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. An innovative methodological approach, called Multi-Level Modelling (MLM), is applied. The empirical results, which are based on a data sample of Australian publicly listed companies during the period 1989 to 2005, indicate that an industry effect is absent.

Field of research: Finance

1. Introduction

When attempting ratio-based modelling of corporate collapse, some researchers found it necessary to make adjustments for industry effects, whereas others did not. Moreover, for those who observed such effects, the variations were not always consistent across all 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.

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).

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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. Among the earliest of these studies, Horrigan (1965, p. 564) concluded that ratios do not differ significantly across industry sectors. However, when comparing the means of financial ratios Bird and McHugh (1977, p. 31) found that they were statistically different across some industry sectors.

Such inconclusive results could explain why some – not all – of the studies between 1968 and 2006 that examined ratio-based models for signalling corporate collapse, considered financial ratios to be significantly different across industry sectors, and as a result restricted their data samples to a single industry group (Hossari, 2006, chapter 7). Of the remaining studies that used data samples from multiple industry sectors, some considered industry differences to be irrelevant whereas some attempted to adjust their financial ratios in order to lessen 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. Considering that such variations could exist necessitates adjusting for the effects they might possibly have on modelling 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 independently from 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

Multi-Level Modelling (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 (2006). 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).

$$y_{ij} = \beta_{0ij} + b_j x_{ij} \qquad (1)$$

Such that,

$$\beta_{0ij} = a + u_j + e_{ij} \qquad (2)$$

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 $P(y_{ij} = 1 | x_{ij})$ 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 1 could be expressed as follows:

$$P(y_{ij} = 1 | x_{ij}) = F(a + b_j x_{ij} + u_j) \tag{3}$$

Where,

$F(.)$: represents 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:

$$\pi_{ij} = F(a + b_j x_{ij} + u_j) \tag{4}$$

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):

$$\pi_{ij} = \frac{1}{1 + \exp(-a - b_j x_{ij} - u_j)} \tag{5}$$

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, $y_{ij} \sim Bin(1, \pi_{ij})$. The variation in the response variable 'y_{ij}' is calculated as $\text{var}(y_{ij} | \pi_{ij}) = \pi_{ij}(1 - \pi_{ij})$, 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, 2006, 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. The ratios are selected based on their usefulness in 84 studies on ratio-based modeling of corporate collapse during the period 1968 to 2006. 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.

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

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

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

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).

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

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:

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

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:

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

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):

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

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):

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

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. How about the *slopes* in Equation 7, do they have to be modified? In order to answer this question, it is necessary to examine level-2 interactions between various industry sectors and the predictive financial ratios. This is done next.

Equation 7 must be modified 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.

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

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

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 modelling corporate collapse.

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