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FINANCIAL DISTRESS MODELLING REVISITED: AN EMPIRICAL ILLUSTRATION OF THE IMPORTANCE OF OVERSAMPLING AND CUT-OFF POINT SELECTION

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ABSTRACT

This paper, employing financial distress data from the period 1981 to 1994 in the UK, investigates the importance of two recurring problems in Financial Distress Modelling, namely the issue of oversampling and the determination of the cut-off point which should be applied to the prediction model. The oversampling problem arises when statistical techniques that assume random sampling are employed to analyse a sample that is non-random. This is often the case in financial distress studies, resulting in biased parameter and probability estimates for the model. The second issue investigated is the impact of empirically determining the correct cut-off point to be employed when predicting financial distress. Too frequently a cut-off point of 0.5 is selected without any justification or discussion. This paper empirically illustrates how these two important issues can be addressed and incorporated in a financial distress modelling process.

INTRODUCTION

The ability to classify accurately or predict those companies which will meet their future obligations and hence remain solvent or go into a state of financial distress has obvious benefits to a wide variety of groups and individuals. Examples of such interested parties are investors, lenders, auditors, employees and academics. The perceived importance of financial distress research is further suggested by the interest it has generated not only in the USA (Beaver, 1966; Altman, 1968) and the UK

(Taffler, 1982; Keasy and Watson, 1987), but also in other countries such as Australia (Izan, 1984) and Sweden (Skogsvik, 1990).

This paper illustrates empirically how one can overcome the matched pairs sampling problems and cut-off point selection issues that are typically associated with financial failure studies. A financial distress model is generated using a recent data set (1981-1994) from the London Stock Exchange. Furthermore, the prediction results of the model which is adjusted to eradicate the problems mentioned above (hereafter referred to as the 'adjusted model'), are compared with a model developed following the more traditional methodology. The latter ('raw model') employs matched pairs samples and an arbitrary cut-off point of 0.5. The organisation of the remainder of the paper is as follows: the next section discusses the literature associated with financial distress studies; this is followed by an outline of the necessary adjustments required to overcome the problems of matched pairs samples and cut-off point selection; the methodology employed is then presented; and finally the results section compares the prediction accuracy of the adjusted model with that of the raw model.

LITERATURE REVIEW

Quantification in relation to the prediction of corporate failure started in the 1930s with the advent and development of accounting in the USA as a distinct and separate profession. Typical studies include those of Smith and Winakor (1935) and Merwin (1942). These researchers indicated that the variation in, or the trend of financial ratios taken from, companies' accounts is significantly different for failing companies as compared with those who prospered. The milestones, however, in corporate failure studies came with the works of Beaver (1966) and Altman (1968). The main finding of Beaver's work was that there were a number of indicators, largely financial ratios, that could enable one to distinguish between a failed company and a non-failed company. Beaver (1966) applies a univariate approach where the predictive ability of the ratios is analysed individually. Altman (1968), on the other hand, used multiple discriminant analysis (MDA). This technique finds the combination of variables which best discriminates between two or more classification groups by means of a statistical technique which estimates the coefficients which are attached to the ratios used as discriminating variables.

In the context of financial failure models, however, serious questions have been raised about the restrictive statistical requirements imposed by MDA (Maddala, 1983). The technique assumes that the independent variables are multivariate normal and the covariance matrices of the two groups are equivalent. Generally speaking, the variables used in bankruptcy models are financial statement based ratios and these ratios frequently violate the normality assumption (Deakin, 1972; O'Connor, 1973; Bird and McHugh, 1977; Bougen and Drury, 1980; Karels and Prakash, 1987).

Models of bankruptcy risk have been developed to overcome the demanding assumptions of MDA. These include logit and probit analysis (Ohlson, 1980; Zmijewski, 1984; Zavgren, 1985; Hall and Stark, 1986), recursive partitioning (Frydman, Altman and Kao, 1985), linear goal programming (Gupta, Ramesh and Bagghi, 1990) and neural networks (Triguerios and Berry, 1991; Altman, Marco and Vareto, 1994). These techniques are not restricted by the same assumptions that constrain MDA but largely their performance is similar to that of MDA.

