

Insolvency Prediction Model Using Multivariate Discriminant Analysis and Artificial Neural Network for the Finance Industry in New Zealand

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Abstract

Models of insolvency are important for managers who may not appreciate how serious the financial health of their company is becoming until it is too late to take effective action. Multivariate discriminant analysis and artificial neural network are utilized in this study to create an insolvency predictive model that could effectively predict any future failure of a finance company and validated in New Zealand. Financial ratios obtained from corporate balance sheets are used as independent variables while failed/non-failed company is the dependent variable. The results indicate the financial ratios of failed companies differ significantly from non-failed companies. Failed companies were also less profitable and less liquid and had higher leverage ratios and lower quality assets.

Keywords: Corporate insolvency, Financial ratios, Multivariate discriminant analysis, Artificial neural networks

1. Introduction

The year 2006-2007 was a turbulent period for the finance industry in New Zealand during which 10 non-bank financial companies went into receivership or failed, leaving debts of more than NZ\$1.14 billion owed to about 52,000 investors (Kiong & Bennett 2007). There are more than one thousand finance companies in New Zealand, offering a wide variety of investment options to investors. Given this wide variety of choice and increasing bad publicity around failed investment companies, financial advisors are facing a daunting task of prudently investing their client's hard-earned money. Thus, models of insolvency prediction that help identify future business failures or provide early warnings of impending financial distress are important tools for financial advisors.

Models of insolvency prediction will also help a manager to keep track of a company's performance over a number of years and will help identify important trends. The models may not specifically tell the manager what is wrong, but it should encourage them to identify problems and take effective action to minimize the incidence of failure. A predictive model may warn an auditor of a company's vulnerability and help protect them against charges of 'negligent of duties' in not disclosing the possibility of insolvency (Jones 1987). In addition, lenders may adopt predictive models to aid in assessing a company defaulting on its loans (Jones 1987). Regulatory agencies are concerned whether a monitored company is in danger of failing. A company may be made exempted from antitrust prohibitions and permitted to merge under the Failing Company Doctrine if it can be demonstrated that it's in danger of insolvency or failure,

The purpose of this study is to develop a theoretical model that will accurately predict failure of financial companies including those in New Zealand via posing and solving the following research questions:

- (1) Are some financial ratios significantly better at detecting the immanent failure of New Zealand's finance companies than others?
- (2) Which financial ratios are the most important for detecting potential insolvency of New Zealand's finance companies?
- (3) Is the Artificial Neural Network (ANN) model superior to the Multivariate Discriminant Analysis (MDA) model

for predicting failures amongst New Zealand's finance companies?

2. Background

Leading causes of corporate failure can be classified into economic, financial, neglect, fraud or disaster (Anderson 2006). Economic factors include industry weakness and poor location while financial factors include excessive debt and cash flow problems. Often financial difficulties are result of managerial neglect.

In this study, 'failure' is defined as a registered company which is insolvent, under receivership or has been liquidated. The word insolvent can have several meanings. Prior to 1985, the crucial method for determining solvency was the 'cash flow test' (Milman & Durrant 1999). Here a company that could not pay debts as they fall due was deemed insolvent even though it could realise sufficient assets to pay all the debts. After 1985, the 'cash flow' test was supplemented by the 'balance sheet test' where a company was deemed insolvent if its liabilities exceeded assets, even when it could pay its debt on time. This study limits itself to registered company insolvency and not to the issue of bankruptcy, i.e. personal insolvency which applies to sole traders and partnership.

2.1 Financial ratios

Considerable attention has been devoted to financial ratio analysis for classifying failed and non-failed companies or for assessing the business performance of a company, summarised in Figure 1.

