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Absence of Industry Effect in Modelling Corporate Collapse in Australia

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This paper investigates whether or not an industry effect is present when modelling corporate collapse in Australia. The investigation is motivated by a lack of consistency in the literature regarding such an effect. Moreover, this paper makes a unique contribution by applying an innovative methodological approach, called Multi-Level Modelling (MLM), for model derivation. Unlike the traditional two-step methodology used so far in the literature, MLM carries out model derivation and tests for an industry effect in a single step. Finally, the effectiveness of MLM is demonstrated using a sample of Australian publicly listed companies during the period 1989 to 2005; empirical results point to the absence of an industry effect.

Field of research: Finance

1. Introduction

Financial ratios are indispensable when it comes to ratio-based modelling of corporate collapse: they are the building blocks for the process, regardless of the methodology used. Notwithstanding this, it is possible for the integrity of the prediction model to be compromised, in case the industry groups to which the companies belong constitute an important aspect in the modelling process. The pertinent literature has been inconsistent in dealing with such industry effects. Thus, when signalling corporate collapse for a data sample of companies that have been drawn from multiple industry sectors, some (but not all) researchers adopted a modelling approach that allows for adjustments to be made to the financial ratios such that any potential industry effects do not diminish the integrity of the empirical results.

However, the adjustments made by those who have taken such effects into consideration, were at times inconsistent across industry sectors. (Bird and McHugh, 1977; Horrigan, 1965; Izan, 1984; Sheppard and Fraser, 1994)
Such lack of consistency in the literature necessitates that researchers determine which industry sectors require attention *before* model derivation is attempted. Traditionally, the process involved a two-step procedure. First, a model is derived for each industry sector, whereby raw financial ratios are used as predictors of collapse. Second, the procedure is repeated, but using ratios that have been adjusted for potential industry variation. Thus, for each industry sector, two models are derived. If the difference in the predictive accuracy of a particular pair of models (for a particular industry sector) were insignificant, this would indicate the absence of an industry effect; otherwise, an industry effect would be prevalent

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The objective of this paper is to investigate the presence, or lack thereof, of industry effects when modelling corporate collapse in Australia. Moreover, the proposed innovative methodology is a one-step procedure, as opposed to the traditional two-step process described earlier. That is, model derivation and adjustments for possible distributional variations occur concurrently. Accordingly, this study fills a gap, which is described as ‘a conspicuous absence of modelling innovation in this literature as well as a failure to keep abreast of important methodological developments emerging in other fields of the social sciences’ (Jones and Hensher, 2004, p. 1011).

Besides the introduction, this paper contains four additional sections. Section two provides a literature review, which is kept brief because of the necessity to devote more space to discussing the proposed methodology due to its novelty, particularly in the context of ratio-based modelling of corporate collapse; this is done in section three. Section four presents the findings based on an empirical investigation in the aforementioned context, using a data sample of Australian publicly listed companies. Finally, section five draws this paper to a conclusion.

2. Literature Review

Although researchers are in agreement when it comes to the effectiveness of financial ratios in signalling collapse, this is not the case regarding whether they differ significantly across industry sectors, and the effect such variations might have on the performance of prediction models. Studies that addressed this specific problem arrived at inconclusive results. Inferences vary, with some studies observing variations across selected – but not all – industry sectors, and some observing variations in selected ratios across all industry sectors. In this regard, the pertinent literature can be assigned to three broad categories concerning the treatment of industry effects.

The first group circumvents having to deal with industry effects altogether; this is achieved by limiting data samples to companies that belong to a single industry (for example, Barniv et al., 1999; Catanach Jr. and Perry, 2001; Harrison, 1995). However, such an approach diminishes the value of the corresponding empirical findings, because they cannot be extended beyond the industry being examined. The second group takes a less extreme approach in that the corresponding data samples of companies are drawn from multiple industry sectors. However, although failed companies in the data samples are matched with financially healthy ones based on some criterion such as the Global Industry Classification Standard (GICS), no effort is made to adjust financial ratios for potential industry effects during model derivation (for example, Clark et al., 1997; Darayseh et al., 2003; Hossari, 2006a; Hossari, 2007; Laitinen and Laitinen, 2000). While the empirical findings generated by this group are more useful than those generated by the first group, they are nevertheless still lacking in that they fail to consider potential industry effects.

