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Minimizing the Costs of Using Models to Assess the Financial Health of Banks

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ABSTRACT

Identifying banks that are likely to experience financial distress in the future can be problematic for bank regulators and investors. Traditionally, bank examiners use a variety of methods, including traditional statistical modelling techniques, to categorize banks as financially healthy or financially distressed. Often, these statistical models are chosen based on overall model error rate. Unfortunately, these statistical models often misclassify banks. Our study compares the ability of multivariate discriminant analysis (MDA), logistic regression (logit) and three types of artificial neural networks (ANNs) to classify banks as financially healthy or financially distressed. We calculate overall error rates, Type I error rates and Type II error rates for all five models. Our results show that both MDA and logit have lower estimated overall error rates and Type II error rates that the three ANNs. However, the ANNs have lower Type I error rates than MDA and logit. We demonstrate that relying solely on overall misclassification error rates to choose a model to analyze the financial viability of banks will result in suboptimal model performance. We find that model performance is directly related to assumptions regarding the relative costs of Type I and Type II errors. Our results indicate that if it is assumed that Type I errors are more costly than Type II errors, then a categorical learning neural network minimizes the overall cost associated with assessing the financial condition of banks.

Keywords: Artificial neural networks, banks, decision support, financial distress, modeling.
JEL Codes: C18, C45, G21, G28.
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1.0 INTRODUCTION

In late 2014, twenty percent of all of the banks in Europe failed financial stress tests. Unfortunately, this type of news has been reported with disturbing regularity since the start of the financial crisis in 2007. However, banking and financial crises are not new to the 21st century. The U.S. Savings and Loan crisis of the 1980s resulted in about 25% of all Savings and Loans in the U.S. being shuttered and ending up costing the U.S. government over $150 billion. The U.S. had 506 banks fail between 2008 and 2014. It also

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is possible for banks to fail in times of a healthy economy, e.g., the Bank of Credit and Commerce International (BCCI) failed in 1991 and Barings Bank failed in 1995. Given the high cost of bank failures, it is important for banking regulators and bank investors to have reliable tools to forecast impending bank financial distress. Too often, bank failures take banking regulators and the public by surprise, resulting in emergency actions by central banks and panic by bank customers. Consequently, the use of statistical techniques, such as multivariate discriminant analysis (MDA) and logistic regression (logit), and artificial neural networks (ANNs) to forecast whether or not a bank will fail can provide very useful information regarding the financial viability of a bank.

While MDA, logit and ANNs are popular techniques for classification and forecasting in the financial community, they perform with varying degrees of accuracy. Two types of misclassifications can occur when evaluating the financial viability of a bank with any of these techniques: (1) classifying a bank that will fail as financially healthy (Type I error), and (2) classifying a bank that is financially healthy as one that will fail (Type II error). In general, the cost of Type I errors is greater than that of Type II errors (Jagtiani et al., 2003).

Two different financial failure prediction models may have the same overall error rate, but different Type I and Type II error rates. Because of the difference in costs associated with Type I and Type II errors, these two models will have different costs of misclassification and, as a result, will have different total costs associated with their use. Consequently, the primary objective of this study is to compare the performance of MDA, logit and ANNs in bank financial viability prediction using their relative misclassification costs. Additionally, this study compares the relative misclassification costs of several types of ANNs (discussed below) when used to predict bank financial viability.

2.0 MODEL COMPARISON AND PERFORMANCE MEASURES

2.01 A COMPARISON OF MODELLING TECHNIQUES USED IN THIS STUDY

Many studies use either logit or MDA to develop financial viability models and to predict the failed and healthy firms in the holdout sample. However, both of these modelling techniques have constraints that reduce their usefulness when used with real-world data (Altman, et al., 1977; Jones, 1987; Pinches & Trieschmann, 1977; Kida, 1980; Ohlson, 1980; Frecka & Hopwood, 1983; Mutchler, 1985; Williams, 1985; Odom & Sharda, 1990; Bell & Tabor, 1991; Chen & Church, 1992; Coats & Fant, 1993).