2.2 Models predicting insolvency

Early models of predicting insolvency employ financial ratios using univariate and multivariate statistics. A univariate approach explores the relationship between individual financial ratios and insolvency (Zavgren 1983). The multivariate approach employs pooled ratios for predicting insolvency. However to construct an optimal multivariate predictive model, one must determine which ratios are best at detecting potential failures, and how the model weights should be established for each. Artificial Neural Networks have more recently been used to predict insolvency as they remove the need for identifying appropriate ratios, before a model is constructed. Given the variety of techniques now available for insolvency prediction, it is not only necessary to understand the uses and strengths of any prediction model, but to understand their limitations as well.

2.3 Multivariate approach

Beaver (1966) pioneered experimental designs for examining corporate failures using financial ratios. Beaver's univariate approach adopts 'paired sampling' for assessing the accuracy of a variety of ratios. His published sample contains 79 companies which failed during the years 1954 to 1964 from 38 industries. Beaver concludes that cash flow to debt ratio is the single best predictor. However, models which focus on a single ratio are simplistic and unable to capture the complexity of financial failure, given that the financial status of a company is multidimensional and no single measure is able to capture all dimensions (Zavgren 1983).

Beaver's (1966) univariate approach was followed by Altman's (1968) use of Multivariate Discriminant Analysis (MDA) to examine corporate failures. Altman selected 33 publicly-traded manufacturing companies that failed between 1946 and 1965 and matched them to 33 companies using a stratified random sample based on their assets and industry. His MDA results (Z-score) using five financial ratios (WCTA, TATURN, RETAINTA, EBITTA and MKTCAPTL) correctly differentiated 94% of failed companies and 97% of the non-failed companies with data one year out from failure. Other studies that utilize the MDA approach include Deakin (1977) and Blum (1974). These studies inspired other researchers to utilize multivariate techniques to predict corporate failure including: logistic regression analysis (Ohlson 1980) and recursive partitioning analysis (Frydman, Altman & Kao 1985).

2.4 Multivariate Discriminant Analysis (MDA)

Discriminant analysis characterizes an individual, or a phenomenon, by a vector of variables which constitute a multivariate density function. The discriminant function maps the multidimensional characteristics of the density function of the population's variables into a one-dimensional measure, by forming a linear combination (Zavgren 1983). The linear discriminant function is as follows:

$$Z_i = XA = a_0 + a_1X_1 + a_2X_2 + \dots + a_nX_n$$

Where; Z = discriminant score for the company i

X = vector of n independent variables or characteristics

A = vector of discriminant coefficients

MDA computes the discriminant coefficients and selects the appropriate weights (cut-off score) which will separate the average values of each group, while minimizing the statistical distance of each observation and its own group means (Altman 1993). By using the Z score and cut-off score, a company is classified into failed or non-failed

categories.

2.5 Logistic regression analysis

Logistic regression analysis is equivalent to two-group discriminant analysis. The logistic procedure fits linear logistic regression models for binary or ordinal response data using Maximum Likelihood estimations and compares the estimated samples using Wald chi-square. The Maximum Likelihood procedure is used in an iterative manner to identify the most likely estimates for the coefficients. The Wald statistic is used to test the hypothesis that a coefficient varies from zero (Hair et al. 1998).

2.6 Recursive Partitioning Analysis (RPA)

Recursive Partitioning Analysis is a nonparametric technique, which minimizes the expected cost of misclassification by a univariate splitting procedure (Altman 1993). However, RPA does not provide the probabilities of group membership, or a means for evaluating the significance of variables.

2.7 Artificial Neural Networks (ANN)

An artificial neural network system (ANN) is a computer algorithm which can be 'trained' to imitate the cellular connections in the human brain (Hertz, Krogh & Palmer 1991). It consists of a large number of interconnected elementary processing units to compute data. The network's processing results are derived from the collective behavior of its units and are dependent on how the units interact with each other (Altman, Marco & Varetto 1993). By processing and evaluating the interactions in a complex set of prior data, a neural network attempts to assign proper weights to the respective inputs to allow for the correct deduction of the ultimate outcome. These input weights are aided by a 'genetic algorithm' optimization procedure, which simulates the model's predictive power under a large number of scenarios and allows the best weighting schemes to survive and reproduce from one generation to the next (Dorsey, Edmister & Johnson 1995).