Variables that are employed in bankruptcy models generally are selected on the basis of a type of ad hoc pragmatism rather than a theoretical background. Typically they are based upon data available from financial statements. Pinches, Mingo and Caruthers (1973) and Chen and Shimenda (1981) list and analyse the multitude of ratios used by various researchers. There seems to be no a priori reason to limit the choice of variables employed in bankruptcy models to financial ratios. It may be that data supplied by the financial markets can be useful in failure models (Taffler, 1982). Furthermore, it has been suggested that such factors as details about directors' appointments enhance the prediction power of models (Peel, Peel and Pope, 1986; Peel and Peel, 1988). Additionally, the importance of reporting lags (Keasey and Watson, 1987), macroeconomic variables (Rose, Andrews and Giroux, 1982), and general or specific price level changes (Mensah, 1983; Skogsvik, 1990) have been investigated. Hall and Stark (1986) address the problem of accounting signals conveying different meanings at different points in time. Platt and Platt (1990), Izan (1984), Lincoln (1984) and Lang and Stulz (1992) examine the effects of industry-relative financial and operating ratios and the change in industry output on the likelihood of corporate failure.

Oversampling

Zmijewski (1984) analysed the distressed firm sample frequency rates (i.e. the percentage of distressed firms included in the sample) of several studies which took place prior to 1983. It was discovered that three studies used rates of less than 40 per cent and eleven studies used a 50 per cent rate (i.e., in a sample of 100 companies 50 are failed and 50 are non-failed). This practice of having a high distressed firm sample frequency rate continues in more recent studies (Zavgren, 1985 – 50 per cent; Gentry, Newbold and Whitford, 1987 – 50 per cent; Keasey and McGuinness, 1990 – 50 per cent).

This sampling approach, according to Maddala (1983), violates the random sampling design assumption and, if conditional probability techniques are employed, causes both parameter and probability estimates to be asymptotically biased. The observed result of this situation is that the oversampled group has higher classification and prediction accuracy rates than would otherwise have been the case. One of the problems associated with attempting to overcome the oversampling issue is the cost involved in obtaining the undoubtedly large randomly selected sample that will contain a sufficient number of failed companies.

Some researchers have attempted to accommodate this oversampling. Ohlson (1980) attempts to avoid the biases mentioned here by using proportions of failed and non-failed companies close to the proportions found in the population. In addition to the increased computational costs, following this policy also means that a holdout sample to test the predictive usefulness of the model may be lost. That is, if all available data for non-failed companies is employed to generate the model, then by definition a holdout sample is not feasible. Stone and Rasp (1993) suggest an approach, based on a formula developed by Efron (1986) which is easy to implement for assessing predictive or classificatory accuracy. Efron (1986) derives formulae for estimating the amount of underestimation or downward bias. These bias estimations can be added to a model's apparent error rate to produce an estimate of the true error rate. Palepu (1986) suggests that this sampling bias can be overcome by adjusting the constant term in the model provided the statistical technique being employed is logit. If probit or some other method is used then the coefficients of the variables will also have to be adjusted.

Palepu (1986) suggests that the adjustment that needs to be added to the constant term of the logit model is given by

$$\ln (P_2/P_1) \quad (1)$$

Where P_1 is the probability that a failed company available in the population is included in the sample.
P_2 is the probability that a non-failed company available in the population is included in the sample.

Therefore, for example, if the population contains 37 failed companies and 1032 non-failed companies and a matched sample of 37 failed and 37 non-failed is selected, then the adjustment required is

$$= \ln ((37/1032)/(37/37))$$
$$= \ln ((37/1032))$$

Determination of Optimal Cut-off Point

Typically tests of prediction involve classifying a group of firms into the failed and non-failed categories based on the estimation acquisition probability. This estimated acquisition probability is compared to some predefined cut-off probability and if it is less than the cut-off probability, the firm is classified as non-failed. The use of arbitrary cut-off probabilities (usually 0.5) in prediction tests has been pointed out as a problem by others (Ohlson, 1980; Altman, Haldeman and Narayanan (1977); Palepu, 1986; Hsieh, 1993). Palepu (1986, p. 12) states:

> The appropriate cut-off probability to be employed in the prediction tests is determined by the decision context in which the model's predictions are to be used.

