AUSTRALIAN CORPORATE FAILUER PREDICTION MODELING: USING NON-PORTFOLIO TECHIQUE

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Abstract: We analyse a database of 500 listed Australian companies including 36 failed companies over the critical period 1989 to 1998 during which Australia suffered its worst financial crisis for many decades. In view of the failure of the frequently used portfolio methods to give early warning signals of company failure in the sub-prime market meltdown in USA, and evidence given to us that the Australian market did not have sufficient depth nor competitiveness and transparency for portfolio analytic methods to work beyond the first 70 most frequently traded stocks, we chose to review and apply non-portfolio methods, settling upon ratio analyses and selecting Logit and Neural Network analyses as our best modelling instruments in this study. A further ulterior motive for using non- portfolio methods was the fact that this team wished to undertake a study of the Chinese corporate market where it is known that portfolio methods are not a suitable as analytic tools. Our results were very pleasing as we obtained over 90 percent prediction of corporate failure from one year beforehand with three of the models. Each model was capable of displaying very good explanatory significance and causality which is normally a serious weakness of heuristic models

Keywords: Bankruptcy diagnosis ; Decision Trees, Linear Regression, Logistic Regression, Neural networks ; Corporate distress risk ; Financial ratio analysis

JEL Classification : G33 ; C49 ; C88

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1. INTRODUCTION

1.1 Research Objectives

Australia with a database of 500 publicly listed Australian companies covering the period 1989 to 1998 provided by Corporate Scorecard Group (CSG)[i]. In this study, we have concentrated on non-portfolio techniques including logistic regression and neural networks. We have also tried to maximize the use of independent (explanatory) variables. Though in the construction of our final models, we endeavoured to use Milton Friedman's description of a good model which is: "One that explains much by little", so we had no more than four independent variables in the equation.

The aim of the study was to identify the most accurate corporate failure prediction model using non-portfolio techniques. The definition of corporate failure may vary in some studies due to jurisdictional differences and database limitations. In our study, corporate failure has been defined as: When a company has been de-listed[ii] on the Australian Stock Exchange (ASX) as a result of (i) liquidation, insolvency or receivership; or (ii) an order being issued by the courts to wind up the company. The objective of model building is to improve the understanding of causality and effectively explaining corporate failure. The model should predict accurately which companies were likely to fail, at least one or two years prior to failure.

As a first step, a training dataset was used to develop several alternative promising models. Secondly, the matched pair method was used in the hold out dataset. Sixteen failed companies from this database were matched with successful companies according to total assets and industry type and a neural network predictive model was built to classify and explain success and failure characteristics[iii] of these two sets of companies. We judged this to be the most efficient way of comparing and analyzing the differences between failed and healthy companies as the dataset was still relatively small and the number of failed companies while statistically significant, needed the matched pair method to highlight the differences between the failed and viable companies.

1.2 Scope of Study

This study explored alternative techniques of corporate failure prediction including decision trees (DT), linear regression (LNR), logistic regression (LGR), the multilayer neural network (MNN), the probabilistic neural network (PNN) and radial basis function (RBF) to select an explanatory combination of relatively independent variables. Logistic regression and artificial neural network architectures have been among the most successful used to build predictive models of corporate failure. For Australia, portfolio methods such as the KMV[iv] approach suit the top 50 listed companies as such models rely on strongly competitive and liquid equity market information. However, our study consists of many companies that are not frequently traded on the stock market and many lack the liquidity, transparency, price reflection and market efficiency characteristics necessary to use portfolio techniques of analysis successfully. The exercise was also designed to train students in analyzing China company data that was even more opaque an non-responsive to market forces. Consequently, non-portfolio methods of analyses were considered to be more suitable for undertaking this study.

