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Signalling Corporate Collapse using a Dual-Classification Scheme: Australian Evidence

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Regardless of the technical procedure used in signalling corporate collapse, the bottom line rests on the predictive power of the corresponding statistical model. In that regard, it is imperative to empirically test the model using a data sample of both collapsed and non-collapsed companies. A superior model is one that successfully classifies collapsed and non-collapsed companies in their respective categories with a high degree of accuracy. Empirical studies of this nature have thus far done one of two things. (1) Some have classified companies based on a specific statistical modelling process. (2) Some have classified companies based on two (sometimes – but rarely – more than two) independent statistical modelling processes for the purposes of comparing one with the other. In the latter case, the mindset of the researchers has been – invariably – to pitch one procedure against the other. This paper raises the question, why pitch one statistical process against another; why not make the two procedures work together? As such, this paper puts forward an innovative dual-classification scheme for signalling corporate collapse: dual in the sense that it relies on two statistical procedures concurrently. Using a data sample of Australian publicly listed companies, the proposed scheme is tested against the traditional approach taken thus far in the pertinent literature. The results demonstrate that the proposed dual-classification scheme signals collapse with a higher degree of accuracy.

Field of research: Accounting and Finance

1. Introduction

A careful examination of the empirical literature for signalling corporate collapse indicates that from the earliest identifiable studies and up until the most recent publications, researchers have been focusing on finding ways to signal collapse more accurately; that is, to increase the percentages for correctly classifying companies into their corresponding categories of either collapsed or non-collapsed.

Studies that adopted a ratio-based multivariate approach for signalling corporate collapse, focused on identifying alternative statistical procedures that could potentially signal collapse with better accuracy compared to some benchmark. As such, the mindset of the researchers involved testing the accuracy of a prediction model using one statistical approach at a time *against* the benchmark. In this sense, two single and independent classification schemes are utilised, with one being pitched *against* the other.

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Accordingly, this paper hypothesises that such an approach could be problematic in that it might compromise the accuracy of classifying collapsed and non-collapsed companies into their corresponding categories. This is because the nature of the problem revolves around making the two independent statistical approaches work *against* each other.

In that regard, the solution that is proposed in this paper involves making the two independent statistical procedures work together, rather than compete against one another. As such, this paper puts forward an innovative dual-classification scheme for signalling corporate collapse, which is implemented as follows: a data sample of collapsed and non-collapsed companies is classified using some benchmark statistical technique; next, the same data sample is classified using an alternative statistical method; for a company to be considered correctly classified, it must have the same categorization using both statistical processes.

The rest of this paper contains four additional sections: section two provides a literature review, section three discusses the benchmark as well as the alternative statistical techniques that will be utilised, section four carries out an empirical investigation using a data sample of Australian publicly listed companies, and finally, section five draws this paper to a conclusion.

2. Literature Review

A careful examination of the empirical research that adopted a ratio-based multivariate approach for signalling corporate collapse reveals that the early studies have unanimously used Multiple Discriminant Analysis (MDA) as the preferred statistical procedure for deriving the prediction model. More specifically, pertinent studies published during the time period from the seminal work of Altman (1968) to Norton and Smith (1979) have collectively utilised MDA as the sole statistical technique for signalling collapse.

It was not until the seminal work of Ohlson (1980) that researchers began experimenting with alternative statistical procedures, with the objective of improving the accuracy of the prediction model. The introduction of alternative statistical methods necessitated establishing a benchmark against which they could be assessed.

Table 1 identifies the primary as well as the benchmark statistical methods used in the pertinent studies for signalling corporate collapse. The analysis considered studies during the period 1968 to early 2009; however, not all studies during this period utilized benchmarks. Those that utilized benchmarks spanned the sub-period 1983 to 2004.

The acronyms used in Table 1 correspond to the following: Multiple Discriminant Analysis (MDA), Logit analysis (Logit), Neural Network analysis (NN), Probit analysis (Probit), ID3 analysis (ID3), Recursive Partitioning Algorithm (RPA), Rough Sets analysis (RS), Going Concern Advisor (GCA), Tabu Search (TS), Koundinya and Puri judgmental approach (KP) and Mixed Logit analysis (ML).