Artificial neural networks overcome most of the limitations of MDA and logit and also have other characteristics that them more attractive as modeling techniques than either MDA or logit. For example, ANNs do not require that data possess specific characteristics, e.g., normal distribution, equal covariance matrices, etc. ANNs also are very good at pattern recognition and can use patterns in financial data and the relationships between data items to determine the financial viability of banks. In turn, they can use these learned patterns and relationships to classify new firms as either failed or healthy (Odom & Sharda, 1990; Coats & Fant, 1993). Because they are nonlinear procedures, ANNs also are more versatile and robust than linear statistical techniques and can use both quantitative and qualitative cues (Liang, et al., 1992; Etheridge & Sriram, 1997).

ANNs are used in a number of business studies, e.g., identifying cases of financial statement fraud (Gaganis, 2009), forecasting earnings per share (Cao & Parry, 2009), forecasting risks (Ballini et al., 2009) and forecasting financial failure (Quek et al., 2009). Some studies show that ANNs outperform statistical modeling techniques such as MDA and logit in classifying firms as financially healthy or failing (Etheridge & Sriram, 1996, 1997), while other studies indicate that ANNs do not perform as well as some statistical techniques in categorizing firms as either financially healthy or financially distressed (Liou, 2008).

2.02 ARTIFICIAL NEURAL NETWORKS

A number of different artificial neural network paradigms have been developed and tested. However, based on previous studies, it appears that three types of ANNs are useful in assessing bank financial viability: (1) categorical learning neural networks (CLN), (2) probabilistic neural networks (PNN), and (3) backpropagation neural networks (BPN). Each of these ANNs represents a different approach to pattern recognition and classification ranging from competition between processing elements (CLN), to probability theory (PNN) to a gradient-descent learning law (BPN). We do not know which type of ANN will minimize misclassification costs, but suspect that CLN and PNN will have lower misclassification costs than BPN because CLN and PNN are designed to categorize observations into separate groups, while BPN is not.

2.03 COSTS OF ERRORS IN FINANCIAL VIABILITY PREDICTION

Misclassification costs of a financial viability assessment method are determined by two factors: (1) the probability of making misclassifications using a specific classification method (estimated error rate), and (2) the cost of making a misclassification error.

Two types of misclassifications can occur when evaluating the financial viability of a bank: (1) classifying a bank that will fail as financially healthy, and (2) classifying a bank that is financially healthy as one that will fail. To simplify further discussion of these errors, we will refer to them as (1) Type I errors, and (2) Type II errors, respectively. If the objective is to minimize the overall error rate (Type I and Type II errors combined), then the following equation can be used to calculate the estimated overall error rates of financial viability models developed using different methods:

Estimated overall error rate = (Type I error rate × .02) + (Type II error rate × 0.98) (1)

The reason that the Type I error rate is multiplied by .02 is that, on average, 2% of banks fail every year (Sinkey, 1975). Consequently, the Type II error rate is multiplied by .98 because, on average, 98% of banks do not fail.

2.04 MISCLASSIFICATION COSTS

Using the estimated overall error rate to select a model to use in assessing a bank's financial viability poses a problem because the cost of a Type I error and the cost of a Type II error are not the same. Type I errors (categorizing a bank that will fail as financially healthy) are more costly than Type II errors (categorizing a healthy bank as one that will fail) (Jagtiani et al., 2003). Consequently, when selecting a model to use in assessing the financial viability of banks, it is critical to consider the relative costs of Type I and Type II errors.

The following equation has been used in previous studies (Koh, 1992; Etheridge et al., 2000) to estimate the misclassification cost associated with a financial viability model:

Misclassification Cost = (Probability of Type I Error × Cost of Error) + (2)
(Probability of Type Ii Error × Cost of Error)

Because the average dollar-cost of a Type I or Type II error is difficult, if not impossible, to determine because certain costs are challenging to quantify, we express the costs of these errors relative to each other as ratios, e.g., 1:1, 2:1, etc. Since the relative cost of a Type I error compared to that of a Type II error cannot be determined with precision, we vary the relative cost to examine how the misclassification cost of a financial viability model behaves in response to changes in the Type I/Type II error cost ratio. For example, we vary the cost ratios from 1:1 to 50:1 to see how the overall cost of misclassification of a specific financial viability model behaves as the cost ratios change.

