PREDICTING THE FAILURE OF COMMERCIAL BANKS IN THE NINETIES

By

R. Franklin Hawkins, Jr.

A DISSERTATION

Submitted to

School of Business and Entrepreneurship

Nova Southeastern University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

1996

Running Head: PREDICTING THE FAILURE

UMI Number: 9640062

UMI
300 North Zeeb Road
Ann Arbor, MI 48103

A Dissertation
entitled

PREDICTING THE FAILURE OF COMMERCIAL BANKS

IN THE NINETIES

By

R. Franklin Hawkins, Jr.

We hereby certify that this Dissertation submitted by R. Franklin Hawkins, Jr. conforms to acceptable standards, and as such is fully adequate in scope and quality. It is therefore approved as the fulfillment of the Dissertation requirements for the Degree of Doctor of Business Administration.

Approved:

Alan Gart — 7/23/96
Alan Gart, Ph.D. — Date
Chairperson

R Jackson — 7/26/96
Raymond Jackson, Ph.D. — Date
Committee Member

Andrew J Sherbo — 8/2/96
Andrew J. Sherbo, Ph.D. — Date
Committee Member

Ronald Needleman — 8/15/96
Ronald Needleman, Ph.D. — Date
Director of Research

Randolph Pohlman — 8/15/96
Randolph Pohlman, Ph.D. — Date
Dean, School of Business and Entrepreneurship

Nova Southeastern University
1996

CERTIFICATION STATEMENT

I hereby certify that this paper constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

Signed R. F. Hawkins Jr.

R.Franklin Hawkins, Jr.

ABSTRACT

PREDICTING THE FAILURE OF COMMERCIAL BANKS IN THE NINETIES

by

R. Franklin Hawkins, Jr.

The purpose of this study is to provide all interested parties or stakeholders, especially depositors, stockholders, bondholders, and management with an easy to apply tool or mathematical model that will identify commercial banks that are likely to fail within at least one year, and possibly within as many as three years, before failure, by using data that is available to the general public. Multiple Discriminant Analysis (MDA) is used to develop simple-to-use predictive models and decision rules useful in identifying the commercial banks likely to be classified as FAILED or NON-FAILED.

Three models and decision rules are developed. The model with the most predictive accuracy is composed of seven variables, and is capable of predicting bank failure at least two years before failure occurs. The second and third best models have five and four variables respectively, and have less predictive capability.

Decision rules for each of the models are developed by examining the trade-off between the additional number of NON-FAILED banks misclassified relative to the number of FAILED banks correctly classified as the z-score cutoff values are moved in increments of .10 from .00 to 1.00. Use of a model with its decision rule increases the predictive capability of the model.

ACKNOWLEDGEMENTS

I wish to thank Mr. Richard A. Brown, Financial Economist with the Division of Research at the Federal Deposit Insurance Corporation in Washington, D.C., who, for several years, provided me with up to date, early information about failed banks. His continued encouragement was most helpful.

I wish also to thank Ms. Sue Miller, Assistant Vice President, Information Center, Crestar Bank in Richmond, Virginia. Sue enabled me to utilize the on-line computer capabilities at Crestar Bank to obtain the data on all the sample banks.

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

LIST OF TABLES

LIST OF TABLES (Continued)

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Background of the Problem

During the period from 1984 through 1993 the banking industry experienced more commercial bank failures than at anytime since the depression years, when they averaged 600 per year (FDIC, 1993). Although failures in the commercial banking industry reached double digits levels as early as 1975, the years 1979 through 1981 experienced only 10 bank failures each. In 1982, however, a jump to 42 failures started an annual rise in commercial bank failures that ascended to a high of 206 in 1989, after which the yearly number began to decline. The first year since commercial bank failures, at 41, numbered less than 100 was 1993. This was followed by only 13 failures in 1994 (FDIC, 1994).

Table 1-1

Number and Deposits of BIF-Insured Banks Closed Because of Financial Difficulties, 1934 through 1995 ($ Thousands)

Year	Number of Insured Banks	Deposits of Insured Banks
1995	6	$617,234
1994	13	$1,390,710
1993	41	$3,132,177
1992	120	$41,150,898
1991	124	$53,751,763
1990	168	$14,473,300
1989	206	$24,090,551
1988	200	$24,931,302
1987	184	$6,281,500
1986	138	$6,471,100
1985	120	$8,059,441
1984	79	$2,883,162
1983	48	$5,441,608
1982	42	$9,908,379
1981	10	$3,826,022
1980	10	$216,300
1979	10	$110,690
1978	7	$854,154
1977	6	$205,208
1976	16	$864,859
1975	13	$339,574
1965-1974	52	$2,975,392
1955-1964	32	$111,122
1945-1954	30	$88,221
1934-1944	400	$499,786
TOTAL	2,075	$212,674,459

From "Federal Deposit Insurance Corporation Annual Report," 1995.

Obviously stakeholders in the failed commercial banks, some of whom lost their entire investment, might have avoided their losses, if a simplistic mathematical model had been readily available to warn them of the impending financial failure of their bank investment. It will be the intent of this study to provide such a model.

History of the Background

E.I. Altman, (1993) defined corporate distress by outlining four generic terms: failure, insolvency, default, and bankruptcy. "Failure" in economic terms occurs when "the realized rate of return on invested capital, with allowance for risk consideration, is significantly lower than prevailing rates on similar investments." It is a legal failure when the business entity cannot pay the legal claims of its creditors. Altman indicates that the firm of Dun and Bradstreet expands the definition to include businesses that cease operations due to such situations as assignment, bankruptcy, foreclosure, receivership, reorganization, voluntary withdrawal leaving unpaid bills, and compromise with creditors.

"Insolvency" is used in a more technical way, such as when current obligations can not be met due to a lack of liquidity (Altman, 1993). At least one writer on bank failures, Demirguc-Kunt, A. (1989) felt it was crucial to make a distinction between economic insolvency and failure. She saw economic insolvency as a market determined event based on the market value of the enterprise-contributed equity, and failure as a regulatory decision swayed by conflicts of interests that exist between regulators, politicians, and taxpayers. She felt both should be emphasized, but studied simultaneously, with failure being modeled as the outcome of the regulatory decision making process.

"Default" can be both technical and legal. It occurs when a debtor does not abide by the terms of a legally enforceable agreement with a creditor. "Bankruptcy" is when a firm formally declares bankruptcy in a Federal District Court with the intent of either liquidating its assets or setting up a recovery program. Altman emphasizes, however, that the problems of business failure generally are internal to the firm itself (Altman, 1993).

"Failed banks" in this study will be defined as those that are closed by their chartering authority, and "Non-failed banks" as those that have no need of financial assistance <u>and</u> which have a net worth/asset ratio of 2% or more (Gart, 1994).

The first commercial bank, as we know it today, was established in the year 1135 in Venice (Sinkey, 1979). U.S.

banks have been chartered by special acts of state legislatures or the Congress since 1789, with the first U.S. commercial bank failure occurring at the Farmers Bank of Gloucester, Rhode Island in 1809. During the period 1921-1929, commercial bank failures rose to average 600 per year. President Roosevelt finally declared a bank holiday in March 1933. The Banking Act of 1933 became law on June 16, 1933, which in turn, created the Federal Deposit Insurance Corporation, Regulation Q, and the Glass-Steagall Act (FDIC, 1994).

Prior to 1933, deposit insurance had been attempted in 14 states unsuccessfully. As far back as 1886, many legislative attempts were made on the federal level as well. FDIC insurance coverage, originally $2,500 in 1933, was increased over the years to $5,000 in 1934, $10,000 in 1950, $15,000 in 1966, $20,000 in 1969, $40,000 in 1974, and finally rose to its present level of $100,000 in 1980 (FDIC, 1994). Before the establishment of deposit insurance, failed banks were generally small and state chartered, but national banks also failed. During the period 1885-1920, most bank failures were related to the dishonesty or incompetence of bank managers. Post-deposit insurance bank failures (1934-1972) averaged only $2 million dollars in deposit size, with the first billion dollar bank failure (ie: United States

National Bank of San Diego) not occurring until October 18, 1973 (Sinkey, 1979).

G.J. Benston, et al. (1986), in their perspectives of the Savings and Loan industry, noted that management of risk is the key to success in banking, and managing risk has become more difficult, causing a significant increase in bank failures since the mid 1940s. David Cates (1985) identified seven kinds of banking risks: (1) Asset Quality, (2) Funding, (3) Interest Rate, (4) Control, (5) Overhead, (6) Strategy, (7) Capital. He noted, however, that the true line of defense against banking risk is management, not the regulator nor the market.

Factors affecting the possibility of bank failure, as explained by Benston, et al. (1986) were: (1) the economic environment, (2) technology, (3) deregulation, and (4) subsidies inherent in the Federal Deposit Insurance System. In explaining the last factor, they claimed banks began to use deposit insurance as a substitute for maintaining proper capital levels. Flat-rate premiums on deposit insurance caused many banks to take greater risks. The new risk rated premiums should have eliminated this concern.

By comparison, a few years later, in 1993, David Rogers noted that bank failures were related to (1) deregulation, (2) technological innovation, (3) globalization, (4) decline of corporate loan business, (5) increasing competition, (6) a rise in capital markets, (7) liquification and securitization of loans, (8) non-payment by less developed countries (LDC) on their loans, and (9) new Federal Reserve Bank capital requirements (Rogers, D. 1993).

Benston, et al. contend that, historically, runs on banks have not been a problem, since a problem only occurs when there is a flight to currency (funds not redeposited to the system). Actually, they note that a flight to currency has not occurred since the FDIC was established (Benston, et al., 1986).

L.J. White, (1991) also attempted to explain the earlier S&L debacle involving the insolvency of many savings and loan associations, by enumerating six themes (causes) which seemed to be evident. For instance, he faults the regulatory process for thrifts and banks, which he states had a flawed information system (ie: use of historical costs rather than market values). A second theme was that congress was unwilling to treat deposit insurance as insurance, by implementing premiums which were risk-based. A third theme was that even though deregulation was sound in the 1980s, it lacked incentives and controls, accompanied by sufficient scrutiny, allowing thrift management to take excessive risks and engage in criminal activities. White also recognized (4th theme) that even though tighter security was provided in 1986, the accounting systems were slow in recognizing the costs.

White acknowledged in his fifth theme that an inappropriate term, "bailout," was used when large sums were expended to "clean-up" the problems created by the insolvent thrifts, instead of noting that the funds were used for insurance obligations to that institution's depositors (White, 1991). In a bailout, the bank remains open, and everyone's interests are fully protected, except for stockholders whose stock value is diluted. In addition, members of executive management usually lose their jobs (Sprague, 1986).

Sprague concluded three things about bailouts during his tenure on the FDIC Board: (1) whether or not a bank fails still depends on management, (2) "the inevitability of repetition," (ie: Continental forgot its history, causing it to repeat its past), and (3) there will be a continuous turf fight among regulatory authorities. His ideas for improving the system were that (1) megabanks should continue to be bailed out, but some price should be extracted for this protection, (2) stockholders as well as management should be treated the same as when there is outright failure, (3) the FDIC assessment should be charged on all foreign and domestic deposits, and (4) final authority for a bailout should remain with FDIC. Sprague felt that only as a last resort were bailouts actually used, and then, only in instances when they clearly served the national interest (Sprague, 1986).

A sixth theme noted that the Financial Institutions Reform Recovery and Enforcement Act (FIRREA) of 1989 did not provide the funds necessary for clean-up, nor did it outline any reforms for the regulation and deposit insurance for thrifts and banks (White, 1991).

White called for the following reforms: (1) replacement of historical cost with market value accounting, (2) improvement in the risk-based elements of higher net worth standards, (3) risk based deposit insurance premiums to replace flat rate premiums, (4) strengthening of the power of the regulating body so that they can intervene before insolvency, and (5) expansion of deposit insurance to all depositors (White, 1991).

Regulatory authorities have used six different failure resolution policies & practices. They are (1) Deposit Payoff -the bank is closed by its supervisory authority, and assets placed in receivership with FDIC as receiver; (2) Insured Deposit Transfer-transfer of insured deposits to another institution while uninsured depositors and uninsured creditors receive certificates of receivership; (3) Modified Payoff-FDIC advances funds, based on anticipated collections, to the receivership to be distributed to uninsured depositors and uninsured creditors after the failed bank closes; (4) Standard Purchase & Assumption Transaction-the acquiring bank receives all uninsured deposits and other general creditor claims of failed bank with no disruption in service; (5) Deposit Preference-the depositors of state-chartered banks are entitled to full recovery before certain other creditors; and (6) Prorata Purchase & Assumption-FDIC makes excess distributions to depositors or to certain creditors who are not depositors. In 1990, deposit insurance reforms called for: (1) elimination of the "too big to fail" policy, (2) enhancement of market discipline, (3) simplification and streamlining of the process for case resolution, (4) elimination of 100% protection, (5) handling of all bank failures in the same way, and (6) incorporating market discipline into the final settlement payment procedures (Deposit Insurance Reform

Committee, 1990).

Benston, et al (1986) found that the efficient functioning of a financial system requires a central bank, properly priced deposit insurance, risk monitoring incentives, and creditor/stockholder control. Since both insured and uninsured depositors were protected in most bank failures, depositors had no incentive to monitor the system. Two suggested remedies would be to provide investors and depositors with access to asset market values rather than the historic cost values, and to implement risk-based insurance premiums to enhance market discipline (Benston, et al, 1986).

J.F. Sinkey, Jr. (1989) notes that only if the depositors and creditors have confidence in individual banks and the banking system will there be safety and stability in the financial system. He states that bank capital is important in providing that confidence, and identifies Tier 1 as core capital, and Tier 2 as supplemental capital.

Tier 1 capital is composed of (a) Common Stock, (b) Surplus, (c) Undivided profits, capital reserves and (d) Minority interests in consolidated subsidiaries. Tier 2 is (a) Perpetual and long term preferred stock, (b) Perpetual debt and other hybrid debt-to-equity instruments, (c) Intermediate-term preferred stock and term subordinated debt (to a maximum of 50% of Tier 1 capital), and (d) Loan loss reserves (to a maximum of 1.25% of risk-weighted assets) (Gart, 1994).

A system of risk-based insurance premiums was mandated by the Comprehensive Deposit Insurance Reform and Taxpayer Protection Act of 1991. Institutions are placed in one of three categories based on its levels of capital. Alan Gart (1994) lists the capitalization levels as follows:

> "**Well capitalized.** Ratio of tier 1 capital to total assets = 5 or 6 percent, and ratio of total capital to risk-weighted assets of 10 to 12 percent.
>
> **Adequately capitalized.** Tier 1 capital to asset ratio of at least 4 percent, and ratio of total capital to risk-weighted assets of at least 8 percent.
>
> **Less than adequately capitalized.** Tier 1 capital to total capital of less than 4 percent and ratio of total capital to risk-weighted assets of less than 8 percent".

Alan Gart (1994) points out that an insured bank's capital is to provide a cushion to protect the FDIC, but actually, until 1990, when maintenance of 7.25% of risk-weighted assets were required of U.S. banks, banks were encouraged to keep less capital, and take more risks, due to the incentives created by the umbrella of protection provided by deposit insurance. At the end of 1992, 8% was implemented as the minimum capital requirement with core capital having at least 4% of risk-adjusted assets. Gart provides a good example of the new risk weights and risk categories in Table 1-2.