Table 1 – Primary and benchmark statistical methods used in the pertinent literature

Study	*Primary statistical method(s)*	*Benchmark statistical method(s)*
Hamer (1983)	Logit	MDA
Casey and Bartczak (1985)	Logit	MDA
Frydman et al. (1985)	RPA	MDA
Gentry et al. (1985)	Logit/Probit	MDA
Lo (1986)	Logit	MDA
Lau (1987)	Logit	MDA
Peel and Peel (1987)	Logit	MDA
Barniv and Raveh (1989)	Logit/Probit	MDA
Aly et al. (1992)	Logit	MDA
Coats and Fant (1993)	NN	MDA
Fletcher and Goss (1993)	NN	Logit
Wilson and Sharda (1994)	NN	MDA
Boritz et al. (1995)	NN	MDA/Logit/Probit
Lacher et al. (1995)	NN	MDA
Wilson et al. (1995)	NN	Logit
Lee et al. (1996)	NN/ID3	MDA
Clark et al. (1997)	KP	MDA
Lenard et al. (1998)	GCA	MDA
Dimitras et al. (1999)	RS	MDA/Logit
Kim and McLeod Jr. (1999)	NN/ID3	MDA/Logit
Kyung et al. (1999)	NN	MDA
Laitinen and Kankaanpaa (1999)	NN/RPA	MDA/Logit
Lennox (1999)	Logit/Probit	MDA
Gritta et al. (2000)	NN	MDA
Zapranis and Ginoglou (2000)	NN	MDA
Drezner et al. (2001)	TS	MDA
Lin and McClean (2001)	NN	MDA/Logit
Ginoglou et al. (2002)	Logit/Probit	MDA
Charitou et al. (2004)	NN	Logit
Jones and Hensher (2004)	ML	Logit

The information in Table 1 indicates that during the period 1968 to early 2009, a total of three benchmarks could be identified; they are MDA, Logit analysis and Probit analysis. Moreover, whenever these benchmarks have been used, they were pitched *against* the primary statistical method.

Thus, regardless of which alternative statistical method was used, and regardless of which benchmark was preferred; the mindset of researchers has been – without exception – to pitch one statistical technique *against* the chosen benchmark. Thus, researchers have invariably approached the issue at hand from the point of view of which method is better than the other for the purposes of signalling corporate collapse – better in the context of improving the accuracy of correctly classifying companies in the data sample in either one of two categories: collapsed or non-collapsed.

Such a process generates one independent classification matrix using the benchmark statistical procedure, and another independent classification matrix using the alternative statistical method. Thus, the traditional approach that characterizes the pertinent literature ultimately generates two classification matrices that compete against each other.

Hence, the focal question raised herein is why pitch one classification scheme against the other? That is, why consider the two independent classification schemes to be competing against each other? Why not make them work together, instead?

As such, this paper puts forward an innovative dual-classification scheme that combines what have traditionally been considered in the pertinent literature to be independent schemes working against each other. The proposed dual-classification scheme allows the two independent matrices to work concurrently, thereby improving upon the overall accuracy of signalling corporate collapse.

The next section discusses the two methodologies that will be utilized in this paper in order to generate the two independent classification matrices as well as the dual-classification matrix, in preparation for the empirical investigation that will be carried out in section four of this paper.

3. Methodology

The previous section of this paper indicated that the early studies in the literature for signalling corporate collapse have unanimously used Multiple Discriminant Analysis (MDA) as the preferred statistical procedure for deriving the prediction model. It also indicated that the introduction of alternative statistical procedures in later studies necessitated establishing a benchmark against which they could be assessed; with MDA, Logit analysis and Probit analysis being cited as the benchmarks of choice during the period 1968 to early 2009 (which covers the entire time-span from the inception of ratio-based multivariate modelling of corporate collapse until the present).

More specifically, a total of 85 pertinent studies could be identified during the time frame from 1968 to early 2009. Of the 85 studies, 30 have used a benchmark; and of the 30 studies, 25 used a single benchmark (see Table 1). Of the 25 studies, four chose Logit analysis. In other words, 21 of the 25 studies chose MDA as the preferred benchmark.

Considering the prominence of MDA both as the dominant statistical procedure in the early state of the literature, and later on as the preferred benchmark against which alternative methods were tested; this paper also adopts MDA as one of the techniques for the empirical investigation that will be conducted later on in section four of this paper.

As explained in the previous section of this paper, the dual-classification scheme that is proposed herein requires the use of a second statistical procedure for deriving a second prediction model. For this purpose, Multi-Level Modelling (MLM) is chosen primarily because it represents the most current methodological construct in the literature for signalling corporate collapse (Hossari, 2009).

Therefore, the analytic underpinnings for both MDA and MLM are presented next, starting with MDA.