Typically, prediction (forecasting) in ANN software involves a three-stage process where:

- (1) Decisions are made about what the input variables and learning parameters will be.
- (2) The network is trained using a subset of the data until the average error between the forecast and an actual value is reduced to a minimum.
- (3) The "trained" neural network is used to test new variables and make improved forecasts.

The commonly used architecture of neural network systems used in insolvency prediction are:

- (1) Multi-layer perceptron (MLP) with a 'back-propagation' algorithm: The most popular ANN architecture used in insolvency prediction (Perez 2006). This architecture deals with classification problems via a sigmoidal or 'squashing' activation function:

$$\text{OUT} = F(X.W) = F(\text{NET}) = 1/(1+e^{-\text{NET}})$$

Where OUT = the final output of a neuron in the output layer

X = the input vector

W = weight vector 'w' between neuron 'i' in layer 'k' and neuron 'j' in layer 'k+1'

- (2) Kohonen's self-organising mapping: Unlike the MLP (above) which reacts in terms of forecast (i.e. which class the company belongs to), the Kohonen's map responds in terms of classification (Perez 2006). For example, the map will determine a certain number of classes and cluster them to set up some groups on its own.

- (3) Perceptron: is a single-layer neural network with binary outputs. It is similar to a 'back-propagation' but does not contain hidden layers (Rahimian et al. 1991). The model utilizes supervised learning and a nonlinear threshold unit:

If NET output \geq Threshold, OUT = 1

Otherwise OUT = 0

2.8 Multivariate approach versus ANN as predictors of insolvency

MDA is one of the most popular techniques used for analyzing insolvency (Perez 2006). The main advantage of the MDA approach to predict corporate failure is its ability to reduce a multidimensional problem to a single score with a high level of accuracy. However, MDA is subject to a number of restrictive assumptions. First, MDA requires the decision set which is used for distinguishing between failed and non-failed companies be linearly separable. Second, MDA does not allow a ratio's signal to vacillate depending on its relationship with another ratio, or set of ratios (Ticehurst & Veal 2000). In practice, a ratio may signal financial distress if it is higher or lower than normal. These problems together with issues such as, bias of extreme data points, the multivariate assumption of normality and equal group variance, may ensure MDA is unsuited to the complex nature, boundaries and interrelationships of

financial ratios (Coats & Fant 1993).

Recursive Partitioning Analysis eliminates many of the statistical problems attributed to discriminant analysis, such as the distribution assumptions associated with the independent or dependent variables. When prior probabilities and the costs of errors are specified, the method will seek to minimize the costs of misclassification. The key assumption for RPA are that the variables describing the group of observations are discrete, non-overlapping and identifiable (Altman 1993). There is evidence that the RPA models are superior to the MDA models although variations in accuracy were not marked (Frydman, Altman & Kao 1985).

Logistic regression analysis has the advantage of being less affected than discriminant analysis, when basic assumptions, such as the normality of the variables are violated (Altman 1993). However, similar to discriminant analysis, their predictive power is time-sensitive. Using linear discriminant analysis and logit analysis, Hamer (1993) recorded misclassification rates lower than would be expected by chance, for each of the three years prior to company failure. In the fourth and fifth year these models yield high rates of misclassification.

The advantages of Artificial Neural Networks is they do not require the prespecification of a functional form, or the adoption of restrictive assumptions about the characteristics of statistical distributions of the variables and errors in the model. By their nature, ANN systems are able to work with imprecise variables and with model changes over time. They are also able to adapt to the appearance of new cases which represent changes in the situation (Altman et al. 1993). However, reviews on the accuracy of neural networks are mixed. Dorsey et al. (1995) argue that ANN is more accurate than RPA. Nag (1991) observes that while the ANN's prediction error was less than with multiple regression models, the residual autocorrelations of the neural networks were higher, indicating that performance may not necessarily be superior. However, Odom & Sharda (1990), Wilson and Sharda (1994), Altman (1993) and Trippi and Turban (1996) all found ANN to be superior to MDA.

