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Juliana Yim
Heather Mitchell
School of Economics and Finance

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Juliana Yim is a PhD student with the School of Economics and Finance. Heather Mitchell is a senior lecturer from the same School. Juliana is the corresponding author for this paper and can be contacted as follows:

Ph. 03 9925 1665
Email: Juliana.Yim@ems.rmit.edu.au

Abstract

This study investigated whether two artificial neural networks (ANNs), multilayer perceptron (MLP) and hybrid networks using statistical and ANN approaches, can outperform traditional statistical models for predicting Australian financial service failures one year and two years prior to the financial distress. The results suggest that hybrid neural networks outperform all other models one and two years before failure. Therefore, the hybrid neural network model is a very promising tool for failure prediction. This supports the conclusion that for researchers, policymakers and others interested in early warning systems, hybrid networks would be useful.

1. Introduction

The last two decades have seen several episodes of banking and financial sector distress around the world (Caprio and Klingebiel, 1996). In order to promote financial stability, many African and Nordic countries had to take action to rescue or restructure their financial system during 1980s. In the 1990s, the Mexican and Asian financial crises showed that is very important to develop a strong financial sector to guarantee a sustainable economic growth. Kaminsky (1999) suggests that with the banking system in a vulnerable situation, the task of protecting the domestic currency becomes more difficult and may lead to a currency crash. As a consequence, researchers and policymakers have demonstrated a great interest in searching for the determinants of financial sector distress to develop early warning systems.

In this study we will consider Australian finance service failures.[i] In Australia deregulation in the mid 1980s increased competition in the financial service sector, because of that, the aim of financial institutions became to achieve high level of returns quickly. This occurred when assets prices were increasing rapidly and the credit evaluation procedures in many financial institutions lacked supervision. The boom of poor credit quality and economy recession provoked financial sector distress. Consequently, the State Bank of Victoria, State Bank of South Australia, Westpac and ANZ recorded large losses. However, after the economy's recovery from the recession of the early 1990s, the Australian banking sector became very strong. This is because an appropriate prudent supervision to regulate the financial system was developed and pressure for mergers between the banking, managed funds and insurance companies increased. Over the 1990's major problems occurred in the reinsurance sector. For instance, between 1998 and 1999, New Cap Reinsurance Australia Corporation, GIO Australia, and HIH Insurance reported enormous losses. So, even though the financial services sector has always been competitive with many changes, there are just a few companies that fail compared to the number in other markets, such as America. The task of developing a failure classification model for financial services sector is made difficult because of the small number failed companies in this sector.

Prior studies indicate that researchers generally test and evaluate bank financial distress models using two popular standard statistical techniques, logit and discriminant analysis (DA). Sinkey (1975) and Santomero (1977) employed DA and Martin (1977) used probit or logit models. There are few studies in Australia that investigated the predictive power of statistical models for predicting firm failures. Castagna and Matolcsy (1981) applied linear and quadratic discriminant models to a sample that consisted of 21 failed firms matched to 21 non-failed firms over the period 1963-1977. The results one year before failure from DA analysis show that the model correctly classified 81% of the failed firms and that of non-failed was 95%. Lincoln (1982) was the first study to use DA to analyze Australian property-finance failures from 1969-1978. The author also considered a more general model with firms from property, retailing and manufacturing. These sectors were combined into two groups: manufacturing-retailing firms and property-finance firms. The predictive accuracy for the manufacturing-retailing model was high, but very low for the property-finance model. Izan (1984) applied DA to a larger sample composed of 53 failed and 50 non-failed firms over the period 1963-1979. These firms were selected from several industrial sectors. The results one year before failure from DA analysis show that the model correctly classified 94% of the failed firms and that of non-failed was 89%.

However, logit, probit and DA models require assumptions such as normality of the data and independence of the predictors. In particular DA assumes the covariance matrix for the failed and non-failed groups are the same. When the data do not satisfy these assumptions, both logit and DA provide non-optimal solutions (Altman, Pinches and Trieschmann 1977; Ohlson, 1980). On the other hand, as a non-parametric and non-linear model, the artificial neural networks (ANNs) do not rely on these assumptions that are often adopted to make traditional statistical methods tractable. No study known to the authors has used ANN for predicting failure of Australian companies.

Some work has been done using ANNs for markets outside Australia, most notably the USA. Most of the papers that have been published on the comparison of ANNs and statistical models for banking failure prediction indicated that ANNs outperformed statistical models. In one of the earliest studies, Bell, Ribar and Verchio (1990) found that the ANN model performed better than logistic regression in predicting commercial bank failures. Salchenberger, Cinar and Lash

(1992) used ANNs and logit models to predict bankruptcy of saving and loans. Their results also indicated that ANNs have higher predictive accuracy than logit models. Tam and Kiang (1992) compared the predictive power of ANN models to DA, logit analysis, K-nearest neighbor, and decision tree approaches for bank bankruptcy prediction. The data consists of Texas banks data one and two years prior to failure on the period 1985 to 1987. Empirical results show that ANNs offer better predictive accuracy than DA, logit, K-nearest neighbor and decision tree approaches. Serrano (1996), used self-organizing networks to analysis failures of Spanish banks from 1977 to 1985. According to the author, the performance of the self-organizing maps was superior to backpropagation networks. Brockett, Cooper and Pitaktong (1994) used various techniques, including ANN, DA and the National Association of Insurance Commissioners' Insurance Regulatory Information System rating to identify early warning signals of insurance company insolvency. They found the ANN was superior to all the other models.

According to the studies described above, neural networks have potential as a forecasting approach and its integration with other statistical techniques might improve its overall performance. There are few papers that discuss the integration between statistical models and ANN. Han, Kwon and Lee (1996) was the first study that suggested hybrid neural networks for firm bankruptcy prediction. This work combined neural network models with other statistical or artificial intelligence models. Empirical results show that hybrid neural network models are very powerful for bankruptcy prediction. Markham and Ragsdale (1995), combined output estimated by DA with ANN to produce more accurate models. The results indicated that the hybrid network performed better than the DA and ANN used individually.

This study investigated whether two artificial neural networks, multilayer perceptron and hybrid networks using statistical and ANN approaches, can outperform traditional statistical models for predicting Australian financial service failures one year and two years prior to the financial distress. The results suggest that hybrid neural networks outperform all other models one and two years before failure. Therefore, the hybrid neural network model is a very promising tool for failure prediction. This supports the conclusion that for researchers, policymakers and others interested in early warning systems, hybrid networks would be useful.