2. LITERATURE REVIEW

Since the discovery of the extrapolative power of financial ratios in corporate bankruptcy diagnosis by (Beaver 1966), fervent interest in this field has been aroused and numerous studies have been conducted to find the best combination of models, financial indicators, variables or ratios that can best be used for bankruptcy prediction in certain settings. The ability to accurately forecast the collapse of a firm is of immense interest not only to the firm's immediate stakeholders but also to regulatory bodies, auditors and in some cases, the governments. The ability to foresee the failure of a firm is of incredible value as early warning systems can be developed and actions can be taken to avoid the financial crisis (Yim & Mitchell, 2004).

Although this study focuses on the use of neural networks as a major bankruptcy prediction paradigm, this overview cannot be complete without touching upon other the important contributors to the field of failure prediction. Beaver (1966) demonstrated the power of univariate financial ratios to predict failure. However, the paradigm of using univariate variables to predict corporate collapse seems to greatly over-simplify the complicatedness of real world situations. Non-financial variables have also been used to see if they confer predictive ability. They, however, failed to provide a significant link between its inclusion and the improved ability to predict failure (Etheridge *et al.*, 2000).

Discriminant analysis as used extensively by (Altman 1968) and (Altman *et al.* 1977 and 1994) required the predictor variables to be multivariate normal and have equal covariance matrices to serve as a good bankruptcy prediction tool. However, this normality assumption is often violated as most of the financial ratios were found to be non-normally distributed (Yim & Mitchell, 2002). Log transform methods and the use of dummy variables can be used to alleviate this problem. Their inclusion however always violates the normality assumption (Etheridge *et al.*, 2000). Logistic regression does not impose strict statistical assumptions like normality and equal covariances but it has the disadvantage of not taking into account the correlation among independent variables and mainly deals with the linear relationships among the dependent and independent variables (Kalapodas & Thomson, 2006). Neural networks, on the other hand, may be a better approach in failure diagnosis as they are a distribution free technique. They are nonparametric and nonlinear whose underlying structural development was inspired by the neural structure of the human brain. In the data generating process, any changes in structure can be both adapted to and responded to. The pattern recognition capabilities of NNs allow them to match large amounts of input information simultaneously and then generate a generalised output. (Trippi and Turban,1993) Their possession of network memory allows them to generate a reasonable network response when presented with incomplete, noisy or previously unseen input (Jain & Nag, 1997). Despite the various advantages that NNs have, the biggest criticism directed at them is their inability to explain the results they derive. The development and implementation of NN models are computationally intensive and time consuming compared to regular statistical models. Further, because NN models are able to implicitly model interactions and nonlinearities, they are resultantly prone to overfitting a training data set (Tu, 1996).

The basic architecture we have used consists of three layers. The first layer, the input layer, receives the inputs. The second layer, the hidden layer, which receives signals from the input layer, is where most of the learning takes places. After signal processing by the processing elements in the hidden layer, the signals are transmitted to the output layer, and the output can be retrieved by the user (Etheridge *et al.*, 2000).

There are many different types of neural networks but the most popular model in research studies is the multilayer neural network (MNN) with backpropagation generally used as the learning algorithm. It adopts the supervised learning system where the desired output is compared with the actual output. The connection weights are adjusted to minimize the error between the actual and desired output (Lee *et al.*, 1996). Backpropagation neural networks are known to be seriously prone to overfitting (Adya & Collopy, 1998). The less frequently used NN model is the probabilistic neural network model. The advantages of PNN include its fast learning and its capacity to model complex data spaces (Yang *et al.*, 1997). The PNN can be better than the backpropagation NN because it adopts the Bayesian classifier technique that puts the outcome into discrete groups (Etheridge *et al.*, 2000). This feature may be especially useful in situations where the desired output is in categories such as in the bankruptcy prediction case where the firm has either failed or not failed.