Table 1-2

AG National Bank: Risk-Based Capital ($ Thousands)

Category 1:0 Percent	Assets	Risk	Risk-Weighted Assets
Cash and Reserve	$ 104,000	0	$ 0
Trading Account	900	0	0
U.S Treasury and Agencies (GNMA)	50,000	0	0
Federal Reserve Stock	6,000	0	0
Category 2:20 Percent			
Due from/in Process	$ 300,000	20	$ 60,000
U.S. Treasury and Agencies(coll repos)	325,000	20	65,000
U.S. Agencies (Govt-Sponsored)	412,000	20	82,400
State and Muni Secured Tax Authority	87,000	20	17,400
C.M.O. Backed by Agency Securities	90,000	20	18,000
Domestic Depository Institution	38,000	20	7,600
Category 3:50 Percent			
C.M.O. Backed by Mortgage Loans	$ 10,000	50	$ 5,000
State and Municipalities/All Other	70,000	50	35,000
Real Estate: 1-4 Family	324,000	50	162,000
Category 4:100 Percent			
Loans:Commercial/Agency/Inst/Leases	$2,000,000	100	$2,000,000
Real Estate:All Other	400,000	100	400,000
Allowance for Credit Loss	(70,000)	100	0
Other Investments	170,000	100	170,000
Premises, Equity, Other Assets	200,000	100	200,000
Total Assets	$4,516,900		$3,222,400
Off-Balance Sheet Items			
Loan Commitment > 1 Year	364,000	50	182,000
Futures and Forwards	50,000	100	50,000
Contingencies	$ 414,000		$ 232,000
Assets and Contingencies	$4,930,900		$3,454,000

Requirement

Tier 1 Capital: .04 X ($3,454,400)=$138,716
Total Capital: .08 X ($3,454,400)=$276,352

Note: From Regulation, Deregulation, Reregulation (p. 125) by A. Gart, 1994, Publisher: John Wiley & Sons

Prior to 1978 the FDIC used a three tiered system to classify problem banks: Serious Problem-Potential Pay-off (PPO), Serious Problem (SP), and Other Problems (OP). In 1978, however, a new rating system was created on the basis of a safety and soundness examination. Banks were rated 1-5 in each of 5 areas identified as the CAMEL system (ie: C = Capital Adequacy, A = Asset Quality, M = Management Quality, E = Earnings, and L = Liquidity). Shortly thereafter, in 1983, commercial bank loan losses rose to a high for the last 40 years, and bank capital ratios were close to their lowest levels since 1939 (FDIC, 1984).

In the mid-80s the Federal Reserve created the Uniform Bank Surveillance System (UBSS) structured around six financial ratios (variables) to estimate CAMEL ratings, but it was replaced in 1993 by the Financial Institutions Monitoring System (FIMS) which has two distinct models called FIMS Rating model (eleven variables) and FIMS Risk Rate model (nine variables). The FDIC created a similar system in the mid-80s called the CAEL which is still in existence and evaluates four CAMEL ratings (Cole, et al, 1995, January).

E.I. Altman, et al. (1981) reviewed the major statistical classification studies of failure prediction for non-financial firms from 1967 to 1977, and pointed out that long ago Secrist (1938) had suggested that sound banks could be differentiated from unsound banks by using their accounting data. Later, Altman similarly noted that Smith and Winakor (1935) found that ratios of firms that fail are different from those that continue to be viable (Altman, 1993). Sinkey (1989) concurred, and outlined in detail the ROE Decomposition Analysis, noting that high performance banks have stronger ROEs due to using their assets more efficiently, rather than by financial leveraging. Specifically, high performance banks maximize revenues, control expenses, and consistently provide good management. Although the best gauge of a company's financial performance in an efficient market may be the price of its stock, 95% of banks have stock which is still not publicly traded (Sinkey, 1989).

One study concluded that banks with undue or excessive risk exposure can be identified by means of early warning systems. It further noted that even though on-site examinations by regulatory authorities were still necessary, regulators were slow to develop early-warning systems, or screening devices, indicative of weaknesses in the regulatory process (Benston, et al, 1986). Those Early Warning studies were classified under certain headings by E.

Altman (1983) in Table 1-3.

Table 1-3

Summary of Failure Prediction and Early Warning Studies for Financial Institutions.

Purpose and Sample Characteristics	Statistical Method and Important Variables	Contribution and Critique
I FDIC Studies		
A. Meyer and Pifer (1970). To develop failure-prediction model for commercial banks. Analyzes 39 banks that failed between 1948 and 1965. Employs paired sample based upon location, size, age, and regulatory agency.	Uses a zero-one regression model, and stepwise procedures to search 160-variable data set. A nine-variable regression model is developed.	Classifies 80% of sample banks within one or two years before failure. Shortcomings: narrow definition of failure, zero-one regression technique, time-series or stationarity problem, and lack of predictive ability beyond two years before failure.
B. Sinkey (1974-1979). Studies have focused upon financial characteristics of problem and failed banks; bank- examination process; and development of so-called early warning systems. Ultimate purpose has been to develop screening models. Both paired and random-sample techniques have been applied.	MDA has been the statistical method. Income-expense ratios are more important than balance-sheet ratios and two or three ratios classify about as well as seven or eight ratios.	Served as catalyst on early warning frontier. First research in banking to use quadratic classification technique. Shortcomings: exclusive use of MDA and ratios; and lack of directional element in outlier technique.
II Federal Reserve Bank of New York Studies.		
A. Martin (1977). To analyze alternative types of early-warning models; to compare Logit analysis with discriminant analysis; and logit analysis to commercial bank failure. Used broad definition of failure. A sample of 58 Fed member bank failures are compared with the population of non-failed member banks.	Used Logit and MDA. Four-variable Logit model consists of net income/total assets, gross charge-offs/net operating income, commercial loans/total loans, and gross capital/risk assets.	Catalogs and explains early-warning models; shows relationship between Logit analysis and MDA; and applies logit analysis to study of bank failures. Shortcomings: small sample and excludes non-member bank failures.
B. Korobow, Stuhr et al. (1974-1977). To investigate statistical techniques to assist in the supervision of banks in 2nd Federal Reserve District. Sample banks restricted to "vulnerable" member banks in Second District.	MDA and arctangent regression employed. Latest (five-variable) probability function consists of loans and leases/total sources of funds, equity capital/adjusted risk assets, operating expenses/operating revenues, gross charge-offs/net income + provision for loan losses, and commercial and industrial loans/total loans.	Along with FDIC's research, the N.Y. Fed's efforts constitute the seminal work on statistical early warning systems for banks. Shortcomings: small samples and use of concept of vulnerability.
III Office of the Comptroller of the Currency		
A. National Surveillance System (Haskins & Sells) NBSS is a device for early detection of problem banks and a management tool based upon peer-group analysis of leading indicators. Used National banks with resources of $100 million to $500 million as a base.	One variable-at-a-time analysis based upon percentile rankings. Fifteen significant ratios and other variables are analyzed.	Shows that operational system can be achieved if management is willing to pay big "bucks." Shortcomings: limited empirical testing and exclusive use of outlier or peer-group approach.
IV Board of Governors of the Federal Reserve System		
A. Hanweck (1977). To develop a simulation model for monitoring so-called problem banks, and to develop a failure-prediction model for commercial banks. Used sample of 32 failed banks and random sample of 177 non-failed banks.	Used Multivariate Probit analysis and developed six-variable failure model. Ratios of net operating income to assets, and loans to capital were the only significant variables.	Adds Probit analysis to the MDA, arctangent, logit analysis arsenal. Attempts simulation model for largest banks. Shortcomings: simulation model requires real world testing whereas failure prediction model is based upon an esoteric technique that will probably prohibit its implementation.

(Table 1-3 Continues)

Purpose and Sample Characteristics	Statistical Method and Important Variables	Contribution and Critique
V Other Studies (Commercial Banking)		
A. Santomero and Vinso (1977). To estimate the cross-section riskiness of banking system and its sensitivity to variations in bank capital. Sample consisted of 224 weekly reporting Federal Reserve banks for period February '65 to January '74	Used MDA to develop a problem bank screen for the safety-index distribution. Capital asset ratio and coefficient of variation of capital-jump size are important variables.	Sound theoretical foundation with a measure of risk that is independent of actual bank failures or examiners' ratings of bank soundness. Failure risk is defined as zero or negative net worth. Shortcomings: sample banks not representative of population, and arbitrary definition of a problem bank.
B. Pettway (1980) To determine if returns on actively traded bank equities are sensitive to increased potential for bankruptcy. Seven failed, merged, or reorganized large banks are analyzed. Control group consisted of 24 banks making up Keefe Bank Stock index.	Used asset pricing model and standard regression model to analyze informational impact on cumulative average residuals. Methodological approach does not permit testing of alternative variables.	Shows that market for large bank stocks exhibits characteristics of efficiency and that market information may be useful as early warning mechanism. Shortcomings: standard criticisms of market model apply (ie: definition of relevant holding period, stationary of Beta); small sample; and lack of rigorous test for decline of residuals.
C. Shick & Sherman (1980). To determine if significant deterioration in bank's (examiner-determined) financial condition is reflected by a decline in price of bank's common stock. Analyzes 25 banks that had major changes in their exam rating over period 1967 to 1976. Control group was S&P's index of banks outside of NYC.	Like Pettway, uses so-called market model. Alternative variables not tested because of model employed.	Concludes that stock price behavior has potential as early warning device, and recommends further investigation. Shortcomings: problem group may be subject to examiners' identification error; market model problem; and test of significance of cumulative residual average may be suspect.
D. Pettway and Sinkey (1980) To develop a screening technique to identify potential bank failure using accounting and market information. Sample banks are from Pettway (1980).	See Pettway (1980) and Sinkey (1979).	Shows that both accounting and market information lead examiners' identification of problem status. Shortcomings: see previous criticisms of Pettway and Sinkey.
E. Cole, Cornyn and Gunther (1995) To explain FIMS models instituted in 1993 by FRBK and compare with previous model, UBSS, by using sample of 262 commercial banks that failed in the mid-to-late eighties.	Using an ordinal-level logistic methodology for FIMS Rating model, a subset of 11 exploratory variables were derived. FIMS Risk Rate model derived a subset of 9 variables using binary logistic regression.	FIMS is superior to UBSS, and provides objective and consistent measures of a bank's financial condition. It is timely and more flexible than UBSS and identifies deterioration or improvement in the banking industry within peer groups and systemwide.
VI Other Studies (Nonbanking)		
A. Altman and Loris (1976). To develop a mechanism for identifying broker-dealers that might be failure prone. Failed group consisted of 40 broker-dealers placed in trusteeship during period 1971-1973. Non-failed group: 113 randomly selected non-failed broker-dealers.	Used quadratic MDA and developed six-variable discriminant function. A composit variable consisting of ten elements selected by NASD personnel as indicative of problem status is the most important variable.	First MDA classification model applied to broker-dealers. Provides further confirmation of the usefulness of accounting data for early-warning purposes. Shortcomings: the ad hoc composite variable.
B. Collins (1980). To compare an Altman-type model with a Meyer and Pifer model for 162 failed credit unions and a random sample of 162 non-failed credit unions.	Used a linear probability model and developed a six-variable function. Important variables are those that measure dividend rate, liquidity, loan quality, asset size, reserve strength, loan activity.	First classification model applied to credit unions. Further confirmation of the usefulness of accounting data for development of early-warning systems for depository institutions.

From <u>Corporate Financial Distress</u> (p.p. 302-306) by E.I. Altman, 1983, Publisher: John Wiley & Sons and Cole, Cornyn, and Gunther (1995, January), <u>FIMS: A new monitoring system for banking institutions</u>.

David Rogers, (1993) described earlier banking culture as one having fixed procedures, long term relationships, minimum risks, the avoidance of change, rules, consensus decision making by committees, and lifetime employment. For the future he sees more consolidation, better capitalization, strategic focus on niche players, seamless organizations (collaboration), energizing types of banks (ie: low cost, high volume consumer services), new organizational forms, and changes in the behavior of regulators (ie: forced intervention).

Alan Gart discussed much about interstate banking, and the need for regulatory reform, early warning systems, bank failures, and deposit insurance. He particularly outlined structural changes occurring in the industry, noting that, although there were approximately 11,400 insured commercial banks in 1993, there will be 4,000 to 6000 less banks by the year 2000 (Gart, 1994).

Gart believes we have entered into an era of consolidations, with the major issues being such things as cost savings, capital adequacy, loan quality, and management succession. According to Gart, 35-50% of the non-interest expense of an acquired bank can be saved in the merger of two banks in the same market, while 15% of the acquired bank's overhead can be saved in a merger between two banks in adjoining markets. Gart noted several categories into which banks may fall, including niche players, and concluded by calling for deregulation in products and geographic location, and for reregulation in such areas as higher risk-based premiums, higher real estate loan-to-value ratios, and reduced maximum lending limits to one customer (Gart, 1994).

Purpose of the Study

The purpose of this paper will be to provide all interested parties or stake-holders, especially depositors, stockholders, bondholders, and management, with an easy to apply tool or mathematical model that will identify commercial banks that are likely to fail within at least one year and possibly within as many as three years before failure, by using data that is available to the general public (Fuller, 1990).

Justification of the Study

In reviewing the literature, most models seemed to be developed for academe and were not "user friendly." This study will be different from those reviewed in at least two aspects. First, it will use data from the early 1990s, a period immediately following the high failure rates of the late 1980s, to build a Discriminant function or model to predict failure. Virtually all the studies to date have been with data in the seventies or eighties. Secondly, a systematic procedure will be used to devise an easily understood decision rule to be used with the discriminant function, something not stressed in many other approaches. Altman (1968), using bankrupt firms, and Fuller (1990), using Savings and Loans, did provide decision rules, but no others were easily discerned. Even so, Sinkey, Terza, and Dince (Autumn, 1987), in applying the zeta model (Altman et al, 1977) to the problem of bank failures, found that, although it was accurate three-fourths of the time, the original zeta model (for bankrupt non-financial firms) was still more accurate. Thus, their findings only provided limited support for cross-industry validity when using commercial banks as opposed to bankrupt non-financial firms.

Statement of the Problem

Often the market place does not realize a firm is in distress until long after the failure is well established (Dimancescu, 1983). A statement of this kind acknowledges that pure accounting figures in and of themselves are not enough to furnish investors enough information with which to evaluate companies that seem attractive as investments (Fuller, 1990).

Rationale for the Study

The Base Theory for this project is that financial ratios can be used to predict bankruptcy or corporate failure.

Studies in the 1930s, particularly Smith and Winakor, (1935), found that ratios of firms that fail are different from those that continue to be viable (Altman, 1993). Altman et al. (1981) further noted that, since the 1930s, many writers have explored the ability of financial ratios to predict failure, and some have even constructed models to explain or predict bankruptcy.

William H. Beaver (1966) was the first to utilize financial ratios to develop a univariate method to predict failure. This effort was followed shortly thereafter by Edward I. Altman (1968), who utilized a linear form of Multiple Discriminant Analysis (MDA) to develop a model, consisting of five variables (financial ratios), to predict bankruptcy for industrial corporations.