This paper is organized as follows. Section 2 introduces the hybrid neural networks. Section 3 describes the data. Section 4 presents the results of estimated models. Section 5 presents an evaluation and comparison of neural network models, hybrid models and statistical models. Section 6 presents concluding comments.

2. Hybrid Neural Network Model

The ANN used in this study uses a multilayer perceptron network (MLP), trained by a gradient descent algorithm called backpropagation[ii] (Rumelhart, McClelland and PDP Group 1986). It is the most common type of formulation and is used for problems that involve supervised learning. This section introduces a methodology to be applied to the classification problems by integrating the variables selected by the statistical models and the outputs of statistical models with those of an MLP network to create hybrid models that might be more accurate than either of the techniques used separately.

We will consider two different approaches to hybrid models. The first approach is to use the statistical models to select the variables to be used as inputs to the ANN. The second is to use output, such as an estimated probability, as an input to a neural net. We decided to combine ANN's and statistical models because ANN's have problem when dealing with large numbers of variables, in particular the time taken for this selection and the possibility of overfitting. By combining statistical models with ANN's we can reduce the problems in the following ways:

- Using statistical models to preselect variables reduces the risk of overfitting and also reduces the time taken to select the model.

- Using output from a statistical model as input to a ANN efficiently condenses information and allows the set of potential variables.

To denote the various hybrid models we use the following system. Firstly, we call ANN models using the logit model and DA as pre-processors for selecting variables ANN-logit and ANN-DA, respectively. Secondly, we call ANN models using the probability of failure predicted by the logit model or DA as input into a network ANN-Plogit and ANN-PDA, respectively. Finally, we call ANN models using logit model and DA as pre-processors for selecting variables and the probability of failure predicted by the logit model or DA as input into a network ANN-logit-Plogit, ANN-logit-PDA, ANN-DA-PDA and ANN-DA-Plogit.

Next, following the formulation used by Markham and Ragsdale (1995), we will describe how the DA, logit and ANN models might be integrated. The output from the neural network can be written as follows:

$$P(ANN) = f\ (x_1, x_2, \ldots, x_m) \qquad \textbf{(2.1)}$$

where P(ANN) is the probability estimated by the ANN and $x_1, x_2, \ldots, x_m$ are the inputs.

The output from the hybrid neural network (ANN_H) using both the inputs and probabilities estimated by DA or logit models as new inputs to the network can be written as follows:

$$P(ANN_H) = f_1\ [P(ANN), PDA)].$$
$$\text{or} \qquad \textbf{(2.2)}$$
$$P(ANN_H) = f_2\ [(P(ANN), Plogit]$$

where PDA, Plogit, P(ANN) and $P(ANN_H)$ are the probabilities estimated by DA, logit, ANN and ANN_H models, respectively.

Using ANN to estimate P(ANN) and a second ANN_H integrate these values with PDA or Plogit, as can be observed in (2). However, $P(ANN) = f\ (x_1, x_2, \ldots, x_m)$. Therefore, (2) might be written as follows,

$$P(ANN_H) = f_1\ (x_1, x_2, \ldots, x_m, PDA).$$
$$\text{or} \qquad \textbf{(2.3)}$$
$$P(ANN_H) = f_2\ (x_1, x_2, \ldots, x_m, Plogit).$$

3. The Description of the Data

A full listing of all the companies used is given in Table 1 of Appendix B, which consists of a total of 70 Australian firms listed on the Australian Stock Exchange (ASX), 11 of which failed between 1995 and 1999. The successful companies were matched to the failed companies by randomly selecting firms with same asset size and year. Because of their importance in the sector we have also included the Commonwealth and National banks. After the initial groups were defined and firms selected, balance sheet and income statement data were collected. The sample consists of companies from financial services industry and the information was obtained from the CD-Financial Analysis Publication 2001. Data used for the failed firm is from the last and penultimate financial statement issued before the firm failed. Thus, the prediction of failure is to be made for up to 2 years in advance. The failed firms come from financial services sector consist of 7 insurance companies and 4 fund management companies. We also tried to use a larger sample, combining firms from the property and financial services sectors. But, due to the low performance of this combined model, we decided to only use the financial services sample.

Most failure prediction studies are interested in developing more accurate predictions by selecting the best financial ratios for the analysis. No unified theory has been recognised as a basis for theoretical ratio selection. Table 3.1 lists 14 variables that comprise candidates for final variables of the failure prediction models. All these ratios have successfully predicted firm failure in previous studies. These variables are classified in six standard ratios categories, including profitability, growth, activity, gearing, employee and liquidity. Table 3.2 shows the descriptive statistics of the financial ratios one and two years before failure. The kurtosis, skweness and Jarque-Bera statistics indicate that most of the financial ratios are non-normal. If the multivariate normality assumption is violated, tests of significance and the estimated classification error rate of the DA may be biased.

Table 3.1: List of Financial Ratios

Category	Financial Ratio	Code
Profitability	OPABT Over Shareholders Funds	OSF
	OPABT Over Sales	OVS
	OPABT Over Total Assets	OTA
Gearing	Shareholders' Interest	SHI
	Debt / Equity	DEQ
	Working Capital / Total Assets	WCT
	Long Term Debt / Total Debt	LTD
Liquidity	Current Ratio (times)	CUR
	Quick Ratio (times)	QUR
	Debt / Gross Cash Flow (years)	DGC
	Trade Debtors Period (days)	TDP
Growth	Growth in Total Assets	GTA
Activity	Sales per total assets	STA
Employee	Sales per Employee	SPE

Table 3.2: Descriptive Statistics (1 and 2 years before failure)

