FINANCIAL RATIOS, SIZE, INDUSTRY AND INTEREST RATE ISSUES IN COMPANY FAILURE: AN EXTENDED MULTIDIMENSIONAL SCALING ANALYSIS

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ABSTRACT

Three-way multidimensional scaling methods are used to study the differences between UK failed and continuing companies from 1993 to 2001. The technique allows for visual representations of the results, so that qualitative information can be brought to bear when judging the health of a company. It is shown that it is important to take into account company size and area of activity. Results also suggest that the ratio structure of the companies varies between years in response to changes in the interest rates, suggesting that the frontier between failing and continuing firms moves in response to the economic cycle.

Keywords: Company Failure, Ratio Analysis, Multidimensional Scaling.

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INTRODUCTION

An earlier paper by Neophytou and Mar Molinero (2004) introduced Multidimensional Scaling (MDS) as a paradigm shift in the prediction of company failure, a subject that has received much attention over the years. It was argued that MDS, by visualising the relevant aspects of the data, makes the analysis accessible to the non-specialist, and opens the way for the inclusion of qualitative information in a quantitative framework.

The Neophytou and Mar Molinero (2004) paper used a relatively small sample of failed and continuing companies; 50 failed and 50 continuing companies. Companies were matched by industry and size and only one year of accounts was used in the case of each company. Company size and area of activity are presumed to be important factors when predicting failure. For this reason, the companies in the sample of failed and continuing firms are often matched by size and area of activity, a procedure that often implies that both samples have to be of equal size. This way of proceeding has serious disadvantages. First, using samples of equal size does not reflect real life, where continuing companies are much more common than failed companies; this can be addressed by means of Bayesian techniques, as suggested by Beaver (1966), but it is rare to find a study that makes such a correction. Second, matching by size and area of activity makes it impossible to assess the importance of such factors. Third, it is unrealistic to assume that the conclusions of an analysis based on a sample that does not take into account time evolution will hold for the future.

This paper extends the work done there in several ways. First, the data is three-way: for each company we use several years of accounts from which financial ratios are derived; three-way refers to the fact that the data set is organised in three ways: companies, ratios, and year of accounts. Second, we use a very large sample both of failed and of continuing companies, probably the largest study in the public domain in the UK[1]. Third, we explore the issues of industry classification, company size, and influence of the economic cycle- in the form of interest rates- on company failure. This is done within an extended MDS framework which maintains the visualisation aspect of the results and, by doing so, reveals aspects of company failure that are overlooked when using other technical approaches.

The data used for this study includes 370 failed companies. All the UK public quoted companies included in the active file of the FAME database satisfying certain criteria have been included. For each failed company, data from three to five reporting periods prior to failure was obtained. In the case of continuing companies, financial data covers up to eight reporting periods. This amounts to 818 companies, and over 6400 company accounts. No matched pairing of companies took place. The data covers the period 1993 to 2001. As it is usual in this type of study, the analysis is based on financial ratios obtained from the balance sheet and the profit and loss account. 19 such ratios were calculated for each company.

The analysis presented here is based on a three-way scaling technique: Individual Differences Scaling (INDSCAL); Carroll and Chang (1970). A literature review of the

[1] For a review of the major UK and US bankruptcy-related studies, see Charitou, Neophytou and Charalambous (2004).

use of scaling models in management, and a discussion of alternative three-way scaling models in this context can be seen in Mar Molinero and Serrano Cinca (2001), and in Serrano Cinca, Mar Molinero and Gallizo (2002).

INDSCAL works from data on proximities. The data takes the form of a multivariate data set in which financial ratios are taken as variables and companies as observations. The natural way of proceeding is to calculate, and represent, the level of similarity between any two companies on the basis of their financial ratios, as done by Neophytou and Mar Molinero (2004). The configuration is later interpreted by superimposing financial ratios as directional vectors. However, because of the limits set by existing software, this method only works when the number of companies is relatively small. Since in this study the number of companies is large, the proximities were calculated between ratios, using companies as observations, and the results were interpreted by plotting companies as directional vectors on the configuration. A proximity matrix between ratio structures was calculated for each financial year and used as input for the INDSCAL model. INDSCAL generates a "common map" that shows the average relationship between financial ratios during the period, and a set of weights that show how the relationship between financial ratios evolves over time.

Companies were projected on the common map. Location differences between failed and continuing companies in the common map were studied by a series of methods that include visual inspection, and Logit. Previously unobserved non-linearities (but suggested by the theory) were discovered. It was found that failed companies tend to concentrate in certain areas of the maps, and that these areas are associated with low profitability, poor cash flow, and unsatisfactory debt structure. The impact of size and area of activity also became clear. These are well known results, but the scaling approach has the advantage of visualising them and, in this way, it helps in the process of decision taking as it makes it possible to combine the qualitative and the quantitative aspects of any decision involving an assessment of the future of a company.

Section 2 of the paper describes the financial accounts data set. Section 3 discusses the financial ratios and gives their definitions. The INDSCAL mathematical is introduced in section 4, while its graphical representation is shown in section 5. Companies are plotted on the ratio maps in section 6, which is the main body of the paper. The existence of areas where failed companies concentrate is explored in section 7 using the complete data set but taking into account only financial ratios. The importance of size and industry are explored in section 8. The impact of the economic cycle on the differences between failed and continuing companies is revealed in section 9. A conclusion ends the paper.

2. COMPANY DATA

All the data was obtained from the FAME database. FAME contains financial information on UK and Ireland companies, both private and public. In common with other studies, companies in finance, insurance, and real estate were excluded; Gilbert, Menon and Schwartz (1990), their financial accounts not being comparable to the rest of the companies.

Failed companies were identified from the UK Bankruptcy & Insolvency Website. For the purposes of this paper, all companies that received an administration order, went into receivership, or were liquidated as per the Insolvency Act 1986, were classified as "failed"[2]. FAME was launched in 1988 and its coverage increased over subsequent years. Its coverage of companies that failed during the initial years of existence was limited, and it was decided not to include companies prior to 1993. The final data set covers the years 1993 to 2001. Failed companies with less than three years of available data prior to failure were also excluded. In total, 370 failed companies met all the requirements; 56% of them were liquidations, 34% went into receivership, and the remaining 10% received an administration order. The proportion of liquidations in the sample is known to be lower than the proportion in the general population, but this is due to the fact that administration often ends up as liquidation, and when that happened, the company was classified in this study as being under administration. Table 1 shows the number of companies with complete financial data for the years preceding failure.

Table 1

Failed Companies: Year of Last Financial Report

Type of Failure	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**Total**
Administrations	6	7	8	11	4	-	-	36
Receiverships	19	26	19	20	30	10	1	125
Liquidations	41	32	34	43	43	14	2	209
Total	66	65	61	74	77	24	3	370

The low number of failed companies in the years 2000 and 2001 is explained by the fact that it takes on average 466 days between the last available report and the formal announcement of failure. Thus, during these two years there may be companies that had already failed but whose failure had not yet been announced. This means that some of the companies appearing in the database as continuing should, in fact, be classified as failed. These will appear as wrongly classified by the model. The reverse is unlikely to be the case; i.e., that a company listed as failed is in reality a continuing company. The consequence of this observation is that one would expect the model to appear to classify better continuing companies than failed companies. This is consistent with modelling experience. The proportion of continuing companies wrongly classified as failed (i.e. Type II error) tends to be larger than the proportion of failed companies wrongly classified as continuing (i.e. Type I error). Table 2 breaks down the companies in the failed sample into the various industry groups, based on their three-digit SIC code.

[2] According to the Insolvency Act of 1986, administration is a moratorium by creditors to allow the company to restructure, receivership is when a receiver is appointed under a charge or debenture to recover a creditor's funding (usually a bank), and liquidation is the winding up of a company either voluntarily or through courts.

Table 2

Failed Companies: Industrial Classification

Industrial Group	Frequency	Perc.
agriculture, forestry & fishing (1)	3	0.81
mining (2)	5	1.35
construction (3)	28	7.57
manufacturing (4)	94	25.41
transportation, communication, electric, gas & sanitary services (5)	17	4.59
wholesale trade (6)	62	16.76
retail trade (7)	27	7.30
services (8)	134	36.22
Total	370	100

Turning now to continuing companies, only those with four or more years of complete data between 1993 and 2001 were included. This restricted their number to 818. The distribution of continuing company accounts over time can be seen in Table 3.

Table 3

Continuing Companies: Year of Accounts

Year	Frequency	Percent
1993	689	10.73
1994	730	11.37
1995	755	11.76
1996	785	12.22
1997	809	12.60
1998	807	12.57
1999	648	10.09
2000	812	12.64
2001	387	6.03
Total	6422	100

Table 4 breaks down the continuing companies into the various industry groups.