E. I. Altman et al., (1977) later constructed and tested a new bankruptcy classification model which he labeled the Zeta Model. It had seven variables and was quite accurate in predicting corporate failure for up to five years in advance of the event. In the same year R. C. Moyer (1977) tested the Altman '68 model by applying a new set of data from larger firms in a different time span, but his overall prediction success rate was only 75% compared to Altman's 96%.

Meyer and Pifer (1970) utilized Ordinary Least Square Linear Regression in the earliest attempt to predict the probability of bank failure. Since that time, many articles have been written on the evolution of bank early warning systems and bank failure prediction models, all of which have utilized numerous techniques such as Factor Analysis, Linear and Quadratic MDA, Logit Analysis, Probit Analysis, and more recently, Neural Networks.

Most of the studies involved building a model with a portion of the data and testing it with a hold-out sample. The data of failed banks for a specific period was generally matched on a one for one basis with non-failed banks from the same period, using attributes such as size, location, number of branches, type of charter/regulatory supervision, etc. The Discriminant functions or models finally developed were derived from a small set of variables reduced from a larger set by the particular methodology used.

Although Beaver (1966) concluded that financial ratios do provide helpful data for determining solvency for the first five years before failure, his univariate approach did not show relationships existing between or among the predictor variables.

Edward I. Altman (1968) recognized that the univariate approach had weaknesses, because it merely called attention to the individual signals of approaching problems. He felt such an approach could be misinterpreted, and sometimes confusing (ie: a firm may have poor profitability, but above average liquidity). He, therefore, chose Multiple Discriminant Analysis (MDA) as the statistical technique for his own study of corporate bankruptcy prediction.

The advantage of MDA is that it considers all characteristics simultaneously, while also noting their interaction. Using selected ratios, Altman calculated, as a linear combination of five financial ratios, an overall index of financial health, named the Z-score. By applying MDA to determine the coefficients, and using a cutoff point previously established for the original sample, Altman classified 95% of his 66 firms correctly (Altman, 1968). This study will build a similar linear combination of selected ratios for a commercial bank Z-score.

Milieu of the Study

The focus of this study will be on bank failures occurring in a bank environment shaken by deregulation, technological innovation, globalization, decline of corporate loan business, increasing competition, new capital market products, liquification and securitization of loans, non-payment by less developed countries (LDC) and commercial real estate borrowers on their loans, and new Federal Reserve Bank capital requirements (Rogers, 1993).

Scope and Limitations

The scope of this study will be on all commercial bank failures (excluding savings banks) occurring in the years 1990 through 1994. It may be limited in the fact that certain regions of the country have experienced more bank failures than others, and at different times.

Preliminary Research Question

What is the predictive ability of the 25 variables (financial ratios) used in this study to distinguish between commercial banks that fail (Failed) and those that do not fail (Non-failed), one, two and three years before the failure occurs?

Hypothesis: Failed scores <=> Non-Failed scores

Appropriately selected financial ratios, designed to measure four out of the five CAMEL (see definitions p. 13) categories (excluding Management), should be able statistically to discriminate between Failed (F) and Non-failed (NF) commercial banks.

Null Hypothesis: Failed scores = Non-failed scores

When using appropriately selected financial ratios, designed to measure four out of the five CAMEL categories (excluding Management), there is no discernible difference (alpha = .01) between the z scores of Failed (F) and Non-failed (NF) commercial banks.

Assumptions of the Study

This study assumes that the differences between failed and non-failed commercial banks are attributable to the same variables regardless of local regional conditions.

Definition of the Terms

The following glossary of key terms were extracted from a book on Multivariate Data Analysis written by J.F. Hair, R.E. Anderson, R. L. Tatham, and W.C. Black, in 1992.

ALPHA: The significance level associated with the statistical testing of the differences between two or more groups. Typically small values, such as .05 or .01 are specified to minimize the possibility of making a Type I error, (ie: rejecting the null hypothesis when it is in fact true).

ANALYSIS SAMPLE: When constructing classification matrices, the original sample should be divided randomly into two groups, one for developing the Discriminant function and the other for validating it. The group used to compute the Discriminant function is referred to as the analysis sample.

CATEGORICAL VARIABLE: Referred to by some as a nonmetric, nominal, binary, qualitative, or taxonomic variable. When a number or value is assigned to a categorical variable, it serves merely as a label or means of identification. The number on a football jersey is an example.

CENTROID: The mean value for the discriminant Z scores for a particular category or group. A two-group Discriminant Analysis has two centroids, one for each of the groups.

CLASSIFICATION MATRIX: Also referred to as a confusion, assignment, or prediction matrix. It is a matrix containing numbers that reveal the predictive ability of the discriminant function. The numbers on the diagonal of the matrix represent correct classifications, and the off-diagonal numbers are incorrect classifications.

COLLINEARITY: A concept that expresses the relationship between two (collinearity) or more independent variables (multicollinearity). Two predictor variables are said to exhibit complete collinearity if their correlation coefficient is 1 and a complete lack of collinearity if their correlation coefficient is 0. Multicollinearity occurs when any single predictor variable is highly correlated with a set of other predictor variables.

CUTTING SCORE: The criterion (score) against which each individual's discriminant score is judged to determine into which group the individual should be classified. When the analysis involves two groups, the hit ratio is determined by computing a single "cutting" score. Those entities whose Z scores are below this score are assigned to one group, while those whose scores are above it are classified in the other group.

DISCRIMINANT FUNCTION: A linear equation in the following form:

$$Z = W_1X_1 + W_2X_2 + \ldots + W_nX_n \qquad (1\text{-}1)$$

where:

Z = Discriminant score

W = Discriminant weight

X = Independent variable

DISCRIMINANT LOADINGS: Referred to by some as structure correlations, they measure the sample linear correlations between the independent variables and the discriminant function.

DISCRIMINANT SCORE: Referred to as a Z score; defined by the previous equation.

DISCRIMINANT WEIGHT: Referred to by some as a discriminant coefficient, its size is determined by the variable structure of the original variables. Independent variables with large discriminatory power usually have large weights and those with little discriminatory power usually have small weights; collinearity among the independent variables will cause an exception to this rule.

HIT RATIO: The percentage of statistical units (banks) correctly classified by the discriminant function.

HOLDOUT SAMPLE: Also referred to as the validation sample, it is the group of subjects (banks) held out of the total sample when the function is computed.

LINEAR COMBINATION: Also referred to as linear composites, linear compounds, and discriminant variates, they represent the weighted sum of two or more variables.

METRIC VARIABLE: A variable with a constant unit of measurement. If a variable is scaled from 1 to 9, the difference between 1 & 2 is the same as that between 8 & 9.

PARTIAL F (or t) VALUES: When a variable is added to DA equation after many other variables have already been entered into the equation, its contribution may be small. The reason is that it is highly correlated with the variables already in the equation. The partial F test is simply an F test for the additional contribution to predictive accuracy of a variable above that of the variables already in the equation. A partial F value may be calculated for all variables by simply pretending that each, in turn, is the last to enter the equation. This method gives the additional contribution of each variable above all others in the equation. A t value may be calculated instead of F values in all instances, with the t value being the square root of the F value.

POTENCY INDEX: A composite measure of the discriminatory power of a predictor variable when more than one discriminant function is estimated. Based on discriminant loadings, it is a relative measure upon which predictors can be compared.

PRESS'S Q STATISTIC: A measure of the classification power of the discriminant function when compared to the results expected from the chance model. The calculated value is compared to a critical value based on the chi-square distribution, and if it exceeds this value, then the classification results are significantly better than would be expected by chance.

PREDICTOR VARIABLE: Independent variable.

SIGNIFICANCE LEVEL: See Alpha.

TOLERANCE: The proportion of the variation in the independent variables that is not explained by the variables already in the model (function). It can be used to protect against multicollinearity. A tolerance of 0 means that a predictor (independent variable) under construction is a perfect linear combination of variables already in the model (equation). A tolerance of 1 means that a predictor is totally independent of the other predictors already in the model. The default option in most computer packages sets the minimum acceptable tolerance at .01. This design allows quite a bit of redundancy or multicollinearity in the predictors. In short, if at least 1 percent of the variable in the response variable remains unexplained by the predictors already included in the function, the predictor variable under construction will be allowed to enter the function.

TYPE I ERROR: The probability of rejecting the null hypothesis when it should be accepted, that is, concluding that two means are significantly different when in fact they are the same. Small values of alpha lead to rejection of the null hypothesis as untenable and acceptance of the alternative hypothesis that population means are equal.

TYPE II ERROR: The probability of failing to reject the null hypothesis when it should be rejected, that is, concluding that two population means are not significantly different when in fact they are.

U STATISTIC: See Wilk's Lambda.

VECTOR: A representation of the direction and magnitude of a variable's role as portrayed in a graphical interpretation of Discriminant Analysis results.

WILK'S LAMBDA: The ratio of within-groups sum of squares to total sum of squares.

Plan of Presentation

This study is divided into five chapters.

Chapter I includes the background and its history, the purpose and justification, a statement of the problem, the rationale and milieu of the study, the scope, limitations, preliminary research question, and assumptions, and definitions of the terms.

Chapter II provides a review of the literature on the failure of commercial banks, and to some extent on S&Ls, and notes the various methodologies utilized.

Chapter III describes the methodology applied to develop the models in this study and the approach used to develop decision rules.

Chapter IV contains a review of the research findings and decision rules that were developed.

Chapter V contains a summary of the study and presents the implication and conclusion drawn from this study.

CHAPTER II

REVIEW OF THE LITERATURE

Historical Background

Since the thirties, many financial researchers have explored the ability of financial ratios to predict failure. From those early studies, such as the work of Smith and Winakor (1935), researchers have found that ratios of failing firms are different from those of firms that continue to be viable (Altman, 1993). These studies generally have analyzed financial ratios constructed from accounting data in bank reports regularly filed with the appropriate government agencies. Information from the analysis is then incorporated into some type of monitoring system used by regulators or other stakeholders in identifying troubled banks when possible. William H. Beaver (1966) devised the earliest corporate bankruptcy model.

An Overview of the Present Chapter

This chapter begins with the explanation of Beaver's work and the earliest work by Altman (1968), both of whom showed they could predict financial distress by using financial data. It next offers explanations of the various banking studies using such multivariate statistical techniques as linear and quadratic Multiple Discriminant Analysis (MDA), Ordinary Least Squares Regression, Factor Analysis, Logit and Probit Analysis, and more recently a technique called Neural Networks.

Summary of Literature Reviewed

Early Studies

Beaver, W. H. (1966) wrote the earliest major article concerning the use of financial ratios to develop univariate methods to predict failure. He defined failure as the inability of a firm to pay its financial obligations. As dependent variables, he selected 79 Failed and 79 Non-failed firms for the period 1954-1964. In doing so, he used size and SIC numbers (industry) as the matching attributes. As independent variables, he started with thirty ratios, grouped in six "common element" groups, and eventually selected six, one from each group. The six ratios were (1) Cash Flow to Total Debt, (2) Net Income to Total Assets, (3) Total Debt to Total Assets, (4) Working Capital to Total Assets, (5) Current Assets to Current Liabilities, and (6) a No-Credit Interval. Beaver found that Cash Flow to Total Debt was the most useful in predicting failure. He concluded that the use of ratio analysis can predict failure at least five years before the actual failure.

Altman, E.I. (1968) used Multiple Discriminant Analysis (MDA) to assess the quality of ratio analysis as an analytical technique for predicting corporate bankruptcy. As dependent variables, he used thirty-three bankrupt and thirty-three nonbankrupt firms with data for the period 1946-1965. Altman also used size and industry as matching attributes. He defined a failed firm as one that had filed for bankruptcy under chapter X of the National Bankruptcy Act. In building a linear discriminant function or model to predict failure, he selected the following five ratios: Working Capital to Total Debt, Retained Earnings to Total Assets, EBIT to Total Assets, Market Value Equity to Book Value of Debt, and Sales to Capital Assets. The result of his work was the development of a general index or Z-score with decision rules for the resulting scores as follows:

Non-bankrupt firms = Scores greater than 2.99
The Zone of Ignorance = Scores between 1.81-2.99
Bankrupt firms = Scores below 1.81

Altman predicted bankruptcy up to two years before bankruptcy occurred.

The Seventies

Meyer, P., and Pifer, H. (1970, September) did the first quantitative study of bank failure, using OLS Linear Regression to discriminate between bankrupt and solvent banks facing similar local and national conditions. They used thirty bankrupt and thirty solvent banks in their original work, and nine bankrupt and nine solvent banks in a holdout study. For the 1948-1965 period, Meyer and Pifer used city, size, age, and similar regulations as their matching attributes. From an original group of thirty-two ratios, they eventually selected 5-9 ratios. Their definition of failure was a "closed" bank. The results of their study show that even when failure is due to embezzlement, financial measures can evaluate the relative strength of banks. Meyer and Pifer were able to categorize banks as to failing or solvent with an accuracy of about 80% with a lead time of one or two years.

Stuhr, D. P. and Van Wicklen, R. (1974, September) developed a scoring technique that provided a measure of the condition of each member bank, compared with other member banks in the Second Federal Reserve District. The long term goal was to identify banking factors that would signal changes in a bank's condition from data available between field exams. Using Discriminant Analysis, they evaluated the degree of discrimination between high-rated and low-rated banks. They did so by measuring the difference between the average scores of the two groups, and how closely the scores clustered around their respective group averages. Using data for the period 1964-1970, they examined all state chartered and national banks in the Second Federal Reserve District for variables measuring asset quality, capital adequacy, management quality, bank size, organizational structure and loan-asset ratio. For the years 1967 and 1968, they correctly classified 106 out of 109 state member banks, and 166 out of 170 national banks as having either high or low ratings. Thus, the fit of the discriminant functions to the process of assigning summary ratings was quite good. Stuhr and Wicklen concluded that the discriminant functions appear to have moderate predictive power, but emphasized that all results should remain tentative until they could be duplicated over a longer period.

Sinkey, J.F. Jr. (1975, March) used Multiple Discriminant Analysis (MDA) to identify and describe characteristics that distinguish problem banks from nonproblem banks by (1) testing for group mean differences, (2) describing the overlap between groups, and (3) constructing rules to classify observations (banks) into either problem or nonproblem groups. For the period 1969-1972, he gathered data from 110 problem banks and 110 nonproblem banks. As matching attributes, Sinkey used geographic market area, total deposits, number of banking offices, and Federal Reserve membership. His definition of failure was any situation where a bank violated a law or regulation, or engaged in an unsafe or unsound banking practice to such an extent that the present or future solvency of the bank was in question. Sinkey used the FDIC classification of problem banks: (1) serious problem-potential payoff (PPO)-a bank with at least a 50% chance of requiring FDIC assistance, (2) serious problem (SP)-one that threatens ultimately to involve the FDIC in a financial outlay, and (3) other problem (OP)-one that had a significant weakness, with a lesser degree of vulnerability, and needing aggressive supervision by The FDIC. Sinkey designed financial ratios to measure the bank's performance in areas such as capital adequacy, efficiency, and liquidity. Using ten-variable sets, the discriminant tests showed that both the group mean vectors and group dispersion matrices were significantly different in all four years. Furthermore these differentials, as expected, increased over time.

