NEURAL NETWORKS AND DISCRIMINANT ANALYSIS: THEIR EFFECTIVENESS IN DESCRIBING BANK PERFORMANCE IN THE CARIBBEAN

by

Marion Williams

and

John Nankervis

**Prepared for the International Symposium on Forecasting
Bridgetown, Barbados, June 19 - 21, 1997**

June 1997

Neural networks and Discriminant Analysis: Their effectiveness in describing bank performance in the Caribbean

by Marion Williams and John Nankervis

This paper investigates whether neural networks (NN) can be usefully employed in collaboration with discriminant analysis to produce models which provide a good representation of corporate performance for the Caribbean and whether such models have good forecasting ability.[1]

The usefulness of the artificial neural networks(NN) often depends on factors such as the kind of data being examined, the nature of the decision points and the complexity of the decision-making system which influences various outcomes. Neural networks has been applied more so in the natural sciences than in economics and finance. Where it is applied in the field of economics and finance it tends to be mostly for evaluation of investment and capital market decisions, and is employed quite often as a means of predicting bond prices, currency movements, and for making determinations on hedging, argbitrage opportunities and similar types investment dealing. In the area of corporate performance the most well known use of the technique is as a means of predicting corporate distress (Altman 1994). In recent years it has been increasingly used in the field of business.

Discriminant analysis, an alternative means of determining the contribution of various components to an overall outcome, has a longer history as a statistical technique. In this case it is employed to estimate an overall performance score for banks. This paper examines how neural networks can be used to supplement the results of investigations obtained by the use of discriminant analysis.

Measures of bank performance

In the case of most corporations, key performance ratios are usually the preferred approach for measuring performance. Traditionally, bank profitability is considered the most important indicator of bank performance, and is measured in various ways, e.g. by interest margins, gross earnings margin, net earnings margin and profits before tax. Most performance scores

---

[1] The data are tested for the case of commercial banks in Barbados, Jamaica and Trinidad and Tobago.

which employ the technique of discriminant analysis, Altman (1984, 1994) tend to consider ratios which include liquid assets ratios, retained earnings, before tax earnings, and some equity measure. In the case of trading companies, a sales ratio would be included as well. In the case of banks the conventional long term survival yardsticks are earnings, capital adequacy, management, liquidity and solvency.

Since some of these measures, e.g. management are not easily measured, the measures employed are those with quantifiable outcomes, e.g profitability, liquidity, risk, solvency and market share. The profitability measure employed is before tax return on assets. Liquidity is defined by reference to banks' holdings of cash and government securities in excess of required amounts. The ratio of capital and reserves to total assets is taken as the measure of solvency. Market share is measured with reference to the share of assets of commercial banks in the combined assets of banks and non-banks. Bank risk is measured by the variability of bank profitability, and is considered a subset of the bank profitability measure, the variability in bank profitability (σ^2_π), where σ^2 is the measure of variance, becomes a measure of bank risk. This avoids the subjective assessment offered by rating agencies.

These data form the basis of the principal components used in the discriminant analysis determination and are also the inputs into the neural network system. Tables 1, 2, and 3 display the input data used.. In the case of the neural network system the output is the bank performance scores shown in table 3 from the discriminant analysis calculations.

Normally, in stand alone neural networks systems it is not necessary to identify the relationship using any other system. The creation of a multilayer network and a training set will be sufficient for the system to learn the relationships.