The third group does not consider the matching process adopted by the second group to be crucial; instead, the emphasis is on adjusting the financial ratios for a random sample of companies for industry effects (for example, Hill and Perry, 1996; Jones and Hensher, 2004; Sheppard and Fraser, 1994). As such, the empirical findings generated by this group are superior to those generated by the other two, because they attempt to capture potential industry effects.

Such observations indicate a lack of a systematic approach in the literature to the treatment of possible variations in financial ratios across industry sectors. It is worth mentioning that although the data samples in the pertinent literature differ from one study to another – particularly with respect to the countries in which companies operate – such divergence should not distract from the issue at hand; namely, the treatment of potential industry effects in modelling corporate collapse. Although geographic location could be a significant factor in the modelling process – and as such worth investigating – it only becomes relevant when a particular sample is sourced from, not only multiple industry sectors, but also from multiple countries. Considering that a particular study in the relevant literature (including this paper) utilises data from a single country, it is safe to ignore the effects, if any, of geographic location in the modelling process.

Therefore, the fact that industry-specific variations could exist necessitates adjusting for the effects they might possibly have on ratio-based modelling of corporate collapse. However, inconsistency in the variations makes it difficult to determine *beforehand* which industry sectors require attention. Therefore, there is a need to, first, identify possible variations *when they exist* and make the necessary adjustments.

In modelling corporate collapse, the innovative methodology proposed in this paper looks for potential variations in financial ratios across industry sectors; significant variations are identified and the necessary adjustments made during model derivation. This differs from the traditional two-step procedure where variations across industry sectors are assessed independent of model derivation. Thus, the proposed methodology is an efficient and parsimonious tool for modelling collapse. The next section takes a closer look at the proposed methodology and research design.

3. Methodology and Research Design

The main hypothesis to be tested in this paper is whether or not an industry effect exists when modeling corporate collapse in Australia. Although such a research question has been raised on numerous occasions in the literature, the results of testing it have been inconclusive primarily due to the inefficient traditional methodological approaches adopted so far. In order to circumvent the major limitations inherent in the traditional approaches, this paper puts forward an innovative methodology, called Multi-Level Modelling (MLM), which is capable of adjusting for *potential* industry variations during model derivation. MLM is discussed in what follows.

MLM finds its roots in the relatively recent seminal work of Lindley and Smith (1972). Although MLM was subsequently utilized in a number of research areas, its application in the context of modelling corporate collapse has been recently brought about in Hossari (2006b).

A salient characteristic of MLM is that it takes into consideration the hierarchical structure of data in which 'units' at one 'level' are grouped within units at the next higher level (Goldstein et al., 2000).

In the context of this study, corporate collapse – being an event rather than a variable - could be measured by considering a number of observable variables, such as financial ratios. Incidentally, financial ratios could be measured at *multiple levels*. For example, they could be calculated at the *company level* as well as the *industry sector level*.

Although any number of levels could be represented, all the essential statistical features are found in the basic two-level model (Raudenbush and Bryk, 2002, p. 7). As such, this study adopts the two-level structure described above.

Considering that the event being modelled (i.e., corporate 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. This is depicted in Equation 1 (Rice, 2001).

$$y_{ij} = \beta_{0ij} + b_j x_{ij} \tag{1}$$

Such that,

$$\beta_{0ij} = a + u_j + e_{ij} \tag{2}$$

And where,

y_{ij}: identifies whether or not a particular company '*i*' in a particular industry sector '*j*' belongs to the collapsed group. For instance, 'y_{ij}' could take on the value '1' if a particular company is classified as collapsed, otherwise it could take on the value '0' if a particular company is classified as financially healthy.

x_{ij}: represents a particular financial ratio '*x*' for a particular company '*i*' in a particular industry sector '*j*'.

a: is the intercept.

b_j: is the slope for the linear relationship for industry sector '*j*'. When the sample of companies in a particular industry sector is drawn from a larger population, then the predicted slope 'b_j' may depart from the average slope, 'b'. Supposing that 'v_j' represents the departure of the predicted slope from the average slope, then $b_j = b + v_j$.