To overcome this problem, the optimal cut-off probability in this study is derived in a specific decision context. The decision is one in which the market is uninformed about the specific failure risk of any given firm. It assumes that the market believes that all firms are equally likely to fail. In this context Palepu (1986), in a study of take-overs, suggests that a firm should be classified as a take-over target and hence purchased if

$$\frac{f_1(p/i=\text{target})}{f_2(p/i=\text{non - target})}\geq 1 \tag{2}$$

Where $f_1(\ )$and $f_2(\ )$ = Conditional probability density functions.
p = predicted take-over probability.

This equation implies that the optimal classification procedure is to classify a company as a target if the predicted take-over probability is such that the marginal probability of observing p if the company is actually taken over is greater than the corresponding marginal probability if the company is a non-target. The optimal cut-off probability is the value where the two conditional marginal densities are equal. If this approach is to be applied empirically, the conditional probability density functions $f_1(\ )$and $f_2(\ )$ need to be determined. Empirical approximations of $f_1(\ )$and $f_2(\ )$ can be obtained by plotting the distribution of the estimated probabilities for the target and non-target companies in the estimate sample. The cut-off probability is the value where the two plots intersect.

Furthermore, Hsieh (1993) considers the importance of Type I and Type II errors (Type I = predicting a failed company as non-failed and Type II = predicting a non-failed company as failed) when determining the cut-off point. Previous studies assume that the cost of Type I and Type II errors are equal. In the case of financial distress this is unlikely to be the case (Clark and Weinstein, 1983). Hsieh (1993) illustrates how the cut-off point should be altered to take account of Type I and Type II errors. Furthermore, Zmijewski (1984) notes that the predictive ability of bankruptcy prediction models depends heavily on the cost ratio of the errors. The only difference between Palepu (1986) and Hsieh (1993) is the decision context of the studies. A comprehensive discussion of the problems associated with selecting a cut-off point in financial failure studies can be found in Hsieh (1993) and Palepu (1986).

METHODOLOGY

Sample Selection

There are two distinct samples, which are collected differently and then combined: a sample of failed companies; and, a sample of firms that did not fail. No attempt is made to match the companies by size or industry category. Ohlson (1980, p. 112) states 'the appropriate criteria to be used for matching purposes are not obvious.' Peel et al. (1986) further suggest that a superior methodology would be to use these variables as predictors rather than to use them for matching purposes. The companies are matched by year-end, however.

Failed Companies

An initial sample of 255 quoted nonfinancial companies, which failed on the London Stock Exchange between 1981 and 1991, is identified. The source documents for this initial identification are:

- Extel Financial Securities Taxation Service Capital Gains Tax, Capital Losses Securities of Negligible Value at 28/2/92. This publication provides 117 companies failing within the specific time period required
- Stock Exchange Year Book, 1991. Two sections of this publication are used, the liquidation and receivership sections. A further 138 companies are identified from this source.

The Stock Exchange Year Book, which provides summary information annually on all those companies quoted on the London Stock Exchange, provides a section highlighting those companies which are in the process of receivership or liquidation. The definition of financial failure used in this study can be stated as:

> Any nonfinancial company which becomes of negligible value or is classified as in a state of liquidation or receivership by the Stock Exchange Year Book during the period 1981 to 1991.

The Datastream Mnemonics for the companies that satisfy the definition of failure defined above were then noted and a 'restricted list' was then generated through Datastream. The desired variables for the failed companies for the year before failure are downloaded using the data channel programs.

There are two forms of data loss at this point. Firstly, company mnemonics cannot be found for all the companies that are identified as failed. As a consequence, companies without mnemonics cannot be included in a restricted list using Datastream. Secondly, any company that does not have a full set of data is deleted from the sample. Some companies are reinstated into the sample after examining Extel Cards and manually generating the data. This leaves a sample of 137 failed companies as illustrated by **Table1**.

Table 1: Analysis of Failed Companies by Year

Year of Data	No. Companies
1980	29
1981	18
1982	9
1983	12
1984	9
1985	9
1986	2
1987	4
1988	19
1989	21
1990	5
Total	137

Maddala (1983) suggests that if incomplete data observations are distributed nonrandomly in the population and the estimating model does not take this factor into consideration, then the estimated parameters and the probabilities will be biased. This bias arises if distressed firms are more likely to have incomplete data. In this study, data loss due to incomplete data occurred both within failed and non-failed firms. Therefore it could not be stated with confidence that it is a phenomenon solely or more generally associated with failed firms.

