in the multivariate analysis literature. MDS encompasses a set of techniques based on graphical representations. The end result of a MDS analysis is a statistical map. It would be inappropriate to describe here the basis of MDS; there are many introductory texts that can serve that purpose such as, for example, the one by Kruskal and Wish (1984).

Ordinary geographical maps are sophisticated mathematical instruments: they contain axes of references (scales) that locate the position of any point by means of a set of coordinates. Several scales may be present: for example, if three scales are present they may be associated with latitude, longitude, and altitude over the level of the sea. Maps also have orientation: it is general practice to locate points that have latitude north towards the top of the map, although other conventions are possible, provided that an indication is given of the way in which the position of the points is related to their latitude. Finally, a map makes it possible to calculate the distance between any two points, and to build a table of distances between pairs of points. If the distance between two points is small, they appear near to each other on the map and if the distance between two points is large, they appear far apart. Thus, visual inspection of the map helps to come to grips with distance considerations.

MDS proceeds in the opposite direction. It produces a map from a table of distances. When the distance between any two points is small, MDS locates them near each other in the map; when the distance between a pair of points is large they get located far apart. In this way, visual inspection of the map may provide insights into the information contained in the distance matrix. MDS creates scales of reference as part of the process of locating points in the space. It is possible to orient a MDS map by giving an indication of the direction in which a particular characteristic (property) of the data is related to its position in the space. This subject will be discussed in full below. The advantage of MDS is that maps can be constructed from information about proximity between any two points: input data does not have to be limited to Euclidean distance. It is, in fact, this characteristic that makes the technique so useful. The technique is robust to many different kinds of input data; see Coxon (1982).
A particularly interesting aspect of MDS maps is robustness to discordant observations. If the distance between a point and the rest is very large, this point will just be situated far apart from the others. The proximity relationships between the remaining points will not be affected (although care has to be exercised when using interpretative techniques such as profit analysis). This contrasts with other techniques that have been employed to analyse failure, which tend to be sensitive to outliers. An extreme case of sensitivity to outliers is Data Envelopment Analysis, Smith (1990) and Fernández Castro and Smith (1994).

MDS is not the only statistical technique that allows the graphical representation of multivariate data. Principal Components Analysis (PCA), which does not rely on distribution theory either, comes to mind as an obvious alternative and, indeed, in the special case when the data has been standardized, correlations are the measure of similarity, and distances are taken to be euclidean, both techniques will produce identical maps; see Chatfield and Collins (1980) or Mar-Molinero (1991). PCA normally starts from a data set made up of variables and cases, while the starting point for a MDS analysis is a set of distances, or dissimilarities, which can be calculated in a variety of ways. Furthermore, PCA relies on the value of the correlation coefficient while MDS can be performed in a metric way, using the actual values of the dissimilarity measures, or in a non-metric way, relying on the ordering of dissimilarities. In this way, MDS is a much more flexible and powerful tool than PCA.

The relationship between MDS and PCA has been a matter of much research, the subject having been discussed by, among others, Shepard (1972), Lingoes (1971), MacCallum (1978) and Balloun and Oumlil (1988). The general conclusion appears to be that both nonmetric MDS and PCA yield 'the same message' about the data. A non-metric version of MDS, due to Kruskal (1964) is used in this research, but PCA was still used in order to assess the number of dimensions in which the map should be constructed.

There are many ways in which measures of dissimilarity can be created. No particular demands are placed on the data other than there must be a message in it. This has been taken advantage of in accounting and finance. An early application of MDS in accounting is given by Green and Maheshwary (1969) who give an account of how the technique works. Rockness and Nikolai (1977) used an extension of MDS to investigate patterns of voting behaviour in the Accounting Principles Board of the United States; their measure of distance required the exercise of judgement in order to evaluate the extent to which any two members of the board behaved in the same manner. Decision-making in the Financial Accounting Standards Board of the US was also studied by means of MDS, Brown (1981). Belkaoui and Cousineau (1977) asked a group of students to exercise judgement in order to assign an index of similarity to pairs of companies on the basis of published accounting information; MDS was then used to test a series of hypotheses on the way the companies are perceived. The same judgemental approach was employed by Belkaoui (1980) to study 'linguistic' differences between various accounting groups and by Pratt (1982) to study the value of accounting information to investors. International comparisons between accounting principles were carried out by Frank (1979)
using MDS. The evolution of accounting research was studied by Beattie (1993) by means of a bibliographic procedure based on MDS.