As with any system, ANN has its limitations. These include (Altman et al. 1993):

- (1) The learning stage can be very long.
- (2) The system might not achieve a stable absolute minimum configuration but might lock on local minimums without being able to move to the optimum.
- (3) The system might give rise to oscillating behavior in the learning phase.
- (4) When the actual situation changes significantly compared with the situation implicit in the training examples or when the set of examples is not representative of the reality, it is necessary to repeat the learning phase.
- (5) The analysis of the weightings is complex and difficult to interpret. There is little network transparency in the examination of the systems logic, making it difficult to identify the causes of the errors/defective responses.

Despite the long heritage of corporate failure prediction modeling, there are disagreements over which ratios and methods (multivariate analysis or ANN or hybrid) are appropriate for predicting corporate failure and the accuracy of results have varied considerably (Appendix 1).

This logically leads onto our three research questions framed by the following hypotheses:

Hypothesis I: Financial ratios do have significantly different predictive abilities for detecting failures of New Zealand finance companies.

Hypothesis II: The predictive accuracy of Altman's five ratios is superior to other financial ratios.

Hypothesis III: The predictive accuracy of ANN's are superior to the MDA models.

3. Conceptual model

The successful completion of an analysis of insolvency involves more than the selection of the correct methodology. This study's focus is on the approach to model building, rather than simply the specifics of each technique to provide a broader base for model development, estimation, and interpretation. This approach to model building is shown in Figure 2 while the conceptualized model for insolvency prediction is presented in Figure 3. Basically, this study recommends a combination of both MDA and ANN to improve the accuracy of corporate insolvency prediction.

The lack of a comprehensive theory of insolvency has resulted in the selection of a variety of financial variables in insolvency prediction. There are disagreements on whether accrual financial ratios are appropriate for predicting corporate failure because it lacks of theoretical justification (Scott 1981; Sharma 2001). Since insolvency is both a cash flow and balance sheet phenomenon, the use of variables based on cash flows is theoretically appealing. However, Visclone (1985) argues that cash flow measures can be misleading because of management's ability to manipulate the timing of the cash flows, such as not paying bills on time or reducing inventory below desired levels.

Alternately, management may inflate the cost of inventory to increase the measure of cash flows from operations reported in the income statement. Such distortions arise more often in companies in financial distress (Sharma 2001; Visclone 1985). Additionally, cash flow measures do not contain any significant information over accrual accounting information (such as accrual earnings) to discriminate between insolvent and viable companies (Watson 1996). By contrast, accrual earnings have information content (ability to predict corporate failure) over and above cash flow measurements.

Financial ratios that are proven to predict insolvency using MDA then become the input to the ANN. The MLP (back-propagation) ANN's architecture was chosen because it has been successful at predicting insolvency (Flecher & Goss 1993; Odom & Sharda 1990; Trippi & Turban 1996) and the means for implementing it are readily available.

Given that there is evidence that prediction models are sensitive to time period and distress situations other than those originally developed for (Perez 2006), the conceptualize model allows for flexibility of data input and a wider selection of ratios to improve insolvency prediction or enhancing precision in the coefficient estimates (MDA) of a failed company as demanded for specific situations. It is not suggested, however, that managers should focus solely on the results of financial ratios when making decisions on the viability of a company. Managers should also consider macroeconomic variables that are known to influence corporate insolvency. These macroeconomic variables can serve as input to the knowledge base of the neural network systems to improve their predictive power and include the rate of inflation, the annual growth rate in real GDP and the unemployment rate. In addition, strict corporate governance systems and strict conformation statutory reporting should be in place. Effective corporate governance systems foster transparency and accountability by ensuring their shareholders receive quality information about the company's performance and the directors' stewardship of their assets. This ensures that shareholders are able to exercise their powers to hold directors to account.

4. Methodology

This study uses secondary data and hypothesis testing to assess the relationships in a pattern of financial ratios of failed and non-failed companies.