Table 4

Continuing Companies: Industrial Classification

Industrial Group	Frequency	Percent
agriculture, forestry & fishing (1)	8	0.98
mining (2)	19	0.98
construction (3)	59	7.21
manufacturing (4)	324	39.61
transportation, communication, electric, gas & sanitary services (5)	58	7.09
wholesale trade (6)	72	8.80
retail trade (7)	64	7.82
services (8)	214	26.16
Total	818	100

The majority of the firms belongs to services, manufacturing, and wholesale trade, just as it was the case with failed companies. No attempt was made to match failed and continuing companies neither by industry sector nor by size, as one of the objectives of the research was to investigate the importance of these factors. Matching has been extensively debated in the literature: see Ohlson (1980), Taffler (1982), Foster (1986), Jones (1987) and Morris (1997). The effect of industry sector and size was found to be important by Lennox (1999) using standard econometric tools.

3. THE FINANCIAL RATIOS

From the beginning, company failure models have been based on financial ratios. Ratios are used in order to control for size effects, although there is an implicit assumption of proportionality that has often been challenged; McLeay and Fieldsend (1987). There is no agreement either on which financial ratios should be chosen in a study of failure prediction and no theory to guide the choice.

There are various aspects of the firm that could be described as latent variables; examples are profitability, liquidity, gearing, and asset utilisation. These can be measured in more than one way. Specific ratios are presumed to be associated with them but no single ratio suffices to capture each latent aspect. Ratios are classified according to the specific latent variable they are supposed to reflect. There are many such classifications, a popular one was proposed by Elliot and Elliot (1999). It is common to calculate many ratios, perform either Principal Components Analysis or Factor Analysis as a data reduction strategy, and then to continue the analysis with a smaller data set, which includes up to six orthogonal variables, the exceptions being Mar Molinero and Ezzamel (1991) and Neophytou and Mar Molinero (2004) who use a scaling approach which does not require data reduction.

This study is based on nineteen ratios, which were calculated for each firm. As there has been some debate about the relevance of operating cash flow in the prediction of failure, four ratios related with this aspect were included in the data set; Gahlon and Vigeland (1988), Gilbert, Menon and Schwartz (1990), Ward (1994), Charitou, Neophytou and Charalambous (2004). The full list of ratios and their definitions can be seen in Table 5.

Table 5
Financial Ratios Calculated

Ratio (variable name)	*Definition*
Profitability	
operating return on equity (roe)	net profit before interest & tax / shareholders' funds
return on capital employed (roce)	net profit before interest & tax / capital employed
net profit margin (npr_mgn)	net profit before interest & tax / sales
gross profit margin (gpr_mgn)	gross profit / sales
Gearing	
financial leverage multiplier (fin_lev)	capital employed / shareholders' funds
gearing ratio 1 (gear1)	(total l/ties - current l/ties) / capital employed
gearing ratio 2 (gear2)	total liabilities / capital employed
shareholders' ratio (shr_rtio)	shareholders' funds / capital employed
interest cover (int_cvr)	net profit before interest & tax / interest charges
Liquidity	
current ratio (cr)	current assets / current liabilities
acid test ratio (lr)	(current assets - stocks) / current liabilities
Asset utilisation (turnover)	
asset turnover (ta_turn)	sales / capital employed
stock turnover (stk_turn)	cost of sales / closing stock
debtor ratio (dbt_rtio)	trade debtors / sales
creditors turnover (crd_turn)	cost of sales / trade creditors
Operating cash flow	
cash flow interest cover (cfint)	cffo / interest charges
cash flow return on capital employed (cffo_ce)	cffo /capital employed
cash flow margin (cffo_trn)	cffo / sales
cash flow to current liabilities (cffo_cl)	cffo / current liabilities

capital employed = total assets
cffo = net cash in(out)flow from operating activities, calculated as operating profit + depreciation +/- changes in working capital

Descriptive statistics for all the financial ratios can be seen in Table 6.

Table 6

Descriptive Statistics of all Company Cases

Ratio	Valid N	Minimum	Maximum	Mean	Std. Dev
CR	7940	0.000	81.420	1.851	3.015
LR	7940	0.000	81.230	1.410	2.700
ROE	7934	-2742.000	152.727	-0.319	32.381
ROCE	7933	-507.633	392.089	0.291	8.546
NPR_MGN	7800	-206.993	73.227	-0.246	5.359
GPR_MGN	6421	-189.222	1.000	0.302	2.418
FIN_LEV	7949	-13023.667	11892.000	3.520	200.207
GEAR1	7836	-0.010	786.788	1.087	15.853
GEAR2	7836	0.006	1009.899	2.756	24.325
SHR_RTIO	7949	-317.265	3940.333	2.490	48.570
INT_CVR	7017	-99.730	980.000	20.504	77.329
TA_TURN	7815	0.000	713.974	4.822	25.708
STK_TURN	5551	0.000	35452.000	41.696	517.530
DBT_RTIO	7495	0.000	17.785	0.169	0.256
CRD_TURN	5982	0.000	2106.566	11.562	56.258
CFINT	6459	-12170.949	35802.000	70.877	972.446
CFFO_CE	6911	-810.763	808.324	0.602	15.464
CFFO_TRN	6876	-264.288	757.357	-0.114	10.545
CFFO_CL	6912	-233.681	19.105	0.195	3.326

Detailed examination of the data revealed a series of problems. Financial data is plagued with outliers, and it is often not clear how to deal with them; for a discussion of this problem see Ezzamel and Mar Molinero (1990). The use of scaling methods in the way to be described next does not totally solve the problem, but keeps its effects to a minimum. A potentially more serious problem was revealed by the descriptive statistics. Three ratios that were expected to have zero as their minimum value had negative minimum values: fin_lev, shr_rat, and gear1. Further work revealed about 100 companies (241 data points) with negative shareholders' funds. Various explanations can be found for this rather surprising finding, one of them relates to the way in which goodwill was dealt with according to the old accounting standard statement of practice (SSAP 22). The question was if the original data should be kept as it is, if it should be modified for all the offending firms, or if it should be modified only for continuing firms. In the end the analysis was repeated several times and the results were found to be robust to the method chosen.

4. INDIVIDUAL DIFFERENCES SCALING (INDSCAL)

Neophytou and Mar Molinero (2004) suggested Ordinal Multidimensional Scaling (MDS), in combination with other classification methods, such as Logit, as a paradigm shift. The aim is not so much to provide a superior classification rule, but to visualise the main characteristics of the data in such a way that qualitative and quantitative information can be brought to bear in the decision to classify a firm as potentially healthy or failing. This methodology has much in common with approaches based on Self-Organising Neural Networks, but is statistically based and is not a "black-box" approach; Serrano Cinca (1997), Charitou, Neophytou and Charalambous (2004). Ordinal MDS has the further advantage of working with relationships of order, and does not suffer from the problem of influential observations or outliers.

The MDS representation of a data set in the way done by Neophytou and Mar Molinero (2004) has the disadvantage that existing computer packages can only cope with a relatively small number of companies. Besides, it is a two-way method: it can represent companies on the basis of their financial ratios (a two-way classification), but cannot cope with three-way data. The particular data set used in this paper is three-way: companies, financial ratios, and year of accounts. Thus, the methodology had to be extended while the desirable features of the MDS approach were kept. This was achieved using the Individual Differences Scaling approach of Carroll and Chang (1970) in the way described in the next section.

INDSCAL, like MDS, works with proximity data. In this case, proximities were calculated between financial ratios using companies as observations. This is done because the number of ratios is relatively small, while the number of companies is large. Since there are various ways in which proximities could be calculated, we proceeded as follows. First, for each year, financial ratios were standardised to zero mean and unit variance. Second, Euclidean distances were calculated, for each year, between standardised ratios. This resulted in nine dissimilarity matrices, one for each year.

Let $\delta_{ij,k}$ be the calculated dissimilarity between financial ratio i and financial ratio j during year k. The model plots financial ratio i in an R-dimensional space by means of a set of co-ordinates, x_{ir} , where $r = 1, 2,\ldots R$. In the same way, financial ratio j is plotted in the same space by means of the set of coordinates x_{jr}. Notice that time, in the form of sub index k, does not enter in the set of co-ordinates x_{ir} and x_{jr}. The representation of the financial ratios in the R-dimensional space is an average over time known as "the common map". There is an implicit assumption that if two financial ratios are close to each other in a particular year, they will be close to each other over the complete period. For example, return on equity (ROE) and gross profit margin (GPR_MGN) are two measures of profitability; if one of them is high, one would expect the other one to be high, and this to happen every year. In other words, the actual position of the financial ratios in the space may change from year to year, but their relative positions are expected to remain unmoved: financial ratios that are close neighbours in a particular year will continue to be close neighbours in all the years of the study. The axes can be stretched or shrunk, an operation that will bring points further apart or closer to each other without altering neighbourhood patterns. This is exactly what INDSCAL does. Stretching and shrinking takes place by means of a set of weights, w_{kr}, one for each dimension in the R-dimensional space for each year.

The function to be estimated takes the form:

$$d_{ij,k} = \sqrt{\sum_{r=1}^{R} w_{kr} \left(x_{ir} - x_{jr} \right)^2}$$

There are various ways in which estimation can proceed, and these are imbedded in the various computer packages available. In theory, they should all return the same values but there are convergence and local minima issues; Cox and Cox (2001). Various routines with various starting and optimisation rules were used in this research. The details will be given in the next section.

Being a model based on a non-linear regression, the quality of the reported results can be assessed by means of the R^2 statistics. R^2 are calculated for the fit achieved between predicted and observed proximities for each individual matrix and for the overall data set.