MDS has also been employed to clarify auditing issues. Libby (1979) studied the message conveyed by the audit report basing his analysis on the judgement of experienced professionals. Bailey et al. (1983) asked whether the wording used in an audit report influences the message that is perceived from it; again, students and subjective ratings of similarity formed the basis of a MDS study.

Conjoint Analysis, a technique akin to MDS has also figured in the accounting literature, examples are Moriariry and Barron (1976) and Emery et al. (1982) and the references given there.

Most published MDS research in accounting use similarity measures based in one way or another on the quantification of judgemental data. There is, however, no reason why MDS should not be used to analyse quantitative data, such as financial ratios. This is what was done by Mar-Molinero and Ezzamel (1991) and Mar-Molinero et al. (1996) who used as a measure of dissimilarity the absolute value of correlation coefficients and the INSCAL model of Carroll and Chang (1970). Mar-Molinero and Ezzamel explored the way in which ratios evolve as a company approaches failure. Ratios were taken to be variables and companies to be cases in the calculation of similarity measures. The situation is reversed in this paper. Banks are taken as variables and ratios as cases. This makes it possible to explore up to what point any two banks are similar or different on the basis of published accounting information. Obviously, the objective of the exercise is to find out if failed banks tend to group in one area of the map and non-failed banks in a different area. If the two areas are disjoint enough, the map can be used for prediction purposes. This is exactly what was found in the case presented here. Multidimensional scaling forms the basis of the study carried out by Mar-Molinero et al. (1996). In that study, the ratings given to a set of companies are analysed in the light of available accounting information.

3. THE PREDICTION OF CORPORATE FAILURE WITH MDS: AN EMPIRICAL APPROACH

Between the years 1978 and 1983 the Spanish private banking system went through a deep crisis. This crisis received little publicity, probably because it did not result in redundancies or bank failures, although a particular bank lost its licence. The whole episode has been documented in Spanish in the yearbooks of the Bank of Spain and of the Deposit Guarantee Fund, its supervisory division. There are good accounts in English by Rodríguez (1989) and Laffarga et al. (1988).

The Spanish banking system had long been accused of oligopolistic practices (Tamames, 1968). An attempt was made to open it to competition with the approval of new banks in the 1960s. It has been argued that some of the new entrants engaged in unorthodox practices such as opening too many new branches, giving large loans to risky customers and issuing new credit facilities to cover up failures to pay. This resulted in high operating expenses, high investment in fixed assets and imprudent management practices. The financial
crisis that swept the world during the 1970s was, at first, unnoticed in Spain due to its relative isolation from international financial markets, but when it arrived it was particularly deep. In 1977 the Bank of Spain, the regulatory body, created the Deposit Guarantee Fund (Fondo de Garantía de Depósitos, FGD) which was to act mainly as an insurance system. The first bank to require support from the FGD was the Banco de Navarra in 1978. In the years between 1978 and 1983, 51 private banks out of a total of 108 needed the support of the FGD. During this time the role of the FGD evolved, being responsible for taking over ailing banks, restructuring their capital and putting them back into private ownership (Rodríguez, 1989). In common with other studies, a bank will be considered to have failed if it had fallen into the safety net provided by the FGD.

The Spanish banking crisis has been extensively studied with the aim of trying to establish if the banks which suffered financial difficulties could have been identified from available public information. Several statistical techniques have been deployed to answer such a question. Laffarga et al. (1988) used both univariate statistical analysis and linear discriminant analysis; Rodríguez (1989) used logit analysis while Martín-del-Brío and Serrano-Cinca (1993) approached the same issue with a model based on self-organizing neural networks. Serrano-Cinca (1997) used another neural network model: the multilayer perceptron.