4.1 *Sample*: Data were collected from companies that filed for receivership or failed during 2005-2007 (extracted from the New Zealand registrar of companies). Data from non-failed companies were derived from New Zealand investment company's financial statements over the accounting period 2004-2007. The various corporate financial statements were collected from their respective websites/brochures. Getting the needed transparency from financial reports was not easy due to different company reporting practices and changing regulations during this period. As of 2006, New Zealand migrated to the international accounting standard. Overall, data were collected from 10 known failed companies and 35 non-failed companies. The failed company's financial data was classified into one year ($t-1$), two years ($t-2$) and three years ($t-3$) prior to a failure.

To reduce the number of independent variables from the list of 36 financial ratios (Figure 1), this study follows the method suggested by Leshno and Spector (1996) being to:

- (1) Include all variables used in Altman's (1968) Z-score model. However, one of Altman's ratio's (Sales/Total Assets) was not selected because of its inappropriateness to financial companies.
- (2) Retain only one variable from each pair of variables with a correlation coefficient >0.9 .
- (3) Exclude the variable with the greater number of missing values from each highly correlated pair of variables.
- (4) If both variables have an equal number of missing values, exclude the one that is intuitively identified as less relevant to insolvency.

4.2 *Estimation of the discriminant model and assessing overall fit*: This study employed a stepwise regression to develop an optimal MDA model. The overall fit of the discriminant function involves three tasks: (i) calculating discriminant Z scores for each observation, (ii) evaluate group differences in discriminant Z scores, and (iii) assesses the accuracy of the predictions for group membership (Hair et al. 2000).

4.3 *Assessing group membership prediction accuracy*: To determine the predictive ability of the discriminant function, a cutting score and classification matrix or hit ratio were predetermined. The samples are divided into two groups to validate the discriminant function through the use of a classification matrix. One group, the analysis sample, is employed for computing the discriminant function. The other group, the holdout sample, is retained for developing the classification matrix. The individual discriminant scores for the holdout samples are compared with the critical cutting score and classified as follows:

An individual is classified into group A if $Z_n < Z_{ct}$, and

An individual is included in group B if $Z_n > Z_{ct}$

where, Z_n = discriminant Z score for the nth individual

Z_{ct} = the critical cutting score

4.4 *Measuring predictive accuracy relative to chance*: The formula for this criterion is: $C_{PRO} = p^2 + (1-p)^2$

where, p = proportion of individuals in group 1

$1-p$ = proportion of individuals in group 2

4.5 *Comparing the hit ratio to chance-based criteria*. The accuracy of classification should be at least 25 percent greater than chance. For example, if the accuracy of chance is 50 percent, the accuracy of classification should be 62.5 percent (i.e. $1.25 \times 50\%$) (Hair *et al.* 1998).

4.6 *Analysis*: Data analysis in this study involved two stages: The first deals with testing of hypothesis I and II while the second stage deals with hypothesis III. Hypothesis I was developed to determine the variables which are most suitable for constructing an efficient model for predicting insolvency. To achieve this outcome, data was analyzed using the SPSS statistical software package, where the individual discriminating ability of financial ratios was tested by comparing the equality of group means using Wilks' lambda and associated F -test. This test compared the difference between the average values of the ratios in failed and non-failed groups. The test also compared the variability of values within each group (μ). The smaller the Wilks' lambda, the greater the differences between the average values of the ratios in failed and non-failed groups.

Ho: $\mu_1 = \mu_2 = \dots = \mu_k$

H₁: $\mu_1 \neq \mu_2 \neq \dots \neq \mu_k$

where, μ_1 = mean of ratio 1 across the failed and non-failed groups

μ_2 = mean of ratio 2 across the failed and non-failed groups

μ_k = mean of ratio k across the failed and non-failed groups

If the value of the calculated F statistic is significant ($F < 0.05$), the null hypothesis is rejected because there are differences in the means of ratios across the failed and non-failed groups.