A decision that needs to be taken is the dimensionality of the space in which the ratios are to be represented. Various approaches are available in this respect. It is possible, for example, to observe how the quality of the representation changes with the number of dimensions in which the configuration is drawn, and to stop when the addition of extra dimensions does not improve the measures of goodness of fit. It is also possible, and this was done in this particular study, to perform Principal Component Analysis on each of the individual discrepancy matrices in order to assess the number of components associated with eigenvalues greater than 0.8 under Jolliffe's (1972) rule. In common with many other studies, a representation in five dimensions was found to be appropriate. It is frequent to attach meaning to each dimension. This will be done below.

5. MAPPING FINANCIAL RATIOS

MDS analyses are plagued with convergence and local minima problems. There is no guarantee that the solution returned by the software is optimal. In order to keep these problems to a minimum the default termination criteria of SPSS, the computer package employed, were modified: precision was sharpened to 0.000001 and the maximum number of iterations was increased to 500. Several starting procedures were employed, including 1000 random starts. This was done using two statistical routines: ALSCAL and PROXSCAL. Besides, ALSCAL solutions were used as initial configurations for PROXSCAL. PROXSCAL solutions were obtained using both the metric and the non-metric versions of the algorithm. The final choice of configuration also relied on the quality of the regressions used to interpret the results, details of which will be given below.

Non-metric versions of PROXSCAL were found to produce configurations that fitted the data very poorly. The best results were obtained with the metric version of PROXSCAL using a simplex-based starting solution. This solution was found not to be sensitive to the various treatments of negative shareholders' funds, and the original unmodified data set was kept.

The common map is a set of 19 points, one for each ratio, on a five dimensional space. The position of the ratios on the common map is a consensus view of the way in which the ratios are related over the period studied. These points can only be represented in the form of projections. The projection of the financial ratios on dimensions 1 and 3 is given in Figure 1; the projection of the ratios on dimensions 2 and 4 is shown in Figure 2, and the projection on dimensions 3 and 5 in Figure 3.

[Figures 1, 2 & 3 here]

It is often possible to attach labels to the dimensions of the common map. In order to do this, one has to observe the points located at the extreme ends of the dimensions. Proceeding in this way, Dimension 1 of the common map was found to be associated with “liquidity”, as four liquidity/turnover ratios (cr, lr, dbt_rtio and ta_turn) fall towards the two ends of this dimension. The ratios that fell at the extreme ends of Dimension 2 were related to “profitability/operating cash flow” (npr_mgn, grp_mgn, cffo_trn and cffo_cl). Gearing ratios were found to be prominent in Dimension 3 (gear1, gear 2 and shr_rtio). Dimension 5 was related to “shareholders’ return”. No clear meaning could be attached to Dimension 4 (roe, roce and cffo_ce).

The common map tells us that, for example, that when the ratio cash flow to turnover is high, the gross profit margin tends to be high as well. We can see this because the two points fall next to each other in the configurations. But our interest is in the financial health of a company, and not on the observed relationship between financial ratios. We need to analyse the financial ratios of a company in the light of the common space. This is done in the next section using the Property Fitting technique; Shiffman, Reynolds and Young (1981).

6. PLOTTING FAILED AND CONTINUING COMPANIES

Companies were plotted in the common space as oriented lines. The logic of this arrangement will now be described.

Take a line through the centre of coordinates of the common space, such as the one that can be seen in Figure 4. We can project on this line the points associated with the financial ratios. We can see in Figure 4 that shr_rtio projects far from the origin, gear1 and gear 2 project far from the origin, and roe projects near the origin. We can project all the ratios on the line and measure the distance of the projections to the origin. Thus, for this line, every financial ratio will be associated with a distance to the origin, measured from the projection of the point to the line. Of course, these distances will change with the direction of the line in the space.

We can now calculate the correlation between the distances calculated along the line and the values of the standardised ratios of a firm. If this correlation is high, we can say that the firm is well described by the line. If the correlation is low, the line will poorly describe the company. For each company there will be a line that maximises the correlation between the distances on the line and the financial ratios of the company. This line will describe the company. But there is no need to plot the complete line. A point in the space and a directional vector of length one-a normalised vector-can describe any line. Since all the lines go through the origin of coordinates, it suffices to know the end point of the directional vector. Thus, each company will appear as a point in the common space, the end point of the directional line that best describes its financial ratio structure.

The calculation of these end points is based on linear regression. Standard statistical tools exist to assess the goodness of fit of the regression, particularly the adjusted coefficient of determination. The regression coefficients are related to the position of the end point of the normalised vector: if a vector lies on an axis, one of the regression components will take the value one and the other regression coefficients will take the value zero.

The normalised vectors are drawn on a five dimensional space but we work with projections on two-dimensional subspaces. If a vector is wholly contained in the subspace, the length of its projection will be near unity, and if the vector is orthogonal to this subspace, it will simply appear as a point near the origin. We hope to find that the points associated with failed or failing firms are situated in a different area of the space than the points associated with the healthy firms, and that by observing such differences it will be possible to assess in what sense the financial ratio structure of a failed firm is different from the financial ratio structure of a continuing firm.

A regression has to be performed for every firm; a total of 7950 regressions. Results were mixed, as one would expect from such a large data set. The average value of the adjusted R^2 coefficient was 0.37 for all companies, 0.36 for continuing companies, and 0.39 for failing companies the last year of accounts. The histograms of R^2 values for continuing and failing companies (one year before failure) can be seen in Figures 5 and 6. These results may appear to be disappointingly low, but we need to remember that the INDSCAL configuration only explains part of the variance in the data, that only financial ratios have been taken into account in the calculations, and that there are missing variables such as size and area of activity that may be relevant. The bankruptcy literature has identified several other indicators of financial distress such as the macro-economic environment, age of the firm, ownership characteristics, and management deficiencies. The inclusion of further variables is expected to improve the results. This issue will be taken up below.

Thus, every company is described by means of a set of five numbers: the coordinates of the end point of the directional vector in the five dimensional configuration. We can now try to answer the question: are there any directions in the space that are associated with failure? Or, in non-mathematical words, is there anything in the financial ratio structure of a company that can tell us if it is going to fail or to survive?

7. FINANCIAL RATIOS AND COMPANY FAILURE

Company distress studies suggest that the financial structure of continuing companies differs from the financial structure of failing companies up to five years before failure; e.g. Beaver (1966). The largest differences, though, are reported to appear between continuing companies and failing companies just before failure. To explore the differences between failed and continuing companies, a logit regression was performed in the following way:

$$ln\ (y_i/1\text{-}y_i) = \beta_0 + \beta_1 d_{i1} + \beta_2 d_{i2} + \beta_3 d_{i3} + \beta_4 d_{i4} + \beta_5 d_{i5} + e_i$$

where y_i is a dichotomy that takes the value 1 if company i fails, and zero if it does not fail. The explanatory variables, d_{ij}, are the coordinates of the end point of the vector that describes the company. The logit regression was run twice. First, y_i took the value 1 if the company did eventually fail. Second, y_i took the value 1 only for failed companies in the last year of accounts.

It was found that all the dimensions contributed significantly to failure, and that there was very little difference between the two sets of results. The only difference was found with Dimension 1 (liquidity) that was not significantly associated with failure when the last year of accounts was used for failing firms, although it was found to be significantly associated with failure with the complete data set. In other words, with the exception of liquidity, a model derived using all the data available on companies that do eventually fail is as good as a model derived with only year before failure data. The fact that all the dimensions returned significant regression coefficients means that there are differences between failing and non-failing companies in terms of liquidity, profitability, debt structure, and shareholders' returns. These will now be explored by examining projections on the configuration space.

[Figures 7a & 7b here]

Figure 7a shows the projection of the continuing companies on Dimensions 1 and 3, while Figure 7b shows the projections of failing companies (one year before failure) on the same dimensions. The two sets of data have been plotted separately because of the large number of points involved. The figures confirm the Logit result that Dimension 1 (liquidity) does not discriminate between financially healthy firms and firms that are approaching failure.

What is apparent from Figures 7a and 7b is the importance of gearing. The majority of failed firms are located towards the positive side of Dimension 3 in Figure 7a, indicating that they are more highly geared than continuing firms. Continuing firms are located towards the centre of figure 7b, indicating moderate levels of gearing. But Figure 6b also shows many failed firms located on the negative end of Dimension 3, where low levels of gearing are observed. . One possible explanation for this observation is the fact that these companies are in such financial distress that they cannot borrow, as banks and other financial institutions are unwilling to give them credit. Further work of a non-statistical nature needs to be done in order to confirm this conjecture.

[Figures 8a & 8b here]

Figure 8a shows the projection of failed companies (one year before failure) against dimensions 2 and 4. Figure 8b shows the projection of continuing firms on the same dimensions. Continuing companies concentrate towards the negative end of Dimension 2, indicating high profitability, while failed companies concentrate towards the positive end of the same dimension indicating lower values of the profitability and operating cash flow ratios. High values in the creditors' turnover ratio are also observed towards the right hand side, suggesting that firms in distress have much higher costs of sales that shrink their profits and operating cash flows. A high creditors' turnover ratio can also imply an inability to buy goods on credit, most likely because the weak financial position makes them untrustworthy.