### 3.1 The data

The data used in this study have been obtained from official sources and has been published by Serrano-Cinca (1997). It consists of nine financial ratios calculated on 66 Spanish banks, 29 of which failed; i.e. were relifted by the FGD. Information for continuing banks refers to the 1982 financial year, while the ratios for failed banks were calculated for the last year before failure. A detailed exploratory data analysis of the financial ratios used is available in Serrano-Cinca (1997). It includes a normality test and a study of the discriminatory power of the ratios. Besides Serrano-Cinca (1997), the data has been analysed by Laffarga et al. (1986), Pina (1989) and Martín-del-Brío and Serrano-Cinca (1993). Among the ratios, the first three measure liquidity, the fourth is associated with the ability to self-finance, the next three are profitability ratios, ratio number eight measures the cost of sales and, finally, ratio number nine relates to cash-flow. The ratios are not subjected to any preliminary analysis in order to remove those that are highly correlated with others. MDS can cope with highly correlated data and with redundant information.

A problem to be faced in a study of this type is that each one of the different ratios used to describe a bank is measured in different units. The easiest way to avoid this problem is to standardize ratios to zero mean and unit variance. This procedure is equivalent to changing the original ratios which describe a bank into a set of multiple orderings, one for every ratio. The advantages and disadvantages of working with orderings have been extensively discussed in the literature; see, for example, French (1985). The main disadvantage of working with orderings is that the introduction of an extra bank in the data set may impact on all the standardized data. This is of no consequence in MDS since the relative position of any two banks in the final representation will not be affected (although the exact coordinates which locate each one of them will change),
thus we chose to standardize each financial ratio to zero mean and unit variance and compare banks on the basis of their standardized ratios.

An analysis of discordant observations was carried out by identifying the banks for which one or more of the financial ratios exceeded a standardized value of two and one half. MDS should be robust enough to cope with discordant observations. To check that this was the case, the full analysis was repeated with and without the discordant banks. The maps were less cluttered, and more visually attractive, when the discordant banks were omitted but, as expected, the relative position of individual banks was not affected, and it was decided to include all the banks in the reported results.

It is possible to think of many ways of comparing individual banks, and various measures of similarity were derived from the data. The results were found to be robust to the choice of similarity measure. To make this study comparable with those published by other authors, the maps produced here employ as similarity measure the correlation coefficient between banks using standardized ratios as variables. This correlation coefficient is then treated as a Euclidean distance. The advantage of proceeding in this way is that the parallelism with PCA is maintained. Furthermore, the use of correlation coefficients as distances will ensure that if the assumptions that underlie discriminant analysis are satisfied, a hyperplane through the final configuration of the MDS map will produce the same classification as LDA. However, MDS results suggest that LDA is not appropriate for this data and that a non-linear classification function should be used. This is consistent with the findings of Richardson and Davidson (1984).

3.2 Results of MDS analysis

The first decision to be taken in any MDS analysis is the choice of the number of dimensions in which the map is to be drawn. To this effect, the similarity matrix was first the subject of a PCA study. It was found that the first three principal components accounted for 93.3% of the variance, the first component accounting for 52.9% of the variance, the second for 28.4, and the third for 12.1%. Thus it appears to be the case that a map in three dimensions is sufficient to describe the data. Martikainen (1993) used 11 ratios in his analysis and commented that the data could be reduced to three or four components. By contrast, Mar-Molinero and Ezzamel (1991), in common with previous studies reviewed there, found it necessary to use seven dimensions to describe the financial health of a company.

Another way of establishing the dimensionality of the map is to produce the MDS map in six, five, four, three, two and one dimensions and observe how the number of dimensions influences the quality of the representation. There are various ways in which goodness of fit can be assessed in MDS. All these measures are based on a normalized sum of squares, the normalization procedure being different in the various approaches (Kruskal and Wish, 1984). As in previous studies, Young's stress 1 formula was chosen. The results are given in Table 1.