Two studies were found to use probabilistic neural networks (PNN) in the case of failure prediction. Etheridge *et al.* (2000) used a sample of 148 failed banks in 1986-1988. The performance of the three different neural network models – the backpropagation neural network, the categorical learning neural network and the PNN – were accessed in terms of their overall error rates and Type I and Type II error rates. Etheridge *et al.* found the backpropagation NN to be reasonably good in the use of bankruptcy prediction although its architecture is more suited for prediction than for classification. The overall error rates of the models showed that PNN was the most reliable approach followed by backpropagation NN and then categorical learning NN.

There are some interesting issues raised by researchers that are worth noting because they not only gave warnings to some of the inherent problems associated with bankruptcy studies but they can also serve as a guide for future research. Firstly, almost all the studies included the matching procedure in the sample preparation process. Matching involves matching each of the failed firms in the sample to a healthy firm based on some criteria. Common criteria include industry grouping, firm size and year, which are used to control for industry-specific characteristics, size-specific characteristics and general economic conditions, respectively. Other matching criteria have also been reported such as firm age and the number of employees. Nevertheless, there is no evidence to suggest that different matching procedures, including no matching at all, improve or worsen the results (Ohlson, 1980). The second issue is sample size. Several studies have raised their concern about the small sample size of failed firms (Izan, 1984). The utilisation of small samples has the potential to undermine the model developed in its application to fresh samples. This is called the lack of “generalisation” and “stability” (Adya & Collopy, 1998). This is especially true for neural networks because its learning process entails learning from a set of examples in the training sample. In relation to ANN, Perez (2006) recommended the reduction of heterogeneity in the training sample if the base examples are scarce. It is because if there are sufficient base examples, ANN can manage the heterogeneity on its own. Yim and Mitchell (2004) also showed that models formed based on narrow industry types may improve the performance of the model. There are studies that focus only on a specific industries such as banks (Etheridge *et al.*, 2000), or private construction companies (Yang *et al.*, 1997). Izan (1994) indicated that ratio averages are disparate enough within one industry type, let alone considering all the industries at one time. In recognition of this problem, he advocated the use of ‘industry relatives’ to reduce the impact of industry differences. There are however more studies that consider the complied samples of businesses from different industries (Lee *et al.*, 1994; Altman, 1968) mainly due to the unavailability of sufficient bankrupt firms within one particular industry group. In addition, it may be economically unfeasible to develop a model for each industry.

3. METHODOLOGY AND RESULTS

3.1 DATA COLLECTION

Two raw datasets were provided by CSG. The first was provided by CSG as a training set to develop the models. Five companies out of 32 had failed. See (Table 1). The second dataset was the holdout sample. (See (Table 2). These were chosen from more than 500 listed companies.

Table 1: Companies in Training Dataset

Failed companies	Healthy Companies				
SLP	TMA	TQL	TOL	SST	ABK
HIH	TNT	TTH	VRL	TWR	GNC
BRN	UNP	ARA	CKS	WFT	
ABT	CCW	ALL	GEP	UEL	
ASR	BPC	SKN	AAU	GUD	
BDL	RBS	SRP	ABC	ABS	

The holdout sample consists of another 32 companies selected from a large dataset using the matched-pair method of analysis. This is also known as the control company approach. In all, 16 failed companies were matched with 16 healthy companies using industry grouping and size of company judged by total assets as the matching criteria. The significant advantage of using the matched pair approach is that by selecting healthy companies that have matching risk characteristics, financial variables and also operate in the same industries as the bankrupt companies, we can minimize the impact of information that is irrelevant. Companies are taken to be from the same industry if they have the same GSIC code. Those healthy companies with the closest matching characteristics to that of the bankrupt company were selected as the benchmark control company. (Table 2)

Table 2: Companies in Holdout Dataset

Failed Companies	Healthy Companies	Failed Companies	Healthy Companies
ALM	PRT	KWL	ARY
ASK	ISR	PIM	BYI
BIY	OPS	PNX	OLH
CCN	GUD	POW	PLW
CRF	SCD	RPC	NET
EXI	SGF	SAB	GLG
JEN	LHS	SEC	SOL
JFA	HGV	WMX	LAC