Although no meaning could be attached to Dimension 4, it is clear that continuing firms tend to be located towards the positive end of this dimension, in line with the ability that this dimension has to discriminate between continuing and failing firms.

[Figures 9a & 9b here]

Figure 9a plots failing companies (one year before failure) on Dimensions 3 and 5, while Figure 9b plots the continuing companies on the same axes. The differences between the positions of the companies on Dimension 3 have already been discussed, so we will concentrate on Dimension 5. Dimension 5 was earlier identified as being related to shareholders' return. A large number of the continuing company cases can be located towards the middle/lower part of the axis, whereas failing companies tend to move towards the upper end of this axis. As the three ratios associated with the shareholders' return cluster on the far negative end of the axis, we can conclude that failed firms generate lower returns to their shareholders. Shareholders' return was also found significant in discriminating failing companies from the more financially healthy ones in Neophytou and Mar Molinero (2004). It is also interesting to observe in Figure 9a that most of the firms in distress have high stock turnover ratio values, again suggesting that they have higher costs of sales, which squeeze profits and cash flows.

Reference has been made in the previous discussion to failed firms one year before failure but, with insignificant differences, all that has been said also holds for the data set that contains failed firms up to five years before failure.

The issues of size and industry classification have not yet been explored; this will be done in the next sections.

8. SIZE, INDUSTRY, AND THE PROBABILITY OF FAILURE

In the previous section, failure was made to depend only on the values of financial ratios. Differences were observed between failed and continuing firms, but much variance was left unexplained. Is it possible to improve the results by adding information about size and area of activity in the model? It will be shown that this is indeed the case.

Size has been found to be associated with failure in many studies; Ohlson (1980), Peel, Peel and Pope (1986), Peel and Peel (1988), Ward (1994), Boritz, Kennedy and Albuquerque (1995), and Lennox (1999). Different size proxies have been used in the literature, including total asset size, sales volume and number of employees. This study uses the natural logarithm of the total assets (lnta) as a measure of company size.

It is known that some industries are riskier than others; Edmister (1972), Lev (1974), El Hennawy and Morris (1983), Platt and Platt (1990) and Lennox (1999). It has also long been recognised that there are systematic differences between many ratios for companies operating in different industries. This arises in part because of differences in the trading cycle and the incidence of accounting conventions.

In order to explore size and industry, the logit equation was augmented with the size variable and with industry proxies.

$$ln\ (y_i/1\text{-}y_i) = \beta_0 + \beta_1 d_{i1} + \ldots + \beta_5 d_{i5} + \beta_6\ lnta_i + \beta_k Dummy_k + e_i$$

Eight industry dummies were created. These are as follows: agriculture, forestry and fishing; mining; construction; manufacturing, transportation, communication, electric, gas and sanitary services; wholesale trade; retail trade; and services.

Size and industry dummies were found to significantly improve the predictive ability of the model. The presence of these variables changed the values of the coefficients associated with the d_{ij} variables, indicating the presence of missing variable bias in the model that included only financial ratios.

The coefficient of the size variable was found to be negative, indicating an inverse relationship between size and probability of failure: the larger the company, the lower the probability of failure. Smaller companies appear to be much more at risk of failure than large companies.

The coefficient of the industry dummies varied in sign and size according to industry. Having established that industry is important, a series of statistical tests were performed to find out if industries could be grouped. The fact that some industries do not have many bankruptcy incidents (e.g. agriculture, forestry & fishing), as well as the fact that certain industry groups can be pulled together due to the nature of their operations (e.g. wholesale and retail trade), suggest that a more parsimonious model could be built (see Table 7 below). In the end, the following groupings were found to be appropriate: *Services*: transportation, communication, electric, gas & sanitary services (ind.5) and general services (ind.8); *Trade*: wholesale trade (ind.6) and retail trade (ind.7); *Industrial*: manufacturing (ind.4), agriculture, forestry and fishing (ind.1) and mining (ind.2); and *Construction* (ind.3). Trade and Construction were found to be associated with higher probabilities of failure than the other groups.

Table 7

Final Logit Model with Size Variable and Industry Dummies

Variable	Coefficient	Significance
dim. 1	0.060	0.516
dim. 2	-0.494	0.000
dim. 3	-1.365	0.000
dim. 4	2.290	0.000
dim. 5	1.310	0.000
lnta	-0.953	0.000
services	-0.286	0.074
trade	0.313	0.063
industrial	-0.597	0.000
constant	6.764	0.000

The proof of the results is in their practical implications. Now that we know that it is important to know the size and area of activity of a company, there are two ways in which these results can be implemented. The first one is to build a mathematical model that includes in its definition financial ratios- or, perhaps, principal components based on the financial ratios-, size and industry dummies. This approach would rather defeat the philosophy of the approach presented here whose attractiveness is based on its ability to visualise the financial structure of a company within the context of other companies. The second way in which the results can be implemented is to build size and industry specific failure models, much in line with current practice. A model built on the industrial sector, not shown here, was indeed shown to produce better results than the general model; Neophytou (2003).

9. TIME EVOLUTION

Up to now, analysis has been based on the study of the common map. INDSCAL, as well as the common map, produces a set of weights, one for each axis and for each year. This means that we can test the hypothesis that the various characteristics of a firm- profitability/cash flow, debt structure, and so on- have different importance (salience) in the different financial years. The implication being that the financial ratio structure of a firm depends on the year when the ratios have been calculated, and that this reflects general movements in the financial structures of all firms. This may have implications for company failure, as the boundary between failed and continuing firms may shift over time reflecting changes in the salience of the various dimensions.

PROXSCAL returns, for every year, a set of five weights, one for each dimension. Given the way in which the algorithm works, the absolute values of the weights is not important, as it reflects only goodness of fit. What is important is, for any year, the relative importance of the different weights. For a given year, it is thus interesting to see if all the weights are equal or if some weights are larger than others. Table 8 gives the values of the weights produced by the industry specific MDS model developed for the industrial sector companies; Neophytou, 2003.

Table 8

Individual Space Dimension Weights of the Industrial Model

Source (Year)	**Dimension** 1	2	3	4	5
2001	0.333	0.290	0.331	0.238	0.307
2000	0.329	0.335	0.321	0.267	0.264
1999	0.281	0.336	0.303	0.306	0.281
1998	0.333	0.349	0.307	0.258	0.265
1997	0.335	0.322	0.320	0.277	0.262
1996	0.345	0.320	0.302	0.281	0.264
1995	0.351	0.327	0.303	0.275	0.256
1994	0.332	0.334	0.332	0.262	0.253
1993	0.319	0.311	0.331	0.279	0.281

Looking at Table 8, it can be observed that ratios associated with dimension 1 (capital structure/gearing) become more salient than the ratios associated with dimension 2 (profitability/operating cash flow), in the years 1993, 1995-1997 and 2001. This means that the individual maps for these particular years are stretched more in the direction of the first axis, indicating that the differences between the failed and non-failed companies are accentuated in respect of their capital structure. During the years 1998-2000, the common map has to be stretched more along dimension 2 to describe the differences in the financial ratios of failed and non-failed firms. These differences are accentuated in respect of their profitability/operating cash flow ratios and they are lessened in respect of their capital structure. In 1994, the two dimensions appear to have an almost equal importance in discriminating corporate failure.

Kruskal and Wish (1978) recommend relating these weights to other, often external, characteristics of the subjects. In this case, the obvious explanation for the differences in the relative importance of the dimensions is that the ratios are influenced by the economic cycle. Indeed, Rose, Andrews and Giroux (1982) found rates of failure in the US to be related to interest rates.

Consequently, the relationship between interest rates on government bonds for the years 1993 to 2001, and the ratio of the weights of the first and second dimension, was studied. Figure 10 shows the plot of the ratio of the weights against interest rates. It can be seen in this figure that during the years 1993-1997, when high interest rates are observed, the differences between failed and non-failed companies appear to be mostly attributed to their capital structure. The points that represent the years 1998-2000 fall towards the middle of the horizontal axis, where lower interest rates are observed, and below the dashed horizontal line. This suggests that during the years from 1998 to 2000, when interest rates were low, the profitability/operating cash flow dimension of the companies becomes more salient than their gearing dimension when it comes to discriminating failure. Year 2001 seems to contradict these findings, as the gearing aspect is dominant despite the low interest rate. However, the low number of observations in this year compared to the average number of observations in the other years (158 vs. 385) raises suspicions as to whether any definite conclusions can be reached.

[Figure 10 here]

The above figure and discussion lead to the conclusion that the frontier between the failed and non-failed companies moves in response to the economic cycle. To confirm this, the long-term interest rate variable was added to the Logit specification and its coefficient was found to be significantly different from zero (see Table 9 below). In conclusion, interest rates are related with a company's probability of bankruptcy, after taking into account its financial position, its area of activity, and its total asset size. The coefficient's sign was as one would expect; i.e. the higher the interest rate in a given year, the much more at risk an industrial company is. Years with low interest rates decrease a company's probability of failure.