Korobow, L. and Stuhr, D.P. (1975, July) identified banks that were potentially vulnerable to financial difficulty, compared with those that were resistant. Their aim was to identify a bank's ability to withstand adverse economic or financial developments from data that were regularly available, without the benefit of an on-site examination. The period studied was 1969-1975. The authors concluded that eight variables (out of twelve ratios) in a discriminant function were sufficient to distinguish between sound and weak banks based on the summary ratings given them by supervisory personnel. They used Data from state member banks and national banks from the Second Federal Reserve District, obtained in an earlier study by Stuhr and Van Wicklen (September 1974). The results suggested that by using several alternate procedures, it was possible to identify vulnerable banks before the deterioration of their financial condition. The discriminant functions developed in this study correctly classified all banks with low summary ratings, and nearly all banks with high summary ratings.

J.F. Sinkey, Jr. and D.A. Walker (Winter, 1975) sought to provide a study of problem banks. They focused on the description of structural features of problem banks, and compared the operating characteristics between problem and nonproblem banks. Also, they used a statistical technique called ANOVA that focused on the difference between groups. This technique yields a test statistic called the F ratio or F-statistic, which decides whether differences between the means of two or more samples are attributed to chance. They studied data for the year 1973 for sixty-two problem and sixty-two nonproblem banks, matched according to geographic market, total deposits, the number of banking offices, and federal examination agency. The authors used proxy variables to measure management's performance in such areas as capital adequacy, operating efficiency, liquidity, and rate of return. Four measures of capital adequacy were: Capital to Total Assets, Capital to Risk Assets, Excess Capital Funds to Risk Assets, and Loans to Capital plus Reserves. The authors again classified banks as Serious Problem-Potential Payoff (PPO), Serious Problem (SP), and Other Problem (OP). Empirical findings suggested that the average problem bank appeared to have financial difficulties at least one year before bank examiners recognized them.

Korobow, L., Stuhr, D. P., and Martin, D. (1976, July) wanted to detect the potential deterioration in banks, specifically to find the smallest set of variables used to detect signs of financial deterioration. They investigated measures of vulnerability using the financial data of 350 Second Federal Reserve District member banks, which were routinely reported to bank regulators on the July 1975 report. They found a set of the following six variables more efficient than any other combination, including a twelve variable combination: Total Operating Expenses to Total Operating Revenues, Total Loans to Total Assets, Commercial and Industrial Loans to Total Loans, Provision for Loan Loss to Total Loans and Investments, Net Liquid Assets to Total Assets, and Gross Capital to Risk Capital. Their observations suggested that vulnerability increases with diminished financial performance as measured by the early warning indicators employed. For any two banks, the one with the lower score (more vulnerable) should have a higher probability of receiving a low supervisory rating following the base year.

Altman, E. I. (1977) developed a system for identifying serious financial problems in S&Ls. He did so by classifying them into categories of relative financial soundness by analyzing the information reported semiannually. Also, he used quadratic Discriminant Analysis to compare the characteristics of problem S&Ls with those in various degrees of good standing. Altman developed an integrated system of three separate, two group, quadratic models. He examined data from 65 S&Ls whose conditions at some time in the past were deemed serious (SP) (ie: receiverships, contribution of loans, purchase of assets, and supervisory mergers), fifty-four temporary problem (TP) S&Ls (those that had serious financial problems like those just described, but did not result in FDIC action), and 126 S&Ls with no-problems (NP). The period studied was 1966-1973, and SMSA locations were the matching attributes. Altman originally started with thirty-two ratios plus twenty-four trends in these ratios, and later reduced this number to twelve. He defined a serious problem S&L as one for which the FSLIC provided financial assistance, or one in which the S&L was supervisory merged with a sounder institution. The final stage in this performance-predictor system was to assign a general composite rating to each association being evaluated. It involved a prediction of group membership using each of the three two-group models (ie: NP vs. SP, NP vs. TP, and TP vs. SP). Although eight possible combinations existed, only four were realistic. The models were extremely impressive for predicting S&L performance up to three semiannual reporting periods before the specified critical date.

Altman, E.I., Haldeman, R.G., and Narayanan, P. (1977) constructed, analyzed and tested a new bankruptcy classification model. In doing so, they used both linear and quadratic Multiple Discriminant Analysis (MDA). There were fifty-three bankrupt and fifty-eight non-bankrupt firms matched using the period 1969-1975, and a minimum asset size of $20 million. Twenty-seven ratios were initially examined, but the final discriminant function contained only seven, which were: (1x) EBIT to Total Assets, (2x) Normalized Measure of Standard Error Estimate around ten year trend in 1. (3x) EBIT to Total Interest Payments, (4x) Retained Earnings to Total Assets, (5x) Current Assets to Current Liabilities, (6x) Common Equity to Total Capital, and (7x) Size Measured by Total Assets. Altman et al. concluded that the ZETA model is quite accurate up to five years before failure, with successful classification of well over 90% one year before failure, and 70% up to five years before failure.

Martin, D. (1977) set out to develop an early warning system model using both Logit and Discriminant Analysis, but chose Logit, since he felt probability estimates to be of greater interest than simple classification. He studied 5,700 nonfailed banks with fifty-eight failed banks for the period 1970-1976, and originally chose twenty-five ratios in the following four broad groups: Asset Risk, Liquidity, Capital Adequacy, and Earnings. Martin's best model, of six tested, had four variables characterizing (1) profitability, (2) asset quality, and (3) capital adequacy. He found no Liquidity variable explicitly included in the model. Martin compared logit and discriminant models in the context of discriminant-analysis. Based on classification results or percent correctly classified, his best variables were (1) Net Income to Total Assets (NI/TA), (2) Gross Charge Offs to Net Operating Income (GCO/NOI), (3) Commercial Loans to Total Loans (CL/TL), and (4) Gross Capital to Risk Assets (GC/RA). He identified failure as an occurrence of failure, or supervisory merger, or other emergency measure to resolve an eminent failure situation. Martin found that, beginning in 1973, bank loan problems began to rise sharply, causing an increase in the importance of earnings, capital, and those factors for which Commercial Loans to Total Loans could be a proxy. The results showed, however, that the relevance of conventional bank soundness varies over business cycles, and the empirical link between capital adequacy and actual occurrence of failure will be weak in periods where bank failures are infrequent. Furthermore, in periods of stress caused by increased loan losses, such measurements of weakness as earnings, capital and asset composition can suggest risk, but the link with failure is not a perfect prediction.

Santomero, A.M., and Vinso, J.D. (1977) sought to obtain evidence on the return to bank capital by obtaining estimates of the cross-section riskiness of the present banking structure. In addition, they studied banks' sensitivity to variations in bank capital. It was accomplished by using a stochastic process technique that integrates the probability distribution of future capital values at the riskiest point in a single bank's expected future path. The study reviewed data from 300 to 400 banks during the period 1965-1974. Their definition of failure was a point at which the regulator suspends the operation of the institution. The study resulted in the first estimates of cross-section failure probabilities for the industry, analyzed the sensitivity of this distribution to capital account shifts, and developed a problem bank screen to isolate outliers. Results further indicated that the industry had only a small risk of suspended operations, but some of the banks exhibited a higher risk potential because of low capital ratios, and/or high variability over the sample period.

Moyer, R.C. (1977, Spring) tested Altman's (1968) model by applying a new set of data to the same variables used in the original model. The variables were (1) Working Capital to Total Assets, (2) Retained Earnings to Total Assets, (3) Earnings before Interest & Taxes to Total Assets, (4) Market Value of Equity to Book Value of Debt, and (5) Sales to Total Assets). Moyer used linear Multiple Discriminant Analysis (MDA), after acknowledging that Altman claimed there was no difference in the predictive accuracy of linear and quadratic MDA. The study used data from twenty-seven bankrupt and twenty-seven non-bankrupt firms, matched by industry and size, for the period 1965-1975. Results showed that parameters applied to a data set of larger firms from a different time span had a general success rate of 75% compared to the original (Altman, 1968) 96%. Moyer felt that by using new data, a better explanatory power could be obtained from the model, if the variable Market Value of Equity to Book Value of Debt, and Sales to Total Assets were eliminated.

Korobow, L., Stuhr, D.P., and Martin, D. (1977, August) reported on the study of a nationwide test of the early warning ideas and procedures developed from information from banks of the Federal Reserve Second District. The authors grouped member banks into four regions and placed in six size classifications, starting with zero to $10 million, and ending with $300 million and over. The ratios used were: Loans and Leases to Total Sources of Funds, Equity Capital to Adjusted Risk Assets, Operating Expenses to Operating Revenues, Gross Charge Offs to Net Income and Provision for Loan Losses, and Commercial and Industrial Loans to Total Loans. Results suggested that these early warning procedures could provide insight into the degree of bank risk and could improve the efficiency of bank supervision. The report showed that several important measures of bank financial condition, namely (1) Capital in relation to Risk Assets, (2) Operating Expenses and Revenues, (3) Loss Provisions, and (4) certain indicators of portfolio risk, can be combined to provide an index of bank vulnerability. However, the forecasts for the largest two size groups were the least efficient.

Hanweck, G.A. (1977, November) conducted the necessary research for a bank screening program, using Probit analysis. Using random sample techniques for the period 1971-1975, they obtained data from 177 insured, nonfailed banks and twenty failed banks. The authors used fourteen banks as the holdout sample to test the predictive performance of the model. The determination of failure was made solely by the chartering authority. Closed banks were those declared insolvent. Factors leading to bank failure were: Net Operating Income to Total Assets, the Proportional Rate of Change of that ratio, and Loans to Capital. The failing bank scenario emerging from these results is one indicative of faltering earnings, leading to an overextension of credit, followed by the inability of the loans to bolster earnings. The usefulness of the model as an early warning system is its ability to predict failure, and it does well.

Sinkey, J.F. Jr. (1977, December) set out to find out what balance sheet and income statement figures could have arrayed in an ex-post early warning system to spotlight the problems of Franklin National Bank. He employed a unique

application (one group) of discriminant analysis, called an "outlier" or "peer-group" model. Using data for the fifty largest banks in the USA for the period 1969-1973, Sinkey used six ratios for the univariate model and seven ratios for the multivariate model. Univariate, bivariate, and multivariate outlier tests suggested that by year-end 1972
it was time to be suspicious of Franklin National Bank. As early as year-end 1971, univariate income measures and risk return analysis showed that Franklin National Bank was a significant outlier. Although the univariate and bivariate tests did better than the seven variable tests, the bivariate tests outperformed the univariate tests due to the risk return dimension.

Sinkey, J.F. Jr. (1978, May) attempted to (1) derive alternate weighted capital ratios from the bank exam process, (2) focus on descriptive Discriminant Analysis models as opposed to predictive ones, and (3) analyze the success of the FDIC's net capital ratio (NCR) in identifying recent bank failures. He used Discriminant Analysis in studying data from 143 problem banks and 163 nonproblem banks randomly selected for the year 1973. Although Sinkey started with twenty-one ratios, he ultimately reduced them to six, and a bivariate combination. Sinkey found that NCR is the most important discriminator between problem and nonproblem banks. It means:

$$NCR = [K + R - C]A \quad \text{where} \tag{2-1}$$

K = total capital accounts

R = valuation reserves

C = "substandard," "doubtful," and "loss" classifications.

A = quarterly average of gross assets for the calendar year, where gross assets are total balance sheet assets including reserves, but excluding expense accounts and cash shortage accounts.

The results suggested that a bank's volume of substandard loans account for about 80% of a problem bank's classified loans. Consequently, the procedure for identifying problem banks depends heavily on the volume of loans designated substandard. Sinkey discovered that, during this period, most failed banks had large volumes of substandard loans, as early as sixteen to twenty-two months before failure, while banks with low NCRs did not fail.

Rose, R.S., and Scott, W.L. (1978, July) examined in detail the financial characteristics of commercial banks that failed during the postwar period. They tested the mean-differences and used quadratic Multiple Discriminant Analysis on data from sixty-nine failing banks, matched by size and market area with sixty-nine solvent banks for the period 1965-1975. Rose and Scott studied 110 measures of profitability, liquidity, asset composition, capital structure, prices, and expenses. They reduced the variables to only four: Loan to Asset ratio, Return on Net Worth, Employee Benefits, and the relative holdings of State and Local Obligations. The results showed that failing institutions are sometimes statistical outliers for an extended period (up to six years), rather than for only one or two years. Failing banks were found to display a greater risk exposure and lower proportions of liquid assets than solvent banks. They also appeared to reduce earnings significantly below the industry norms for an extended period. Although their revenues compared with earning assets were higher, their net operating earnings dropped well below those of other banks. The failing banks were vulnerable for an extended period until overwhelmed by economic, financial or legal problems. In general, the linear equations did better than the quadratic functions, except the years immediately preceding failure. Quadratic equations consistently classified solvent banks more accurately, while linear functions were more successful at classifying failed banks.

The Eighties

Pettway, R.H., and Sinkey, J.F. Jr. (1980, March) suggested (1) an early warning technique using accounting and market information, which might be useful in creating a more efficient method of scheduling bank examinations, and (2) tested the proposed dual-screening techniques on a population of banks that had recently failed. In doing so, they used Sinkey's failure prediction model with Discriminant Analysis, and the same variables, but different coefficients, depending upon the year of failure for the accounting screen. The market model was developed by Sharpe (1963) and later refined by Sharpe (1974) and Lintner (1968). Data for the accounting screen were taken from thirty-three failed and thirty-three nonfailed banks matched as to deposit size, number of branches and location (SMSA or county). Data for the market were taken from twenty four large non-failed banks with actively traded securities. The period studied was 1970-1975. Failure was defined as occurring when there was a declaration of insolvency by the chartering agency, or a reorganization to avoid de jure failure. The accounting filter used a two variable MDA classification model with (1) a measure of efficiency (Operating Expenses as a percent of Total Operating Income) and (2) a measure of safety (Investments as a percentage of Total Assets). The results were that a dual screening system would be useful in scheduling examinations. Specifically, the system would have scheduled examinations for six of the largest banks, which subsequently failed at least one full year before the beginning of the classifying examination. However, the same system did not flag any of the six non-failed banks as problem banks during a three year test period.

Pettway, R.H. (1980, March) examined the returns on bank equities to determine if these returns were sensitive to an increased potential for bankruptcy. He applied the market model developed by Sharpe (1963) and later refined by Sharpe (1974) and Lintner (1968). Pettway used data from the five largest bank failures, and two merged or reorganized banks for a total of seven banks with sufficient trading. The control group were twenty-four non-failed large banks with actively traded securities for the period 1972-1976. He found that the examination and classification information was not uniquely important. The markets for equities of these large failed banks exhibited characteristics of efficiency, as they quickly translated increasing potential for bankruptcy into share prices and returns.

Shick, R.A., and Sherman, L.F. (1980, Autumn) tested the usefulness of stock prices as indicators of changes in a bank's financial condition, applying the logic derived from the efficient market hypothesis. They used the modified version of Fama, Fisher, Jensen and Roll's (1969, February) Residual Analysis approach, which employed the one factor version of the Capital Asset Pricing Model. The model described the relationship between returns on the individual security, as well as returns on the market. Data from twenty five banks were studied for the period 1967-1976. The average residuals for the sample showed a significant downward trend for the period of fifteen months before the bank's ratings were revised, clearly indicating that bank stock prices do reflect changes in bank condition. The authors cautioned that the findings were preliminary, since the sample size was relatively small, and the banks were not randomly selected.