Non-failed Companies

Table 2 indicates the number of companies quoted on the London Stock Exchange from 1981 to 1991. These figures were obtained from the corresponding Stock Exchange Year Books. The non-failed sample of companies consists of all those companies that are listed in 1991 and satisfy the data requirements. These companies are then traced back to 1981 and the corresponding numbers of companies that existed with complete data can be seen in **Table 2**. This indicates that out of the 1276 companies in 1991, 648 of them existed in 1981. The approach followed by Ohlson (1980) is applied and as a consequence only one observation from each of the non-failed companies is used. The following method is applied to determine which observation should be selected.

Table 2: Analysis of Non-failed Companies in Estimation Sample

Year	Number of Companies Quoted on LSE	Number of Companies with Complete Data	Estimation Sample Number of Companies Allocated to Each Year
1981-82	2301	648	96
1982-83	2269	666	97
1983-84	2322	715	102
1984-85	2572	736	105
1985-86	2648	776	115
1986-87	2644	852	120
1987-88	2799	916	115
1988-89	2709	1017	133
1989-90	2628	1120	133
1990-91	2697	1207	138
1991-92	2373	1276	122
Total	28322		1276

The number of companies quoted each year is calculated as a percentage of the total. For example in 1981/82 there are 2301 companies. Therefore, 1981/82 companies account for (2301/28322) x 100 = 7.5 per cent. Then 7.5 per cent of the 1276 companies in the sample is calculated to give 96 companies. Ninety-six companies are then selected randomly from the 1276 companies and their observations for year 1980 (i.e. one year before) are included (i.e. 96 non-failed companies were selected from 648 available in 1980). These 96 companies are then removed from the sample of 666 in 1982, leaving 570. This procedure is repeated for each subsequent year resulting in 1276 companies allocated as shown by **Table 2**.

The Holdout Sample

Companies for the holdout sample are selected from the period February 1991 to February 1994. The failed companies for the holdout sample are identified using the same definition that is used in the estimation period. This provides an initial list of 41 companies, which reduced to 29 when the data constraints are applied. The 29 failed companies, which have complete data, as shown in **Table 3**, predominantly fail in 1991 and 1992.

Table 3: Number of Failed Companies on Each Market by Year

Year Failed	Number of Companies
1991	17
1992	11
1993	0
1994	1
Total	29

Table 4 indicates the number of companies quoted on the London Stock Exchange from 1991 to 1994 (February is the cut-off month) and illustrates the corresponding number of non-failed firms with complete data. The non-failed sample of companies consists of 1152 companies. The smallest number of companies available over the four year period, 1991 to 1994, was taken as illustrated in **Table 4**. This approach of employing a holdout sample, which is significantly large and from a different time period, is consistent with the literature (Neter, 1966) and is in a fashion that replicates how the model could be used in practice.

The same approach is followed as when analysing the estimation sample. That is, only one observation from each company is used. The companies are selected and allocated to each of the corresponding years in exactly the same manner as with the estimation sample. **Table 4** illustrates the number of observations allocated to each year. There is an apparent overlap between the estimation sample and the holdout sample. This occurs because there is a small number of failed companies dated between January 1991 and February 1991 (five companies) in the estimation sample but a considerably larger number of failed companies post-February 1991 in the holdout sample (17 companies). Furthermore, a check is made to ensure that a selected non-failed company does not appear in both the estimation and the holdout sample.

Table 4: Analysis of Non-failed Companies Quoted on the London Stock Exchange during Holdout Period

Year	Number of Companies Quoted	Number of Companies with Complete data	Number of Companies Allocated to Holdout Sample
1991	2273	1152	296
1992	2186	1254	283
1993	2183	1291	281
1994	2258	1222	292
Total	8900		1152

The Model

This study employs the conditional probability logit model, estimated by the maximum likelihood procedure with the aid of the statistical package SPSSPC+. Logit is used to avoid some of the frequently stated problems with MDA. Another appealing attribute of the logit function is the shape of the logistic distribution. In comparison to the linear function, the logit function implies: the marginal effect of the independent variable is not constant; and, the changes in the independent variables will have their greatest impact on the probability of a given option, in this case financial distress, at the midpoint of the distribution. The low slopes towards the end points of the logit distribution suggest that large changes in the independent variables are necessary to bring about a small change in the probability of financial distress.