Table 9

Industrial Logit Model with Interest Rates

Variable	Coefficient	Significance
dim. 1	0.144	0.648
dim. 2	0.510	0.001
dim. 3	0.709	0.000
dim. 4	2.417	0.000
dim. 5	0.280	0.039
lnta	-0.861	0.000
int_rate	0.558	0.000
constant	1.642	0.002

10. CONCLUSIONS

This paper has extended the Multidimensional Scaling approach to company failure so that it can be used to deal with companies, financial ratios and year of accounts in order to study company failure over a number of years. A large sample of 370 failing companies and 818 continuing companies, covering the years from 1993 to 2001, was used for a three-way scaling analysis. A minimum of three reporting periods and a maximum of five reporting periods before the failure year was used for the bankrupt company sub-sample, while all the available financial reports between the years 1993 to 2001, were used for the continuing companies. To study the effect of industry classification and company size on the probability of failure, no matching of the two groups of companies took place.

The three–way analysis indicated that the most important discriminators between the financial ratios of failing and non-failing firms over a number of reporting years are the capital structure/gearing position, the profitability/operating cash flow aspect and the shareholders' return levels. Activity/efficiency ratios were found to provide useful insights to a company's financial health only when examined within the broader company context.

The inclusion of information on company size, industry activity, and interest rates to the basic model that includes only financial ratios, was shown to add significantly to the explanatory power of the model. Larger companies were shown to have a lower probability of failure than smaller companies. The impact of the industry classification on the bankruptcy risk suggested that different failure models should be used for companies operating in different industries.

The main conclusion of this research is that industry and size specific models need to be developed to assess better the financial health of a company. The conclusion that the frontier between failed and non-failed firms moves in response to the economic cycle emphasises the importance of not relying solely on statistical results. In order to assess the probability that a firm will fail we need to know, not only the relative position of the firm on the configuration, but the future behaviour of interest rates, and this is a fine art that goes beyond statistical analysis.

Given a particular company it is possible to plot it in the common map using Property Fitting techniques. If the company is situated where clearly healthy companies concentrate there is little to worry about, but if the company is located where failed companies fall, then one has to make an assessment of why it is located there, how exposed it is to changes in interest rates, and other market considerations. The model presented here is a decision support tool. The decision to grant credit to a company, or to buy its shares, or to have it as a partner will always rely on judgement and there will always be a risk involved when making it.

The study shows that MDS is a powerful multivariate analysis tool, which can provide important insights to a company's financial position, while offering, at the same time, pictorial representations of all the underlying relationships. The visualisation aspect of MDS enables the user to understand better the results, based on which he/she can take an informed decision.

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Figure 1

MDS Common Space of Financial Ratios (dimension 3 vs. dimension 1)

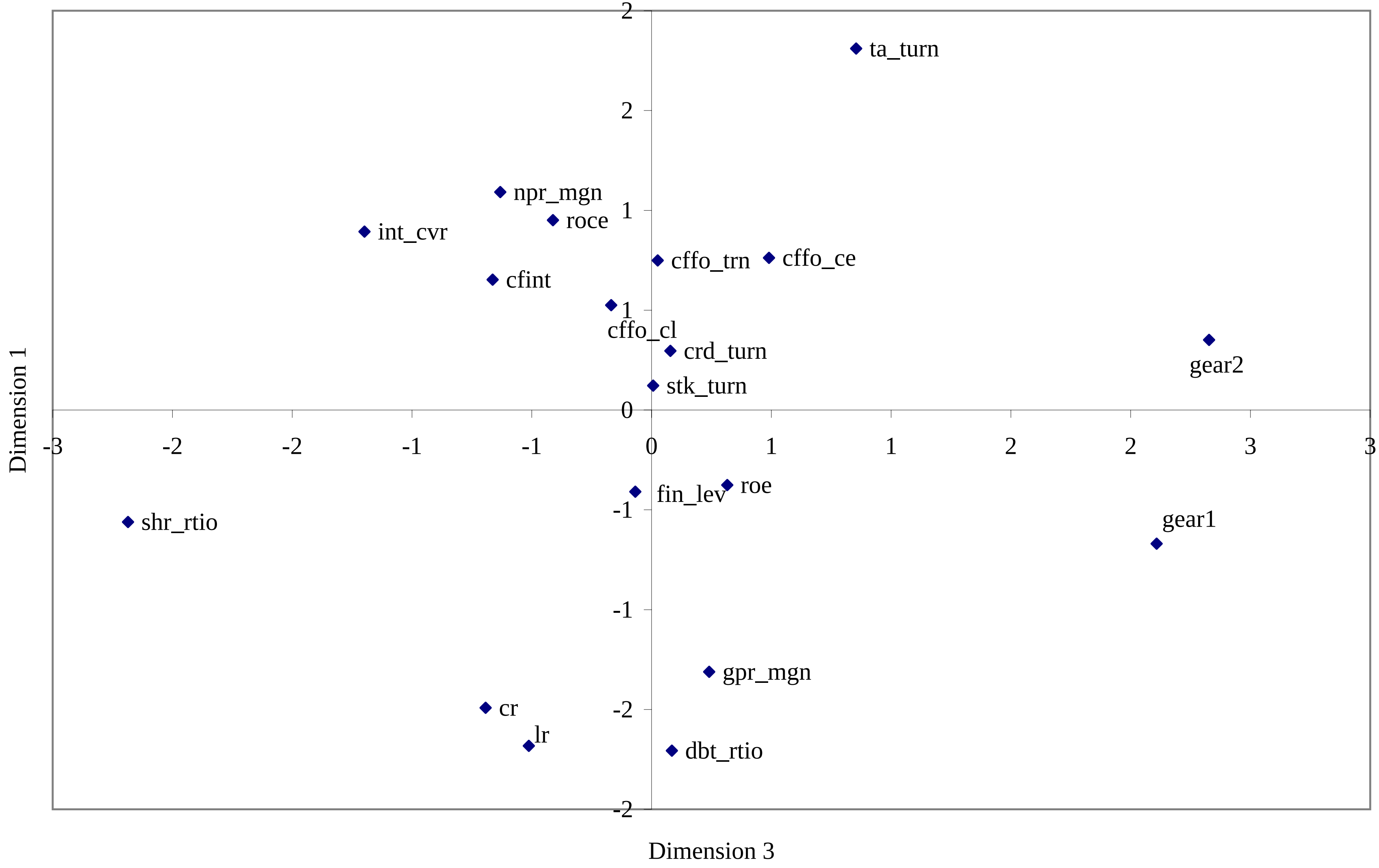

Figure 2

MDS Common Space of Financial Ratios (dimension 2 vs. dimension 4)

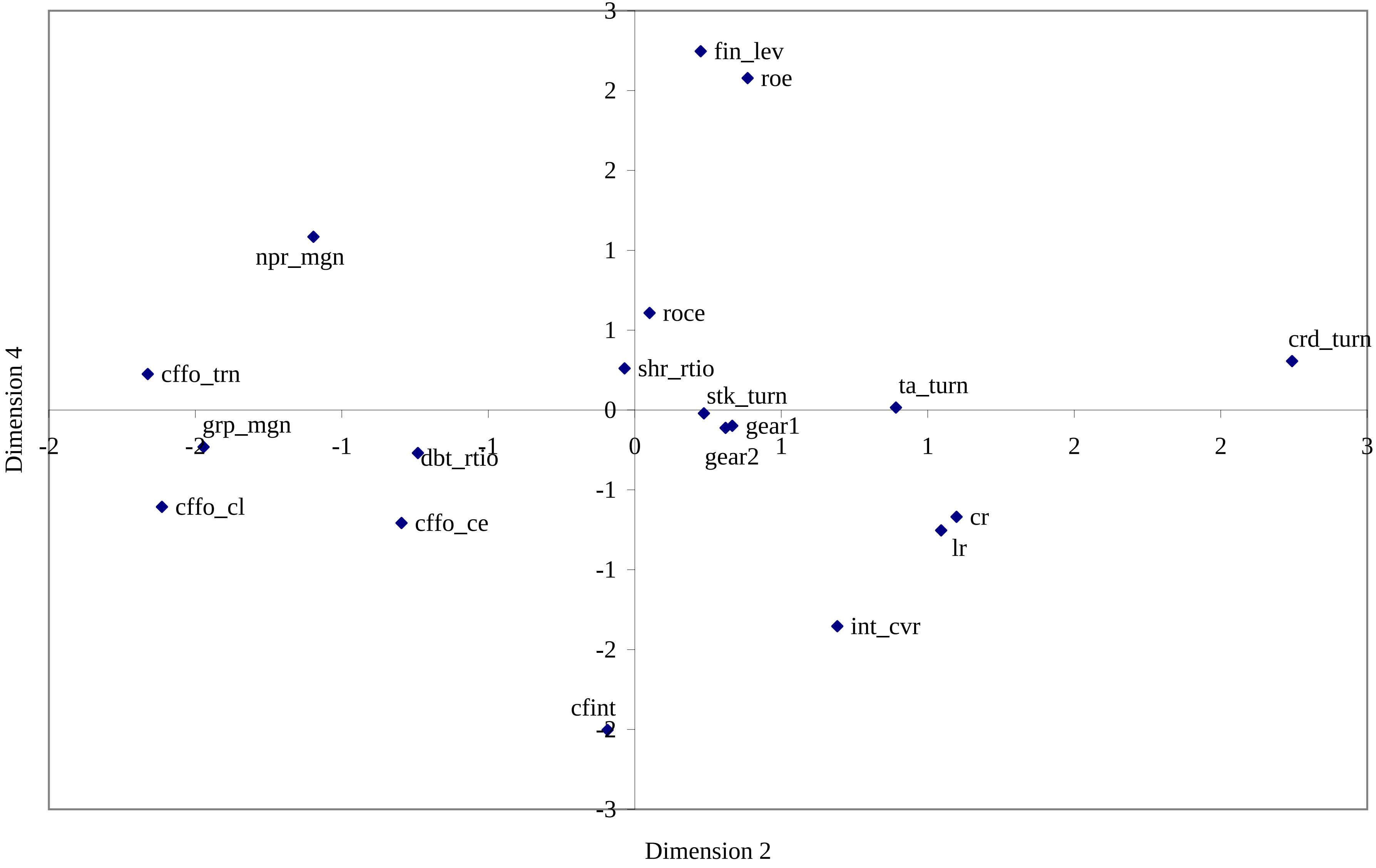

Figure 3
MDS Common Space of Financial Ratios (dimension 3 vs. dimension 5)