It is apparent from the results that a solution in six dimensions gives an almost perfect representation of the data, a conjecture that is confirmed by
Table 1. Values of the raw stress coefficients (Young's stress 1 formula)

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Stress</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.211</td>
</tr>
<tr>
<td>2</td>
<td>0.060</td>
</tr>
<tr>
<td>3</td>
<td>0.027</td>
</tr>
<tr>
<td>4</td>
<td>0.015</td>
</tr>
<tr>
<td>5</td>
<td>0.006</td>
</tr>
<tr>
<td>6</td>
<td>0.002</td>
</tr>
</tbody>
</table>

examining Sheppard's diagram, which collapses into a straight line. Perhaps a solution in three dimensions, as suggested by PCA, is appropriate for most purposes, but it was decided to work in the first instance with six dimensions. The solution gave, for every bank, a set of six coordinates that locate the bank in the space. It is, however, possible that some of the dimensions may not be associated with the probability of failure. The projection of the six-dimensional map in the first two dimensions can be seen in Fig. 1.

The map, like all other statistical results reported in this paper, was obtained by means of the package SPSS PC for WINDOWS, Provan (1993). Each point in Fig. 1 is a bank. Each point is identified by means of a number, which corresponds to the number given to it by Serrano-Cinca (1997). In this way it is possible to compare the MDS results given here with the results obtained with other techniques, such as logit, LDA and MLP. Another characteristic of a bank that has been displayed is whether the bank has failed or is continuing to trade. It can clearly be seen that failed banks fall towards the right-hand side of the map while continuing banks fall towards the left-hand side. This suggests that the first dimension is a powerful failure indicator. It is also possible to draw a curved line that leaves most failed banks on the right-hand side and most continuing banks on the left-hand side. This would be the exact equivalent of doing non-linear discriminant analysis. A more sophisticated approach would be to accept that there is a region of space clearly associated with failure, a region of the space clearly associated with success, and a region of space where anything can, and does happen. What is surprising is the narrowness of the region where failed and non-failed banks coexist.

Visual inspection of the maps produced by projecting the points of the space on different pairs of dimensions suggests that only the first two are related to failure prediction and that the relationship is non-linear. To confirm this conjecture two logit analyses were performed.

First, a traditional logit model was estimated, as done by most researchers such as Ohlson (1980). The dependent variable was a dichotomy, zero in the case of a continuing bank and one in the case of a failed one. The coordinates in the six-dimensional space of the points that represented the banks were used as explanatory variables. Only the first two dimensions returned coefficients which were significantly different from zero at the 95% level. The fourth dimension returned a coefficient that was just marginally insignificant at the 90% level. This
suggests that a map in the first two dimensions may give an appropriate visual representation of the salient features in the data. The fourth dimension may have something to contribute to the prediction of company failure, but given its relative little weight and the uncertainty associated with the relevant coefficient, it was decided that what was to be gained by working in two dimensions far outweighed the loss in predictive ability that might derive from the exclusion of the fourth dimension.

Non-linearities were explored in the second set of logit estimations. If, as Richardson and Davidson (1983 and 1984) suggest, different variance-covariance matrices should be used in the modelling of failed and non-failed companies, then QDA is more appropriate than LDA as a discrimination tool, in line with Eisenbeis (1977). This, in turn, implies that if logit is used, non-linear terms should be included in the regression. In line with generalized linear models.

**Fig. 1.** Multidimensional scaling representation of banks in Spain. Projection on the first two dimensions with profit analysis results. Empty circles correspond to continuing banks, and full circles to failed banks.
standard practice, a saturated model, with quadratic and interaction terms, was first estimated and later simplified using standard procedures (Dobson, 1990). It was found that the only non-linear term that could be said to be needed in the logit analysis was the square of the second coordinate. This suggests that the second dimension acts as in a non-linear way, and that linear discriminant analysis fails to capture the richness of the data set.