4.6.1 *Testing of hypothesis II*: F values are used for interpreting the discriminating abilities of the independent variables. This is accomplished by ranking the significant F values. Large F values indicate that an independent variable has superior discriminatory power (Hair *et al.* 1998).

4.6.2 *Second stage (testing of hypothesis III)*: Hypothesis III considers whether ANN is more accurate than MDA. Initially, classifier of Alyuda Neuro Intelligence software (variation of the 'back propagation' algorithm) was used to identify failed and non-failed companies in ANN and its average accuracy recorded. The testing procedure for hypothesis III was as follows:

Ho: $PMDA = PANN$

Ha: $PMDA \neq PANN$

where, $PMDA$ = the average accuracy of MDA

$PANN$ = the average accuracy of ANN

(Note: the average accuracy figures are expressed as percentages)

The test of hypothesis III was conducted (using SPSS) by comparing the t -test with the critical value of the t statistic. The null hypothesis would be rejected if the absolute value of the t -test exceeded the critical value.

5. Results

5.1 *Stage I (test of hypothesis I and II)*: After examining variability in the ratio means, many variables were found to be significant at the 0.05 level, indicating substantial differences in variables between groups. This shows there is significant variety in the ratios of failed and non-failed companies. These findings indicate that *Hypothesis I: Financial ratios do have significantly different predictive abilities for detecting failures of New Zealand finance companies* (H₁: $\mu_1 \neq \mu_2 \neq \dots \neq \mu_k$) should be accepted as the means across all groups are not equal. So there is strong evidence to support the view that financial ratios have different predictive abilities for detecting financial failures amongst New Zealand finance companies.

As early warning signals; four out of Altman's (1968) five financial ratios derived from financial statements one year prior to failure, are the most accurate (largest F -values) for predicting corporate insolvency (Figure 4, in bold). This provides evidence to support hypothesis II that the Altman's ratios are more superior in predicting corporate

insolvency in New Zealand. Other ratios that are able to discriminate between failed and non-failed finance companies in New Zealand were found to include DARATIO, INTERAT, ROA and QUIRATIO. It was also found that DERATIO and FAEQLTL (*in italic*) are not good predictors of corporate insolvency in New Zealand.

This study also found that prior to failing companies tend to have the following:

- (1) Low profitability, as indicated by their significantly smaller EBITTA, RETAINTA and ROA.
- (2) Higher leverage ratios, as indicated by their significantly larger DARATIO and INTERAT.
- (3) Less liquidity, as indicated by smaller QUIRATIO.
- (4) Lower asset quality, as indicated by lower WCTA.

5.2 *Stage II (Test of hypothesis III)*: Preliminary findings suggest that satisfactory results (62% accuracy of classification) were achieved with a MDA model using those four of Altman's (1968) five financial ratios which were found earlier to be effective in predicting insolvency in New Zealand, namely: working capital/total assets, retained earnings/total assets, EBIT/total assets and market value of equity/total liabilities. Currently, this study is in the process of optimizing the MDA model and 'pruning' the ANN model (phasing out of neurons that achieve similar performances to provide a simpler model) to achieve greater efficiency of prediction. This indicates that adopting ANN for insolvency prediction is more thorough and a creative process than earlier models .

6. Limitations of this study

This study has several limitations which may affect the accuracy of ANN and MDA including:

- (1) Only data on a relatively small sample of failed companies and non-failed companies was available. Hence, there is some risk that the results have been affected by sample size.
- (2) The companies were not selected at random.
- (3) The data analysed in this study was obtained from public financial statements which may subject to creative accounting. Companies facing failure may distort their published accounts and this will skew the results of the model.
- (4) Some corporate financial statements did not disclose figures on cash flow or operating expenses. This study was restricted to balance sheet and income statements.
- (5) The MDA methodology violates the assumptions of normality for independent variables.