Financial Ratios	1 year before failure								2 years before failure							
	Failed				Non-failed				Failed				Non-Failed			
	mean	Skewness	kurtosis	J-B	mean	skewness	kurtosis	J-B	mean	skewness	kurtosis	J-B	mean	skewness	kurtosis	J-B
OPBAT Over S'holders' Funds	-6.34	-2.43	7.69	20.95	8.85	0.091	6.01	22.47	14.13	-0.21	2.01	0.52	7.10	-2.97	23.67	1138
OPBAT Over Sales	5.07	-0.42	3.95	0.74	6.02	-1.65	12.06	228.99	11.25	2.23	6.87	16.5	24.57	7.16	53.82	6855
OPBAT Over Total Assets	3.048	0.83	2.88	1.29	3.094	0.17	11.51	178.51	5.96	0.98	2.56	1.88	3.00	-1.48	9.69	131.90
Shareholders' Interest	40.50	0.48	1.46	1.49	65.25	-0.68	1.81	8.02	49.38	0.024	1.28	1.34	62.24	-0.54	1.60	7.76
Debt / Equity	105.20	1.01	2.70	190	222.6	2.48	7.75	116.55	86.81	2.29	6.97	16.91	179.4	2.85	10.11	204.4
Working Capital / Total Assets	41.96	0.39	1.50	1.30	7.26	0.24	3.81	2.21	23.07	1.59	4.95	6.40	5.94	0.20	3.69	1.60
Long Term Debt / Total Debt	58.68	-0.31	1.65	1.00	13.92	2.067	5.94	63.41	55.07	-0.21	1.40	1.24	17.45	1.63	4.35	30.66
Current Ratio (times)	8.23	2.10	6.20	12.82	10.41	4.71	24.68	1374	1.87	2.33	7.50	19.32	8.99	4.58	24.09	1301
Quick Ratio (times)	7.96	2.09	6.10	12.62	10.31	4.71	24.67	1373	1.70	2.00	6.54	13.20	8.90	4.59	24.12	1305
Debt / Gross Cash Flow (years)	3.81	1.69	5.32	7.76	2.10	-4.91	35.45	2826	3.47	1.92	5.62	9.97	5.51	1.29	8.35	87.00
Trade Debtors Period (days)	29.25	1.47	3.79	4.27	33.23	4.35	23.91	1261	41.57	1.81	5.40	9.68	55.78	7.10	53.13	6675
Sales/employee	17648	2.37	7.10	18.41	2352	4.60	23.83	1276	2.35	2.80	8.95	30.34	2358	4.86	25.57	1485
Growth in Total Assets	46.23	2.20	6.44	14.35	45.38	4.01	18.56	753	12.73	0.80	4.84	2.74	16.15	2.79	12.79	312.80
Sales per total assets	0.29	0.15	2.10	0.40	0.18	2.21	8.11	108.50	0.27	0.79	3.03	1.16	0.20	2.11	7.34	88.91

4. Empirical Investigation:

Predicting Australian Financial Service Failures

4.1 Discriminant Analysis

This section analyses the ability of DA to predict Australian financial service failures. The analysis was divided into three stages. The first part involves estimating the discriminant function and determining whether or not they are statistically significant. The second part carries out various tests on the adequacy of the model and determine which of the independent variables contributes the most to discriminate between the groups. The last part evaluates further the predictive accuracy of the discriminant function.

First we will estimate an optimum discriminant function and determine whether or not it is statistically significant. Several different models[iii] were estimated and the best was found to contain five variables: long term debt over total debt, working capital over total assets, shareholders' interest, OPBAT over shareholders' funds and quick ratio. The stepwise[iv] procedure is shown in the Table 4.1.1:

Table 4.1.1: The Stepwise Selection of the DA Model

Step	Variable Selected	Min.D Squared Statistic	Exact F Statistic	Sig.
1	Long Term Debt / Total Debt	2.182	20.230	0.0000
2	Working Capital / Total Assets	4.328	19.768	0.0000
3	Shareholders' Interest	5.195	15.581	0.0000
4	OPBAT/Shareholders' funds	6.023	13.345	0.0000
5	Quick Ratio	6.863	11.977	0.0000

The final discriminant function is:

$$Z= 0.257 - 0.015\ OSF + 0.027\ WTA + 0.024\ LTD - 0.014\ SHI - 0.014\ QUR$$

The main assumptions required by DA are that the predictors should have a normal distribution and the covariance matrices of the two group (failed and non-failed) should be equal. Based on the Jarque-Bera statistics in Table 3.2 only one of the variables, working capital over total assets, is normal in both groups. The assumption of equal covariance matrices is tested using Box's M[v] test, which tests the equality of the determinants. The value of this statistic is M = 59.417, p-value = 0.000 using the F approximation, so the assumption of constant variance is not satisfied. This means that the tests of model adequacy which follow may not be reliable.

Next we carry out various tests on the adequacy of the model. The canonical correlation is used because it is a measure of association between the groups formed by the dependent and given discriminant function. The discriminating function for the best model is highly significant and displays a canonical correlation of 0.695. One interprets this correlation by squaring it $(\text{canonical correlation})^2 = 0.48$, and concluding that 48% of the variance in the dependent variable can be accounted for by this model. The Wilk's lambda test is used for analyzing the significance of each discriminant function. The model produced a Wilk's lambda of 0.517, which indicates that the selected discriminant function is significant.

The second part consists of determining which of the independent variables contributes the most to discriminating between the groups. The structure coefficients are used to indicate the correlation of each variable with each function in DA. From Table 4.1.2, the structure matrix reveals that variable long-term debt over total debt assets has the best explanatory ability.

Table 4.1.2: Structure Matrix

Independent Variables	coefficient
Long Term Debt / Total Debt	0.564
Working Capital / Total Assets	0.337
Shareholders' Interest	-0.257
OPBAT/Shareholders' funds	-0.236
Quick Ratio	-0.030

The final part consists of evaluating the predictive accuracy of the discriminant function. Here the value of the discriminant function at the group centroid is used to establish the cutting point for classifying cases. The mean score for the non-failed cases on discriminant function for the model is -0.412, while that for the group of failed companies is 2.208. These group centroids can be interpreted as the number of standard deviation each group is away from the average of the two groups.

<u>Table 4.1.3: Probability of Failure and Discriminant Score for Misclassified Firms (1year before failure)</u>

ASX Code	Companies	Predicted Status	Z-Score	Prob. of failure
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Success	0.03	0.91
AFI	AUSTRALIAN FOUNDATION INVESTMENT CO LTD	Failure	1.42	0.80
CHP	CHAPMANS LTD	Failure	1.82	0.92
EZL	EUROZ LTD	Failure	1.01	0.57
FEC	FLEET CAPITAL LTD	Failure	1.02	0.58
NGL	NOALL GROUP LTD	Failure	1.03	0.59
QBE	Q.B.E. INSURANCE LTD	Failure	1.84	0.92

For this study, the critical cutting score is zero, so a firm is classified as non-failed if its discriminant score is negative and as failed if its discriminant score is positive. Table 4.1.3 lists the predicted status, the discriminant score and the probability of failure for misclassified firms. The overall success rate of the model was 87.1%. More specifically, the success rate of predicting failure was 90.9% and that of success, 86.4%.