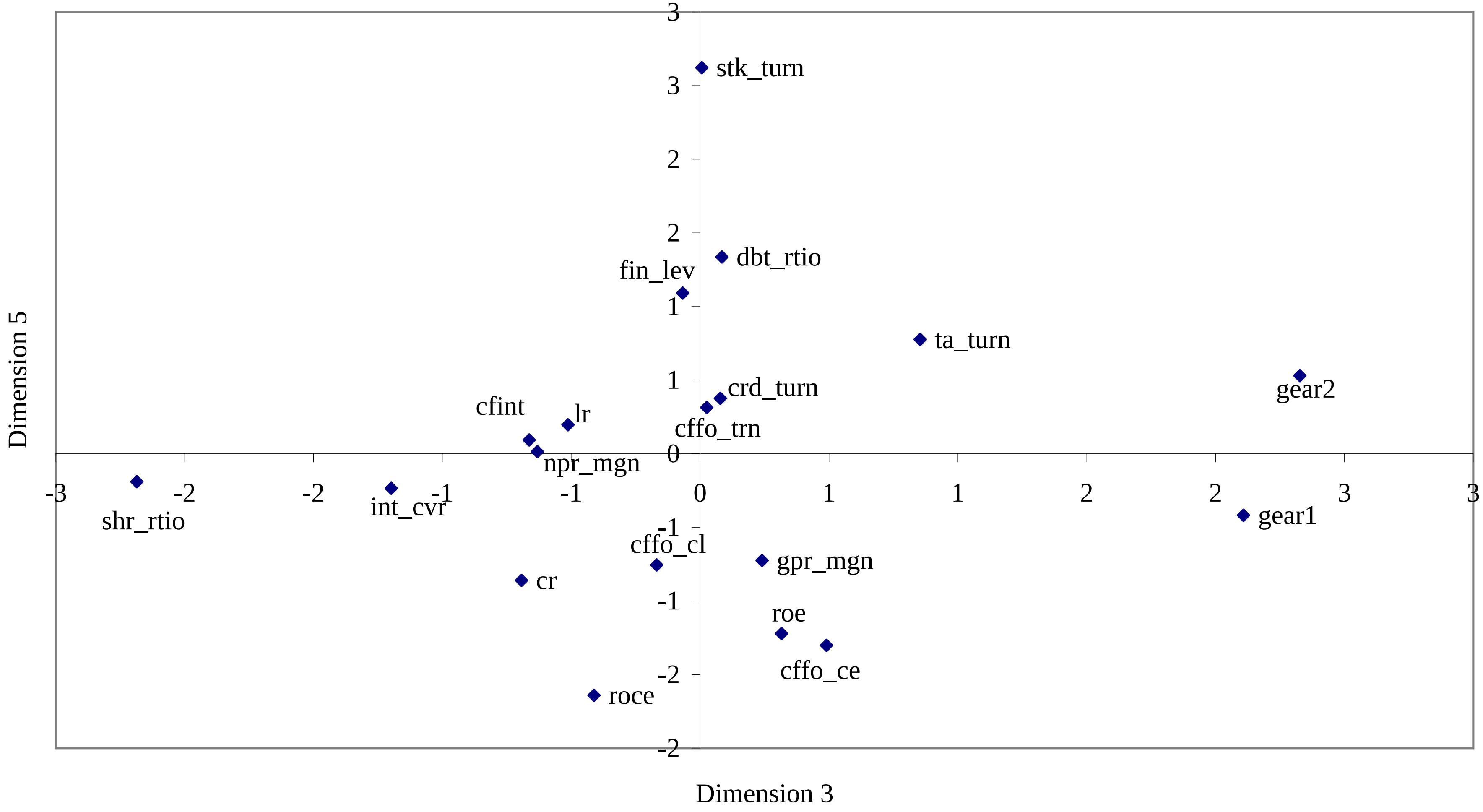

Figure 4

MDS Common Space of Financial Ratios (dimension 3 vs. dimension 1)