Using relative cost ratios also allows us to directly calculate and compare the estimated relative costs of financial viability models using the following equation:

Estimated Relative Cost (RC) = (PI x CI) + (PII x CII) (3)

where PI is the probability of a Type I error, CI is the relative cost of a Type I error, PII is the probability of a Type II error, and CII is the relative cost of a Type II error (Koh, 1992). Choosing the model with the lowest estimated RC will result in the lowest expected misclassification error cost.

3.0 SAMPLE AND DATA

We developed MDA and logit models as well as CLN, PNN and BPN ANNs to categorize banks as either financially healthy or financially failing. The sample of banks in our study is composed of 1139 banks (991 healthy and 148 failed) in various regions of the U.S. Our sample contains 57 financial variables for each bank for the years 1986 to 1988, a time period with a high rate of bank failures. See Table A1 in the appendix for a listing of the independent variables in our data. We use the FDIC definition of failure to operationalize failed banks as assisted mergers and liquidated banks (The Federal Deposit Insurance Corporation, 1992). The FDIC assumed the operations of the failed banks in 1989, so we use the years 1986, 1987, and 1988 to represent three years, two years, and one year prior to failure.

An observation from the original sample is excluded from the final sample if it is missing one or more variables. We eliminate 61 observations (50 nonfailed and 11 failed) from 1988, 57 observations (50 nonfailed and 7 failed) from 1987, and 32 observations (23 nonfailed and 9 failed) from 1986. Therefore, the final sample is composed of 1078 observations (941 nonfailed and 137 failed) in 1988, 1082 observations (944 nonfailed and 138 failed) in 1987, and 1107 observations (968 nonfailed and 139 failed) in 1986.

The final sample is randomly separated into two subsamples: the training sample and the holdout sample. The training sample has the following composition: 1988 has 863 observations (749 nonfailed and 114 failed), 1987 has 867 observations (752 nonfailed and 115 failed), and 1986 has 892 observations (776 nonfailed and 116 failed). The holdout sample contains 215 observations (192 nonfailed and 23 nonfailed) for each year.

4.0 RESULTS

We use a stepwise process with a significance level of .10 to develop both the MDA and logit models used in this study. The resulting models include independent variables with the highest levels of correlation with the dependent variable. The resulting MDA model has 16 independent variables including allowance for loan and lease loss to net loans and losses (ALLNLNS), commitments to total assets (COMTASST), loans and commitments to total deposits (COMTDEPS), earning assets to total assets (EARNASST), loans to insiders to net loans (INSIDRS), jumbo time deposits to net loans (JUMBNLNS), jumbo time deposits to total deposits (JUMBODEP), large time deposits to total assets (LARDPAST), net loans to total deposits (NLNSDEPS), nonperforming assets to total assets (NPASST), total operating expense to total operating income (OEOPINC), total operating income to total assets (OPINCAST), restructured loans to gross loans (RESTLNS), return on average total assets (ROA), return on total assets (ROAOLD), and total securities to total assets (SECASST). The logit model includes 13 variables: allowance for loan and lease loss to net loans and losses (ALLNLNS), cash and due to total assets (CASHASST), commitments to total assets (COMTASST), large time deposits to total assets (LARDPAST), nonperforming assets to total assets (NPASST), nonperforming loans to total assets (NPLNSAST), primary capital adequacy (PRMCAPAQ), restructured loans to gross loans (RESTLNS), return on average total assets (ROA), return on total assets (ROAOLD), total securities to total assets (SECASST), total assets (TACURR), and yield on loans (YLDLNS).

The three ANN paradigms used in this study are trained with a subsample of the original data set containing the 55 remaining independent variables and then tested using a holdout sample, which consists of 192 healthy and 23 failed banks for each of the three years prior to failure. The error rates for the MDA, logit, and the ANN models are presented in Table 1.
Although the estimated overall error rate (EOER) is low for all three ANNs, both MDA and logit outperform the three ANNs. Also, comparing the EOERs of the ANNs shows that BPN and PNN have lower EOERs (ranging from 2.4% one year before failure to 6.57% three years before failure) than CLN.