In order to try to determine if this technique can predict for more than one year in advance, the 14 variables based on the data from two years prior were calculated. The program automatically selected long-term debt over total debt for the best model. The value of this statistic is M=2.587, p-value = 0.114 using the F approximation, so the assumption of constant variance is satisfied. The final discriminant function is:

$$Z = -0.73 + 0.031\ \text{LTD}.$$

The mean score for the non-failed cases on discriminant function for the model is -0.183, while that for group of failed companies is 0.964. The model produced an eigenvalue of 0.181, which is considered poor. The discriminant function for the model displays a canonical correlation of 0.392. As discussed previously this means 15.3% of the variance in the dependent variable can be accounted for by this model. Table 4.1.4 lists the predicted status, the discriminant score and the probability of failure for misclassified firms. Even though, the predictive power of this model declined in the second year, the overall success rate was 75.7%, the success rate of predicting failure was 63.6% and that of non-failed, 78.0%, using just long-term debt over total debt.

Table 4.1.4 : Probability of Failure and Discriminant Score for Misclassified Firms (2 years prior failure)

ASX Code	Companies	Predicted Status	Z-Score	Prob. of Failure
EMA	EMERGING MARKETS CO LTD	Success	-0.73	0.22
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Success	-0.73	0.22
NCC	NEW CAP REINSURANCE CORPORATION HOLDINGS LTD	Success	-0.73	0.22
CGH	COLONIAL LTD	Success	-0.04	0.38
AFI	AUSTRALIAN FOUNDATION INVESTMENT CO LTD	Failure	1.42	0.76
AMP	A.M.P. LIMITED	Failure	0.83	0.62
CHP	CHAPMANS LTD	Failure	2.34	0.90
EQT	EQUITY TRUSTEES LTD	Failure	2.34	0.90
EZL	EUROZ LTD	Failure	1.90	0.85
QBE	Q.B.E. INSURANCE LTD	Failure	1.60	0.80
TRU	TRUST COMPANY OF AUSTRALIA LTD	Failure	2.34	0.90
WBB	WIDE BAY CAPRICORN BUILDING SOCIETY LTD	Failure	0.72	0.59

4.2 Logistic Regression

This section analyses the predictive ability of logistic regression for forecasting Australian financial service failures. The probit model was also tried, but its results were not reported in this study. This is because its outputs were very similar to the ones estimated by logistic regression. Several different models[vi] were estimated using maximum likelihood and the best used six financial ratios. The regression coefficients and significant variables at 5 percent error level are given in Table 4.2.1. The selected financial ratios were divided in four categories: The leverage category is formed as shareholders' interest, working capital over total assets and long term debt over total debt. The employee category is constituted by sales per employee. The growth category consisted of growth in total assets. The efficiency measure consisted of trade debtor period.

Table 4.2.1: The Final Logit Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Shareholders' Interest	-0.158057	0.067729	-2.333675	0.0196
Working Capital / Total Assets	0.160322	0.068626	2.336161	0.0195
Long Term Debt / Total Debt	0.090780	0.039383	2.305050	0.0212
Trade Debtors Period	-0.025158	0.012032	-2.090830	0.0365
Sales Per Employee	0.000240	0.000112	2.133677	0.0329
Growth in total assets	-0.051439	0.025700	-2.001517	0.0453

The final logistic function is:

Pr (failure)= $\frac{1}{1+e^{E(\text{logit})}}$

where E(logit) = $-0.1580SHI + 0.1603WTA + 0.0907LTD - 0.0251TDP + 0.0002SPE - 0.0514GTA$

The test statistic for the log likelihood ratio test is 80.0, which has the p-value=0.000(χ_6^2), indicating that the model fits to the data. Also, the Hosmer and

Lemeshow test (1989) was used to compare the fitted expected values to the actual values by group. If these differences are large, we reject the model as providing an insufficient fit to the data. Table 2 of Appendix B shows the Hosmer and Lemeshow goodness-of-fit test has a p-value of 0.993, which is greater than 0.05, implying that the model's estimates fit the data at an acceptable level.

For the logistic regression, the institutions were classified as failed if the probability of failure exceeds a cut-off point of 0.5. Table 4.2.2 shows probability of failure for misclassified firms. The overall success rate of the model was 95.7%. More specifically, the success rate of predicting failure was 90.9% and that of non-failure, 96.6%.

Table 4.2.2: Probability of Failure for Misclassified Firms (1 year before failure)

ASX Code	Companies	Predicted Status	Prob. of failure
EQK	EQUITILINK LTD	Success	0.08
CHP	CHAPMANS LTD	Failure	0.76
MBL	MACQUARIE BANK LTD	Failure	0.53

For two years before failure, the financial ratios of the best model were divided in two categories: The leverage category is formed as shareholders' interest, working capital over total assets and long term debt over total debt. The liquidity category consisted of the quick ratio. The final logistic function is:

Pr (failure)= $\frac{1}{1+e^{E(\text{logit})}}$

where E (logit) = $-0.0227\,SHI + 0.0469\,WTA + 0.0141\,LTD - 0.6199\,QUR$

The test statistic for the log likelihood ratio test is 48.89, which has the p-value=0.000. Table 2 of Appendix B shows that the Hosmer and Lemeshow goodness-of-fit test has a p-value of 0.493. Table 4.2.3 shows probability of failed and non-failed firms. The overall success rate of the model was 87.1%. The success rate of predicting failure was 54.5% and that of non-failure, 93.2%.