Table 1
Bank performance indicators: Barbados

Year	Profita bility	Liqui d-ity	Risk	Solvency	Market share
1977	1.47	0.95	0.008	0.00	94.4
1978	2.19	9.01	0.046	1.23	92.7
1979	2.46	7.06	0.080	1.24	91.2
1980	2.50	6.34	0.036	1.01	90.5
1981	2.67	2.39	0.018	1.11	88.7
1982	2.21	2.91	0.013	0.84	87.7
1983	1.50	1.03	0.038	0.72	87.5
1984	1.15	3.05	0.066	0.66	86.7
1985	0.90	2.67	0.140	1.75	87.5
1986	1.51	3.21	0.038	1.63	86.1
1987	1.97	3.90	0.040	1.89	86.1
1988	2.11	4.38	0.064	1.83	83.6
1989	2.81	1.25	0.012	1.34	82.6
1990	2.15	1.84	0.016	1.15	83.2
1991	2.01	1.26	0.014	1.26	82.1
1992	1.78	1.22	0.011	1.22	82.6
1993	0.74	2.4	0.011	1.90	84.4
1994	2.01	1.26	0.014	1.26	85.8
1995	1.35	-0.2	0.013	3.38	87.1

Source: Central Bank of Barbados Annual Digests of Statistics various issues and statistics supplied by the Central Bank.

Table 2
Bank performance indicators: Jamaica

Period	Profit ability	Liqui d-ity	Risk	Solvency	Market share
1977	1.01	7.61	0.07	4.83	84.72
1978	1.03	6.96	0.00	4.10	85.69
1979	0.86	6.62	0.01	3.68	86.65
1980	0.79	6.10	0.06	3.41	90.64
1981	1.35	7.95	0.00	2.28	93.62
1982	2.21	4.91	0.06	3.43	92.50
1983	3.15	5.64	0.14	3.72	89.64
1984	3.22	-0.06	0.00	3.81	89.49
1985	1.92	1.12	0.00	0.70	86.83
1986	2.60	5.76	0.01	3.91	81.39
1987	2.44	4.61	0.01	5.13	84.25
1988	2.79	20.89	0.04	3.76	81.91
1989	3.26	10.42	0.29	4.34	80.14
1990	0.90	1.18	0.00	5.15	80.00
1991	3.75	5.98	0.17	4.62	81.84
1992	7.40	6.44	3.68	5.06	81.24

Source: Central Bank of Jamaica and Jamaica Stock Exchange.

Table 3
Bank performance indicators: Trinidad and Tobago

Period	Profit a-bility	Liqui d-ity	Risk	Solvency	Market share
1975	1.01	14.12	0.01	13.68	87.2
1976	1.43	14.94	0.04	17.56	85.3
1977	1.71	7.74	0.16	15.90	84.7
1978	1.55	2.95	0.01	12.85	82.1
1979	1.44	8.83	0.01	10.90	83.7
1980	1.59	5.68	0.00	10.21	80.9
1981	3.11	2.74	1.37	8.69	79.8
1982	2.85	5.54	0.24	6.00	82.0
1983	2.76	1.63	0.03	6.98	78.3
1984	2.48	-0.27	0.18	7.76	76.3
1985	1.72	2.04	0.56	8.76	75.8
1986	0.64	-0.08	1.58	6.73	75.6
1987	0.57	-0.05	0.61	6.15	77.7
1988	0.49	0.13	0.13	6.31	74.1
1989	0.76	0.65	0.02	6.75	76.1
1990	0.72	1.45	0.04	6.89	81.3
1991	1.06	-0.47	0.11	6.43	81.5
1992	1.43	-0.13	0.21	7.24	78.8

Source: Central Bank of Trinidad and Tobago and Trinidad and Tobago Stock Exchange.

Neural Network: the methodology

The neural network system used for estimation is a back propogation learning algorithm. It trains on a pattern of in-sample data. The system is intended to simulate the activity and learning procedures of the human brain and hence, it is argued, is more likely to be able to predict behaviours. Each neuron responds to each other neuron and to the output of other neurons in a lattice of responses.

Mathematically the network computes
1. The output of the hidden layer (treating the bias as another input):

h(j) Sum (w(i,j)* i(i) i= 1, 3)
s(j) f(h(j))

2. For the outer layer calculate:
h'(k) = Sum (w'(j,k)* s(j), j=1,3
O(k) =f(h'(k))

i(i) - are the network inputs
O(k) are the network outputs.
W(i,j) - represents the weight connecting neutron in layer 1 to neutron j in layer 2.
W'(j,k) represents the weight connecting neutron j in layer 2 to neutron k in layer 3.
(f(x) is the neutron transfer function, for example a sigmoid:

f(x) = 1/ (1+exp (-x))

Training such a network involves using data base of examples which are values for the input and output of the NN.
The NN would learn by adjusting the weights to minimise the error of the outputs. The objective is to minimise the error function.