A basic prerequisite for MDA is that a data item can be classified in two (or more) groups, which in the context of signalling corporate collapse include companies that have collapsed and those that are still a going concern. Thus, the statistical procedure involves deriving a mathematical algorithm that successfully assigns a particular company to either one of these two groups. Equation 1 below achieves this objective (Klecka, 1982).

$$f_{km} = u_0 + u_1 X_{1km} + u_2 X_{2km} + ... + u_p X_{pkm} \qquad (1)$$

Where,

f_{km}: The value (also known as the *score*) that Equation 1 generates for company 'm' in group 'k'.
X_{ikm}: The value for the financial ratio 'i' for company 'm' in group 'k', where 'i' goes from '1' to 'p'.
u_i: The coefficients associated with each financial ratio 'X_{ikm}'; 'u_0' is the intercept.

The objective in Equation 1 is to determine the combination of financial ratios that optimizes the overall accuracy for classifying companies in their corresponding groups. This is achieved by using a forward stepwise procedure based on Wilk's lambda with the default values of 3.84 for *F*-to-enter and 2.71 for *F*-to-remove; these values correspond to probabilities of 0.05 and 0.10, respectively (Huberty, 1994).

The analytic underpinnings for MLM are discussed next.

The application of MLM in the context of signalling corporate collapse has been recently brought about in Hossari (2009). Considering that the event of collapse is of a binary nature (i.e., a company has either collapsed or is still a going concern) requires a binary specification of the multi-level model, which is depicted in Equation 2 below (Rice, 2001).

$$y_{ij} = \beta_{0ij} + b_j x_{ij} \qquad (2)$$

Such that,

$$\beta_{0ij} = a + u_j + e_{ij} \qquad (3)$$

And where,

y_{ij}: Identifies whether or not a particular company '*i*' in a particular industry sector '*j*' belongs to the collapsed group.
x_{ij}: Represents a particular financial ratio '*x*' for a particular company '*i*' in a particular industry sector '*j*'.
a: The intercept.
b_j: The slope for the linear relationship for industry sector '*j*'.

'u_j' and 'e_{ij}': Random quantities.

Although the announcement of the event of collapse is in itself sudden, the process is gradual. Therefore, it is best to assign a *probability* of collapse; whereby, the closer a company is to collapse, the higher the probability would be.

The notation $P(y_{ij} = 1 | x_{ij})$ represents the probability that collapse – defined by '$y_{ij} = 1$' – would occur based on a specific value for a financial ratio 'x_{ij}' (or a set of financial ratios). Therefore, Equation 2 could be expressed as follows:

$$P(y_{ij} = 1 | x_{ij}) = F(a + b_j x_{ij} + u_j) \quad (4)$$

Where,

$F(.)$: The cumulative distribution function for the residual 'e_{ij}'.

Finally, replacing $P(y_{ij} = 1 | x_{ij})$ by the term 'π_{ij}' gives the following:

$$\pi_{ij} = F(a + b_j x_{ij} + u_j) \quad (5)$$

Equation 5 is called a *link function*. When conducting Multi-Level Modelling it is recommended that the logit or logistic specification of the link function be adopted. To complete the specification of the logit link function 'π_{ij}' in Equation 5 must be expressed as follows (Goldstein, 2003):

$$\pi_{ij} = \frac{1}{1 + \exp(-a - b_j x_{ij} - u_j)} \quad (6)$$

Where, 'exp' represents 'exponential'.

The assumption is that the observed binary responses 'y_{ij}' follow a binomial distribution, which is what is needed in the context of modelling corporate collapse due to the binary nature of the response variable 'y_{ij}'. Thus, $y_{ij} \sim Bin(1, \pi_{ij})$. The variation in the response variable 'y_{ij}' is calculated as $\mathrm{var}(y_{ij} | \pi_{ij}) = \pi_{ij}(1 - \pi_{ij})$, where 'var' is short for 'variance'. Estimation of the variance allows testing for the statistical significance of the random coefficients in the binary response multi-level model. (Goldstein, 2003)

Therefore, the binary response multi-level model in Equation 2, could be expressed in the form of a binary response *logit* multi-level model, as follows (Goldstein, 2003):

$$y_{ij} = \pi_{ij} + e_{ij} z_{ij} \quad (7)$$

Where,

z_{ij}: denotes the estimated binomial standard deviation; that is,

$z_{ij} = \sqrt{\pi_{ij}(1 - \pi_{ij})}$, such that '$\sigma_e^2 = 1$'.

Having discussed the analytic underpinnings for the two statistical approaches that are utilized in this paper, the next section presents the empirical findings regarding the innovative dual-classification scheme that is proposed herein.

4. Findings

Financial items – for a data sample of 37 Australian publicly listed companies that have collapsed since 1989 and 37 non-collapsed companies – have been collected from the 'Fin Analysis' database published by 'Aspect Huntley'. From these items a total of 28 financial ratios are calculated. The ratios have been chosen based on their usefulness in the 85 studies that have been mentioned earlier in this paper. These ratios and their corresponding acronyms are listed in Table 1 below.