If EOER is used to determine the desirability of a bank financial viability model, then both logit and MDA would appeal to bank regulators and investors. However, overall error rates are not sufficient to determine the adequacy of financial viability models because the EOERs do not incorporate the rates of misclassifying failed and nonfailed banks (Type I and Type II errors). Therefore, we also compare the models on the basis of their Type I and Type II error rates from the testing phase.

Both BPN and PNN perform better than CLN in categorizing nonfailed banks (see Table 1); however, logit and MDA again perform better than the ANN models. The Type II error rates for the logit model ranges from 1.04% one and three years prior to failure to 1.56% two years prior to failure. The MDA model has Type II error rates of 1.04% one and three years prior to failure and 2.08% two years prior to failure. The Type II error rates for the ANNs are not as low. The Type II error rate for BPN is less than 4% one year before failure and less than 6% three years before failure. For PNN, the Type II error rate is less than 2% one year before failure and less than 4% three years before failure.

However, the logit and MDA models do not classify failed banks as well as the ANN models and neither BPN nor PNN correctly classify failed banks as well as CLN. CLN has Type I error rates ranging from 0% to 22% one to three years before failure, while BPN and PNN have Type I error rates ranging from 13% to 52% one to three years before failure.

Table 1: Estimated error rates

Model	Year	Type I Errors Fail as Nonfail	Type II Errors Nonfail as Fail	Overall Error Rate
Logit	1988	0.2609	0.0104	0.0154
	1987	0.5652	0.0156	0.0266
	1986	0.7826	0.0104	0.0259
MDA	1988	0.2609	0.0104	0.0154
	1987	0.6087	0.0208	0.0326
	1986	0.6957	0.0104	0.0241
BPN	1988	0.1304	0.0365	0.0383
	1987	0.4348	0.0469	0.0546
	1986	0.4783	0.0573	0.0657
CLN	1988	0.0000	0.0729	0.0715
	1987	0.1739	0.0781	0.0800
	1986	0.2174	0.1198	0.1217
PNN	1988	0.4348	0.0156	0.0240
	1987	0.4783	0.0313	0.0402
	1986	0.5217	0.0313	0.0411

Because regulators should use the model that minimizes costs of misclassifying a failed bank as a healthy bank, we also calculate the estimated relative costs (RCs) for each of the models using costs ratios ranging from 1:1 to 50:1. The performance rankings (1, 2, 3, 4, or 5, with 1 representing the lowest relative cost and 5 representing the highest) of the five models for the various cost ratios are presented in Table 2. To compare the performance of the models, we compute a simple sum of the ranks (rank-sums) of the models for each of the three years prior to failure and for different RC ratios. However, because the costs of Type I errors are believed to be greater than the costs of Type II errors (Jagtiani et al., 2003), we exclude the rankings for the RC of 1:1 from the calculations of the rank-sums.

Table 2: Models ranked by estimated relative cost

Model	Cost Ratio	1988	1987	1986	Total of Ranks
Logit	1:1	1	1	2	
	10:1	2	3	5	
	20:1	3	4	5	

	30:1	3	4	5	
	40:1	3	4	5	
	50:1	3	4	5	**58**
MDA	1:1	1	2	1	
	10:1	2	5	2	
	20:1	3	5	4	
	30:1	3	5	4	
	40:1	3	5	4	
	50:1	3	5	4	**57**
BPN	1:1	4	4	4	
	10:1	1	4	3	
	20:1	2	2	3	
	30:1	2	2	2	
	40:1	2	2	2	
	50:1	2	2	2	**33**
CLN	1:1	5	5	5	
	10:1	4	1	4	
	20:1	1	1	1	
	30:1	1	1	1	
	40:1	1	1	1	
	50:1	1	1	1	**21**
PNN	1:1	3	3	3	
	10:1	5	2	1	
	20:1	5	3	2	
	30:1	5	3	3	
	40:1	5	3	3	
	50:1	5	3	3	**51**

The rank-sum measure is 21 for CLN, 33 for BPN, 51 for PNN, 57 for MDA, and 58 for logit. A lower rank-sum indicates lower relative costs associated with misclassification errors. Consequently, users should expect CLN models to minimize the costs of misclassification, followed by BPN and PNN models. It is notable that the two techniques traditionally used to develop financial viability models, MDA and logit, have the highest estimated relative costs.