7. Implications for further study

Future studies could use quarterly rather than annual data, or analyse changes in the size of ratios over a number of time series. While this study's adoption of a stepwise regression analysis to reduce the number of variables to prevent over-fitting of data in the derivation sample, has been effective, factor analysis could be used in future research. Further research is needed to develop and understand the model's full potential. This is likely to include using different neural network architectures such as the ID3-assisted neural network and the SOFM-assisted neural network. An alternative method of estimation is the 'jackknife' method to produce unbiased estimates for the probability of misclassification. This method involves holding one example out of the training set and using the estimated discriminant function to predict the extracted example.

8. Summary

This study employed financial ratios for differentiating between failed and non-failed financial companies (non-bank) in New Zealand. These financial variables were derived from the financial statements of both failed and non-failed companies. Methodologies adopted included univariate tests, MDA (stepwise regression) and ANN (back propagation algorithm). The univariate tests indicate that failed companies' financial ratios differ significantly from non-failed companies. Failed companies were less profitable and less liquid. They also had higher leverage ratios and lower quality assets. The results of the optimal MDA model indicate that the models are more accurate with data one year prior to failure.

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Name of financial ratio	Definition	Symbol
Leverage		
1) Equity market value to total debt	Market capital/total liabilities	MKTCAPTL
2) Equity market value to total assets	Market capital/total assets	MKTCAPTA
3) Equity market value to total equity	Market capital/equity	MKTCAPEQ
4) Debt to equity ratio	Total liabilities/equity	DERATIO
5) Debt to total assets	Total liabilities//total assets	DARATIO
6) Financial leverage multiplier	Total assets/equity	TAEQ
7) Fixed assets to equity & long term liabilities	PPE/(equity + long term liability)	FAEQLTL
8) Retained earning to total assets	Retained earnings/total assets	RETAINTA
Profitability		
9) Return on assets	Net income/total assets	ROA
10) Return on equity	Net income/equity	ROE
11) Gross profit margin	(Sales- Cost)/sales	GPMARGIN
12) Net profit margin	Net incomes/sales	NPMARGIN
13) Operating profit margin	EBIT/sales	EBITSALE
14) EBIT to total assets	EBIT/total assets	EBITTA
Turnover		
15) Working capital to sales	(Current assets -current liabilities)/sales	WCSALES
16) Inventory turnover	Cost of sales/inventory	INVETURN
17) Fixed assets turnover	Sales/PPE	FATURN
18) Total assets turnover	Sales/ total assets	TATURN
19) Equity turnover	Sales/equity	EQTURN
20) Inventory to sales	Inventory/sales	INVSALLES
21) Receivables turnover	Sales/account receivables	RECETURN
22) Quick assets to sales	(Cash + account receivables)/sales	QUISALES
23) Current assets to sales	Current assets/sales	CASALES
Liquidity		
24) Working capital to total assets	(Current assets - current liabilities)/total assets	WCTA
25) Cash ratio	Cash/current liabilities	CASHCL
26) Cash to total assets	Cash/total assets	CASHTA
27) Cash to sales	Cash/sales	CASHSALE
28) Current ratio	Current assets/current liabilities	CCRATIO
29) Current assets to total assets	Current assets/total assets	CATA
30) Current liability ratio	Current liabilities/equity	CLEQUITY
31) Quick ratio	(Cash + account receivables)/current liabilities	QUIRATIO
32) Quick assets to total assets	(Cash + account receivables)/total assets	QUITA
33) Inventory to current assets	Inventory/current assets	INVECA
Others		
34) Interest expense rate	Interest expense/total assets	INTERATE
35) Interest coverage ratio	EBIT/interest expense	INTERCOV
36) EBIT Per share	EBIT/ no. of shares	EBITSHAR

Figure 1. Financial ratios for prediction of corporate failures (business performance)