Ho, T., and Saunders, A. (1980, December) developed a model of bank failure based on the theory of catastrophe, originally suggested by Rene' Thom (1968 & 1972) and developed by E.C. Zeeman (1973). The findings demonstrated that, under certain reasonable behavioral conditions, a catastrophic jump in the probability of bank failure, called (F), could occur, even if the Federal Reserve Bank was willing to act as a continuous source of lender of last resort loans. It was shown that even if regulators intervened, or heavily aided banks when their Fs were very high, their action was not sufficient to prevent catastrophic jumps in F.

Booker, I.O. (1983, November) described the Cates Risk Monitoring System (RMS), the objective of which was to identify poorly managed, or exceptionally aggressive banks from a given population. David C. Cates is a bank stock analyst with his own firm. Banks were placed in one of five categories after a series of tests were performed. Closer scrutiny was required of banks with higher risk (4's and 5's). The five critical areas assessed were: profitability, liquidity, asset quality, capitalization and holding company status. Some tests compared the bank's ratio against its peer group, while some used absolute standards, and others examined trends. A pass or fail mark would then be assigned by the clerk, along with a rating based on the number of fails. RMS used thirty one tests with twenty three being applicable to banks and eight to holding companies. The process resulted in assigning a summary rating to failed banks, and indicating performance categories that contributed to a lower rating.

Bovenzi, J.F., Marino, J.A., and McFadden, F.E. (1983, November) studied such questions as: (1) did prediction models improve when exam data was used, as opposed to those with call data only, and (2) as the lead time before failure was lengthened, did the accuracy of the model deteriorate. They used Probit analysis, which yielded a measure of the probability of failure for each bank, and developed three models. The authors used data from four failures in 1980, eight in 1981, thirty four in 1982, and twenty six in the first half of 1983, plus a random sample of nonfailures from call reports of 1977-1981. All commercial banks that required outlays from the deposit insurance fund were defined as failures. The results showed that when examination data was included, it generally improved the accuracy of the model's classification capability, but it was less useful relative to call data as the interval between the data and the failure year increased.

Korobow, L., and Stuhr, D.P. (1983, November) sought to report on refining peer groupings, improving the efficiency of the early warning screen, and providing a realistic appraisal of the vulnerability of banks in light of their business orientation. Starting with eleven ratios, they finally selected the following five ratios: (1) Loans and Leases to Total Sources of Funds, (2) Equity Capital to Adjusted Risk Assets, (3) Total Operating Expenses to Total Operating Revenue, (4) Gross Loan Losses to Net Operating Income plus Provision for Loan Losses, and (5) Commercial & Industrial Loans to Total Loans, Gross. The results suggested that early warning systems could consider some form of peer groupings along the lines developed here, but it required that bank size itself not affect calculation of the composite scores. The authors found that the influence of bank size could be controlled by a subgroup scoring approach, such as devising segments for those banks with foreign offices and those having none.

Putnam, B.H. (1983, November) explained early warning systems and Federal Reserve screening ratios, and identified those institutions requiring special supervisory action based on their financial data. Putnam noted that the three federal bank regulatory agencies, by combining resources, devised the Uniform Bank Performance Report, which was fifteen pages of detailed data and financial ratios. For the report, bank peer groups were based on size, number of branches and location. He found that there were four primary determinants of financial soundness: earnings, liquidity, asset quality, and capital adequacy. When these four were weighted and aggregated into a composite score, they were capable of ranking banks according to their financial condition.

Avery, R.A., and Hanweck, G.A. (1984, September) examined empirically the factors associated with bank failure. The objective was to estimate a failure model based upon recent experience, and contrast its implications with model estimates constructed in an earlier era. Using logit analysis, they studied data for all failed banks (100) during the period 1979-1983, and a 10% random sample of non-failed banks (1190) as of year end 1976, eliminating banks over $250 million in assets. Failed banks were treated as nonfailures for all periods except the one in which they failed. Nonfailed banks were weighted with a factor of ten, and failed banks were weighted with a factor of one. Starting with the nine original ratios, they eventually selected (1) Net Income After-tax to Total Assets, (2) Net Loans (Total Loans less Loan Loss Reserve Allowance) to Total Assets, (3) Equity Capital plus Loan Loss Reserve Allowance to Total Assets, and (4) Commercial & Industrial Loans to Net Loans. The evidence showed that a small number of financial ratios could predict the short term failure probability of a bank. In addition, it noted that local economic variables, and lagged financial variables added little to the forecast. The authors qualified the analysis by reminding us that the findings might not apply to large banks since there sample was of banks less than $250 million in assets.

West, R.C. (1985) explored a new approach to early warning systems, by creating composite variables that describe banks in terms of their financial and operating characteristics. He used Factor Analysis and Logit Analysis to measure the condition of individual banks and to assign them a probability of being a problem bank. In factor analysis, the observed variables can be expressed as linear functions of one or more common factors, and another factor that is unique to each observed variable. He used sixteen ratios from call reports and three from bank examinations. Each bank's score on a given factor was a normalized standard deviation, and therefore provided information about each bank with respect to the mean of the sample. For the period 1980-1982, data was obtained from 1900 banks from seven states (all state member banks and holding company banks), each having at least one exam in the data bases. The study indicated that Factor Analysis, combined with multivariate Logit estimation using factor scores as inputs, is a promising technique. Assignment of the probability of bank failure was based on factors reflecting the different financial and operating characteristics of banks. Of the common factors emerging, four closely resembled the CAMEL components: capital adequacy, asset quality, earnings, and liquidity. The results show that examination generated information verifies the crucial role that asset quality plays in determining bank soundness.

Korobow, L., and Stuhr, D.P. (1985) presented a new measure to evaluate models which predict severe bank weakness or failure. Using the probability approach, they resolved the problem in conventional measures of percentage classified correctly (CC) by weighting CC by (1) banks that actually weakened or failed, as a percentage of those that fail a model's hurdle test, and (2) the percentage of all weak or failed banks correctly classified. With the new measure, they compared the performance of several early warning models that had recently been developed. Probability estimates have not been used in most forecasting models, but the process can rate the financial condition along a continuous scale, instead of denoting banks as either strong or weak. Weighted efficiency (WE) is defined as:

$$WE = \frac{(BWF)(BWF)}{(VB)(TWF)}(CC) \tag{2-2}$$

where

CC = % of banks classified correctly (Standard measure)

BWF = Weak (or failed) banks correctly identified by model

VB = Banks failing a hurdle test by the model

TWF = Total number of weak (or failed) banks in sample

$\frac{BWF}{VB}$ = % of banks failing hurdle test that actually weakened (or failed)

$\frac{BWF}{TWF}$ = % of all weak (or failed) banks correctly classified by the model

Results of the study showed that the Korobow and Stuhr model, which does not use examination data, was second best in performance to the West model. As compared to probability models, failure prediction models incline to yield low weighted efficiency scores, consequently, models of bank failure that hinge on financial factors will tend to overpredict failure, and score low on efficiency.

Short, E.D., Driscoll, G.P. Jr., and Short, F.D. (1985, May) (1) quantified the extent to which differences in risk decision making influence the probability of failure, and (2) determined whether the explanatory power of risk decision variables changed over time. Using a Probit estimation technique, they compared asset and liability portfolios of failed banks with those of nonfailed banks from reports for the years 1964, 1975, and 1982-1983. The banks selected were taken from a stratified random sample in millions of dollars as follows: 0-25, 25-100, 100-500, 500-1,000, and over 1,000. In addition, the banks were matched according to size and state. Five ratios were selected: (1) Capital to Assets, (2) Loans to Assets, (3) US Treasury Securities to Assets, (4) Core Deposits to Liabilities, and (5) Purchased Funds to Liabilities. The results suggested that managerial decisions involving higher risk were significant in the determination of bank failures. They also indicated that decision variables in the 1982-1983 estimation period had higher explanatory power than those in earlier periods such as 1964 and 1975.

Peterson, R.L., and Scott, W.L. (1985, May) looked at the causes of bank failures for the period 1982-1983 and the first quarter of 1984. Their results indicated that bank failures can be categorized as (1) related to fraud or manipulation, (2) related to poorly managed rapid growth, or (3) related to sustained low performance. The primary contributors to failure were low performance and loan losses, but many times they were not noticeable until the year before failure. A low Equity to Assets ratio was consistently an early indicator of impending failure, although it was not a cause of failure itself. Other indicators of possible failure included: (1) sustained Asset or Time and Savings Deposit growth of 20% or more per year, (2) growth in Other Liabilities relative to other banks of same size, and (3) elevated ratios of Loans to Assets. The results indicated that deregulation and management laxity, uncorrected by regulation, were the primary causes of bank failures.

Rose, P.S., and Kolari, J.W. (1985, Winter) examined the statistical adequacy of the FDIC's Integrated Monitoring System (IMS), whose key feature was its screening procedure called "Just a warning system" (JAWS). The system tested financial performance by comparing selected bank ratios with established critical values. Without performing a peer group analysis, or formulating a composite bank performance score, it ranked individual banks according to the number of failed performance tests. Rose and Kolari used both univariate and multivariate statistical methods to judge the ability of the system variables to recognize a worsening financial condition before a bank closes. Matching size differences of no more than 10%, identical supervisory authority and regulations, and location in the same county, the authors used data for the period 1965-1977, and observed twenty-three ratios. The authors found many variables on a univariate basis significant in discriminating a bank's condition up to six years before failure. However, multivariate statistical techniques showed only a limited overall classification ability and high Type I error rates. Furthermore, they found that as to predictive accuracy, linear models outperformed quadratic models in all years, and their most important ratio was Total Loans to Total Deposits. Two other variables that were highly discriminatory were (1) Net Operating Income to Total Assets, and (2) Interest Expense on Deposits and Fed Funds Purchased to Total Operating Income.

W.R. Lane, S.W. Looney, and J.W. Wansley (1986) applied the Cox Proportional Hazards Model to the prediction of bank failures. Their methodology was to use linear and quadratic analysis with one hundred thirty failed and three hundred thirty four matching non-failed banks for the period 1979-1983. Their sample was matched according to geographic location (SMSA), charter status, asset size, holding company affiliation, and age. Using twenty one original ratios, the resulting discriminant functions used the following ratios:

One Year Cox and MDA:	CLTL, LODE, TCTA, OEOI, and NITA.
Two Year COX:	MSTA, LOTA, CLTL, OEOI, NITC, TCTA, and TEBT.
Two Year MDA:	MSTA, LOTA, CLTL, OEOI, NITC, and LODE.

The authors found that the Cox model was not vulnerable to criticisms toward parametric techniques, since the methodology was essentially nonparametric, and it provided information regarding the expected time to failure not available from more other classification techniques. Overall, the model's classification rates were found to be similar to those developed from discriminant analysis, but it was useful in detecting financial distress.

Looney, S.W., Wansley, J.W., and Lane, W.R. (1987, May) focused on the misclassifications from the Lane, Looney, and

Wansley Model, and the causes of a bank's success or failure, by using MDA to standardize the ratios for each bank. With data from 1984-1986, the authors analyzed two hundred sixty five failed banks and two hundred ninety nonfailed banks for the two year model, as well as two hundred fifty failed and two hundred seventy eight nonfailed banks for the two year model. As matching attributes, they used geographic location, charter status, age, holding company membership, and size. The results indicated the pitfalls in traditional MDA models, since these models were built with a weighted average of five years away from the data to which they were applied. This resulted in expanding critical Type I error rates to over 50% for the MDA models, and the conclusion that major changes in the economy could not be assimilated unless the model was re-estimated frequently. By including variables to measure agricultural loans and state branching laws, the authors found that the Cox model would be improved. Furthermore, they found that failed banks were typically smaller, had a larger proportion of assets in commercial and industrial loans, and experienced higher operating expenses and lower profitability.

Hirschhorn, E. (1987, July/August) sought to find out if the information generated by regulatory agencies in evaluating bank condition was better than appraisals by market analysts. He used the Market Model, also known as the Capital Asset

Pricing Model (CAPM), to determine if bank examination ratings have information not otherwise available to the public. Evidence from Hirschhorn's analysis was mixed on the information content of CAMEL ratings. His findings showed that the CAMEL ratings did not contain information on bank condition beyond what was already available to the public. Also, none of the individual components of the CAMEL rating contained information that could consistently predict changes in stock returns, except for Capital Adequacy, indicating minimal support that examination ratios of banks have an information advantage over stock prices. He further found that the composite CAMEL rating does not predict future stock performance.

Pantalone, C.C., and Platt, M.B. (1987, July/August) addressed the issue of whether the usual measures of bank performance and risk taking are always able to predict the future success or failure of commercial banks. To do so, they built an early warning model of bank failure, and tested it by comparing it with earlier models to detect changes in risk factors that might be due to deregulation or changes in the intensity of economic activity. The authors used Logit Regression Analysis to develop a linear model built for each of three time periods: twelve months, eighteen months and twenty four months before failure. They then classified a bank as zero if healthy, and one if failed. Using data for the period 1981-1984, they analyzed one hundred thirteen Failed banks and two hundred twenty six nonfailed banks, selected by random sample. Starting with nineteen original ratios, the authors ultimately selected four as the best predictors: (1) Net Income to Total Assets, (2) Equity Capital to Total Assets, (3) Total Loans to Total Assets, and (4) Commercial and Industrial Loans to Total Loans. The findings showed that, even with publicly available data, bank failures can be predicted accurately, in advance of failure. The authors concluded that poor bank management, causing excessive risk taking, fraud and embezzlement, continues to be the principal cause of bank failure. They further found that deregulation affected the overall rate of bank failure, but not the pattern among banks, while economic conditions had only a peripheral effect on either.

Sinkey, J.F. Jr., Terza, J.V., and Dince, R.R. (1987, Autumn) took a successful bankruptcy prediction model for non-financial corporations, called the zeta model, and tested it's ability to predict bank failures. This study used Probit and MDA techniques, and called attention to the fact that Probit has an advantage over MDA, in that it allows discussion of the significance of individual coefficients, plus it does not require the assumption of multivariate normal distribution of variables. The authors analyzed thirty failed and forty eight nonfailed banks, matched according to location, size, and regulatory jurisdiction. A hold-out sample of thirty four failed and two hundred fifty nonfailed were matched similarly. The initial sample was for the 1980-1982 period, while the holdout sample was for 1983. Of the eight ratios used, liquidity (Liquid Assets divided by Total Assets) and capitalization (Total Assets divided by Total Equity Capital) were found to be the best discriminators. The findings showed that, although not as accurate as the original zeta model, the version of the zeta model in this study was 75% successful in identifying bank failure. Consequently, the study, as applied to commercial banks, can only attest to limited support for cross industry validity of the model, and it did not find a subset of variables that was more accurate than Altman et als' (1977) original set of seven. The authors concluded that bank failure prediction models may not be as accurate as those for nonbanks because of (1) the inability of bank accounting data to reflect market values, (2) the criminal misconduct in bank failures, and (3) the process of declaring banks insolvent.