3.2 Ration Calculation

Sixteen financial ratios were calculated from over 100 items of raw data supplied for each company. The choice of the ratios was based on the studies done by Hossari (2005) where the ratios were ranked according to their popularity in multivariate modelling. It was thought that the ratios frequently used in past failure research were more important for failure prediction than the ones that were infrequently used. We also felt that the more frequently used techniques reflected greater success in achieving positive research findings. Additionally, the debt coverage ratio was also calculated because it was postulated that a firm must be able to generate enough revenue to cover its interest obligations. The accuracy of the data and calculation of results were cross checked with the companies' annual reports. In preparation of the T-1 ratios for failed companies, data were from one year prior to bankruptcy. For the healthy companies, ratios were compiled using the most recent available data.

3.3 CHOOSING A BETTER PREDICTING MODEL

(a) Analytic Technique

Attempts were made to observe the comparative failure forecasting abilities of various commonly-used predictive models including a linear regression model (LNR), a radial basis function (RBF), decision trees (DT), a probabilistic neural network (PNN), logistic regression (LGR) and a multilayer neural network (MNN) using Altman's Z-score ratios. It was observed from the validation reports at the default 0.5 cut-off rate that some models were evidently better in predicting corporate failure than others. LNR and RBF offered no predictability (0%). LNR did not offer any predictive power as the dependent variables and the independent variable were not linearly related. We know that the LNR technique is recommended when "an ordered or continuous dependent variable" is available. In this study, the binary nature of the dependent variable (failed or non-failed) renders the LNR approach inappropriate. RBF networks use linear regression for obtaining the weighting connections between the hidden layer and the output layer of the neural network after the computation of the locations of the hidden node centres (Alexandridis *et al.*, 2003). The employment LNR is likely to have hindered RBF from its use in binary decision making for the same reasons as previously-mentioned in our treatment of LNR.

(b) Cut-Off Rates and Type I and Type II Errors

Although the DT model obtained quite a high validation percentage by using T-1 ratios, 81.25% ((32-6)/32 non-failed companies), it was unable to detect any failed companies or to distinguish distressed companies from healthy companies. When a cut-off of 0.5 was used, it classified all the companies as sound. However, when it was lowered to 0.2, DT classified all the companies as bankrupt. We therefore concluded that the DT model was unsuitable for ratio analysis in this instance as it had poor discriminating power. On the other hand, we found that PNN, displayed very strong predictive ability as demonstrated by its 100% correct classification at 0.25. LGR and MNN were not considered not considered as good as the PNN approach, because of the strong trade off between type II and type I errors. As type II errors decreased; type I errors increased.

Table 3. No. of failed coys correctly predicted at 0.5, 0.4, 0.3 and 0.25 cut-offs

Predictive Model/ Cut-off	0.5	0.4	0.3	0.25
DT	0	0	0	0
LGR	2	2	2	3
MNN	2	3	3	3
PNN	4	4	5	6

Table 4. No. of healthy coys incorrectly classified as failed at 0.5, 0.4, 0.3 and 0.25 cut-offs

Predictive Model/ Cut-off	0.5	0.4	0.3	0.25
DT	0	0	0	0
LGR	0	1	2	2
MNN	0	1	4	4
PNN	0	0	0	0

Table 3 shows the number of failed companies that were successfully predicted at different cut-off rates. Those failed companies that were not predicted contributed to type II error. It can be seen that the lower the cut-off rate, the lower the type II error was. Table 4 shows the number of healthy companies that were incorrectly predicted as failure companies at different cut-off rates. It can be seen that the lower the cut-off rate, the higher the type I error was. There is therefore a trade-off between them. It is necessary to balance type I and II errors when choosing an optimal cut-off as that can incur economic loss to a related party. There is no coherent and generalised theory on selection of optimal cut-off rate.