SSE = Sum (Sum (t(p,k)-O(p,k) 2, k = 1, K max) p=1, Pmax)

where
O(p,k) - is the NN output k for pattern p.
t(p,k) - is the output training pattern p for output k.
The reported RMS Error is calculated as RMS =sqrt(SSE/Pmax)

WinNN uses a simple back-propogation algorithm to adjust the weights, in an iterative fashion and trains in batch mode with a variable epoch length.

Frequently, the behaviour of variables exhibits non linearity, and where it is supposed that several influences impact on the outcomes, and that these influences are multi- directional, then neural networks provides a useful method of analysis.

Diagram: How neural networks work.

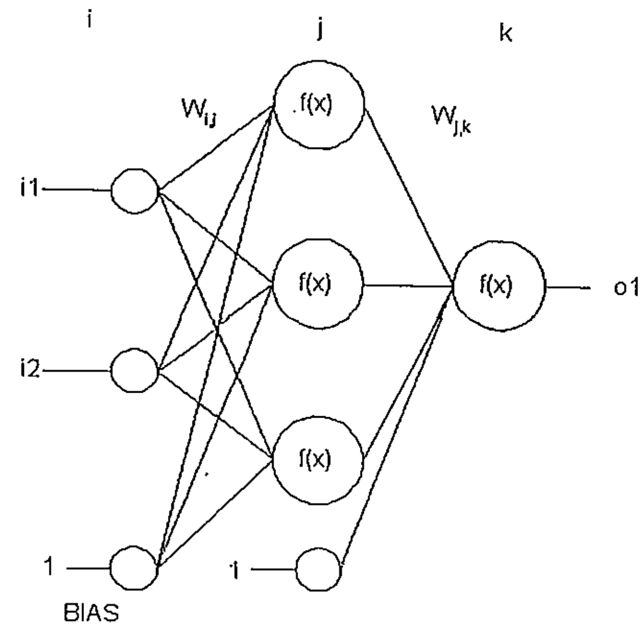

Figure 1

Discriminant analysis: calculating composite measures of bank performance.

The technique multiple discriminant analysis does not utilise such multidimensional simulation. The procedure, groups the data assigns weights to each variable and adds these products together. The result is a single composite discriminant score for all individual categories within the group. A composite score derived from this procedure is of the form

$$Z = a_1X + a_2Y + a_3K$$

The usual procedure is to divide the total sample into groups or functions. A covariance or correlation matrix is then derived. These can be standardised to produce a correlation matrix of standarised variates i.e. the deviation of a variable mean divided by its standard deviation.

$$z = \sum_{i=1}^{N} a_i z_i$$

Eigenvectors are then derived[8]. Using the notationa linear combination of the X variables is formed, as a linear combination of the Y variables. Of the large number of possible linear combinations for each set, coefficients are chosen such that the resultant linear combination of the X set variables is maximally correlated with the linear combination of the Y set variables.
Of the large number of linear combinations of the two sets of variables we have found that a particular pair was most highly related to each other. The correlation coefficient between x^* and y^* is termed a canonical correlation.
The eigenvector with the eigenvalue yielding the highest variance is identified as the canonical function which contributes to the maximum amount of variation. These are the canonical discriminant functions and are identified in descending order of importance.
A structure matrix of component loadings is then developed. Each component loading factor represents the correlation coefficient between the canonical discriminant function and the set of standardised discriminating variables. Discriminant loadings referred to as structural correlations, measure the simple linear correlation between each dependent variable and the discriminant function. The solution is rotated to produce a structure which lists the variables of each function in the order of its contribution to variability.