Abrams, B.A., and Huang, C.J. (1987, October) explained bank failures during the 1982-1983 period using a Probit model, and the following sixteen ratios: Net Worth/Total Assets, Net Income/Total Assets, Net Income/Total Assets in preceding year, Loans/Assets, Farm Loans/Assets, Securities maturing 10 years or more/Total Assets, Real Estate Loans/Total Assets, CDs/Total Assets, Total Asset Size, Dummy Variable for Affiliation with Holding Company, Dummy Variable indicating Unit Bank or otherwise, Market Share of five largest banks in the reporting bank's central office SMSA or County, Growth rate in Total Deposits during preceding five-year period, Allowance for Loan Loss divided by Total Loans, Asset Growth in preceding year, and Share of Deposits in SMSA. Their findings suggested that a bank's balance sheet and income accounting data are important information as to its' likelihood of failure. Also, holding company banks, or larger banks, have a significantly lower probability of failure. The authors concluded there is a higher probability of failing for banks with a heavy percentage of assets in large CD deposits, and having a relatively large loan portfolio.

Whalen, G., and Thomson, J.B. (1988, Ist Quarter), in order to predict a bank's examination rating using only publicly available data, used a Logit Regression technique to construct a model to classify banks as either problem or nonproblem institutions. Factor scores for each sample bank were developed by using the Factor Analysis method, and Logit regressions were then estimated using the factor scores as independent variables. The estimated coefficients of financial ratios or factors were anticipated to be positive if they evidenced greater risk or financial weakness (such as lower capital, lower asset quality and lower earnings). The three Logit models were: (1) large sample (seventy observations), (2) small sample (fifty eight observations), and (3) random sample (forty banks from small sample), and used data from the period 1983-1986. There were originally twenty two ratios, with the primary measure of prediction being an indicator of asset quality (Non-performing Loans and Leases to Primary Capital) with a positive coefficient as expected. Banks were assigned to the groups with higher risks by using the 50% probability cut-off, or critical value. They found that a bank was placed in high-risk group if it had a predicted probability value above the cut-off, and the misclassification costs of Type I and Type II errors were equal. The results demonstrated that banks can be classified into different risk categories by using a limited number of ratios in relatively simple models constructed solely from publicly available data. The finding also show the best discriminator was the net capital ration (PCNCA/TA).

Graham, F.C., and Horner, J.E. (1988, May) identified and evaluated the factors contributing to the failure of national banks. The authors collected factual information about each bank's geographical location, size, type of ownership, and changes in control, and evaluated each bank's performance in eight broad categories. Data was collected for one hundred seventy one failed banks, fifty one rehabilitated banks, and thirty eight healthy banks (CAMEL 1 & 2) for the period 1979-1987. The results showed the determination of whether a bank will succeed or fail is still manifested in the policies and procedures of a bank's management and board of directors. Even so, poor economic conditions do cause problems in bank profitability. Specific difficulties were found to be in loan policies, identification of problem loans, and compliance systems. More than one-third of the failed and problem banks were affected by insider abuse and fraud.

The Office of Comptroller of the Currency (1988, June) sought to determine the factors that were commonly responsible for poor asset quality. The results were similar to Graham/Horner (1988) in that the primary internal factors of problem and failed banks were the inadequacies existing within boards of directors and management. They found that the harm from adverse external environment conditions were influenced by a banks internal factors. In other words, the study found that the caliber of management, and its reaction to external influences through the establishment and adherence to adequate policies made a difference between failed and healthy banks.

Demirguc-Kunt, A. (1989, May) sought to develop a model of large bank failures, by studying insolvency and failure simultaneously, and using economic insolvency as just one of the factors in the failure decision. She used a simultaneous-equations model to study the determinants of economic insolvency and regulators' reaction to financial condition at the same time. Three equations, were constructed with the first modeling economic insolvency, the second net economic value, and the third estimating the probability of the regulator' failure decision. The Statistical Market Value Accounting Model (SMVAM) was used as an alternate. The author hypothesized that since failure was an event determined by the regulators, their constraints to the failure determination were significant. She defined economic insolvency as negative stockholder contributed equity, and failure as the legal recognition of economic insolvency, noting that the latter was an option that the regulators may or may not choose to exercise. Demirguc-Kunt found that the net equity value (ie: estimated guarantee value less market value) best summarized a bank's financial condition. She further concluded that the best failure model was one whose decision-making process allowed for both the financial condition of the bank, as well as regulator constraints.

Gajewski, G.R. (1989, May) in seeking to present and evaluate a tool to measure changes in the risks that confront banks, constructed a model to predict probability of failure for a bank during a calendar year. He used the Logit method, and from a population of all FDIC insured banks, he selected a choice-based sample of 100% of the failures in 1986 (one hundred forty one banks), and a 20% random sample of surviving banks (2,747), for the period 1987-1989. He defined failure as any bank which is declared insolvent and closed by the regulators, plus those receiving open bank assistance from FDIC to prevent closure. The regulatory concerns were hypothesized to depend on a bank's size, and the number of subsidiary banks in the bank's holding company. The results showed that the constructed model, designed to forecast a bank's failure probabilities, could provide regulators and bankers with useful information. Specifically, the study showed that some banks, when faced with a high probability of failure, will adopt high risk management strategies such as higher yielding commercial real estate loans.

Thomson, J.B. (1989, December) constructed a bank closing model based on the regulatory decision to close being a call option, and bank closings as regulatorily time events. The two equation model so developed was constructed from the Call Option Closure Model, and was compared with two single-equation models in terms of both in-sample and out-of-sample predictive adequacy. Once failure for one year was classified by the model, failures in subsequent years were used to determine the out-of-sample predictive ability of the model. Thomson used a random sample of 1,736 non-failed banks, and all failed banks for the period 1984-1987. He defined failure as occurring whenever a bank closed, merged with FDIC assistance, or required FDIC assistance to remain open. The results showed, that, since bank failures are regulatory timed events, the decision to fail can be modeled as a call option whose value is a function of the bank's charter, its solvency, and the cost to the FDIC of closing the bank. Thomson compared his two equation model with alternative single equation models, and found that the latter had slightly better classification capabilities, but that, with the addition of variables for economic condition, the failure predictive accuracy of the single equation model was improved.

The Ninties to the Present

Gajewski, G.R. (1990) developed a two step model of bank closure, modelled as a regulatory event, which he estimated and compared to several single equation models, and then validated on out-of-sample data. He developed a two step approach using a bank's primary capital-asset ratio for one period, and the bank's probability of closure in the next period as endogenous variables. By imitating the regulators' screening process, a two step Logit estimation method produced parameter estimates for the model. The probability of closure in 1986 was a function of the bank's condition at mid year 1984 and 1985, and the dependency of the bank's home county on the oil and gas sector in 1982. Gajewski studied 100% (one hundred thirty four) of the banks failing in 1986, and a 20% random sample of the survivors (2,747). The results found that profits will be lower with deregulation that intensifies competition, forcing out of business banks that are less efficient and lack diversification.

Seballos, L.D., and Thomson, J.B. (1990, September 1) investigated bank failure between 1982 and 1989 caused by economic slumps in specific regional areas, and the behavior of bank management in markets that were deregulated and competitive. They found that, while many banks failed during the period due to the economic problems in various regions, a bank's ultimate survival was resolved based on the exercise of good management techniques. During the decade regional energy and agricultural problems caused volatile performance for the local economies, but banks were hurt primarily because their portfolios diversification was limited by geographical restrictions in branching. Because markets for banks were found to be less regulated and more competitive, bank loan margins shrunk, and their exposure to risk became more difficult to manage. Deregulated deposit markets and volatile interest rates caused managers in the 1980s to struggle with new sources of risk.

Gilson, S.C. (1990, October) reviewed changes in the ownership and control of corporations that defaulted on their debt. He studied one hundred eleven publicly traded companies experiencing financial distress during the period 1979 through 1985. Debt was restructured for fifty of the one hundred eleven companies, while the remaining sixty one declared Chapter 11 bankruptcy. He found that significant changes occurred in the ownership of residual claims when corporations default, and in the manner in which corporate resources were managed and allocated. Specifically, he found that both the incumbent management and the board lose control to creditors and holders of large blocks of stock, each of which place their representatives on the boards. Commercial banks may even gain control through restrictive covenants in their loans. The empirical data showed that only 46% of directors and 43% of CEOs were retained after a firm has restructured, or taken bankruptcy.

Espahbodi, P. (1991) developed and tested four models to identify potential bank failures, and measured the relative ability of Logit and Discriminant Analysis in distinguishing between failed and nonfailed banks. The models were used to assign a probability of failure to each bank, and to rank banks in terms of their failure probabilities. Variables were added to or dropped from each model one at a time based on their contribution to the overall fit of the model. The author used the weighted efficiency measure defined by Korobow/Stuhr (1985), as well as data from forty eight failed and forty eight non-failed banks matched on: FDIC membership status, geographical location, and size for the year 1983. From a group of thirteen ratios, he found four to be significant: (1) Total Loan Revenue to Total Operating Income, (2) Interest Income on State & Local Government to Total Operating Income, (3) Interest Paid on Deposits to Total Operating Income, and (4) Total Time and Savings Deposits to Total Demand Deposits. The results showed that failed banks have a higher percentage of their income from loans, and a lower percentage from state and local government obligations. In addition, greater risks increase the odds of failure, especially when loan quality is poor and mismanagement exists. The Logit and Discriminant models, developed on financial ratios for one and two years before failure, proved to be successful in distinguishing failed from nonfailed banks.

Thomson, J.B. (1991, First Quarter) modeled bank failures of all sizes, which precluded the use of market data, available only for a limited number of large banks. He used a single equation Logit Regression Model, which did not formally distinguish between insolvency and failure, nor did it allow for a study of the bank closure policy. Thomson used data from the years 1982-1988 for banks that failed in 1984-1989, and 1,736 nonfailed banks. The nonfailed sample was split into two random samples of 868 banks each, one of which was used for in-sample forecasting, while the other was used for out-of-sample forecasting. The author used sixteen variables, some of which reflected proxies for CAMEL components, and others for economic conditions. The study showed that the probability that a bank will fail is a function of the variables related to (1) solvency, including capital adequacy, (2) management quality, (3) earnings performance, and (4) relative liquidity of portfolio. He found that, for as much as four years before failure, most CAMEL and economic variables were significantly related to the probability of failure, and that both in-sample and out-of-sample tests indicated good classification accuracy. It was concluded that the differentiation between official failure and economic insolvency was an important one. Finally, up to thirty months before failure, solvency and liquidity were the most important predictors of failure, but as time to failure increased, asset quality, earnings, and management gained in importance.

Whalen, G. (1991, First Quarter) examined the Cox Proportional Hazards Model (PHM), an early warning model that estimated the probability that a bank, providing it had a certain set of characteristics, would survive longer than some specified time in the future, in this case, between zero and twenty-four months. The model's advantages were the ability (1) to produce estimates of the probable time to failure, (2) to generate a survival profile for any commercial bank, and (3) to not require the user to make assumptions about the distributional properties of the data. Whalen studied all failed banks for 1987-1990, and 1,500 non-failed banks, using twelve ratios. The results showed PHM was an effective tool, even when constructed from a small number of variables derived only from publicly available data, The overall classification accuracy was high, while Type I and Type II error rates were relatively low.

Demirguc-Kunt, A. (1991, April) developed a model of the regulators' failure decision process. Her study emphasized that economic insolvency is a market determined event, and that failure is not an automatic consequence. She felt that only when regulatory authorities made a conscious decision to recognize a bank's weakened condition did failure result, because even when market value insolvency exists, authorities may delay closure. She believed bank failures need to be modeled within the framework of a regulatory decision-making process, and used publicly traded banks to determine economic insolvency. In the decision-making process, regulators are always faced with the alternatives of failure versus continued operation. Using a binary choice model, Demirguc-Kunt used data from thirty two failed and fifty nonfailed banks for the period 1973-1989. Banks were matched based on a random sample from the same geographical and asset size dispersion. The results showed that the model performed well out-of-sample, but when regulatory constraints were considered, classification accuracy increased to more than 90%.

Thomson, J.B. (1992) modeled the regulator's decision to close a bank as a Call Option by constructing a two equation model of bank failure that treats bank closings as an event timed by bank regulators, and in addition, estimates bank failures. Using Ordinary Least Squares Regression and Logit Analysis, Thomson studied data from 1,736 randomly selected non-failed banks for the period 1984-1989. His definition of a failed bank was a one that was either liquidated, taken into conservatorship, merged with FDIC assistance, or required FDIC assistance to remain open. The results showed that the decision to close a bank can be modeled as a call option, whose value is a function of the bank's charter, its solvency, and the cost to the FDIC to close the bank. The study recognized insolvency and official failure as separate events, and its results supported the Call Option Closure Model. Tests that were conducted favored the two equation bank failure model over the alternative one-way equation, which did not differentiate between insolvency and failure. The results concluded that delayed closure of insolvent banks was a function of the incentive system confronting bank regulators, and that changes should be made.

Wheelock, D.C. (1992, July) examined bank failures during the 1920s to see if deposit insurance contributed in any way. He used a Probit Model with bank data from Kansas, where membership in state insurance was voluntary. He found that insured banks indicated greater risk taking in their balance sheets, and were more likely to fail than uninsured banks. Risk taking seemed to increase for insured banks when capital declined. The findings indicated that, since Kansas regulations were so strict, other states, with deposit insurance, may have experienced even greater effects on bank failures.

Tam, K.Y., and Kiang, M.Y. (1992, July) introduced to business research a Neural Net approach, which consisted of a non-linear function represented by a number of interconnected homogeneous processing units used to accomplish Discriminate

Analysis (DA). Each unit was a simple computation apparatus, which could model its behavior by means of mathematical functions. After receiving input signals from other units, a unit would generate an output signal based on the output or transfer function, and the network topology determined the routing of output signals to the other units. The sample of bank data was taken from the State of Texas for the years 1985-1987, with fifty nine failed banks and fifty nine nonfailed banks for each of two periods, each matched as to asset size, number of branches, age, and charter status. The authors used nineteen financial ratios that closely followed the CAMEL criteria, and they were grouped into four of the five CAMEL categories (ie: excluding management which is reflected in the other ratios). Their goal was to identify both Neural Net potential, and its limitations as a DA tool, and in doing so, they compared Neural Networks to such techniques as DA, Logistic Regression, kNN (nearest neighbor), and ID3 (Decision Tree). They found that a Neural Network was more accurate than the others, and was a promising method of evaluating the condition of banks.

Satchenberger, L.M., Cinar, E.M., and Lash, N.A. (1992, July/August) developed a Neural Network (NN) model whose discriminating ability between failed and nonfailed banks could be compared to a traditional Logit model. By performing step-wise regression, the researchers reduced twenty nine variables into five, representing one for each of the CAMEL categories (ie: GAAP Net Worth/Total Assets, Repossessed Assets/Total Assets, Net Income/Gross Income, Net Income/Total Income, and Cash Securities/Total Assets) . The results of this study indicated that Neural Networks perform as well as or better than Logistic Regression. The study's conclusions were that NN uses the same financial ratios, but requires fewer assumptions, predicts more accurately, and is more robust. Sample data for savings & loans during the period 1986-1987 were used, and tests were performed for six months, twelve months and eighteen months prior to failure.