This is intuitively appealing in relation to financial failure because, a priori, one would expect that an increase in the linear combination of variables up to a particular level might have little impact on the probability of failure. For example, if a financial distress model is considered which includes four variables (a measure of gearing, a measure of profitability, a measure of efficiency and a measure of liquidity), small changes in these variables may occur without a significant change in the probability of failure. However, when these variables approach their acceptable limit (i.e., profitability approaches zero, return on capital employed becomes negative etc.) any additional change in the linear combination of the variables will impact on the probability of failure very significantly. The probability of failure will continue to rise until an upper limit is reached at which point any subsequent change in the linear combination of variables is deemed to have little impact on the probability of failure.

Variable Selection

As indicated previously, there is no 'theory' of financial failure. As a consequence, the variables included in this study were selected on the basis that they were found helpful in providing statistical evidence for impending failures in other studies and are thought likely to provide a parsimonious but effective model. This selection procedure is common in financial failure literature (Ohlson, 1980). The variables included in this study are illustrated in **Table 5**.

The traditional variables used in financial failure models can be summarised under the following headings: profitability; efficiency; gearing; and, liquidity. The last four variables are from these categories respectively. In addition, a measure of size is included as used by Ohlson (1980) and Peel et al. (1986) and found to be significant.

Table 5: Definition of Variables

Variable	Description	Units
Total Assets Employed (TAE)	Total assets less current liabilities (deflated to base year 1981)	£000s
Return on Capital Employed (ROCE)	(Total Interest Charges + Pre-tax Profits) / (Total Capital Employed — Total Intangibles)	%
Turnover to Assets Employed (TO/TAE)	Total Sales / Total Assets Employed	Ratio
Capital Gearing (CG)	(Preference Capital + Subordinate Debt + Total Loan Capital) / (Total Capital Employed — Total Intangibles)	%
Quick Assets (QA)	(Total Current Assets — Stocks and Work in Progress) / Total Current Liabilities	Ratio

Notes: The following variables are also defined to distinguish between failed, non-failed, Official List (OL) and Unlisted Securities Market (USM) companies:

F Non-failed = 0, Failed = 1

Market OL = 0, USM = 1.

Calculation of Adjustment Required for Oversampling

As indicated in Palepu (1986), an adjustment needs to be added to the constant term of the logit model generated. The amount to be added to the constant term equals ln (P2/P1) where P1 is the number of failed companies in the sample divided by the number of failed companies in the population that fulfil the data requirements, and P2 is the number of non-failed companies in the population that fulfil the data requirements.

Therefore in this study

$$P1 = 137/137 = 1 \tag{3}$$

and,

$$P2 = 1276/9929$$

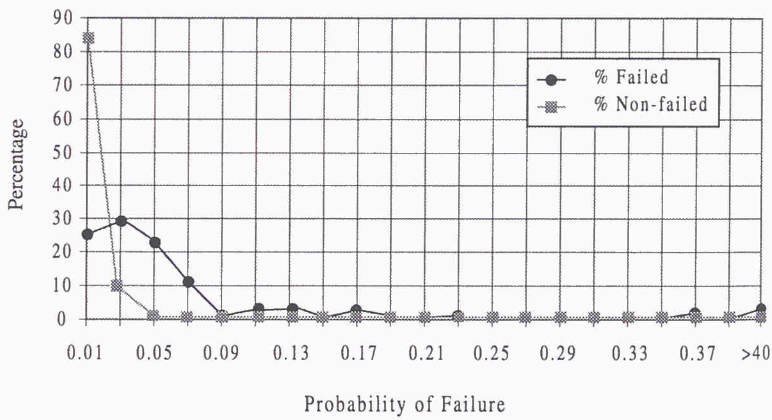
Therefore the adjustment

$$= \ln\left(\frac{1276}{9929}\right) = -2.05172 \tag{4}$$

Empirically Calculated Cut-off Point

Two types of cut-off points are used. First, the commonly used but arbitrary cut-off of 50 per cent is employed. Second, an optimal cut-off point is calculated using the methodology outlined by Palepu (1986). Empirical approximations of the conditional probability density functions $f_1(\ )$ and $f_2(\ )$ need to be determined. These can be obtained by plotting the distribution of the estimated probabilities for the failed and non-failed companies in the estimate sample (**Table 6**). The optimal cut-off probability is the point where the two plots intersect as illustrated by **Figure 1**.