We also test whether the differences in the model RCs are statistically significant. Table 3 presents the yearly means of the model RCs across cost ratios. Since one of the primary foci of our study is to determine whether differences between pairs of RC means are statistically significant across models and years, we conduct t-tests on the relevant pairs of RC means to test whether these differences are statistically significant. Table 4 presents the two-tailed t-tests and p-values by year across model means.

Table 3: Annual RC means

Model	**1988**	**1987**	**1986**
Logit	0.1667	0.3544	0.4798
MDA	0.1667	0.3856	0.4276
BPN	0.1140	0.3068	0.3431
CLN	0.0715	0.1809	0.2478
PNN	0.2762	0.3176	0.3437

The t-tests yield the following results. Two years immediately prior to failure, CLN has the lowest average relative cost relative to all of the other financial viability models. No statistically significant differences exist among the average relative costs of the other models for the two years preceding financial failure.

Three years prior to failure, the average relative costs of all of the models are approximately the same (even though CLN appears to have a lower relative cost than the other four models, the differences are not statistically significant).

Table 4: t-statistics of differences between means

Year	Model	MDA	BPN	CLN	PNN
1988	Logit	0.000 (1.000)	1.278 (.249)	2.582 **(0.061)**	-1.526 (0.174)
	MDA		1.278 (0.249)	2.582 **(0.061)**	-1.526 (0.174)
	BPN			2.306 **(0.082)**	-2.526 **(0.056)**
	CLN				-3.329 **(0.029)**
1987	Logit	-0.266 (0.797)	0.472 (0.650)	2.075 **(0.096)**	0.352 (0.734)
	MDA		0.745 (0.480)	2.287 **(0.075)**	0.622 (0.552)
	BPN			1.901 **(0.094)**	-0.117 (0.909)
	CLN				-1.899 **(0.094)**
1986	Logit	0.352 (0.734)	1.053 (0.323)	2.019 (0.104)	1.023 (0.340)
	MDA		0.707 (0.502)	1.744 (0.144)	0.682 (0.516)
	BPN			1.283 (0.250)	-0.005 (0.996)
	CLN				-1.199 (0.281)

5.0 CONCLUSIONS AND IMPLICATIONS

Banking regulators and investors wishing to minimize the costs of using a bank financial viability model should choose a model that minimizes their costs instead of selecting a financial viability model that minimizes overall error rates. Expected overall error rates alone cannot be used to judge the desirability of financial viability models, since Type I errors generally are considered to be more costly than Type II errors.

This study shows that when the cost of Type 1 errors is high, ANN models perform as well or better than traditional statistical models. However, since different ANN paradigms are designed to work differently, choosing an appropriate ANN to use when evaluating a bank's financial viability is an important decision. When the costs of Type I and Type II errors are assumed equal, MDA and logit outperform (have lower estimated relative costs than) all ANNs examined in this study. However, as the cost of a Type I error relative to that of a Type II error increases, the ANN models began to exhibit lower estimated relative costs than both logit and MDA. As relative cost ratios increase, the categorical learning network (CLN) has a lower expected relative cost than those of any of the other models examined in this study, including BPN and PNN. Based on the results of our tests, CLN is the preferred ANN with which to develop a model of financial viability to minimize the costs associated with an incorrect assessment of a bank's financial health. Although BPN is more suited for solving forecasting problems, it appears to have performed reasonably well in classifying failed and nonfailed banks. However, our results show that better alternatives to BPN as a modeling technique in bank financial viability prediction exist.

In summary, our results show that bank financial viability models developed using artificial neural networks can significantly reduce the costs of bank financial viability misclassification compared to models developed using either discriminant analysis or logit. Categorical learning artificial neural networks (CLN) yielded financial viability models with estimated relative costs that are significantly lower one and two years prior to failure than those of models developed with backpropagation neural networks (BPN), probabilistic neural networks (PNN), multivariate discriminant analysis (MDA), and logit.