Hooks, L.M. (1992, August) investigated how to evaluate risk in an early warning system, based on input as to the makeup of a bank's portfolio of assets. In order to estimate the model's accuracy, asset risk was measured in the following four ways: (1) sample risk weighting measure, (2) non-sample risk weighting measure, (3) Herfindahl index measure, and (4) loan-to-asset ratio. Using Probit Analysis, and data from banks in the Eleventh District, she estimated models for the years 1985, 1987, and 1989. Among the ratios used for variables as proxies for CAMEL ratings were: (1) CAPITAL ADEQUACY-Equity Capital to Assets, (2) ASSET QUALITY-Net Charge-offs to Total Loans, (3) MANAGEMENT EXPERTISE-(a)

Overhead (non-interest) Expenses to Assets, and (b) Loans Extended to Bank Officers to Assets, (4) EARNINGS-Net Income to Assets, and (5) LIQUIDITY-Cash and Securities to Assets. The results indicated that asset risk measures were more important for predicting bank failures in the mid-80s, than in the late 1980s. After the downturn, bank asset risk measurements were less important, while asset quality and bank capital position, reflecting past risk positions, became more important.

Hooks, L.M. (1992, September) examined the stability of the estimates of models of bank failure across the stages of a banking crisis. She proposed an alternative measure of bank portfolio risk, and reexamined several measures of bank portfolio risk. When she estimated the models, Hook's technique was to hold the time to failure interval constant, which enabled comparisons of the model estimates across different time periods. The study found that over time coefficient estimates change notably, suggesting that early warning models are limited by their time-specificity. This implies that policies based on fixed relationships between bank riskiness, and financial variables will be imprecise. The results showed that the asset risk measures were more important for predicting bank failure in the mid-1980s, than in the late 1980s. The higher overall prediction errors of

1985 relative to 1987 and 1989 indicated that it remained difficult to accurately predict bank failures in time periods in which problems were not advanced. By assigning different weights to different categories of assets, differences in risk among categories could be identified at a single point in time, but such action could not control changes in the riskiness of the categories over time.

Martinez, J.E., and Courington, J.M. (1993, Spring) investigated banks in the energy producing states of Louisiana, Oklahoma, and Texas to identify the causes of variation in loan performance. Their basis for doing so was that diversification was made difficult because of geographic barriers to expansion. By measuring the loan loss ratios of sample banks for the years 1985-1990, and using Regression Analysis, the researchers estimated the relationship between the severity of asset problems and their initiatives in risk-taking. They found that much of the variation in problem assets was attributed to differences in local economic conditions, and to poor performance by industries in the energy and agricultural field. They also found that a critical role in bank loan problems was due to excessive risk taking. The authors noted that the FDIC improvement Act of 1989, which controls the amount of federal supervision to the amount of a bank's capital, required the FDIC to eventually assess insurance premiums based on the relative riskiness of banks.

Bansal, A., Kauffman, R.J., and Weitz, R.R. (1993, Summer) examined the effects of inaccurate data on the forecasting performance of both Regression Analysis and Neural Network Analysis. The sample data was from 1,170 observations, one half of which evaluated alternative models, and the other half tested each model's performance. They found that Linear Regression performed better than neural networks in forecasting accuracy, but the reverse was true when the business value of the forecast was used. As the accuracy of data was degraded, however, Neural Net forecasts were more robust than linear regression.

Cole, R., and Gunther, J. (1993, July) examined failure, and the timing of failure, to determine if the two depend on forces in nature. The authors simultaneously modeled bank failure, and bank survival time, by using a Split Population Survival Time Model, developed by Schmidt and Witte. In effect, the determinants of failure and survival time are different. The sample data was taken from quarterly call reports of 10,943 (811 or 7.5% failed) FDIC insured commercial banks for year end 1985 through second quarter 1992. Fifteen variables relating to CAMEL criteria were used, but the results showed that just a small number of variables explain survival time. Although the authors found that equity, capital, troubled assets, and net income are significantly related to the time to failure, they did not find measures of liquidity to be statistically significant.

Coats, P.K., and Fant, L.F. (1993, Autumn) studied Neural Networks (NN) to determine how well they are able to discern patterns or trends in financial data, and to use them to signal an early warning of distress in currently healthy firms. Their objective was to formalize the unarticulated knowledge of experts by uncovering a consistency among them. Their methodology was to build and test four Cascor models for predicting financial distress, with the models representing four different lead times. The authors described each firm using a set of five ratios from Altman's Z-score. They then built four MDA models, based on Z-scores and data used by auditors in identifying troubled firms. Data was obtained from Compustat for years 1970-1989 for ninety four distressed firms, and one hundred eighty eight viable firms chosen randomly. The two sample group sets each contained forty seven distressed and ninety four viable firms. Using auditors' going concern opinions, half were randomly selected to train NN to recognize patterns, while the others tested the network's predictive ability. The results of the study showed that NN was effective than MDA for early detection of distress, and was able to correctly predict the findings of the auditors 80% of the time, when the lead time was up to four years.

Barrow, J., and Horvitz, P. (1993) examined alternative management structures and the extent to which they have affected the behavior of thrifts which were financially distressed. The authors used Logit Analysis to develop a model to predict insolvency, and to show that the probability of returning to solvency is reduced for those firms assigned to the Management Consignment Program (MCP). The results of this study indicated that during the time MCP firms were in the program, the probability of returning to solvency actually declined. The Logit scores indicated that, as compared to thrifts not under government control, the probability of MCP thrifts returning to solvency actually decreased much more so. The results suggested that the management of firms under MCP did behave differently.

Cole, R., Cornyn, B. and Gunther, J. (1995, January) explained the Financial Institutions Monitoring System (FIMS) which was instituted in 1963 by the Federal Reserve to provide estimates of the financial condition of commercial banks insured by the Bank Insurance Fund between on-site examinations. FIMS provides two models using distinct econometric models. One, the FIMS Rating model, uses an ordinal-level logistic regression methodology and assesses a bank's current condition by estimating what a bank's CAMEL rating would be if it were assigned during the current quarter. The other, the FIMS Risk Rating model, uses a binary logistic regression methodology and provides a longer term assessment of a bank's expected future condition by providing an estimate of the probability that a bank will fail during the subsequent two years. Starting with 30 potential exploratory variables, the authors, by means of a step-wise procedure that included only variables that were found to be statistically significant, derived a subset of variables for each of the two models that produces the best estimates of CAMEL ratings. The subsets of variables derived totaled eleven for the FIMS Rating model and nine for the FIMS Risk Rank model. Four in each subset related to Asset Quality, and three others related, one each, to Capital, Earnings and Liquidity. Using a sample of 262 banks that failed during the mid to late eighties, the authors compared the accuracy of the two FIMS models with its predecessor the Uniform Bank Surveillance Screen (UBSS). They concluded that FIMS is superior to the UBSS. It provides objective and consistent measures of a bank's financial condition (ie: determined by rigorous statistical testing, not judged subjectively). It is timely (ie: calculated as soon as a bank files its quarterly Call Report). It is more flexible than alternate systems (ie: UBSS previously used by Federal Reserve, and CAEL, still used by FDIC). Finally, FIMS identifies deterioration or improvement in the banking industry within peer groups and systemwide. By providing estimates of component ratings as well as a composite rating, FIMS allows supervisory authorities to focus on those areas of performance needing the most attention.

In this chapter, the many different approaches used to identify problem and failed banks from a population of banks were reviewed, noting particularly such matters as purpose, methodology, and results. As explained in the "Justification of the Study," Altman (1968) and Altman, et al (1977), using bankrupt non-financial firms (not banks), did provide linear equations showing the value of coefficients and decision rules, but some years later, Sinkey, Terza and Dince (Autumn, 1987) applied the zeta model (1977) for non-financial firms to test its cross-industry validity in the problem of predicting bank failure. They found that although their version of the zeta model was able to identify bank failure about 75% of the time, the original zeta model for non-financial bankrupts was still more accurate. Therefore the new zeta version, as applied to commercial banks, provided only limited support for cross-industry validity of the Altman et al. (1977) zeta model. Similarly, the model developed by Fuller (1990) was only for savings and loans, hence the need to provide a simple, easy-to-use mathematical model strictly for commercial banks.

This study is different from those reviewed in at least two aspects. First, it uses data from the early 1990s, a period immediately following the high failure rates of the late 1980s, to build a new discriminant function. Secondly, a systematic procedure is used to devise an easily understood decision rule to be used with the discriminant function, something not stressed in many of the other approaches. The next chapter presents the methodology used in this study.

CHAPTER III

METHODOLOGY

Choice of Statistical Techniques

Discriminant Analysis (DA) and Logit Analysis are the statistical techniques most frequently used to forecast commercial banking failure. Daniel Martin (1977) compared Logit and linear and quadratic MDA models in classifying banks, and concluded that when the purpose of the study is to classify institutions, as contrasted with estimating probability, MDA is preferred because it requires less computational effort. Also, in using the linear and quadratic forms of MDA to predict bank failures, Martin found no significant difference in the ability of linear and quadratic discriminant functions to distinguish firms which were apt to fail. Pouran Espahbodi (1991) also used both Logit Analysis and MDA in his study. He found that, even though both models were successful in predicting failure one to two years before failure, classification accuracy was better one year before failure for Logit, while MDA was more accurate two years prior to failure.

For the above reasons, Discriminant Analysis was the statistical technique utilized in this study to generate a Predictive Model, otherwise known as a Discriminant Function, to distinguish banks that are apt to be classified within one, two, or three years as (1) FAILED (banks that are closed by their chartering authority), or (2) NON-FAILED (banks that will not need financial assistance and which have a net worth/asset ratio of 2% or more (Gart, 1994)). After the model was produced, the scores of the banks used in the formation of the model were scrutinized to form a Decision Rule for the year 1991 (Fuller, 1990).

Hair, Anderson, Tatum and Black stated in their book, (1992) that if the dependent variable is categorical (FAILED or NON-FAILED), and the independent variables are metric (bank financial ratios), the Discriminant Analysis technique should be used. In addition, Hair et al. contended that DA is appropriate when testing the hypothesis that the group means of the two groups are equal, as in this study. If a study involves only two classifications (two groups), as was the case here, the approach is referred to as a Two-group Discriminant Analysis, whereas Multiple Discriminant Analysis is used to describe three or more classifications (Hair et al., 1992).

Discriminant Analysis

The objectives of Discriminant Analysis are to: (1) ascertain whether the average score profiles of the two groups have statistically significant differences, (2) classify the units (commercial banks) into groups (Failed or Non-Failed) using the scores derived from several variables, and (3) determine which variables account for most of the differences in the average scores of the two groups (Hair et al., 1992).

DA identifies the combination of financial ratios which best discriminates between the two groups, and its linear discriminant function is expressed as follows (Hair et al., 1992, Fuller, 1990):

$$Z = W_1X_1 + W_2X_2 + \ldots + W_nX_n \qquad (3\text{-}1)$$

where:

Z is the discriminant score

W_1, W_2, ..., and W_n are discriminant coefficients or weights, and

X_1, X_2, ..., and X_n are the financial ratios, or independent variables.

Application of the Discriminant Function

In applying the Discriminant Function, financial ratios (see Table 3-1) were first calculated, then multiplied by their coefficients, after-which their products were added together to derive the score.

Table 3-1

Measures of the Operating Characteristics and Expected Relationship between Non-Failed and Failed Commercial Banks

CAMEL CATEGORIES AND VARIABLES	EXPECTED RELATIONSHIPS
BALANCE SHEET	
1-Loan/Deposit (LDR)	F > NF
CAPITAL (CAMEL "C")	
2-Equity Capital/Average Assets (ECAA)	F < NF
3-Total Qualifying Capital/Risk Based Assets (TQCRBA)	F < NF
4-Tier 1 Capital/Risk Based Assets (T1CRBA)	F < NF
5-Tier 1 Capital/Average Assets(Leverage) (T1CAA)	F < NF
6-Dividends Declared/Net Income (DDNI)	F < NF
PROFITABILITY (CAMEL "E")	
7-Net Income/Average Assets) (NIAA)	F < NF
8-Net Income/Average Equity Cap) (NIAEC)	F < NF
9-Net Interest Margin (NIM)	F < NF
10-Net Interest Income/Average Assets (NIIAA)	F < NF
11-Noninterest Income/Average Assets (NOIAA)	F < NF
12-Noninterest expense/Average Assets (NOEAA)	F > NF
ASSET QUALITY (CAMEL "A")	
13-Nonperforming Loans + ORE/Total Loans + ORE (NPLOTL)	F > NF
14-Nonperforming Assets/Equity + Loan Loss Res (NPAELLR)	F > NF
15-Loan Loss Reserves/Nonperforming Loans (LLRNPL)	F < NF
16-ORE/Total Assets (ORETA)	F > NF
17-90+ Day Delinquent Loans/Total Loans (90DDLTL)	F > NF
18-Loan Loss Reserves/Total Loans (LLRTL)	F < NF
19-Net Charge-Offs/Average Loans (NCOAL)	F > NF
20-Domestic Risk RE Loans/Total Domestic Loans (DRRLTDL)	F > NF
LIQUIDITY (CAMEL "L")	
21-Brokered Deposits/Total Domestic Deposits (BDTDD)	F > NF
22-$100+ Time Deposits/Total Domestic Deposits (100TDTDD)	F > NF
23-Int. Earning Assets/Int. Bearing Liab. (IEAIBL)	F < NF
24-Pledged Securities/Total Securities (PSTS)	F < NF
25-Market Value/Book Value Securities (MVBVS)	F < NF

Ratios and Categories only are from on-line financial services of Ferguson & Company, Irving, Texas

For example, if FAILED banks have scores of less than 1.2 and NON-FAILED banks have scores greater than 1.7, a bank that has a score of .9 will be classified as an FAILED bank. Sometimes a bank's score will fall within a "zone of ignorance" such as between 1.2 and 1.7. This zone, then, is the range in which a bank's classification is considered unknown, and the trade off between the identification of additional FAILED banks will not be large enough to compensate for the cost of incorrectly identifying NON-FAILED banks (Fuller, 1990).

MDA Assumptions

MDA is based on the assumptions that the variables being analyzed have a multivariate normal distribution, and that each population variance and covariance are equal (Norusis, 1988, Hair et al. 1992). Joseph Hair et al. (1992) notes, however, that MDA is not very sensitive to any breach of these assumptions unless there are broad violations. Some studies note that when the variance-covariance matrices are not equal the quadratic form of MDA is preferred, although the quadratic form of MDA is more sensitive to a breach of the assumption of multivariate normal distribution (Fuller, 1990).

Type I and Type II Error

This study used trial-and-error to identify linear

Predictive Models which had an acceptable Type I error in relation to their Type II error. The percentage of FAILED commercial banks misclassified was displayed as Type I error, while the Type II error denoted the percentage of NON-FAILED commercial banks misclassified. Because closed (FAILED) banks incur a cost, Type I error was considered more costly than Type II error (Fuller, 1990).

Stepwise Method-Wilk's lambda

A stepwise method was used based on the Wilk's technique, which maximized the overall multivariate F ratio for differences among groups. The stepwise approach ascertained the best discriminant variable, followed by the next best, then the next best, etc. and added each of them to the discriminant function providing their partial F values were equal to or exceeded a 3.84 F-to-enter criterion. Partial F values are the measurements of a ratio's ability to discriminate among the groups of commercial banks after recognizing the ability of the function's other ratios to discriminate among the groups. If partial F values were equal to or less than 2.71 F-to-remove, a previously selected ratio was removed from the discriminant function (Fuller, 1990).