Table 4.2.3: Probability of Failure for Misclassified Firms

(2 years before failure)

ASX Code	Companies	Predicted Status	Prob. of Failure
ANS	A.S.C. LIMITED	Success	0.16
EMA	EMERGING MARKETS CO LTD	Success	0.07
EQK	EQUITILINK LTD	Success	0.34
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Success	0.06
FLL	F.A.I. LIFE LTD	Success	0.20
BWA	BANK OF WESTERN AUSTRALIA	Failure	0.66
EZL	EUROZ LTD	Failure	0.69
QBE	Q.B.E. INSURANCE LTD	Failure	0.57
QST	QUEST INVESTMENT LTD	Failure	0.51

4.3 ANN Models

This section analyses the predictive ability of ANNs and hybrid ANNs for predicting Australian financial service failures. Two types of hybrid ANNs were considered. The first uses statistical models to pre-select variables. The second uses the output from logit model and DA as input for an ANNs. Each network was trained for 20,000 iterations. The sigmoid function was the activation function specified in all neural networks, because it provided the best results. The number of hidden neurons in the hidden layer was selected experimentally based on the testing set performance of each neural network. Learning rates and momentum for each of the models were chosen experimentally. The final values chosen for each of the models, one year and two years before failure, are given in Table 3 of Appendix B.

First a model was developed for one year before failure. From all ANN models[vii] tried, the best specification consisted of six variables in the input layer. The selected input variables were working capital over total assets, long-term debt over total debt, OPBAT over shareholders' fund, shareholders' interest, growth in total assets and quick ratio. Two neurons were selected in the hidden layer by experimentation and one neuron in the output layer. The overall success rate of the model was 92.8%. More specifically, the success rate of predicting failure was 90.9% and that of non-failure, 89.8%. The institutions were classified as failed if the probability exceeds a cutoff point of 0.5. Table 4.3.1 shows the probability of failure for misclassified firms for one year before failure.

Table 4.3.1: Probability of Failure for Misclassified Firms

(1 year before failure)

Code	Companies	Predicted Status	Prob. of Failure
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Success	0.49
AFI	AUSTRALIAN FOUNDATION INVESTMENT CO LTD	Failure	0.63
CHP	CHAPMANS LTD	Failure	0.52
FEC	FLEET CAPITAL LTD	Failure	0.78
QBE	Q.B.E. INSURANCE LTD	Failure	0.80

For two years before failure, from all ANN models tried, the best specification consisted of five variables in the input layer. The selected input variables were working capital over total assets, long-term debt over total debt, growth in total assets and quick ratio. Five neurons were selected in the hidden layer and one neuron in the output layer. The overall success rate of the model was 94.3%. More specifically, the success rate of predicting failure was 72.7% and that of non-failure, 98.3%. Table 4.3.2 shows the probability of failure for misclassified firms for two years before failure.

Table 4.3.2: Probability of Failure for Misclassified Firms

(2 years before failure)

Code	Companies	Predicted Status	Prob. of Failure
EMA	EMERGING MARKET	Success	0.49
EQK	EQUITILINK LTD	Success	0.06
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Success	0.13
IEQ	INTERNATIONAL EQUITIES CORPORATION LTD	Success	0.51

When we compare the results from the DA, logit and ANN models we see that each technique misclassified different firms. So, each approach must be using the information in different ways. For that reason, the combination of statistical models and ANN may produce better results. The ANN models were combined with the best statistical models estimated in the previous section to perform hybrid neural networks. Firstly, we used statistical models to pre-select the variables used in the ANNs. The ANN-logit and ANN-DA models used DA and logit models as pre-processors for selecting the appropriate input variables, which are then used, by the MLP networks. Secondly, the outputs from the statistical models were used as inputs into a network (ANN-Plogit and ANN-PDA). Finally, we combined the preselected variables from the statistical models and the output from the statistical models (ANN-logit-Plogit, ANN-logit-PDA, ANN-DA-PDA and ANN-DA-Plogit). The final topology chosen for each of the hybrid network, one year and two years before failure, are given in Table3 of Appendix B. The classification for the best hybrid networks is shown in Table 4.3.3:

Table 4.3.3: Classification Accuracy for the Best Hybrid Network Models

Hybrid ANN model	1 year before failure			2 years before failure		
	Non-failed firm correctly classified (%)	Failed firms correctly classified (%)	Overall (%)	Non-failed firm correctly classified (%)	Failed firms correctly classified (%)	Overall (%)
ANN-Logit	91.5	100	92.8	100	72.7	95.7
ANN-DA	93.2	100	94.2	94.9	36.3	85.7
ANN-Plogit	98.3	100	98.5	100	81.8	97.1
ANN-PDA	94.9	90.9	94.2	100	63.6	94.3
ANN-logit-Plogit	96.6	90.9	95.7	100	81.8	97.1
ANN-DA-PDA	94.9	90.9	94.2	94.9	45.4	87.1
ANN-logit-PDA	98.3	100	98.5	100	45.4	87.1

For one year before failure, the best hybrid models are the ANN-Plogit network and the ANN-logit-PDA network. The overall success rate of the models was 98.5%. The success rate of predicting failure was 100% and that of non-failed, 98.3%. For two years before the failure, the best hybrid models are the ANN-Plogit network and the ANN-logit-Plogit network. The overall success rate of the models was 97.1%. The success rate of predicting failure was 81.8% and that of non-failed, 100%. Table 4.3.4 shows probability of failure for misclassified firms for one and two years before failure.