The results of our study have several implications for both banking regulators and investors. First, our study demonstrates that the complexity of the decision of determining whether a bank will remain financially viable over the next year or two necessitates using a decision support technique that (1) can utilize all relevant data and (2) model complex, nonlinear relationships. Consequently, artificial neural networks should be used by banking regulators and investors to develop models of financial viability when assessing the financial health of banking institutions rather than traditional statistical techniques such as multivariate discriminant analysis or logit. However, when designing financial viability models, using artificial neural networks that are designed specifically to categorize data into groups, e.g., categorical learning ANNs or probabilistic neural networks, is preferable to using more generic artificial neural networks, backpropagation ANNs. Finally, focusing on minimizing the overall error rate of a model rather than minimizing the Type I error rate while holding the Type II error rate low will result in higher costs to banking regulators and investors. Therefore, financial viability models should be chosen only after comparing Type I and Type II error rates and determining which model is likely to be least costly to use.

REFERENCES

Altman, E., Haldeman, R., & Narayanan, P. (1977). ZETA analysis: New model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, 1(1), 29-54.

Ballini, R., Mendonça, A. R. R., & Gomide, F. (2009). Evolving fuzzy modelling in risk analysis. *Intelligent Systems in Accounting, Finance and Management,* 16(1/2), 71 – 86.

Bell, T. B. & Tabor, R. H. (1991). Empirical analysis of audit uncertainty qualifications. *Journal of Accounting Research*, 29(2), 350-371.

Cao, Q. & Parry, M. E. (2009). Neural network earnings per share forecasting models: A comparison of backward propagation and the genetic algorithm. *Decision Support Systems,* 47(1), 32 – 41.

Chen, K. C. W. & Church, B. K. (1992). Default on debt obligations and the issuance of going-concern opinions. *Auditing, A Journal of Practice and Theory,* 11(2), 30-49.

Coats, P. K. & Fant, L. F. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management,* 22(3), 143-154.

Etheridge, H. L. & Sriram, R. S. (1996). A neural network approach to financial distress analysis. *Advances in Accounting Information Systems,* 201-222.

Etheridge, H. L. & Sriram, R. S. (1997). A comparison of the relative costs of financial distress models: Artificial neural networks, logit and multivariate discriminant analysis. *International Journal of Intelligent Systems in Accounting, Finance and Management,* 4(1), 235-248.

Etheridge, H. L., Sriram, R. S. & Hsu, K. H. Y. (2000). A comparison of selected artificial neural networks to help auditors evaluate client financial viability. *Decision Sciences,* 31(2), 531–550.

Frecka, T. J. & Hopwood, W. S. (1983). The effects of outliers on the cross-sectional distributional properties of financial ratios. *The Accounting Review*, 58 (1), 115-128.

Gaganis, C. (2009). Classification techniques for the identification of falsified financial statements: a comparative analysis. *Intelligent Systems in Accounting, Finance and Management,* 16(3), 207 – 230.

Jagtiani, J., Kolari, J., Lemieux, C., & Shin, H. (2003). Early warning models for bank supervision: Simpler could be better. *Economic Perspectives: Federal Reserve Bank of Chicago,* 3rd Quarter, 49 – 60.

Jones, F. L. (1987). Current techniques in bankruptcy prediction. *Journal of Accounting Literature,* 6, 131-164.