(c) Simplicity & Complexity of the Model: Number of Explanatory Variables Included

Our analysis was conducted again using all the 16 available ratios to check the sensitivity of the models to the number of ratios used. RBN and LNR showed no predictive power whatsoever as we may have anticipated from our previous analysis. LGR gave the strongest result (Table 5) indicating that its predictive ability increased as more inputs were included. However, with 16 ratios included, the model was noisy, cumbersome and inefficient insofar as fewer explanatory variables fitted as well and offered simpler causal explanations.. Table 3 also showed the poorer forecasting ability of MNN. Often by increasing the number of input nodes one increases the complexity of Neural Network (NN) and this can result in poorer fitting and over-fitting. As observed in Tables 3, 4 and 5, while both MNN and PNN are NN models, type I and type II errors are dissimilar. The PNN model offered better results than MNN as the MNN model had higher type I and type II errors for all cut-off rates except the 0.5 cut-off. This may have been due to the “memory/learning effects” employed in its design (Angoss instruction manual, 2003). The NN operates more like a human brain that allows better retrieval of data gained from past experience. We can conclude that, LGR, MNN and PNN are the workable models for bankruptcy prediction. However, due to the presence of high type II errors associated with the MNN model, we considered it to be inferior to the LGR and PNN models.

Table 5. Result of using 16 ratios of companies to predict failure of companies at 0.5 cut-off.

	LGR	MNN	PNN
Fail to predict failed companies (type II error)	0	4	1
Incorrectly classified healthy companies as failed (type I error)	0	0	0

3.4 Ratio Combination Testing and Analysis

The Angoss software package did not have a stepwise function to add or subtract the number of explanatory variables (ratios) to the ANN model so this needed to be done manually. As stated previously, a total of 16 ratios, which include 15 highly ranked ratios plus the debt coverage ratio, were calculated and subsequently classified into 7 different categories. (Table 6)

Table 6 Categorising of ratios

	Categories	RATIOS				
1	*Debt coverage*	DCR				
2	*Operating Efficiency*	EBIT/TA				

3	*Leverage*	OE/TA				
4	*Activity ratios*	Sales/TA	CA/Sales			
5	*Market v Book*	BVE	MVE			
6	*Profitability*	RE/TA	NY/TA	OPBAT/Sales	OPBAT/TA	
7	*Liquidity*	WC/TA	Quick Ratio	CA/CL	CA/TA	Cash/TA

Ratio Key

DCR - Debt Coverage Ratio
TA - Total Assets
TL – Total Liability
OE - Owners' Equity
RE - Retained Earning
MVE - Market Value Equity
OPBAT – Operating Profit Before Abnormal and Tax
WC - Working Capital
CA - Current Assets
CL - Current Liabilities
EBIT - Earning Before Interest and Tax
NY - Net Income
BVE - Book Value Equity

Two or more ratios from the same category were not used in the same model. This was to minimise the correlations between independent variables. The lower were the correlation ratios, the greater the independence. (Rummelhart, 1986).The ratio combination testing started from 3 categories that only have one ratio in each. That is Debt Coverage Ratio, EBIT/TA and OE/TA. (Refer to Table 7 Part 1*) Those 3 ratios together gave 90.63% prediction rate. Then one of the liquidity ratios was added into the model sequentially. From Table 7, part 2*, it can be seen that CA/TA performed better than the other 4 liquidity ratios in our corporate failure models. In this case, the prediction rate achieved rate 100%. CA/TA measures the ease of assets converting to cash. It is generally accepted that the easier of the assets can be released to cash, the less likely there will be a liquidity problem and there will be more flexibility in managing a company's assets.

To check the significance of the first 3 ratios used in this model, we sequentially dropped one of the variables to test the significance of that variable. This was based on the logic that if the prediction rate lowered on the omission of a specified variable or ratio, that indicated the significance of that variable or ratio. For example, if the prediction rate remained 100% without that ratio, it meant that the ratio was not significant in that model. The result of the step 3 of testing was that OE/TA and CA/TA were more important than Debt Coverage Ratio and EBIT/TA. (Table 7, part 3*) However, by using OE/TA and CA/TA only, the prediction rate was lowered to 96.88%. Some intuitive testing was also necessary as some ratios and variables can be significant in combination. The sum of the combined ratios or variables inclusion is greater than their individual inclusion.