A test of the null hypothesis that the means of all discriminant functions in all groups in the population are really equal to 0 can be based on Wilk's lambda. It provides a test of the null hypothesis that the population means are equal. When the significance level using the F test or Chi square test, is small (less than 0.05) the hypothesis that all group means are equal is rejected.
The pooled within - group correlation matrix is obtained by averaging the separate correlation matrices for all groups and then computing the correlation matrix.
The contribution of a variable to a discriminant function (its discriminant loading or weight) and the relative contribution of the function to the overall solution (a relative measure among the eigenvalues of the functions) can then be calculated. It is obtained by dividing the component weight of each variable by the corresponding eigenvalue.
The composite is the sum of the overall indices across all significant discriminating functions. The weights do not add to unity and may be negative. If this occurs, they can be rescaled to unity by adding 1 to each component and multiplying by 100, thus retaining the relative distance between coefficients.
The SPSS package used for calculation of discriminant functions removes outliers from the list of eligible variables, but these can be reintroduced if desired, if it is the intention to show the contribution of all variables regardless of their contribution to the composite score.

The Analysis

Applying first the technique of discriminant analysis, a bank performance indices are calculated for Barbados, Jamaica and Trinidad and Tobago.

The performance measures are the same as the earlier analysis: profitability (ROA), Liquidity (LIQ), risk (RISK), solvency (SOLV) and market share (MKS).

Structure matrix

The structure matrix represents pooled-within-groups correlations between discriminating variables and canonical discriminant functions. Variables are ordered by size of correlation within function.

Table 4
Structure matrix

	Function 1	Function 2	Function 3
LIQ	0.00030	0.97844	-0.2065
SOLV	-0.30281	0.94870	-0.0909
MKS	0.27392	-0.90361	-0.3293
RISK	0.43295	-0.85294	0.2916
ROA	0.00276	0.14688	0.9891

The eingenvalue for each function is the ratio of between group to within group sum of squares.

The entire solution is rotated with the varimax procedure to provide a simpler structure in the profiling of each function. The results are as follows:

Table 5
Varimax rotation transformation matrix

	Function 1	Function 2	Function 3
% Variance	95.02	2.49	2.49
Function 1	0.97566	-0.15355	-0.15658
Function 2	0.12569	0.97660	0.17452
Function 3	0.17971	-0.15059	0.97212

Table 6
Rotated standardised discriminant function coefficients
(Variables ordered by size of coefficient within function)

	Function 1	Function 2	Function 3
LIQ	3.21852	0.50597	0.51340
SOLV	-3.21704	0.50756	-0.50707
ROA	0.19445	0.00010	1.04335

Since weights which employ all variables are desired, correlations between rotated canonical discriminant functions and discriminating variables are then produced using all variables and the appropriate weights calculated as an average across each function.

Table 7
Correlation between canonical discriminant functions and discriminating variables

	Function 1	Function 2	Function 3	Weights
ROA	-0.15661	-0.00594	0.98764	0.275
SOLV	-0.15985	0.98669	0.02970	0.285
LIQ	0.16038	0.98660	-0.02998	0.392
MKS	0.21286	-0.87494	-0.43494	0.465
RISK	0.26280	-0.94338	0.20243	0.116

The performance index can therefore be written:

$$P^* = 0.275\,ROA + 0.116\,RISK + 0.392\,LIQ + 0.285\,SOLV + 0.465\,MKS \quad (1)$$

On the basis of the above weights, performance indices were then calculated for commercial banks in Barbados

Similarly, bank performance indices are calculated for Jamaica and Trinidad and Tobago. The rationale for using the same weights is based on the similarities in the responses of banks and the