'u_j' and 'e_{ij}': are random quantities and therefore are expected to vary. The variation in 'u_j' is measured by its variance 'σ_u^2' and the variation in 'e_{ij}' is measured by its variance 'σ_e^2'. Variance estimates allow testing for the statistical significance of the random coefficients. The assumption is that each of the two variances is normally distributed with a mean equal to zero. The two variances 'σ_u^2' and 'σ_e^2' are referred to as the *random parameters*. (Goldstein, 2003, chapter 2)

Although the announcement of the event of collapse is in itself sudden, the process is gradual and could extend over many years. 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 $P\left(y_{ij}=1\middle|x_{ij}\right)$ 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 1 could be expressed as follows:

$$P\left(y_{ij}=1\middle|x_{ij}\right)=F\left(a+b_jx_{ij}+u_j\right) \qquad (3)$$

Where,

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

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

$$\pi_{ij}=F\left(a+b_jx_{ij}+u_j\right) \qquad (4)$$

Equation 4 is called a *link function* (McCullagh and Nelder, 1995). When conducting Multi-Level Modelling it is recommended that the logit or logistic specification of the link function be adopted (Breslow and Clayton, 1993; Goldstein, 1991; Goldstein and Rasbash, 1996; Moerbeek et al., 2001; Rodriguez and Goldman, 2001).

To complete the specification of the logit link function 'π_{ij}' in Equation 4 must be expressed as follows (Goldstein, 1991):

$$\pi_{ij}=\frac{1}{1+\exp\left(-a-b_jx_{ij}-u_j\right)} \qquad (5)$$

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, $y_{ij}\sim Bin\left(1,\pi_{ij}\right)$. The variation in the response variable 'y_{ij}' is calculated as $\mathrm{var}\left(y_{ij}\middle|\pi_{ij}\right)=\pi_{ij}\left(1-\pi_{ij}\right)$, where 'var' is short for 'variance' (Goldstein, 1991). As mentioned earlier, estimation of the variance allows testing for the statistical significance of the random coefficients in the binary response multi-level model.

Therefore, the binary response multi-level model in Equation 1, could be expressed in the form of a binary response *logit* multi-level model, as follows (Goldstein, 1991):

$$y_{ij} = \pi_{ij} + e_{ij} z_{ij} \quad (6)$$

Where,

z_{ij}: denotes the estimated binomial standard deviation; that is, $z_{ij} = \sqrt{\pi_{ij}(1-\pi_{ij})}$, where the level-1 variance, 'σ_e^2' should be constrained to unity; that is '$\sigma_e^2 = 1$'.

Equation 6 represents the general specification of the binary response logit multi-level model used in this study. The next section presents the findings regarding the research question raised in this paper: namely, whether an industry effect is present or absent when modeling corporate collapse in Australia.

4. Discussion of Findings

Using the 'Fin Analysis' database published by 'Aspect Huntley', complete financial statements are accessible for a total of 37 companies that were de-listed from the Australian Stock Exchange (ASX) as a result of going bankrupt during the period 1989 to 2005.

Based on recommendations in the literature, each collapsed company is paired with a financially healthy counterpart according to industry sector and size of assets; with the Global Industry Classification Standard (GICS) being used in determining industry classification (Hossari, 2006b, chapter 7). Accordingly, a total of seven industry sectors are identified; these are, 'Energy', 'Materials', 'Industrials', 'Discretionary', 'Staples', 'Information Technology (IT)' and 'Telecommunications (Telecom)'.

For each company in the sample, financial statement items are collected, from which a total of 28 financial ratios are calculated (refer to Table 1). The ratios are selected based on their usefulness in 84 studies on ratio-based modeling of corporate collapse during the period 1968 to 2006.