Table 7 Ratio combination prediction results in PNN

Prediction Rate	Independent Variables	Ratios Used			
1*Start from the 3 categories that only have one ratio in each					
90.63%	3	DCR	EBIT/TA	OE/TA	
2*Add one of liquidity ratios to be multi-dimensional					
90.63%	4	DCR	EBIT/TA	OE/TA	WC/TA
87.50%	4	DCR	EBIT/TA	OE/TA	Quick Ratio
87.50%	4	DCR	EBIT/TA	OE/TA	CA/CL
100.00%	4	DCR	EBIT/TA	OE/TA	CA/TA
90.63%	4	DCR	EBIT/TA	OE/TA	Cash/TA
Result: One optimal models obtained; CA/TA performs better in the model than other liquidity ratios					
3*Carry on the 100% model, delete one of the four ratios to find out which is important					
100.00%	3		EBIT/TA	OE/TA	CA/TA
100.00%	3	DCR		OE/TA	CA/TA
93.75%	3	DCR	EBIT/TA		CA/TA
90.63%	3	DCR	EBIT/TA	OE/TA	
Result: 2 optimal models obtained by using 3 ratios. DCR and EBIT/TA are less important than OE/TA and CA/TA. Because the absence of OE/TA or CA/TA lowers the prediction rate.					
4*Carry on OE/TA and CA/TA. Add one of profitability ratios.					
96.88%	2	OE/TA	CA/TA		
96.88%	3	OE/TA	CA/TA	RE/TA	
96.88%	3	OE/TA	CA/TA	NY/TA	
100.00%	3	OE/TA	CA/TA	OPBAT/Sales	

100.00%	3	OE/TA	CA/TA	OPBAT/TA	
Result: 2 more good models found by using 3 ratios;					
5*Carry on OE/TA and CT/TA. Add ratios relating to market value vs. book value					
96.88%	3	OE/TA	CA/TA	MVE/TL	
96.88%	3	OE/TA	CA/TA	BVE/TA	
Result: The 2 ratios do not make any distinction or add productivity.					
6*Carry on OE/TA and CA/TA. Add one of Activity ratios.					
100.00%	3	OE/TA	CA/TA	Sales/TA	
96.88%	3	OE/TA	CA/TA	CA/ Sales	

These two most important ratios were carried forward to step 4, in which, one of the profitability ratios was added into the testing model. The result in Table 7, part 4* shows that OPBAT/TA and OPBAT/Sales could both provide a 100% prediction rate when individually combined with OE/TA and CA/TA. Steps 5 and 6 were similar to step 4, combining one of the equity ratios and then one of activity ratios respectively. The result was that the combination of OE/TA, CA/TA and Sales/TA together could achieve 100% prediction rate. In our results, there were 6 ratio combinations that could produce a 100% prediction rate in PNN. (Table 8)

Table 8 Successful model developed from training data.

100.00%	4	OE/TA	CA/TA	DCR	EBIT/TA
100.00%	3	OE/TA	CA/TA	DCR	
100.00%	3	OE/TA	CA/TA	EBIT/TA	
100.00%	3	OE/TA	CA/TA	OPBAT/Sales	
100.00%	3	OE/TA	CA/TA	OPBAT/TA	
100.00%	3	OE/TA	CA/TA	Sales/TA	

The same methodology was used on LGR and MNN models. The best prediction results were 93.75%and 96.88%, respectively with these methodologies. Therefore, not only as examined in the literature review, but also from our own empirical study results of the training dataset, it has been concluded that PNN outperformed the other models by testing the training data with the neural network software in our training data, and therefore was concentrated on in this study.