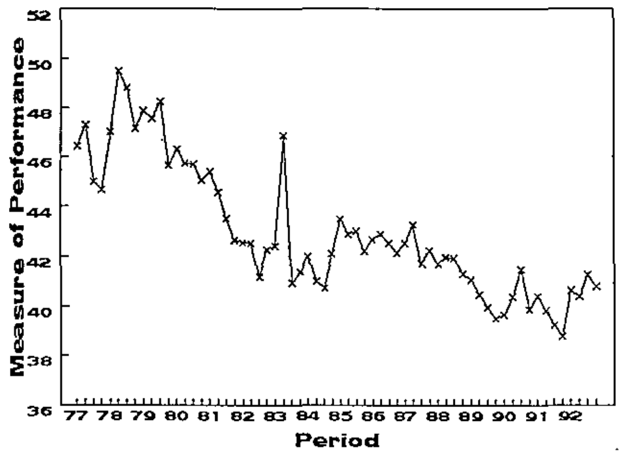

Figure 2 Composite bank performance index: Barbados

assumption that companies in the same industry have the same overall objectives with regard to bank performance. Table 4 displays bank performance indices for Jamaica and Trinidad and Tobago.

Measured by the indices calculated, except for Jamaica, the performance of commercial banks in the Caribbean was generally less than robust and declined in at least one case.

Table 8
Index of bank performance: normalised
(Barbados, Jamaica and Trinidad and Tobago)

Year	Barbados	Jamaica	Trinidad and Tobago
1977	100.0	100.0	100.0
1978	105.57	99.96	91.53
1979	102.20	100.52	96.72
1980	100.84	103.99	91.04
1981	95.43	108.13	87.84
1982	94.60	105.18	90.27
1983	94.63	103.20	83.89
1984	94.23	97.96	80.71
1985	94.48	97.90	82.37
1986	94.30	94.58	78.84
1987	94.52	97.46	80.29
1988	92.46	108.69	76.85
1989	88.42	98.32	79.63
1990	89.27	90.17	85.46
1991	86.84	96.45	83.99
1992	91.32	98.87	82.35

Base year 1977 = 100

Applying discriminant bank performance scores in neural networks.

The score obtained from this analysis was used as the output for developing training patterns in the neural network. While this cuts down on the number of iterations it does have the disadvantage of feeding a good fit into the network. However, neural network systems have no bias and based on the number of neurons and the number of layers they will make a determination of the output irrespective of the output fed in. The objective is to minimise the error term.

SSE = Sum (sum(t (p,k)-O(p,k)2, k=1, Kmax), p=1, Pmax)
where
O(p,k) -is the NN output k for pattern p.
t(p,k) -is the output training pattern for output k.
The reported RMS error is calculated as RMS =sqrt (SSE/Pmax)

A pattern file was prepared containing the input and output training patterns for the software WinNN. Thirteen sets, 65 observations. were used. Data were normalised so as to prevent their moving out of range of the neurons inputs or outputs. Initial weights were selected. The number of neuron layers chosen was 3. A greater number of layers was found to increase processing time considerably, but may have provided an improved result.

A sigmoid function was used of the form

f(x, P) = 1/(1+exp(-xP))

New weights are a function of the derivatives and the previous weights, for example,

$$dWW=\eta W(i,j,t)= \alpha \text{ Old } dWW(i,j,t-1)$$
$$W(i,j,t+1)= W(i, j,t)+dWW$$
$$OlddWW(i,j,t)=dWW$$

Eta(η) is the learning parameter
Apha(α) the momentum

The system can add input noise to each input node. Training with noise makes the trained network less sensitive to changes in the input values, and helps to avoid local minima. The system performs a number of iterations aimed at minimising the error function

O(p,k) - is the NN output k for pattern p
t(p,k) - is the output training pattern p for output k

The reported RMS is calculated as

RMS -sqrt(SSE/Pmax)

A minimum acceptable error rate of 0.01 was set and several iterations were conducted. The error rate for the sample was 3%. When the trained pattern was applied to out of sample data, however, the error slightly exceeded this, at 11.8%. The small size of the sample and the parsimonious nature of the model may a have accounted for this. Also the software is a basic neural netware programma and lacks features.