Table 4.3.4: Probability of Failure For Misclassified Firms

1 year before failure									
Code	Companies	Actual Status	ANN -DA	ANN - PDA	ANN -DA- PDA	ANN- logit	ANN- Plogit	ANN- logit- Plogit	ANN- logit- PDA
EQK	EQUITILINK LTD	Failure	0.51	0.54	0.51	0.51	0.58	**0.37***	0.53
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Failure	0.79	**0.43**	**0.08**	1.00	0.98	0.51	0.94
AFI	AUSTRALIAN FOUNDATION INVESTMENT CO LTD	Success	0.48	**0.60**	0.26	0.42	**0.61**	0.36	**0.53**
CHP	CHAPMANS LTD	Success	**0.59**	0.46	0.43	**0.55**	0.49	**0.52**	0.43
ECL	ECAT DEVELOPMENTS LTD	Success	**0.54**	0.21	**0.59**	0.11	0.09	0.13	0.26
FEC	FLEET CAPITAL LTD	Success	0.41	**0.60**	**0.59**	**0.60**	0.13	0.21	0.42
HIC	HUNTLEY INVESTMENT CO LTD	Success	0.09	0.10	0.05	**0.76**	0.08	**0.72**	0.09
MBL	MACQUARIE BANK LTD	Success	0.07	0.32	0.11	**0.62**	0.18	0.48	0.16
QBE	Q.B.E. INSURANCE LTD	Success	**0.79**	**0.95**	**0.92**	**0.74**	0.31	0.46	0.37
TRU	TRUST COMPANY OF AUSTRALIA LTD	Success	**0.56**	0.43	0.12	0.06	0.39	0.25	0.33
2 years before failure									
Code	Companies	Actual Status	ANN -DA	ANN - PDA	ANN -DA- PDA	ANN- logit	ANN- Plogit	ANN- logit- Plogit	ANN- logit- PDA
CGH	COLONIAL LTD	Failure	**0.05**	**0.00**	**0.05**	**0.49**	1.00	1.00	**0.28**
EMA	EMERGING MARKET	Failure	**0.02**	**0.00**	**0.03**	0.78	**0.05**	**0.00**	**0.01**
EQK	EQUITILINK LTD	Failure	0.58	**0.35**	0.59	0.77	1.00	1.00	**0.34**
FAF	FIVE ARROWS AUSTRALIA FUND LTD	Failure	**0.02**	**0.00**	**0.03**	**0.10**	**0.01**	**0.00**	**0.01**
FAI	**F.A.I. INSURANCES LTD**	Failure	**0.24**	1.00	1.00	1.00	1.00	1.00	**0.26**
FLL	**F.A.I. LIFE LTD**	Failure	**0.23**	1.00	**0.26**	**0.03**	0.99	1.00	**0.34**
HIH	**H.I.H. INSURANCE LTD**	Failure	**0.15**	1.00	**0.16**	0.97	1.00	0.95	0.96
NCC	**NEW CAP REINSURANCE CORPORATION HOLDINGS LTD**	Failure	**0.02**	0.99	**0.03**	0.74	1.00	1.00	0.74
TRU	TRUST COMPANY OF AUSTRALIA LTD	Success	**0.58**	0.35	**0.59**	0.12	0.00	0.14	0.35
EQT	EQUITY TRUSTEES LTD	Success	**0.58**	0.35	**0.58**	0.03	0.08	0.14	0.34
CHP	CHAPMANS LTD	Success	**0.58**	0.00	**0.59**	0.00	0.01	0.00	0.01

* Figures in bold represent a misclassification.

5. Comparison of the Models

According to Table 5.1, for one year before failure, the best statistical model was the logit model. The results from ANN were very similar to the statistical models. For two years before failure, the best statistical model was the DA, but ANN results outperformed all statistical models. The performance of the ANN was improved when the hybridization with DA and logit models was considered. For one year before failure, the best models were ANN-Plogit and ANN-logit-PDA networks and for two years before failure the best models were ANN-Plogit and ANN-logit-Plogit. So, the results show that hybrid neural network model is very promising model for failure prediction in terms of predictive accuracy.

Table 5.1: Classification Accuracy from the Best Models

BEST MODEL	1 year before		2 years before failure	
	Non-failed firm correctly classified (%)	failed firms correctly classified (%)	Non-failed firms correctly classified (%)	failed firms correctly classified (%)
DA	86.4	90.9	78	63.3
Logit	96.6	90.9	93.2	54.5
ANN	89.8	90.9	98.3	72.7
ANN-DA	93.2	100	94.9	36.3
Hybrid (ANN-PDA)	94.9	90.9	100	63.6
Hybrid (ANN-DA-PDA)	94.9	90.9	94.9	45.4
ANN-logit	91.5	100	100	72.7
Hybrid (ANN-Plogit)	98.3	100	100	81.8
Hybrid (ANN-logit-Plogit)	96.6	90.9	100	81.8
Hybrid (ANN-logit-PDA)	98.3	100	100	45.4

The last step to complete this study is to test the prediction models using an independent holdout sample. Each prediction model was applied to an independent sample of 3 failed companies in 1998, 1999 and 2000 and 11 non-failed companies to test the validity of the model. Two of the failed firms failed after the selection of the original sample. Table 4 of Appendix B lists names of firms in the holdout sample. Table 5.2 indicates that DA is superior to logit model for predicting failed firms correctly. The best model is ANN-logit-PDA network, 100% of failed firms and 100% of non-failed firms are accurately predicted on the one statement prior failure. These holdout test results for the hybrid ANNs are very encouraging.

Table 5.2: Classification Accuracy-Holdout the Sample from the Best Models

BEST MODEL	1 year before	
	Non-failed firm correctly classified (%)	failed firms correctly classified (%)
DA	81.8	66.6
Logit	90.9	33.3
ANN	90.9	33.3
ANN-DA	100	33.3
Hybrid (ANN-PDA)	90.9	33.3
Hybrid (ANN-DA-PDA)	90.9	66.6
ANN-logit	100	66.6
Hybrids (ANN-Plogit)	100	33.3
Hybrids (ANN-logit-Plogit)	90.9	33.3
Hybrid (ANN-logit-PDA)	100	100

6. Conclusion

This study investigated whether two artificial neural networks, multilayer perceptron and hybrid networks, can outperform traditional statistical models for predicting Australian financial service failures one year and two years prior to the financial distress. The results in-sample from the statistical models are similar to multilayer perceptron, but inferior to hybrid networks. Also, we moved further away from the failure date, both multilayer perceptron and ANN combined with logit models performed better than statistical models. The results holdout sample indicated that the hybrid network that combined ANN with DA and logit models presented a superior performance to all other models for one year before the failure. Therefore, hybrid neural network model is very promising tool for failure prediction. Further, it has the additional advantage over the simple ANN of reducing the time required for selecting input variables. This supports the conclusion that for researchers, policymakers and others interested in early warning systems, hybrid networks would be useful.

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Appendix A

Backpropagation Algorithm

The first phase of the backpropagation algorithm consists of repeatedly presenting the network with examples of input and expected output. Suppose that the q^{th} neuron of the hidden layer receives the activation signal, H_q, given by:

$$H_q = \sum_j v_{qj} x_j \ , \qquad (1)$$

where x_j is the signal to the input neuron j and v_{qj} is the weight of the connection between input neuron j and the hidden neuron q.