Figure 1: Empirically Derived Optimal Cutoff Point using the Adjusted Probabilities



This provides an optimal cut-off probability of 0.025. This means that any company with a probability of less than 0.025 is classified as healthy and any company with a probability greater than 0.025 is classified as failed.

Table 6: Distribution of Adjusted Estimated Failure Probabilities for the Failed and Non-failed Companies [a]

	FAILED No. of Companies	NON-FAILED No. of Companies	M-P (p)[b]	FAILED %Failed $f_1(p)$	NON-FAILED %Non-failed $f_2(p)$
	35	1085	0.01	25.55%	85.03%
	40	137	0.03	29.20%	10.74%
	31	21	0.05	22.63%	1.65%
	15	10	0.07	10.95%	0.78%
	2	8	0.09	1.46%	0.63%
	2	2	0.11	1.46%	0.16%
	3	1	0.13	2.19%	0.08%
	0	0	0.15	0.00%	0.00%
	2	1	0.17	1.46%	0.08%
	0	1	0.19	0.00%	0.08%
	0	1	0.21	0.00%	0.08%
	1	0	0.23	0.73%	0.00%
	0	1	0.25	0.00%	0.08%
	2	0	0.27	1.46%	0.00%
	0	0	0.29	0.00%	0.00%
	0	1	0.31	0.00%	0.08%
	0	0	0.33	0.00%	0.00%
	0	0	0.35	0.00%	0.00%
	1	0	0.37	0.73%	0.00%
	0	0	0.39	0.00%	0.00%
	3	7	>40	2.19%	0.55%
TOTAL	137	1276		100.00%	100.00%

Notes: [a] The failure probabilities are computed for the 137 failed and 1276 non-failed companies in the estimation sample using the coefficient estimates of the model in **Table 7**. The range 0 to 0.4 is divided into 10 equal intervals. The number of companies that fall within each of these intervals are tabulated separately for the failed and non-failed. The figures in the column under $f_1(p)$ are calculated by dividing the number of failed companies in each probability interval by 137 and expressing the result as a percentage. Similarly, the figures under $f_2(p)$ are calculated by dividing the number of non-failed in each interval by 1276 and expressing the result as a percentage.

[b] M-P(p) is the midpoint of each probability interval.

RESULTS

Sign and Significance of Variables

Here, the individual variables are analysed in terms of the sign and significance of their coefficients. The signs of the coefficients are compared to those which are predicted based on previous studies. **Table 7** provides the results for the model.

Table 7: Sign and Significance of Variables

Variable	Coefficient	Significance	Predicted Sign	Estimated Sign
TAE	(2.9E-08)	0.7129	-	-
ROCE	(0.0197)	0.0000 *	-	-
TO/TAE	(0.0409)	0.3762	-	-
CG	0.0329	0.0000 *	+	+
QA	(0.5293)	0.0233 **	-	-
Constant	(2.6239)	0.0000		-

Notes:

* Significant at 1 % level

** Significant at 5% level

The signs of the estimated coefficients compare favourably with what is expected. The estimated signs of the coefficients suggest that the probability of a firm failing will decrease if TAE, ROCE, TO/TAE and QA increase and if CG decreases. ROCE and CG are statistically significant at the 0.01 level while QA is statistically significant at the 0.05 level. This suggests that measures of profitability, gearing and liquidity are important when attempting to explain financial distress. This is in line with the perception that a company with decreasing profitability, decreasing liquidity and increasing gearing is likely to fail.

Prediction Accuracy

Table 8 illustrates the predictive accuracy of the model based on the estimation sample and the holdout sample when both the arbitrary 0.5 cut-off point and the empirically derived cut-off point, 0.025, are employed.