For every bank, logit analysis returned a probability of failure based on its position in the six-dimensional space. In fact, probabilities of failure could also be calculated for other points in the space which could be occupied by hypothetical banks. Thus, every point of the space can be allocated a probability of failure. Points in the space which had the same value for this probability of failure were joined by what we decided to call an iso-solvency surface. MDS provides a methodology to display the main features of the data. It is not an inferential tool, and no diagnostic statistics exist, as is the case in other statistical techniques such as logit, although attempts have been made, notably by Ramsay (1982), to develop a statistically based approach to MDS. What we are doing in this case is to combine the statistical properties of logit with the insights provided by MDS.

Since only two dimensions are included as explanatory variables in the logit model, the iso-solvency surfaces become lines in the projection of the map into those two dimensions. Figure 2 shows these iso-solvency lines. The iso-solvency lines extend the concept of discriminant analysis in the sense that they show that there is no simple frontier between the area occupied by failed banks and the area occupied by non-failed banks. Nevertheless, a simplistic classification rule, which ignores the cost of misclassification, would be to take the 0.5 iso-solvency line as discriminant. When this was done, it was pleasing to see that the best model explored only misclassified four points, and the worse, seven. These results are consistent with the findings of previous studies: Laffarga’s et al.
al. (1986) linear discriminant model misclassified seven points, Pina’s (1989) logit misclassified four and Serrano-Cinca’s (1997) MLP misclassified four.

3.3 Profit analysis

The previous section has concentrated on the construction of a map in which it can be seen that failed banks, the year before they fail, are different from continuing banks. This section explores the possible interpretation of the above results.

A first attempt at interpreting the data was done by means of cluster analysis, and this, combined with knowledge of the individual banks, revealed some interesting features of clearly failed and clearly non-failed banks. The results are not reported here. Much more informative was the attempt to see how the position of a bank in the space was associated with the financial structure of the bank. This was done by means of profit analysis. A good description of this technique can be found in Schiffman et al. (1981).

Profit analysis is regression based. It attempts to explain up to what point the value that a particular ratio takes for a given bank is associated with the position in the space of the point that represents the bank. There are various ways in which profit analysis can be conducted. We chose the metric, rather than the non-metric approach, to benefit from the relationship between profit and regression analysis, as described by Mar-Moliner (1991). A set of multiple regressions were run using as dependent variable, each financial ratio in turn, and as independent variables the coordinates of the points in the space. The results were represented in a graphical way in Fig. 1. Regression does, of course, generate many diagnostic statistics but these are not reported here. The results were surprisingly good. In every case, the value of the $R$-square statistic was well in excess of 0.9. For every ratio, a line is drawn through the space in such a way that the value of the ratio increases in the direction of the line. Profit analysis clearly shows the first dimension to be associated with profitability and the second to be associated with liquidity. If one looks at the lines that represent profitability and liquidity ratios, the clear message is that profitability was the most important determinant of bank failure although liquidity also played a part.

3.4 A case study

The approach discussed here can improve decision-making since it improves the quality of the information available. We now have more than a mere solvency indicator. It is easy for a user to evaluate the characteristics of a bank in the context of the other banks for which data is available, it is also possible to put qualitative information into context. First, the model shows whether the bank is solvent or at risk and, second, the probability of failure that would have been allocated by a logit model. Beyond this, profit analysis highlights the financial characteristics that stand out. As an example of the application of the technical apparatus described here we will follow the evolution of a particular bank, the Banco de Descuento, from 1973 to 1990. Each year is treated as a different point in the space. Only 1979 accounts have been used to construct the map.
This case study raises the issue of how the MDS diagrams can be used in practice to evaluate the financial health of a bank that was not included in the original analysis. Like in most research devoted to financial scoring, the normal mode of operation would be to derive a map such as the one in Fig. 1 from historical data, and superimpose on it a point that would correspond to the bank under consideration. If this new point falls among the banks that are classified as healthy, then there is nothing to worry about. If the new point falls amongst the failed banks, then it should be concluded that the ratio structure of the new bank is similar to the financial structure of other banks that failed in the past, and that bankruptcy is a possibility that should be seriously contemplated.

There are various ways in which a new bank can be added to the data set, and in which the evolution of such a bank can be represented. Two alternatives come to mind: re-estimation and reverse use of the profit results.