Kida, T. (1984). The effect of causality and specificity on data use. *Journal of Accounting Research, 22*(1), 145-152.
Koh, H. C. (1992). The sensitivity of optimal cutoff points to misclassification costs of type I and type II errors in the going-concern prediction context. *Journal of Business Finance & Accounting,* 19 (2), 187-197.
Liang, T. P., Chandler, J. S., Han, I. & Roan, J. (1992). An empirical investigation of some data effects on the classification accuracy of probit, id3, and neural networks. *Contemporary Accounting Research,* 9 (1), 306-328.
Liou, F. M. (2008). Fraudulent financial reporting detection and business failure prediction models: a comparison. *Managerial Auditing Journal,* 23 (7), 650 – 662.
Mutchler, J. F. (1985). A multivariate analysis of the auditor's going concern opinion decision. *Journal of Accounting Research,* 23 (2), 668-682.
Odom, M. D. & Sharda, R. (1990). A neural network model for bankruptcy prediction. *Proceedings of the International Joint Conference on Neural Networks 2,* 1-23.
Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research,* 18 (1), 109-131.
Pinches, G. E. & Trieschmann, J. S. (1977). Discriminant analysis, classification results and financially distressed property-liability insurers. *Journal of Risk and Insurance,* 44(2), 289-298.
Quek, C., Zhou, R. W. & Lee, C. H. (2009). A novel fuzzy neural approach to data reconstruction and failure prediction. *Intelligent Systems in Accounting, Finance and Management,* 16(1/2), 165 - 188.
Sinkey, J. F., Jr. (1975). A multivariate statistical analysis of the characteristics of problem banks. *The Journal of Finance,* 30(1), 21-36.
The Federal Deposit Insurance Corporation. (1992). *FDIC Statistics on Banking.* Washington, D.C.: Division of Research and Statistics.
Williams, R. J. (1985). Learning internal representatives by error propagation. *Institute for Cognitive Science Report 8506.* San Diego, CA: University of California, San Diego.

APPENDIX

TABLE A1: Descriptions of independent variables

Variable	Description
ALLNLNS	Allowance for loan and lease loss to net loans and leases
BRKEVEN	Yield to breakeven
BROKDEPS	Brokered deposits to total deposits
CAPADQ	Capital Adequacy
CASHASST	Cash and due to total assets
COMTASST	Commitments to total assets
COMTDEPS	Loans and commitments to total deposits
COREDEPS	Core deposits to total deposits
EARNASST	Earnings assets to total assets
FUNDINC	Net interest income (expense) on federal funds purchased (sold) to total interest income
GRCHARGE	Gross charge-offs to gross loans
GRRECOVR	Gross recoveries to gross loans
INSIDRS	Loans to insiders to net loans
INTBRDEP	Interest bearing deposits to total deposits
INTEXPOI	Total interest expense to total operating income
JUMBNLNS	Jumbo time deposits to net loans
JUMBODEP	Jumbo time deposits to total deposits
LARDPAST	Large time deposits to total assets
MARGIN	Net interest margin

NETCHARG	Net charge-offs to gross loans
NLNSASST	Net loans to total assets
NLNSDEPS	Net loans to total deposits
NONACRLN	Nonaccrual loans to gross loans
NONINTOI	Noninterest income to total operating income
NPASST	Nonperforming assets to total assets
NPCAP	Nonperforming loans to primary capital
NPLNSAST	Nonperforming loans to total assets
NPNLNS	Nonperforming loans to net loans
NPRESTGL	Total nonperforming and restructured loans to gross loans
OEOPINC	Total operating expense to total operating income
OPINCAST	Total operating income to total assets
OTHREAST	Other real estate owned to total assets
OVHROPIN	Total overhead expense to total operating income
OVRTA	Total overhead expense to total assets
PDLNSGRL	Past due loans to gross loans
PERSONL	Personnel expense to total operating income
PRMCAPAD	Primary capital to adjusted assets
PRMCAPAQ	Primary capital adequacy
PROVNLNS	Provision for loan and lease loss to net loans and leases
PROVOPIN	Provision for loan and lease loss to total operating income
PROVTAST	Provision for loan and lease loss to total assets
PUBLICDP	Public deposits to total deposits
RATE	Total interest expense to total assets
RESTLNS	Restructured loans to gross loans
ROA	Return on average total assets
ROAADJ	Return on assets adjusted for unrealized loss on marketable securities
ROAOLD	Return on total assets
ROE	Return on equity
ROEOLD	Return on total equity
SECASST	Total securities to total assets
SWAPS	Interest rate swaps to total deposits
TACURR	Total assets
UNDVTAST	Undivided profit and capital reserve to total assets
YIELD	Total interest income to total assets
YLDLNS	Yield on loans