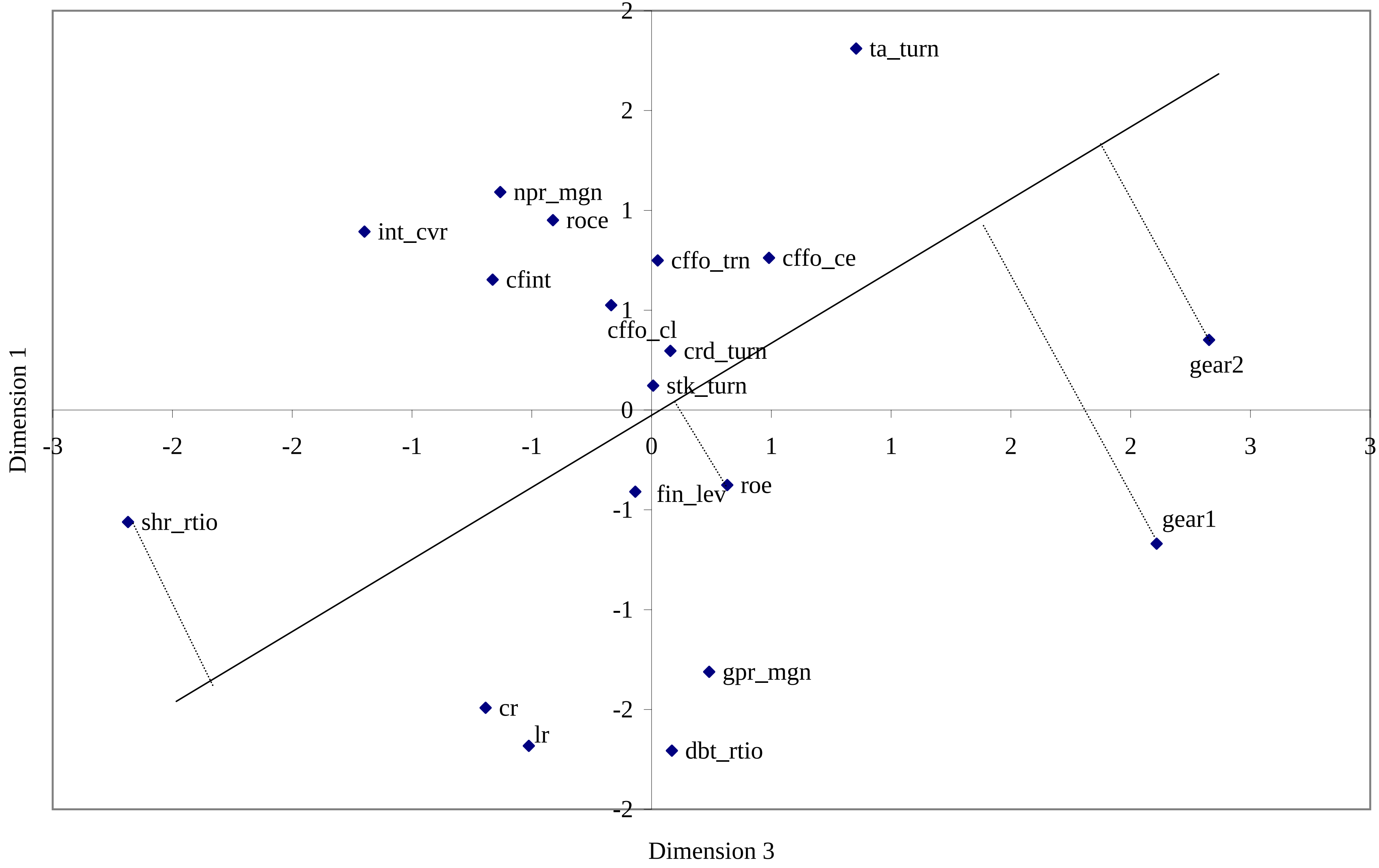

Figure 5

Histogram of R-sq Adjusted for Continuing Companies

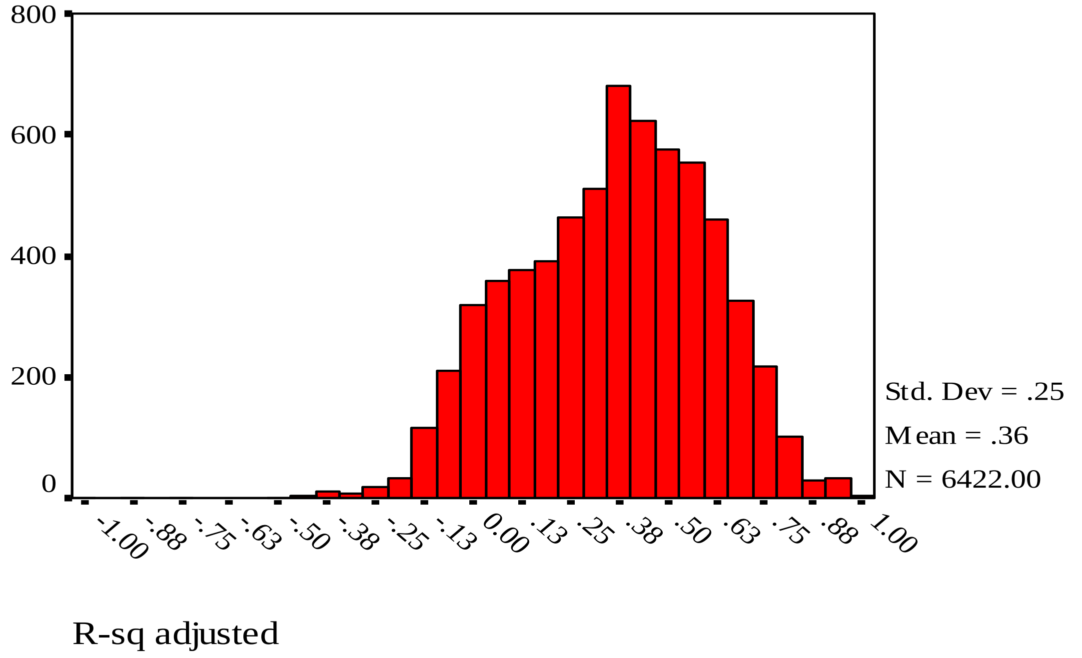

Figure 6

Histogram of R-sq Adjusted for Failed Companies

(1st year before failure)

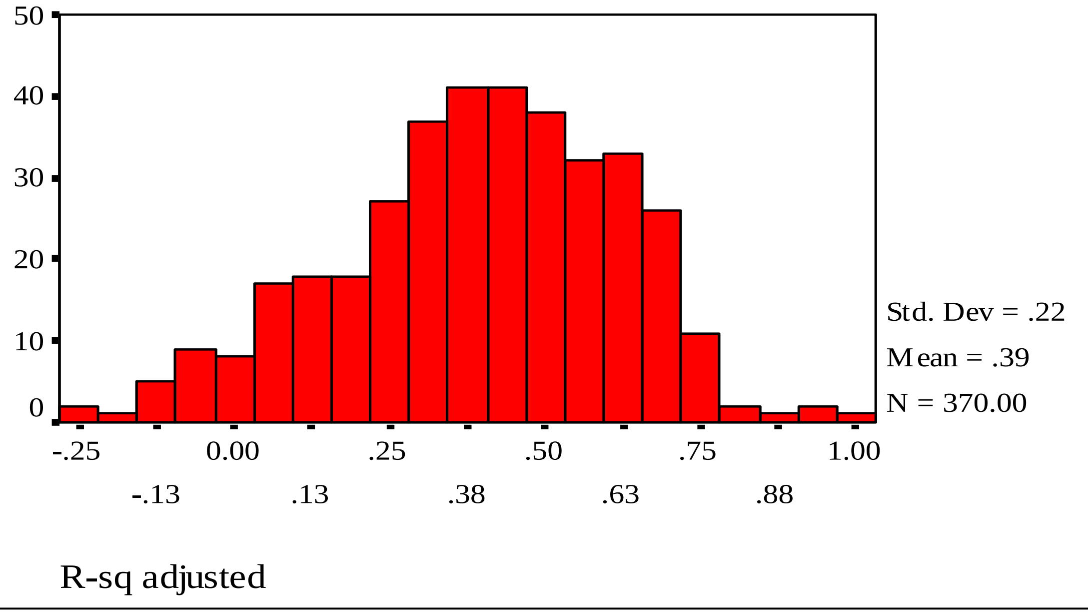

Figure 7a

MDS Common Space of Failed Companies

(dimension 3 vs. dimension 1)

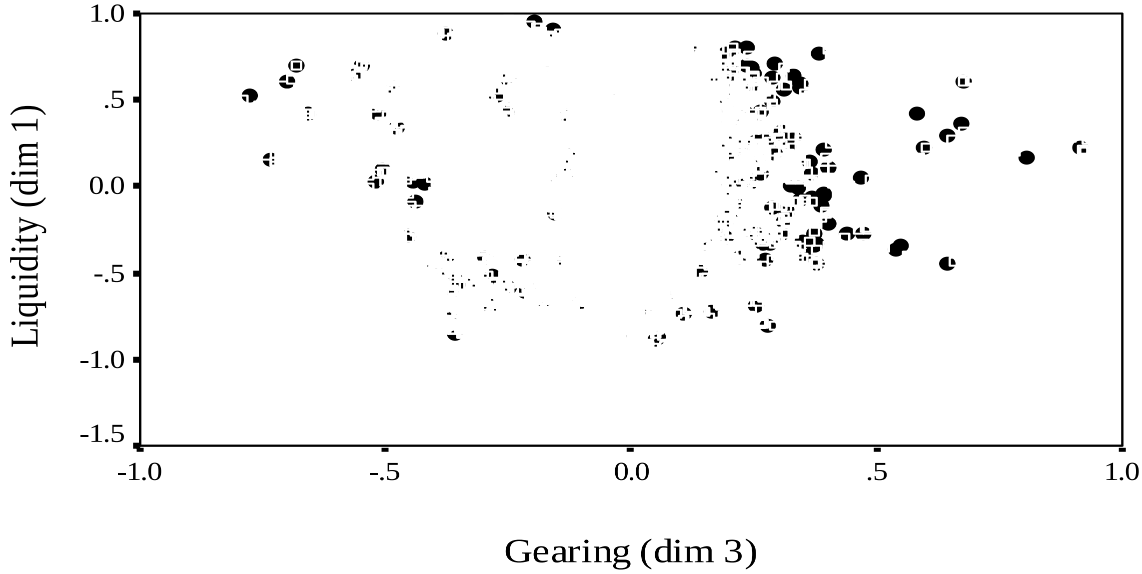

Figure 7b

MDS Common Space of Continuing Companies

(dimension 3 vs. dimension 1)

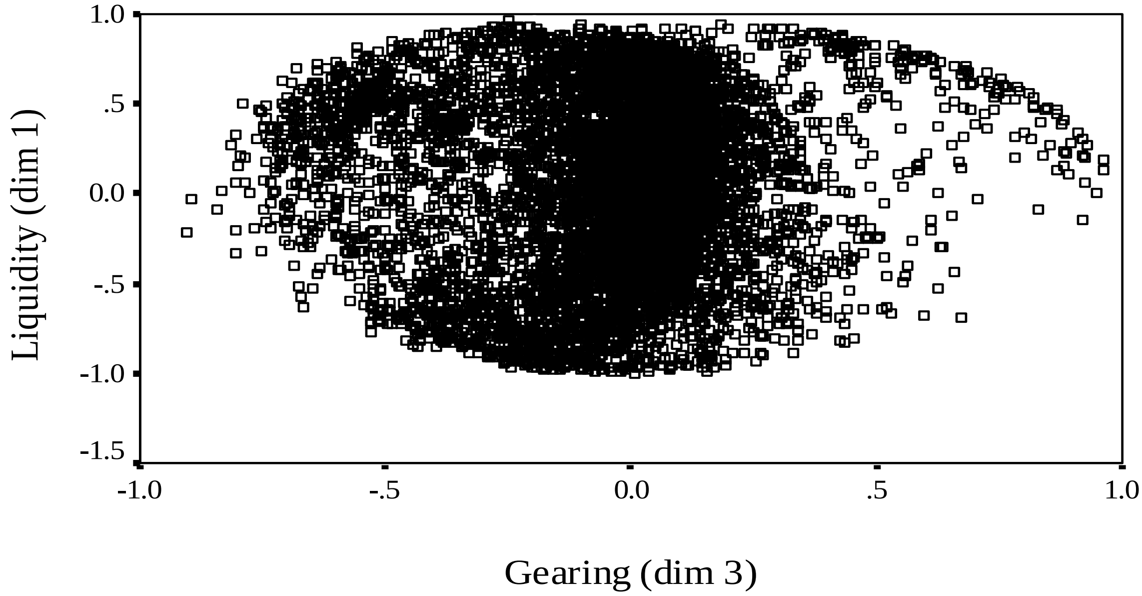

Figure 8a

MDS Common Space of Failed Companies

(dimension 2 vs. dimension 4)