Table 8: Predictive Accuracy of Model

	Estimation Sample					
	E_1			E_2		
Cut-off	NF	F	OA	NF	F	OA
0.5	98.82	8.76	90.09			
0.025				93.73	62.77	90.73
	Holdout Sample					
	H_1			H_2		
Cut-off	NF	F	OA	NF	F	OA
0.5	94.53	20.69	92.72			
0.025				80.38	62.07	79.93

where:

E_1 = Estimated Probability from estimate sample without adjustment suggested by Palepu (1986) to overcome state based sampling bias

E_2 = Estimated Probability from estimate sample with adjustment suggested by Palepu (1986) to overcome state based sampling bias

H_1 = Probabilities for holdout sample without adjustment suggested by Palepu (1986) to overcome state based sampling bias

H_2 = Probabilities for holdout sample companies with adjustment suggested by Palepu (1986) to overcome state-based sampling bias

NF = % of non-failed companies correctly predicted

F = % of failed companies correctly predicted

OA = overall prediction accuracy

The prediction results both for the estimation sample and holdout sample are comparable to previous studies as indicated by **Table 9**.

Table 9: Overall Classification Accuracy of Bankruptcy Prediction Studies

Year 1 (Prior to Failure)		
Author	*W/S*	*H/O*
Beaver (1966)	90%	87%
Altman (1968)	95%	73%
Wilcox (1971)	94%	-
Blum (1974)	93%	95%
Altman et al. (1977)	91%	93%
Ohlson (1980)	85%	-
Zavgren (1985)	82%	-
Clarke (1990)	83%	-

Notes:

W/S = tested against same sample from which dichotomous classification test was estimated

H/O = tested against holdout sample

The - indicates that there are no results available

The interesting issue from this comparison is the percentage of failed companies correctly predicted. That is, employing the raw model and arbitrary prediction cut-off point 0.5, 8.76 per cent of failed firms are predicted correctly within the estimation sample, and 20.69 per cent in the holdout sample. The adjusted model performs significantly better, using the empirically determined cut-off point of 0.025 62.77 per cent of failed companies within the estimation sample are predicted correctly and 62.07 per cent in the holdout sample. Since the cost of mis-classifying failed firms as non-failed is greater (Clark and Weinstein, 1983), this result is particularly important. Another way of highlighting the importance of this result is to analyse the loss functions of Type I and Type II errors. When the loss functions are equal it is equivalent to minimising the total error costs. However, it is evident from the literature (Clark and Weinstein, 1983; Hsieh, 1993) that Type I and Type II loss functions are not equal. Therefore **Table 10** illustrates that the adjusted model minimises total error costs compared to the more frequently employed raw model, although the raw model minimises total error probabilities. If the cost ratio of T1:T2 is approximately 3:1 as suggested by Hsieh (1993), then the associated cost saving by employing the adjusted model is 45.2 per cent.

Table 10: Analysis of Type I (T1) and Type II (T2) Error Costs for Holdout Sample Results

Cut-off Point	T1	T2	Total Cost when cost of T1=T2	Total Cost when cost of T1= 2T2	Total Cost when cost of T1= 3T2
0.5	79.31	5.47	84.78	164.09	243.4
0.025	37.93	19.62	57.55	95.48	133.41

CONCLUSIONS

This paper illustrates empirically how two problem areas in financial distress modelling, oversampling and determination of the prediction cut-off point, can be solved. The findings suggest the importance of empirically deriving the cut-off point and making the necessary adjustment for oversampling. The adjusted model predicts correctly approximately three times more failed companies than the raw model for the holdout sample, although the overall classification accuracy for the raw model is better than for the adjusted model. This corresponds to a 45.2 per cent cost saving, assuming the cost of Type I errors is approximately three times the cost of Type II errors, as suggested by Hsieh (1993).

Further research regarding the actual cost of Type I and Type II errors is required to complement this paper. In addition, although the prediction accuracy of the raw and adjusted models is comparable to past studies, as illustrated by **Table 9**, further research adjusting the model of Altman et al. (1977), and perhaps Taffler's (1982) model, should provide additional empirical support for employing the methodology outlined in this paper.

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