Consider first the reverse use of profit analysis. Each profit line can be calibrated by adding a scale of measurement. These scales can then be used to approximately locate any new bank on the configuration. This is a simple and effective way of operating. It may not be exact, but it is not an exact result that is required in a normal way of operation, all that we want to know is if the bank is healthy, or dubious, or whether it is borderline. Such a procedure would be very easy to operate.

As far as re-estimation is concerned, this can be done in a variety of ways. One possibility is to fix in the space the points that represent previously studied banks and estimate the optimal position for the new bank with a restricted version of the MDS algorithm. This option is available in some packages like MDS(X) (1981) but is not programmed in the version of SPSS that was used for this study. Another possibility is to add the new data to the original data set and start all over again. Figure 3 was obtained in this last way.

In Fig. 3 it can be seen that between 1973 and 1976 the financial structure of the Banco de Descuento was similar to the financial structure of solvent banks. It scores high in the second dimension, which was earlier associated with liquidity. In 1977 it moves towards the area where failed banks are situated. The situation worsens in 1978. After a slight improvement in 1979, the bank failed in 1980. At that moment it was restructured and refloated with the name of Bank of Credit and Commerce. The MDS configuration shows a deep move towards the failed region which is associated with low profitability and low liquidity. Over the years profitability continued to be low although liquidity improved. In 1988 the bank moved into the ‘safe’ part of the configuration but the situation deteriorated again during the following two years. Definite failure took place in 1990 as part of the general controversy of the Bank of Credit and Commerce International.

A common criticism of models used to predict failure is that they do not explain the possible causes of failure, or the path followed by firms on their way to failure. The MDS model described here addresses both questions. It can be seen, in the case of the Banco de Descuento, that it was a bank with high liquidity ratios. The cause of failure was low profitability. This bank could have been identified as being ‘at risk’ several years, probably four years, before
failure took place. Similarly, the path to failure of other banks could have been explored, but it is not our intention to do a detailed study of the Spanish Banking crisis, fascinating as this might be.

MDS trajectories could be compared to Argenti's trajectories. Argenti (1976) suggested the calculation of an indicator which summarizes a series of symptoms, mistakes, and deficiencies in the firm under study. This approach has been empirically assessed by, among others, Clarke et al. (1994) who study, one by one, the failure of thirty Australian firms.

3.5 Univariate analysis

MDS has served a double purpose: to explore the value of the information contained in the financial ratio data, and to generate a tool to be used to evaluate the financial position of a new bank. In this section we further explore the first aspect. Having understood the role played by profitability and liquidity

Fig. 3. Evolution of the Banco de Descuento through the MDS configuration with an indication of the dates of the accounts.
in the process of failure we ask what, if any, lessons could have been learned from the univariate analysis of financial ratios. To do this we will use the tools of Initial Data Analysis (IDA). We will follow the evolution of the financial ratios of the Banco de Descuento with IDA tools. We leave aside the last 10 years of this bank under the name of Bank of Commerce and Credit.

IDA encompasses a set of simple but powerful statistical tools which attempt to display the main features of the data without resorting to complex calculation. Chatfield (1985) has argued that much can be learned from IDA, and that often IDA will suffice for decision purposes. In this case we are proceeding in the opposite direction: having understood the structure of the problem by means of MDS, we explore whether the simple tools of IDA are sufficient for decision purposes. Among the IDA tools, we will concentrate on box and whiskers diagrams. A discussion of box and whiskers diagrams and their application in financial ratio analysis can be found in Mar-Molinero and Ezzamel (1991).

To produce a box and whiskers diagram we start from a vertical scale. This is calibrated to measure a particular ratio. The box of the diagram attempts to portrait ‘normal’ behaviour. We have chosen to draw the box in such a way that it covers the values observed in 50% of the banks. The top whisker covers the top 20% of the values of the ratios, and the lower whisker the bottom 20%. In this way ‘normal behaviour’ is described by the content of the box, and extreme behaviour and outliers are relegated to the whiskers. The average value of the ratio is also drawn and divides the box into two parts. When the distribution of the ratio is symmetric, the two parts will be of equal length. Box and whiskers diagrams have been produced both for failed and healthy banks and displayed side by side for every one of the nine ratios included in the study. They can be seen in Fig. 4. A time series of the ratios of the Banco de Descuento has also been displayed in Fig. 4.