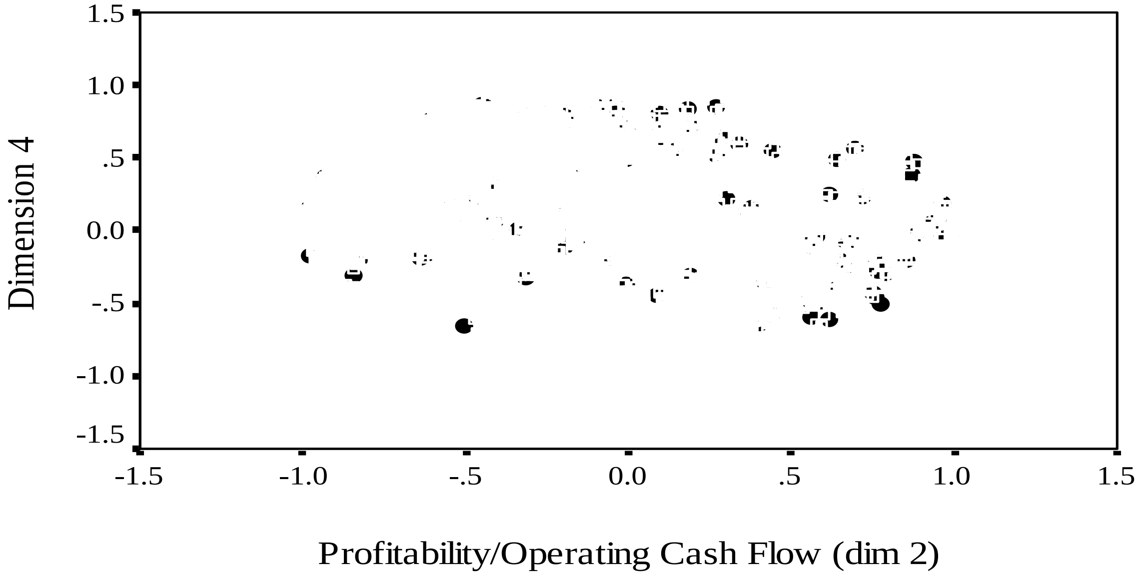

Figure 8b

MDS Common Space of Continuing Companies

(dimension 2 vs. dimension 4)

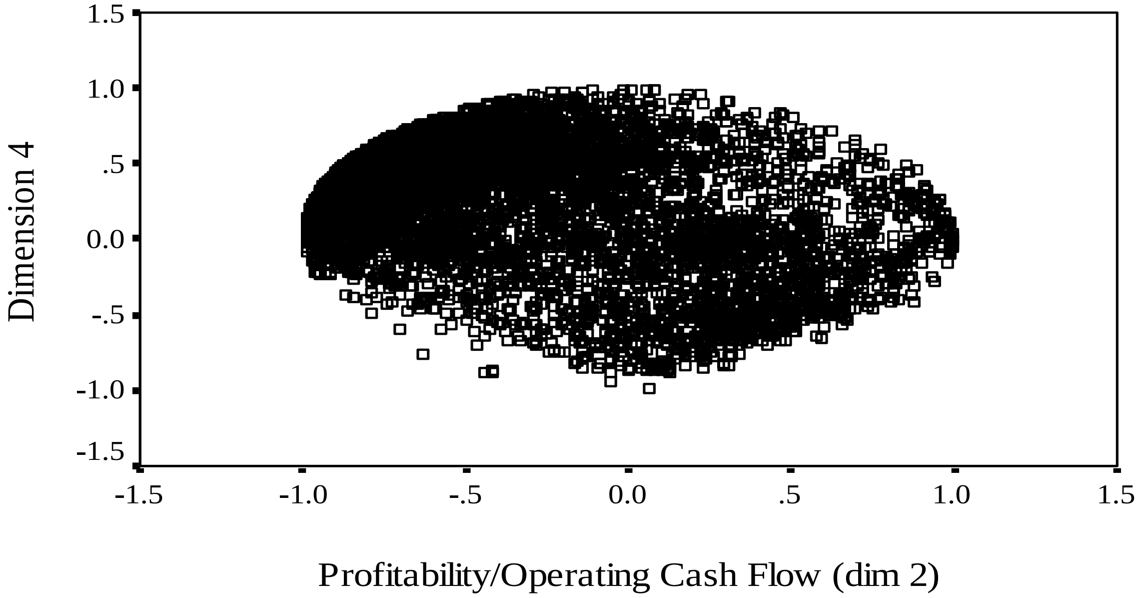

Figure 9a

MDS Common Space of Failed Companies

(dimension 3 vs. dimension 5)

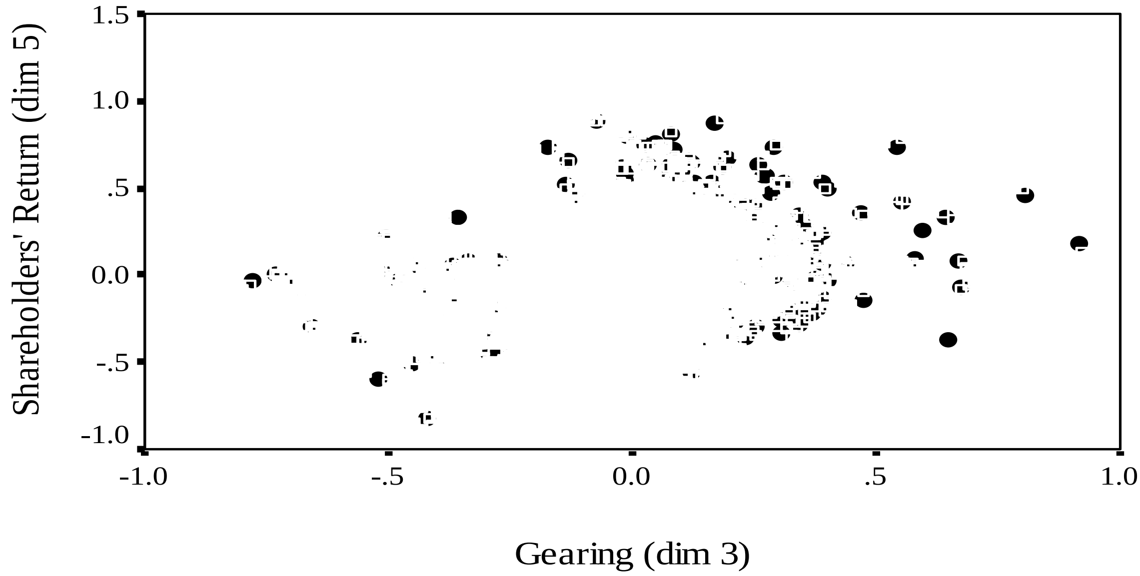

Figure 9b

MDS Common Space of Continuing Companies

(dimension 3 vs. dimension 5)

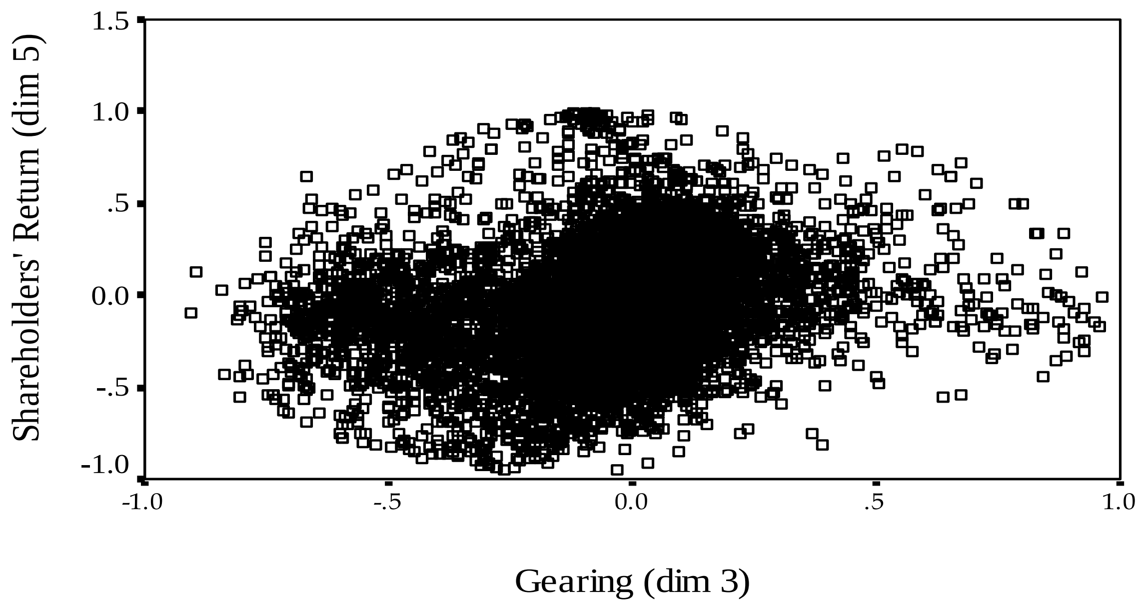

Figure 10

Long-Term Interest Rates vs. Gearing / (Profitability, Operating Cash Flow) Weights