This activation signal is then transformed by a transfer function f in the hidden layer to give the output

$$h_q = f(H_q). \qquad (2)$$

The output neuron i now receives the activation signal, O_i , from the hidden nodes given by:

$$O_i = \sum_q w_{iq} h_q \ , \qquad (3)$$

where w_{iq} is the weight of the connection between hidden neuron q and output neuron i. This is transformed again to give the output signal

$$o_i = f(O_i). \qquad (4)$$

This is then compared with the desired, or actual value of the output neuron, and the function of squared errors for each node, which is to be minimized, is given by:

$$E(w) = \frac{1}{2} \sum_i (d_i - o_i)^2, \qquad (5)$$

In the second phase the weights are modified to reduce the squared error. The change in weights, Δw_{iq}, used by the backpropagation is given by:

$$\Delta w_{iq} = -\gamma \frac{\partial E(w)}{\partial w_{iq}} \ . \qquad (6)$$

where $0 < \gamma < 1$ is the learning rate.

Using the chain rule, it can easily be shown that

$$\Delta w_{iq} = -\gamma \frac{\partial E}{\partial o_i}\frac{\partial o_i}{\partial O_i}\frac{\partial O_i}{\partial w_{iq}} = \gamma (d_i - o_i) f'(O_i) h_q = \gamma\delta_{oi} \mathrm{h}_q, \qquad \textbf{(7)}$$

where δ_{oi} is the error signal of neuron *i* and is given by

$$\delta_{oi} = (d_i - o_i) f'(O_i). \qquad (\textbf{8})$$

To avoid oscillation at large γ, the change in the weight is made dependent on the past weight change by adding a momentum term

$$\Delta w_{iq}(t+1) = \gamma\delta_{oi} h_q + \alpha\Delta w_{iq}(t), \qquad (\textbf{9})$$

where α is a constant chosen by the operator. Similarly it can be shown that the change in the weight between the hidden neuron *i* and the input neuron *j*, ,Δv_{ij}, is given by:

$$\Delta v_{qj} = \gamma\ \delta_{\mathrm{hq}} x_j\ , \qquad (\textbf{10})$$

where δ_{hq} is the error signal of neuron *q* and is given by:

$$\delta_{hq} = f'(H_q)\sum_{\mathrm{i}} \delta_{oi}\ w_{iq}. \qquad (\textbf{11})$$

As before a momentum term can be used to prevent oscillation.

Appendix B

Table 1: Financial services companies used in the failure study[viii]

ASX Code	Companies	Last balance	Status
ANS	**A.S.C. LIMITED**	**Dec-98**	**Failure**
CGH	**COLONIAL LTD**	**Dec-99**	**Failure**
EMA	**EMERGING MARKETS CO LTD**	**Jun-96**	**Failure**
EQK	**EQUITILINK LTD**	**Jun-97**	**Failure**
FAF	**FIVE ARROWS AUSTRALIA FUND LTD**	**Jun-95**	**Failure**
FAI	**F.A.I. INSURANCES LTD**	**Jun-98**	**Failure**
FLL	**F.A.I. LIFE LTD**	**Jun-98**	**Failure**
GIO	**G.I.O. AUSTRALIA**	**Jun-99**	**Failure**
HIH	**H.I.H. INSURANCE LTD**	**Jun-99**	**Failure**
MMU	**M.M.I. LTD**	**Jun-98**	**Failure**
NCC	**NEW CAP REINSURANCE CORPORATION HOLDINGS LTD**	**Sep-97**	**Failure**
AMP	A.M.P. LIMITED	Dec-99	Success
ADB	ADELAIDE BANK LTD	Jun-98	Success
ARG	ARGO INVESTMENTS LTD	Jun-96	Success
ABK	ASSET BACKED HOLDINGS LTD	Dec-98	Success
AFI	AUSTRALIAN FOUNDATION INVESTMENT CO LTD	Jun-97	Success
AUI	AUSTRALIAN UNITED INVESTMENTS LTD	Jun-95	Success
AVA	AVIVA CORPORATION LTD	Jun-98	Success
AXA	AXA ASIA PACIFIC HOLDINGS LTD	Sep-99	Success
BTE	B.T. AUST'N EQUITY MANAGEMENT LTD	Jun-98	Success
BTG	B.T. GLOBAL ASSET MANAGEMENT LTD	Jun-96	Success
BWA	BANK OF WESTERN AUSTRALIA	Fev-99	Success
BAY	BAYCORP HOLDINGS LTD	Jun-95	Success
BEN	BENDIGO BANK LTD	Jun-98	Success
CBI	CAMBOOYA INVESTMENTS LTD	Jun-98	Success
CIN	CARLTON INVESTMENTS LTD	Jun-95	Success
CHP	CHAPMANS LTD	Jun-99	Success
CHO	CHOISEUL LTD	Jun-95	Success
CID	CITADEL POOLED DEVELOPMENT LTD	Jun-98	Success
CBA	COMMONWEALTH BANK OF AUSTRALIA	Aug-99	Success
DAD	DATA ADVANTAGE LTD	Jun-98	Success
DJW	DJERRIWARRH INVESTMENTS LTD	Jun-97	Success
ETR	E*TRADE AUSTRALIA LTD	Jun-96	Success
ECL	ECAT DEVELOPMENTS LTD	Dec-99	Success

ASX Code	Companies	Last balance	Status
EKL	EQUITILINK ELINK LTD	Jun-99	Success
EQT	EQUITY TRUSTEES LTD	Jun-96	Success
EZL	EUROZ LTD	Jun-99	Success
FEC	FLEET CAPITAL LTD	Jun-99	Success
FIF	FRANKED INCOME FUND	Nov-96	Success
HCL	HELM CORPORATION LTD	Jun-95	Success
HGV	H-G VENTURES LTD	Jun-97	Success
HIC	HUNTLEY INVESTMENT CO LTD	Jun-96	Success
HPL	H.P. J.D.V. LIMITED	Jun-95	Success
IEQ	INTERNATIONAL EQUITIES CORPORATION LTD	Jun-97	Success
IAL	INVESTMENT AUSTASIA LTD	Jun-95	Success
MBF	M.B.F.I. CARPENTERS LTD	Dec-96	Success
MCL	M2M CORPORATION LTD	Jun-95	Success
MBL	MACQUARIE BANK LTD	Mar-98	Success
MAX	MAXILINK LTD	Jun-95	Success
MLT	MILTON CORPORATION LTD	Jun-97	Success
NAB	NATIONAL AUSTRALIA BANK LTD	Sep-97	Success
NGL	NOALL GROUP LTD	Jun-96	Success
OMP	O.A.M.P.S. LIMITED	Jun-96	Success
PMT	PERMANENT TRUSTEE CO LTD	Sep-95	Success
PMC	PLATINUM CAPITAL LTD	Jun-95	Success
QBE	Q.B.E. INSURANCE LTD	Jun-98	Success
QST	QUEST INVESTMENTS LTD	Jun-96	Success
RMG	R.M.G. LIMITED	Dec-97	Success
RAC	REINSURANCE COMPANY OF AUST LTD	Dec-96	Success
RFS	RIVKIN FINANCIAL SERVICES LIMITED	Jun-98	Success
ROK	ROCK BUILDING SOCIETY LTD	Jun-98	Success
SGB	ST. GEORGE BANK LTD	Sep-99	Success
SYL	SYLVASTATE LTD	Jun-97	Success
TGG	TEMPLETON GLOBAL GROWTH FUND LTD	Jun-95	Success
TRU	TRUST COMPANY OF AUSTRALIA LTD	Feb-96	Success
USH	U.S. MASTERS HOLDINGS LTD	Jun-96	Success
VIT	VITAL CAPITAL LTD	Dec-95	Success
WRF	W.R.F. SECURITIES LTD	Mar-95	Success
WHF	WHITEFIELD LTD	Mar-95	Success
WBB	WIDE BAY CAPRICORN BUILDING SOCIETY LTD	Jun-98	Success