Table 2 - The financial ratios used in model derivation

Financial Ratio	Acronym	Financial Ratio	Acronym
Net Income / Total Assets	NITA	Total Equity / Total Assets	TETA
Current Assets / Current Liabilities	CACL	Quick Assets / Total Assets	QATA
Total Liabilities / Total Assets	TLTA	Total Equity / Total Liabilities	TETL
Working Capital / Total Assets	WCTA	Cash / Current Liabilities	CCL
Earnings Before Interest and Taxes / Total Assets	EBITTA	Earnings Before Interest and Taxes / Total Equity	EBITTE
Cash Flow / Total Liabilities	CFTL	Fixed Assets / Total Assets	FATA
Total Liabilities / Total Equity	TLTE	Fixed Assets / Total Equity	FATE
Retained Earnings / Total Assets	RETA	Long-Term Liabilities / Total Assets	LTLTA
Sales / Total Assets	STA	Cash Flow / Current Liabilities	CFCL
Cash / Total Assets	CTA	Current Liabilities / Total Assets	CLTA
Current Assets / Total Assets	CATA	Current Liabilities / Total Equity	CLTE
Quick Assets / Current Liabilities	QACL	Inventory / Working Capital	InvWC
Cash Flow / Total Assets	CFTA	Long-Term Liabilities / Total Equity	LTLTE
Net Income / Total Equity	NITE	Sales / Total Equity	STE

Using Multiple Discriminant Analysis (MDA), all 28 financial ratios are entered one at a time into the model in Equation 1 and their coefficients, represented by 'u_i', checked for statistical significance. Of the 28 ratios, three are statistically significant at the 95% level of confidence as indicated in the extract from the statistical output that is presented in Table 3.

Table 3 – Extract from the statistical output for MDA

<table>
<tr><th>Step Number</th><th>Financial Ratio Selected</th><th>Wilk's lambda</th><th>Significance</th></tr>
<tr><td>1</td><td>NITA</td><td>0.838</td><td>0.000</td></tr>
<tr><td rowspan="2">2</td><td>NITA</td><td rowspan="2">0.793</td><td rowspan="2">0.000</td></tr>
<tr><td>InvWC</td></tr>
<tr><td rowspan="3">3</td><td>NITA</td><td rowspan="3">0.751</td><td rowspan="3">0.000</td></tr>
<tr><td>InvWC</td></tr>
<tr><td>CFTL</td></tr>
</table>

Thus, the ensuing MDA-based corporate collapse prediction model is presented below in Equation 8:

$$f_{km} = -0.490 - 3.319NITA + 0.109InvWC + 0.100CFTL \quad (8)$$

The decision for classifying the companies in the data sample into either the collapsed category or the non-collapsed one is based on comparing the score, 'f_{km}', to some cut-off value. In that regard, the naïve approach is adopted; whereby, the cut-off value is calculated as one half the sum of the scores for the two groups of companies (Klecka, 1982).

Accordingly, the resultant classification matrix is presented in Table 4 below.

Table 4 - Independent classification matrix using MDA

Collapsed Companies	
Number of companies	37
Number of companies that could not be classified	0
Number of companies that could be classified	37
Number of correctly classified companies	32
Percentage of correctly classified companies	86%
Non-collapsed Companies	
Number of companies	37
Number of companies that could not be classified	0
Number of companies that could be classified	37
Number of correctly classified companies	22
Percentage of correctly classified companies	59%

The results in Table 4 indicate a classification accuracy of 86% for collapsed companies and 59% for their non-collapsed counterparts, when considering the MDA-based prediction model. These results correspond to an overall classification accuracy of 72% (i.e., the average for 86% and 59%).

Using Multi-Level Modelling (MLM), the 28 financial ratios utilised earlier are also entered one at a time into the model in Equation 7 and their coefficients, represented by 'b_j' in Equation 6, checked for statistical significance. Of the 28 ratios, three are statistically significant at the 95% level of confidence.

The resultant MLM-based corporate collapse prediction model is presented below in Equation 9:

$$\log it(\pi_{ij}) = -5.088NITA_{ij} + 1.681TLTA_{ij} + 0.271CFTL_{ij} \quad (9)$$

For consistency, the naïve approach is also used to determine the cut-off value. The consequential classification matrix is presented in Table 5 below.