3.5 Testing the Models Using the Holdout Dataset

Those models exhibiting 100% prediction from the training dataset were then tested in the holdout dataset to validate those very good results. The companies in the holdout dataset were also identified as having failed or not. The comparison of prediction results are listed in Table 9.

Table 9: Comparison of the Prediction Results

Ratios used				Prediction Rate in Training Data	Prediction Rate in Holdout Data	Averaged Prediction Rate
OE/TA	CA/TA	DCR	EBIT/TA	100.00%	90.63%	95.32%
OE/TA	CA/TA	DCR		100.00%	84.38%	92.19%
OE/TA	CA/TA	EBIT/TA		100.00%	90.63%	95.32%
OE/TA	CA/TA	OPBAT/Sales		100.00%	84.38%	92.19%
OE/TA	CA/TA	OPBAT/TA		100.00%	87.50%	93.75%
OE/TA	CA/TA	Sales/TA		100.00%	93.75%	96.88%

The prediction rates generated from the holdout dataset were not as good as in the training dataset but were still very good and up to commercial modelling standards. The holdout dataset was much larger and had more failed companies than the training dataset. Modifying factors may have included external economic factors, qualitative factors such as internal control, management and so on of the period.

We next look at the validation matrix to analyse failure prediction in the model. The best model above has a 93.75% successful prediction rate in Table 9 has the following validation matrix as shown below in Table 10:

Table 10: Validation Matrix

	Predicted		
Actual		0=Healthy companies	1=Failed companies
	0	16	0
	1	2	14

The above result shows that none of healthy companies were wrongly predicted as failed companies. That is type I error was indifferent from 0 in this case. Meanwhile, there were two failed companies misclassified as being healthy. Therefore the type II error rate was 2/32. The model was not able to give an early warning signal for these two companies out of the 32 companies. For the lending industry, the accuracy and predictive power of models can protect against default by the failing companies.

3.6 Explanation of Significant Ratios

It is obvious from the results as shown in the above tables that ratios Current Assets/Total Asset and Owner's Equity/Total Assets make the most significant and powerful contributions in the final set of corporate failure prediction models. Let us therefore look closely at what these ratios to see why they are so significant.

Current Assets/Total Assets represent the proportion of assets that can be easily converted to cash. It follows that the easier it is to convert to cash, the lower is cash flow risk. In other words, the more liquid are the assets, the more flexible sustainable is the corporation's financial position in relation to insolvency.

Leverage ratio is Total Liabilities/Owners' Equity (TL/OE). TL/OE is equal to long-term debt divided by common shareholders' equity. The data from the prior fiscal year were used in our calculations. Investing in a company with a higher TL/OE ratio would be riskier, *cet. par.*, or especially in times of rising interest rates because of the additional interest that has to be paid out for the debt. Taking an inverse indicator of the leverage ratio to be, Owners' Equity/Total Assets (OE/TA) as was used in our final models, we find that OE/TA measures the robustness to withstand insolvency of a company is determined by the proportion of total assets that are financed by equity rather than debt. The higher the OE/TA ratio, the lower is the insolvency risk of the company.

Taking the other less significant ratios in the final models, Sales/TA is a sales ratio that measures activity efficiency in relation to the use of a certain quantum of assets. Although this ratio relates neither directly to profitability, nor to cost aspects, a low ratio indicates that the total assets of the business are not providing adequate revenue. If the percentage is low, it indicates that a business is not being aggressive enough in its sales efforts, or that its assets are not being effectively or fully utilized. A high ratio is less concerning but may indicate a business is selling more than can be safely covered by its assets.