Table 1 – A list of the 28 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

All 28 financial ratios are entered one at a time into the model in Equation 6 and their coefficients, represented by 'b_j' in Equation 5, checked for statistical significance. Of the 28 ratios, only three are statistically significant at the 95% level of confidence; these are:

NITA: Net Income / Total Assets
TLTA: Total Liabilities / Total Assets
CFTL: Cash Flow / Total Liabilities

Accordingly, the ensuing model is presented in Equation 7.

$$\log it\left(\pi_{ij}\right) = -5.088 NITA_{ij} + 1.681 TLTA_{ij} + 0.271 CFTL_{ij} \qquad (7)$$

In addition, the following statistical output is associated with Equation 7, where the numbers in brackets represent standard errors:

$$a = 0.126(0.303) + u_j$$
$$u_j \sim N\left(0, \Omega_u\right) : \Omega_u = 0.000(0.000)$$

The additional statistical output indicates that the constant term is statistically insignificant, which means that for all practical terms 'a' is to be treated as zero. Moreover, the statistical output indicates that 'u_j' is also zero, which implies that level-2 interactions between various industry sectors or between various industry sectors and various predictor financial ratios may not be statistically significant.

Therefore, it can be stated that an industry effect is absent when modelling corporate collapse in Australia. Although such a conclusion is confirmed without further analysis, the detailed testing in what follows is merely for validation.

Equation 8 provides the results for level-2 interactions between various industry sectors with respect to the *intercept* (numbers inside brackets represent standard errors for the corresponding coefficients).

$$\begin{aligned}\operatorname{log}it(\pi_{ij}) &= -6.161(1.952)NITA_{ij} + 2.109(0.906)TLTA_{ij} + 0.296(0.134)CFTL_{ij}\\ &-2.208(1.483)Materials_j - 2.645(1.650)Industrials_j\\ &-2.660(1.507)Discretionary_j - 2.843(1.612)Staples_j\\ &-3.553(1.834)IT_j - 2.445(1.627)Telecom_j\end{aligned} \quad (8)$$

Only six out of the total of seven industry sectors appear in Equation 8. This is not an oversight. The reason is that the 'Energy' sector, which is the seventh sector, is the reference sector. That is, the coefficients corresponding to each of the three financial ratios in Equation 8 are for the 'Energy' sector. Consequently, the *intercept* can be modified for each other industry sector based on its corresponding coefficient. To illustrate, based on Equation 8, the probability 'π_{ij}' that a company 'i' in industry sector 'j' in the sample herein may collapse is calculated as follows:

$$\pi_{ij} = 1/\left[1 + \exp\left\{-\left(-5.088NITA_{ij}\right) - \left(1.681TLTA_{ij}\right) - \left(0.271CFTL_{ij}\right)\right\}\right] \quad (9)$$

However, when level-2 interactions between various industry sectors are taken into consideration, then based on Equation 8, the probability '$\pi_{iEnergy}$' that a company 'i' in the 'Energy' sector may collapse is calculated as follows:

$$\pi_{iEnergy} = 1/\left[1 + \exp\left\{-\left(-6.161NITA_{ij}\right) - \left(2.109TLTA_{ij}\right) - \left(0.296CFTL_{ij}\right)\right\}\right] \quad (10)$$

Similarly, the probability '$\pi_{iMaterials}$' that a company 'i' in the 'Materials' sector may collapse is calculated as follows (it is noted that the intercept in Equation 11 is now –2.208, instead of zero):

$$\pi_{iMaterials} = 1/\left[1 + \exp\left\{-(-2.208) - \left(-6.161NITA_{ij}\right) - \left(2.109TLTA_{ij}\right) - \left(0.296CFTL_{ij}\right)\right\}\right] \quad (11)$$

Likewise, the probability '$\pi_{iIndustrials}$' that a company in the 'Industrials' sector may collapse is calculated as follows (it is noted that the intercept in Equation 12 is now –2.645, instead of -2.208):

$$\pi_{iIndustrials} = 1/\left[1 + \exp\left\{-(-2.645) - \left(-6.161NITA_{ij}\right) - \left(2.109TLTA_{ij}\right) - \left(0.296CFTL_{ij}\right)\right\}\right] \quad (12)$$

Therefore, the probability 'π_{ij}' that a company 'i' in industry sector 'j' in the sample herein may collapse can be calculated in a similar fashion for the remaining industry sectors. However, the standard errors in Equation 8 indicate that the coefficients associated with each of the industry sectors are not statistically significant at the 95% level of confidence. Therefore, it can be stated that level-2 interactions between industry sectors do not exist regarding the *intercept*. This implies that the *intercept* in Equation 7 does not have to be modified in order to adjust for variations in the financial ratios across industry groups.