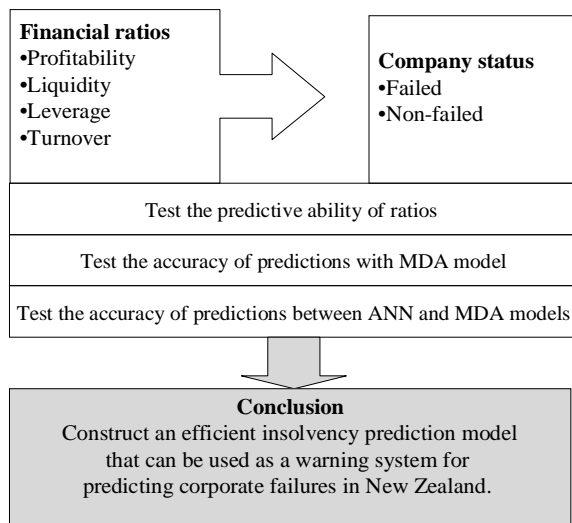


Figure 2. Approach to corporate insolvency prediction: MDA and ANN

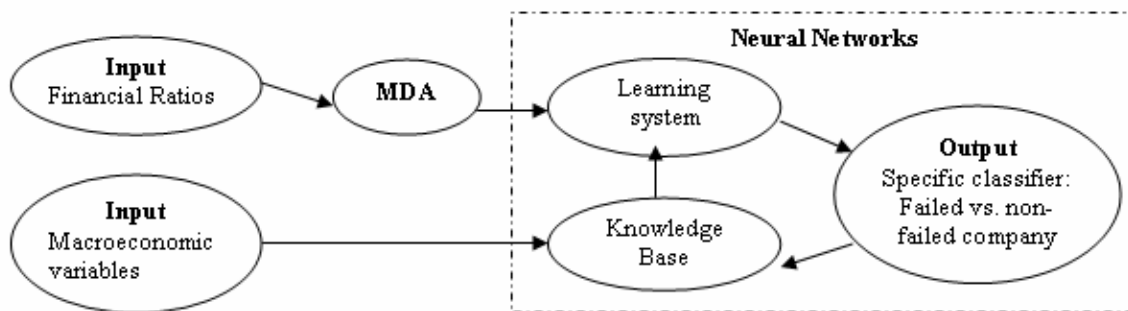


Figure 3. Conceptual model of insolvency prediction for New Zealand financial companies

<i>Financial Ratio</i>	<i>Wilks' Lambda</i>	<i>F-ratio</i>	<i>Significance</i>
Earnings Before Interest and Tax/Total Assets (EBITTA)	0.58	51.03	0.0000
Retained Earnings/Total Assets (RETAINTA)	0.61	49.29	0.0000
Working Capital/Total Assets (WCTA)	0.70	24.67	0.0002
Market Value of Equity/Total Debt (MKTCAPTL)	0.73	18.36	0.0073
Quick ratio	0.76	16.33	0.0004
Interest rate expense (INTERAT)	0.79	13.55	0.0087
Debt to total assets (DARATIO)	0.81	15.10	0.0097
Return of Assets (ROA)	0.82	14.43	0.0124
<i>Debt to equity ratio (DERATIO)</i>	<i>0.94</i>	<i>2.86</i>	<i>0.1921</i>
<i>Fixed asset to equity & long term liabilities (FAEQLTL)</i>	<i>0.98</i>	<i>1.37</i>	<i>0.2321</i>

Figure 4. Top and worst predictors of corporate insolvency in New Zealand

Appendix 1. Empirical results of prior studies

Researcher	Model	% of correctly classified
Altman (1968)	MDA	95%
Deakin (1972)	MDA	97%
Altman, Haldeman and Narayanan (1977)	MDA	93%
Ohlson (1980)	LOGIT	96%
Nittayagasetwat, Tirapat and Withisuphakorn (1997)	MDA, LOGIT	65%, 85%
Khunthong (2000)	MDA, LOGIT, PROBIT	95%, 91%, 92%
Odom and Sharda (1990)	ANN, MDA	81%, 59%
Rahimian et al. (1991)	ANN, MDA	82%, 75%
Coats and Fant (1993)	ANN, MDA	95%, 88%
Altman, Marco and Varretto (1993)	ANN, MDA	95%, 96%