4. GENERAL LIMITATIONS OF USING RATIOS TO PREDICT CORPORATE FAILURE

Independent of the models we have used to predict corporate failure; all models using financial ratios share some common disadvantages. For example, they rely solely on the data provided by the financial reports, which is a limitation in itself. Deliberate manipulation of accounting data in the form of window-dressing can affect the reliability of the financial ratios in depicting the health of a company. However, we also know that NNs are better at overcoming this problem because they learn from past experience and that is an advantage of using NNs. Secondly, the accounting standards and regulations may change over time. In our study, the data used of failed companies was for the year before insolvency, and the data used for solvent companies was the most recent available data given. We have endeavoured to ensure that differences in accounting standards have not biased our results. Thirdly, companies had the discretion of some part of accounting policies to choose among some alternatives. This may involve tax arbitraging and may affect profitability figures. Such discretion distorts the comparability of ratios across companies and across time. Fourthly, because the ratios used were from different years, some external factors may have been different. Fifthly, the definition of a "failed company" has varied between studies and while we have endeavoured to define failure in terms that are common to most studies, this may also affect the comparability of our results with other studies using a different definition of company failure.

5. CONCLUSION

We had undertaken our study using non-portfolio techniques of corporate failure prediction for two major reasons. The first was that portfolio techniques such as the KMV method were difficult and costly to access, and secondly, we were looking for a technique or techniques that may be used for later studies in the Chinese corporate market. Again we know anecdotally that portfolio methods are unlikely to work where the equity market is opaque and lacking in liquidity and competition. In Australia, roughly the performance of the first seventy most traded listed stocks can be predicted reasonably well via portfolio analytic techniques, but the other stocks are predicted by a variety of methods.[v] We understand that in China, the position is even worse as no credit analyst or ratings agency has been successful in predicting corporate failure or constructing a reliable ratings scale with reasonable accuracy and stability.[vi] The techniques we have come up with show very good results – with the weakness always being an explanation of the results. An understanding of the explanatory significance and causality of the model's structure is necessary to understand the processes it goes through to produce the outcome. Otherwise the implementation of it is just a 'black-box' approach where the steps taken to generate outcomes are incomprehensible to the financial analyst. This is often seen as a major disadvantage of neural networks and similar heuristic approaches. We feel that our explanation of the significance of the main ratios has taken the mystery out of the black box as one can see how the main factors we have found: (1) the liquidity of the company, (2) its robustness to resist insolvency and (3) business aggression measured by efficient asset utilisation by management are very important factors in influencing a company's failure or success.

Through the empirical study, we were able to determine the best combination of financial ratios that would give the highest accuracy in predicting corporate failure. Bankruptcy models may differ in their structure but the common theme is that all the models aim to minimize Type I and Type II errors. Type I error is the false classification of non-failed firms as failed. It is commonly accepted that making Type II errors are costlier than Type I errors. The Type I error may not involve real loss – only the opportunity cost of not doing the business. The Type II error will involve real losses by classifying a firm that will fail as being healthy. It is therefore necessary to examine and analyse the number of correct and incorrect classifications, not just the validated prediction percentage.

One can see therefore how the variables included in our models are relevant to the understanding of company survivorship and failure. It is the intention of the authors to experiment further with the parameters of the model to build better models, particularly with the objective in mind of developing a better theory – particularly in the light of the partial failure of a number of portfolio techniques to give early warning signals to ratings agencies and regulators in the US sub-prime market.

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Endnotes

[i] CSG provide corporate failure prediction analytics software and a credit ratings service in Australia. As such a database is difficult to access or acquire, we were extremely grateful to CSG for providing access to their database for the years shown. The period was significant as it included Australia's own financial crisis between the years 1989 and 1992.

[ii] The definition of de-listed company is from www.delisted.com.au.

[iii] Matched pair approach was employed by Beaver (1966), (1968a) and (1968b).

[iv] KMV is a San Francisco based company that sells credit analysis software to financial institutions. It combined with Moody's Investor Services to become Moody's KMV.

[v] Discussions with the Corporate Scorecard Group.

[vi] Result of survey undertaken by my research unit of all credit rating agencies and credit analysts and consultants operating in China (2009)