The level-2 interactions between various industry sectors and the predictive financial ratios are considered next; in order to do so, the *slopes* in Equation 7 are examined. However, this necessitates modifying Equation 7 in order to examine interactions between industry groups and each of the three predictive financial ratios, NITA TLTA and CFTL. As a result, three different models are generated and presented in Equations 13 to 15, starting with the model for the first predictive ratio, NITA. As before, the numbers inside brackets represent standard errors for the corresponding coefficients; moreover, the 'Energy' sector, being the reference sector, is not explicitly stated in any of the equations.

$$\begin{aligned}&\log it(\pi_{ij}) = 5.010(7.018)NITA_{ij}\\&-6.449(7.270)Materials.NITA_{ij} - 11.091(8.708)Industrials.NITA_{ij}\\&-10.097(7.425)Discretionary.NITA_{ij} - 13.897(8.991)Staples.NITA_{ij}\\&-10.855(8.392)IT.NITA_{ij} - 32.493(23.959)Telecom.NITA_{ij}\end{aligned} \quad (13)$$

The coefficients in Equation 13 are statistically insignificant at the 95% level of confidence, which implies a lack of level-2 interactions between various industry sectors and the financial ratio '$NITA_{ij}$'.

Similarly, Equations 14 and 15 indicate a lack of level-2 interactions between various industry sectors and the financial ratios '$TLTA_{ij}$'and '$CFTL_{ij}$', respectively.

$$\begin{aligned}&\log it(\pi_{ij}) = 2.422(3.158)TLTA_{ij}\\&+2.350(3.759)Materials.TLTA_{ij} - 5.805(3.310)Industrials.TLTA_{ij}\\&+0.704(3.639)Discretionary.TLTA_{ij} - 0.696(3.669)Staples.TLTA_{ij}\\&-2.941(3.579)IT.TLTA_{ij} + 0.259(4.319)Telecom.TLTA_{ij}\end{aligned} \quad (14)$$

$$\begin{aligned}&\log it(\pi_{ij}) = 1.694(2.263)CFTL_{ij}\\&-0.567(2.396)Materials.CFTL_{ij} - 0.615(2.735)Industrials.CFTL_{ij}\\&-1.705(2.267)Discretionary.CFTL_{ij} - 0.960(2.502)Staples.CFTL_{ij}\\&-0.890(2.404)IT.CFTL_{ij} + 0.384(3.162)Telecom.CFTL_{ij}\end{aligned} \quad (15)$$

Therefore, the results in Equations 13 to 15 validate a lack of level-2 interactions between industry sectors and the three predictive financial ratios. This implies that the *slopes* in Equation 7 do not have to be modified in order to adjust for variations in financial ratios across industry groups.

Having validated that neither the *intercept* nor the *slopes* in Equation 7 vary from one industry sector to another, it can be re-stated that an industry effect is absent when modeling corporate collapse in Australia.

5. Conclusion

This paper raised a question about the presence, or lack thereof, of an industry effect when adopting a ratio-based approach to modelling corporate collapse in Australia. The validity of asking such a question is grounded in the lack of consistency in the literature regarding effects of this nature.

In answering the question, this paper introduced an innovative methodological approach called Multi-Level Modelling (MLM), which is capable of capturing potential significant variations in financial ratios across industry sectors. Unlike the two-step process utilised so far in the literature, with MLM model derivation and adjustments for possible industry effects occur concurrently.

Considering a sample of 37 collapsed Australian publicly listed companies matched with 37 financially healthy ones across seven industry sectors during the period 1989 to 2005, the empirical results supported the absence of an industry effect when modeling corporate collapse.

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