It can be seen in Fig. 4 that as far as the first three ratios are concerned, there is little difference between failed and non-failed banks. Examination of ratio 3 suggests that the Banco de Descuento started with very high current assets given the loans it had made, and that the level of coverage decreased all through the 1970s, although when failure took place the value of this ratio was still in step with the value observed in other banks that did not fail. The remaining ratios are much more valuable for discrimination purposes. There is little, if any, overlap between the boxes corresponding to failed and non-failed banks. It can also be seen that the distance between the top and the bottom of the box is different for the two types of banks. This suggests that the failed population is different from the non-failed population not only in that means are different but in that variances are different, and that LDA is inappropriate as a classification tool. This is consistent with our earlier discussion. Profitability ratios for the Banco de Descuento appear to have deteriorated over time. After 1977 they all had fallen within the range of values observed in banks that failed.

It is, of course, easy to be wise with the benefit of insight. During the late 1970s and 1980s the banking situation in Spain was in a state of flux and no box and whiskers diagrams were available to estimate the risk of failure. However, the above discussion suggests that if banks are ordered according to their
Fig. 4. Box and whiskers diagrams for failed and solvent banks and evolution of financial ratios for the Banco de Descuento.
values of ratios 4 to 9, a bank whose ratios systematically appear towards the bottom of the table is to be treated with great caution. It is difficult to think that this is not already being done by supervisory authorities as a matter of course.

4. CONCLUSIONS

It has been shown how MDS techniques can be of use in order to give a visual presentation of multivariate data. In the particular case of Spanish banks, a representation on two dimensions, which can be labelled profitability and liquidity was sufficient for the analysis of company failure. Experience with other data sets suggests that it is often the case that an appropriately chosen two-dimensional map will display the relevant features of the data for the decision at hand; for other examples in different contexts see Mar Molinero (1988), Mar Molinero and Portilla (1993) and Mar Molinero et al. (1996).

An assessment of the financial health of a bank can be made by adding it to a previously derived configuration. If it clusters with the failed banks, then it must be treated with care on the grounds that its financial structure is not different from the financial structure of other banks that failed in the past. If the new bank clusters with non-failed banks the concern disappears. There is also a region in the space where anything can happen. It has been shown that probabilities of failure can be attached to banks that fall in this region.

The addition of a new bank to the data set can be performed in various ways. The most desirable one would be to repeat the study with one more point in the space. Besides the technical skills required to conduct such a study, there is the added disadvantage that computer packages have a limit on the number of points that can be included in the analysis, and this may limit the useful life of MDS as a tool. A second alternative would be to keep the results of the previous study unchanged and add the new point to the configuration. The third option is a pragmatic one: auxiliary scales produced by means of PROFIT analysis can be used to approximately locate the new point on the space. All that is required is a chart with some scales and predefined regions: failed, non-failed, and uncertain. The banks used to generate the chart need not be included in it. Any new bank can be placed in the chart by means of the auxiliary scales. This last option would be a black-box type of approach where the results of a fairly sophisticated analysis support a simple decision tool but remain hidden from the user. This philosophy opens the door to other black-box type of approaches such as the neural network approach of Martín-del-Brío and Serrano-Cinca (1993).

Another issue that has been explored is the use of Initial Data Analysis techniques for the analysis of financial health. It has been seen that the evolution of the financial ratios of a bank can be put in perspective with the help of box and whiskers diagrams.

There are other avenues that have not been explored here. There is the issue of using data for a limited sample in a given year in order to assess the financial health of different companies in another year. There is also the issue of up to what point year to year fluctuations that affect the whole industry may affect
the results of a MDS study. It is possible to extend the MDS model to address these issues, but that falls beyond the scope of the present paper.

REFERENCES


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