A chart of the output, that is, a bank performance score using neural net works, compared with a performance score employing discriminant analysis were not too dissimilar. (Compare figures 3 and 4).

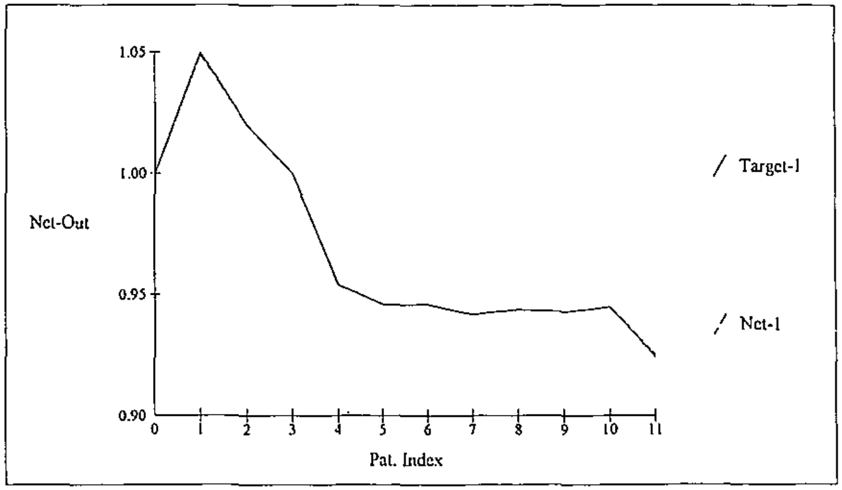

Figure 3 Bank Performance index using Neural Networks

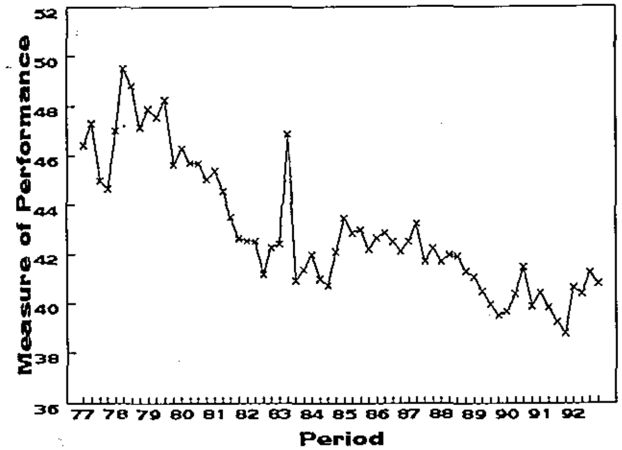

Figure 4 Comparison with figure 3 - Composite bank performance index for Barbados-using discriminant analysis

Several further modifications can be made to the technique. The input data can be lagged to convert it into a dynamic model and retested to judge the predictive capability of the neural network system. This was not attempted as the data frequency employed was annual, quarterly or monthly data would have been preferable.

Also, performance benchmarks, for banks can be derived if data scores are calculated on an individual bank basis. The performance scores of banks in distress determined by discriminant analysis and refined by neural networks could be monitored to determine the historical levels of scores when banks are in distress, and this level could be a trigger to the bank's management of its situation.

The above does not in any way suggest that the statistical analysis is any substitute for strong bank supervision and oversight by regulatory authorities, but the possibility exists for using such systems as tools in applying offsite analysis. Customers of banks might also find them interesting.

The foregoing is an exploratory analysis of the banking system performance using neural networks. it points the way for future studies of bank behaviour using neural networks.

Bibliography

Altman, E.I, Marco,G, Varetto,F, 1994,"Corporate distress Diagnosis of Companies using Linear Discriminant analysis and Neural networks" (the Italian experience) Journal of Banking and Finance, 18(3), pp.505-529.

Downes. A. 1985 "Industrial Growth and employment in small Developing countries, the case of Barbados 1955-80" PhD thesis, University of Manchester.

Williams, M.V 1996. Liberalising a Regulated Banking System: the Caribbean Case. Avebury.