Table 5 - Independent classification matrix using MLM

Collapsed Companies	
Number of companies	37
Number of companies that could not be classified	0
Number of companies that could be classified	37
Number of correctly classified companies	30
Percentage of correctly classified companies	81%
Non-collapsed Companies	
Number of companies	37
Number of companies that could not be classified	0
Number of companies that could be classified	37
Number of correctly classified companies	28
Percentage of correctly classified companies	76%

The results in Table 5 can be interpreted in the same manner as for those in Table 4. More specifically, the classification accuracy for collapsed companies is 81%, and for non-collapsed companies it is 76%. Thus, using an MLM-based prediction model, the overall classification accuracy is 78% (i.e., the average for 81% and 76%).

Next, the innovative dual-classification scheme put forward in this paper is applied in order to generate a matrix. The procedure involves the following steps:

1. For a particular company, generate an independent classification (i.e., either collapsed or non-collapsed) using MDA.
2. For the same company, generate another independent classification using MLM.
3. If the two independently generated classifications match, then an identical dual-classification is recorded; otherwise, the company is considered unclassifiable.
4. The three steps above are repeated for each company in the data sample.

The corresponding matrix based on the proposed dual-classification scheme is presented in Table 6 below.

Table 6 - Dual-classification matrix using both MDA and MLM

Collapsed Companies	
Number of companies	37
Number of companies that could not be classified	4
Number of companies that could be classified	33
Number of correctly classified companies	29
Percentage of correctly classified companies	88%
Non-collapsed Companies	
Number of companies	37
Number of companies that could not be classified	8
Number of companies that could be classified	29
Number of correctly classified companies	21
Percentage of correctly classified companies	72%

The results in Table 6 indicate that when using a dual-classification scheme, the classification accuracies for collapsed and non-collapsed companies are 88% and 72%, respectively. This corresponds to an overall classification accuracy of 80% (i.e., the average for 88% and 72%).

The results in Table 6 compare favourably to those in Tables 4 and 5. When used independently, MDA generates an overall classification accuracy of 72%; likewise, when used independently, MLM generates an overall classification accuracy of 78%. However, when a dual-classification scheme that combines both MDA and MLM is used, the overall classification accuracy of 80% exceeds each of the independently generated ones.

Therefore, it appears that the innovative dual-classification scheme that is put forward in this paper is superior to the traditional independent classification approach that has so far characterised the pertinent literature.

Having provided the empirical evidence to support the main premises for this study, the next section brings this paper to a conclusion.

5. Conclusion

This paper questioned the appropriateness of the classification system used thus far in the empirical literature that adopts a ratio-based multivariate approach for signalling corporate collapse. Using one statistical approach at a time, researchers traditionally examined the accuracy of a prediction model by pitching it *against* some benchmark statistical technique. In this sense, two single and independent classification schemes were utilised. Accordingly, this paper hypothesises that such an approach could be problematic in that it might compromise the accuracy of classifying collapsed and non-collapsed companies into their corresponding categories. This is because the two independent statistical approaches work *against* (rather than *with*) each other.

Therefore, in an effort to circumvent this problem, this paper proposed making the two independent statistical procedures work together, rather than compete against one another. As such, this paper put forward an innovative dual-classification scheme for signalling corporate collapse.

The dual-classification scheme that has been proposed herein was examined empirically using a data sample of 37 collapsed Australian publicly listed companies matched with 37 financially healthy ones. The collapsed companies were selected starting from 1989. For each company, a total of 28 financial ratios were calculated from the corresponding financial statements.

For the purposes of model derivation, two statistical procedures were utilised; these were Multiple Discriminant Analysis (MDA) and Multi-Level Modelling (MLM).

Using first MDA, three of the 28 ratios were statistically significant for the purposes of signalling collapse; the three ratios were 'Net Income divided by Total Assets' (NITA), 'Inventory divided by Working Capital' (InvWC) and 'Cash Flow divided by Total Liabilities' (CFTL).

Using then MLM, also three of the 28 ratios were statistically significant in signalling collapse; the three ratios were 'Net Income divided by Total Assets' (NITA), 'Total Liabilities divided by Total Assets' (TLTA) and 'Cash Flow divided by Total Liabilities' (CFTL).

The results indicated that a dual-classification scheme that concurrently used both MDA and MLM generated 80% overall classification accuracy, which compared favourably to each of the two independent classification schemes where the one using only MDA produced 72% overall accuracy and the one using only MLM delivered 78% accuracy. Thus, the findings indicated that the dual-classification approach that was proposed in this paper has indeed delivered better classification accuracy compared to the independent classification schemes that have so far characterised the literature. In that regard, this paper has made a contribution to the literature for ratio-based modelling of corporate collapse.

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