Table 2: Contingency Table for Hosmer and Lemeshow Test

	Results for 1 year before failure							
	Quantile of Risk			Dep=0		Dep=1	Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	1.E-07	7	7.00000	0	3.5E-07	7	3.5E-07
2	2.E-07	3.E-07	7	7.00000	0	1.6E-06	7	1.6E-06
3	4.E-07	1.E-06	7	6.99999	0	5.2E-06	7	5.2E-06
4	1.E-06	4.E-05	7	6.99986	0	0.00014	7	0.00014
5	5.E-05	0.0009	7	6.99822	0	0.00178	7	0.00178
6	0.0010	0.0022	7	6.99013	0	0.00987	7	0.00988
7	0.0025	0.0376	7	6.90270	0	0.09730	7	0.09867
8	0.0401	0.3269	6	6.03446	1	0.96554	7	0.00143
9	0.4557	0.7653	4	2.70611	3	4.29389	7	1.00855
10	0.7712	1.0000	0	0.33787	7	6.66213	7	0.35501
		Total	59	57.9693	11	12.0307	70	1.47546
H-L Statistic:			1.4755			Prob[Chi-Sq(8 df)]:		0.9931
	Results for 2 years before failure							
	Quantile of Risk			Dep=0		Dep=1	Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	0.0026	7	6.99702	0	0.00298	7	0.00299
2	0.0049	0.0193	7	6.90102	0	0.09898	7	0.10039
3	0.0204	0.0554	7	6.73389	0	0.26611	7	0.27663
4	0.0560	0.0687	6	6.56657	1	0.43343	7	0.78947
5	0.0695	0.0912	6	6.46186	1	0.53814	7	0.42941
6	0.0932	0.1123	7	6.27288	0	0.72712	7	0.81140
7	0.1275	0.2535	5	5.68477	2	1.31523	7	0.43900
8	0.2586	0.3978	6	4.71957	1	2.28043	7	1.06633
9	0.3987	0.5703	6	3.52789	1	3.47211	7	3.49240
10	0.6397	0.9186	2	2.00304	5	4.99696	7	6.5E-06
		Total	59	55.8685	11	14.1315	70	7.40803
H-L Statistic:			7.4080			Prob. Chi-Sq(8)		0.4933

Table 3: The Best ANN Topologies

1 year before failure			
Name	Model	Learning rate	Momentum
ANN	6x5x1	0.5	0.7
ANN-DA	5x4x1	0.7	0.9
ANN-PDA	7x5x1	0.5	0.7
ANN-DA-PDA	6x4x1	0.5	0.7
ANN-logit	6x4x1	0.5	0.7
ANN-Plogit	7x5x1	0.5	0.7
ANN-logit-Plogit	7x2x1	0.5	0.5
ANN-logit-PDA	7x5x1	0.5	0.7
2 years before failure			
Name	Model	Learning rate	Momentum
ANN	5x5x1	0.5	0.7
ANN-DA	1x3x1	0.5	0.7
ANN-PDA	6x3x1	0.5	0.5
ANN-DA-PDA	2x2x1	0.5	0.7
ANN-logit	4x5x1	0.5	0.5
ANN-Plogit	6x4x1	0.5	0.5
ANN-logit-Plogit	5x4x1	0.7	0.7
ANN-logit-PDA	5x3x1	0.7	0.7

Table 4: Financial services companies used in the failure study[ix]

Code	Companies	Last balance	Status
ACD	**AUSTRALIAN CENTRAL CREDIT UNION LTD**	**Jun-99**	**Failure**
APL	**AUSTRALIAN PLANTATION TIMBER LTD**	**Jun-00**	**Failure**
SGI	**SGIO INSURANCE**	**Jun-98**	**Failure**
AMH	AMCIL LTD	Jun-99	Success
CCP	CREDIT CORP GROUP LTD	Jun-00	Success
CPH	C.P.H. INVESTMENT CORP	Jun-99	Success
GTP	GREAT SOUTHERN PLANTATIONS LTD	Jun-98	Success
HHL	HUNTER HALL INTERNATIONAL LTD	Jun-00	Success
HSC	HUDSON SECURITIES CORPORATION LTD	Dec-00	Success
IGP	INVESTOR GROUP LTD	Jun-00	Success
IWI	INTERNATIONAL WINE INVESTMENT FUND	Jun-99	Success
TPX	TASMANIAN TRUSTEES LTD	Sep-98	Success
WIT	WILSON INVESTMENT TAURINE FUND	Jun-00	Success
YTL	YATES LTD	Jun-00	Success

Endnotes

[i] See Gizycki and Lowe (2000) for further details on the Australian financial crisis of the 1990's.

[ii] Details of the backpropagation method are given in Appendix A.

[iii] Estimated using the software package SPSS 10.0.

[iv] Full detail of all steps can be obtained from the authors by request.

[v] For full detail of this procedure see Norusis (1990).

[vi] Estimated using the software package SPSS 10.0.

[vii] Estimated using the software package Neuroshell 2.

[viii] Values of ratios for each company can be obtained from the authors by request.

[ix] Values of ratios for each company can be obtained from the authors by request.

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