Not all combinations of variables were examined in the stepwise method, but within the constraints of the 3.84 F-to-enter and 2.71 F-to-remove criteria, it ascertained the set of ratios which maximized the overall multivariate F ratio. The sequential selection process of using the next best discriminant variable, produced a reduced set of ratios that was as good or better than a complete set (Fuller, 1990).

Prior Possibilities and Misclassifications

The study considered the Prior Probabilities and Misclassification Costs. Prior Probabilities have to do with the likelihood of a bank failing the categories being scrutinized (i.e., NON-FAILED, or FAILED), while Misclassification Costs are those that are incurred when a commercial bank is identified in the wrong category (Fuller, 1990).

Fuller (1990) claimed Barth et al. (1985) and Wang et al. (1987) used several priors or probability cutoff values to study their model's accuracy when influenced by different probability cutoff values. This study, however, used only a 50% probability factor, since each FAILED bank was pair matched with a NON-FAILED bank. Instead, this study examined the differences in z-score cutoff values. When different z-score cutoff values are used, the impact of applying different misclassification costs can be better reflected. There will be more correct classifications of FAILED banks and more misclassifications of NON-FAILED banks, as the z-score cutoff value for the NON-FAILED banks is lowered (Fuller,1990).

Specifically, this study utilized several z-score cutoff values for NON-FAILED banks ranging from 1.00 to .10, in order to show the difference in the misclassification cost between FAILED and NON-FAILED banks (Fuller, 1990).

Application of Discriminant Analysis

Step 1-Variable Selection

(a) Dependent (Categorical): FAILED or NON-FAILED banks.

(b) Independent (Metric): The twenty-five (25) financial ratios (Table 3-1) were those reflected on the Financial Highlights printout report from Ferguson and Company, Irving, Texas (recently merged with Sheshunoff Information Services Inc. of Austin, Texas), an electronic publishing firm for the Financial Services Industry. The source of the printouts was the on-line computer service between Ferguson and Company and Crestar Bank, Richmond, Virginia. The ratios, except for one (loans to deposits) were categorized in four out of the five

CAMEL categories (excluding Management). The name CAMEL is the acronym for Capital, Asset Quality, Management, Earnings (Profitability), and Liquidity, the five characteristics used by the FDIC to rate banks on a failure-to-quality basis. Ratings are scaled from 1 (excellent) to 5 (poor), but the composite rating is not necessarily derived by taking the mean of all five characteristics. Banks in good condition are indicated by ratings of 1 or 2, and problem banks are those with ratings of 4 or more (Gart, 1994)).

Step 2-Data Collection

(a) A list of failed banks (closed by their chartering authority) for the years 1991, 1993, 1994, and 1995 was obtained from the FDIC.

(b) The FDIC list was scrutinized to eliminate all savings banks, so that the final list was comprised only of commercial banks.

(c) Using the on-line computer terminal at Crestar Bank, a Financial Highlight sheet for each failed commercial bank on the final list was printed for the years 1991, 1993, 1994 and 1995. The final list (minus Savings Banks) contained the following number of failed banks: 101 for 1991, 40 for 1993, 11 for 1994, and 6 for 1995.

(d) Data also was drawn from the same years for NON-FAILED banks (having a positive net worth of 2% or more, and still open at the end of the year of comparison). Each FAILED bank was matched with a NON-FAILED bank according to 1) location (either city or state), and 2) asset size, in one of the following categories: $0 to $25 Million, $25 to $50 Million, $50 to $100 Million, $100 to $500 Million, $500 to $1 Million, and over $1 Million.

Step 3-Sample Division

(a) Data from 1990 was used to develop the 1991 Model (1991 Failed banks). The 1991 sample consisted of 202 banks, 101 FAILED and 101 NON-FAILED. All banks that failed (closed by their chartering authority) during the year 1991 were classified as FAILED. They were pair-matched (as previously described) with an equal number of NON-FAILED banks which were still open on December 31, 1991, and had a positive net worth of 2% or more.

(b) Next, data from 1992 was used to develop a sample of 80 banks, 40 FAILED and 40 NON-FAILED. All banks that failed (closed by their chartering authority) during the year 1993 were classified as FAILED. They were then pair-matched (as previously described) with an equal number of NON-FAILED banks which were open on December 31, 1993, and had a positive net worth of 2% or more.

Similarly, data from 1993 was used to develop a sample of 22 banks, 11 that FAILED in 1994 and 11 that were NON-FAILED in 1994. All banks that failed (closed by their chartering authority) during the year 1994 were classified as FAILED. They were then pair-matched (as previously described) with an equal number of NON-FAILED banks which were open on December 31, 1994, and had a positive net worth of 2% or more.

(d) Finally, data from 1994 were used to develop a sample of 12 banks, 6 that FAILED in 1995 and 6 that were NON-FAILED in 1995. All banks that failed (closed by their chartering authority) during the year 1995 were classified as FAILED. They were then pair-matched (as previously described) with an equal number of NON-FAILED banks which were open on December 31, 1995 and had a positive net worth of 2% or more.

(e) The 1991 sample was used as the analysis sample to develop the 1991 model, and the 1993 sample was used to validate the results of the 1991 model.

(f) The Discriminant Function or Predictive Model (1991 Model) was then used to test its predictive accuracy for one, two or three years before failure by using the 1994 sample for the years 1992 and 1993, and the 1995 sample for the years 1992, 1993 and 1994.

Step 4-Computer Input & Commands

1-Using SPSS Professional Statistics 6.1 Software marketed by SPSS Inc. of Chicago. Illinois (Norusis, M.J. 1996):

(a) A data file of each the 25 ratios for each of the FAILED and NON-FAILED banks selected for the 1991 sample was established and saved.

(b) Similarly data files of each of the 25 ratios for each of the FAILED and NON-FAILED banks selected for the sample years 1993, 1994 and 1995 were created and saved.

(c) Once the four data files were established, and were accessible on the computer, the 1991 sample data file was opened, and the Classify and Discriminate commands were selected.

(d) Next a grouping variable was selected and minimum and maximum ranges were defined. Afterwards the independent variables were selected.

(e) Next descriptive statistics, function coefficients and matrices were selected.

(f) Next the stepwise variable selection rule selected was to minimize Wilk's Lambda.

(g) Next, the minimum F-To-Enter and F-To-Remove numbers were selected (defaults were 3.84 F-To-Enter and 2.71 F-To-Remove).

(h) Next a selection was made to display the results at each step as well as a summary.

(i) Equal (50%) prior probability for each group (FAILED and NON-FAILED) was then selected.

(j) At this point Plots and Covariance Matrices were selected.

(k) Finally the minimum tolerance level selected was the default (.00100).

2-Computer Analysis to Derive Function (Hair et al., 1992).

(a) The analysis began by examining the unweighted group means and corresponding standard deviations for each of the independent variables based on data from the 1991 FAILED and NON-FAILED banks.

(b) Then it reviewed the tests for equality of group means (chart contains univariate F values, and Wilk's Lambda (U-Statistic) for each variable) used to assess the significance between the means of independent variables for the two groups. The F value is the square of the t value from the two-sample t test, while Lambda is the ratio of the within-group sum of squares to total sum of squares.

(c) It next reviewed the pooled within-groups correlation matrix to determine which variables had large correlation coefficients.

(d) SPSS produced a list of the unstandardized discriminant function coefficients for all variables.

(e) At this point SPSS began the stepwise procedure to determine which variables were most efficient in discriminating between banks. The process started with all the variables excluded from the model, after which it selected the variable that maximized the overall multivariate F ratios for differences among groups.

(f) A minimum F value of 3.84 was required for entry, and the program eliminated any variable whose univariate F ratio fell below 2.71.

(g) Then the variable with the maximum F ratio (smallest Wilk's Lambda for the Discriminant Function) was selected for entry.

(h) The program then entered the first selected variable into the model, with the remaining variables being evaluated on the basis of the distance between their means, after the variance associated with the first selected variable was removed.

(i) Again variables with F values less than 2.71 were eliminated from consideration for entry at the next step.

(j) Then the program selected from the remaining variables the one with the highest F value (smallest Wilk's Lambda) to enter the model and join the first selection.

(k) The second selected variable then entered the model, and variables not in the analysis were eliminated from entry in the next step, if their F values were lower than 2.71. Also, if any previously selected variable had an F value of 2.71 or less, that variable was removed from the model.

(l) After each step SPSS printed a table showing the variables in the model as well as those that were not.

(m) After going through this process until all independent variables had either been included in the function, or the excluded variables had been judged as not contributing significantly to further discrimination, the SPSS program provided a summary table identifying a reduced set of variables which were significant discriminators based on Wilk's Lambda values.

(n) The multivariate aspects of the model were reported under the heading "Canonical Discriminant Functions." It was here that the significance of the discriminant function was noted as well as the canonical correlation figure that when squared, indicates the percentage of the variance in the dependent variable that can be accounted for (explained) by this model.

(o) The standardized canonical discriminant function coefficients are the weights that were used in the validation phase. The loadings were reported under the "Structure Matrix" and were ordered from highest to lowest. Group centroids were also reported and they represented the mean of the individual Discriminant Function scores for each group.

3- Discriminant Function Validation (Hair et al., 1992)

To actually determine predictive ability, it was necessary to construct Classification Matrices, from which the Hit Ratio (percentage of banks correctly classified) revealed how well the Discriminant Function classified the banks. Since the function may do no better than chance, an Optimum Cutting Score or critical Z value was first determined. The process was performed by the computer using prior possibilities and the derived group centroids.

a) Having derived the Discriminant Coefficients (selected variables) that make up the Discriminant Function, the Discriminant Score for each bank was calculated by multiplying each of the Discriminant Variables by its derived coefficient. The Discriminant Score then used the sum of the products of each plus the constant, to produce the individual bank scores.

b) The form in which values or scores were displayed or written calls for six positions, including a decimal point and three decimal digits.

c) A chart was then produced which showed the bank ID and score plus each bank's figures (ratios) for each of the variables selected to be in the Discriminant Function.

d) Basic descriptive statistics were then produced for the discriminant scores in the two groups.

e) Next, a classification output was produced showing each bank by ID number, its actual group, an asterisk indicating if it was misclassified, the highest and 2nd highest probability groups, and the Discriminant Score. It also produced a Classification Matrix or "Confusion Matrix) showing the number and percentage of correct and incorrect classifications, followed by the percentage for overall predictive accuracy. The PLOT CASES command produced histograms showing group overlap, and distribution of the Discriminant Scores.

f) Next Press's Q Statistic was used to test for the discriminatory power of the classification matrix when compared to the Chance Model. Press's Q statistic is a measure that compares the number of correct classifications with the total sample size and the number of groups. The calculated value was then compared with a critical value (the chi-sq value for 1 degree of freedom at the desired confidence level of .01). If it exceeded this criterion value, the classification matrix was deemed statistically better than chance.

$$\text{Press's } Q = \frac{\{N - (n \times k)\}^2}{N(k-1)} \qquad (3\text{-}2)$$

where

N = Total sample size

n = number of observations correctly classified.

k = number of groups.

Step 5-Interpretation

Since the discriminant function was statistically significant and the classification accuracy was acceptable, the process continued in two distinct phases.

a) In the first phase the Discriminant Function was examined to determine the relative importance of each independent variable in discriminating between groups by using one or more of the following methods: Standard Discriminant

Weights, Discriminant Loadings, and/or Partial F Values.

b) The second phase profiled the characteristics of the groups based on the group means, in order to understand the character of each group based on the predictor variables.

Specifically in this phase:

1) The independent variables were ranked in terms of both their weights (partial F values) and loadings--indicators of their discriminating power. Signs did not affect the rankings; they indicated only a positive or negative relationship with the dependent variable. For interpretation purposes, only those variables that had been found to be significant in the discriminant function were considered.

2) The characteristics of the groups were profiled by attempting to understand what the differing group means on each variable indicated. For instance, for all variables in the model, higher scores indicated greater importance.

Decision Rules

This study utilized several z-score cutoff values for NON-FAILED commercial banks that ranged from 1.00 to .10. The different z-score cutoff values were employed to identify the z-score cutoff values acceptable to use as reference points in developing a decision rule. A decision rule was developed by examining the trade-off between the additional misclassified NON-FAILED commercial banks relative to the additional FAILED commercial banks correctly classified as the NON-FAILED bank's z-score cutoff value was lowered from 1.00 to .10 in increments of .10 (Fuller, 1990).

The commercial banks' scores as well as actual and predicted classifications were examined at the two z-score cutoff values which had the most acceptable trade-offs. The accuracy of the model's decision rule was compared to the model's accuracy at the z-score cutoff value, which had a classification scheme that most closely resembled that of the established decision rule (Fuller, 1990).

In developing the decision rule, a zone of ignorance may be established, although none was needed here. A zone of ignorance represents the range of z-scores where the trade-off between the misclassification of non-failed and correct classification of failed commercial banks does not clearly warrant the assignment of commercial banks to a particular category (Fuller, 1990).

A test of the Null hypothesis that the means of all derived discriminant functions in both FAILED and NON-FAILED commercial banks are really equal and 0 can be based on Wilks' Lambda. This is due to the fact that the significance level of the observed Wilks' Lambda can be based on a chi-square transformation of the statistic (Norusis, 1988). Accordingly, a review of the significance level of Wilks' Lambda for each discriminant function derived in this study was the test of the Null Hypothesis that FAILED and NON-FAILED commercial banks had the same means.

Initially, the financial data from 1990 was used to calculate discriminant functions to predict the classification of commercial banks in 1991. Afterwards, the discriminant function was used to predict the sample banks' classifications in 1993, 1994, and 1995. By applying the 1991 data for each 1993, 1994, and 1995 bank in the sample to the Discriminant Function, its predictive accuracy for one, two, or three years before failure was tested.

Summary

In summary, this study, using Discriminant Analysis as the statistical technique:

1) Selected two dependent (categorical) variables, and tested twenty-five independent (metric) variables for their ability to discriminate between the two (categorical) groups (FAILED and NON-FAILED).

2) Collected data for all FAILED commercial banks in the years 1991, 1993, 1994 and 1995, as well as all selected NON-FAILED commercial banks, matched with a specific FAILED bank according to asset size and location (city or state).

3) Created computer data files in SPSS Professional Statistics 6.1 software for each of the years 1991, 1993, 1994 and 1995.

4) Using the SPSS data file for the 1991 as the analysis sample for developing the Discriminant Function and the 1993 sample for Validation, derived a linear Discriminant Function (predictive model), accompanied by a classification matrix showing its predictive accuracy.

5) Interpreted the Discriminant Function to determine the relative importance of each independent (predictive) variable in discriminating between groups, as well as to understand the character of each group based on the predictor variables.

6) Tested the Null Hypothesis.

7) Utilized several z-score cutoff values for NON-FAILED commercial banks to identify a Decision Rule for the Predictive 1991 Model based on the trade off between the additional misclassified NON-FAILED banks, relative to the additional FAILED banks correctly classified.

8) Applied the 1991 Predictive Model and its Decision Rule to the 1993, 1994 and 1995 data, and developed classification matrices for each of the years showing the predictive accuracy for one, two, or more years before failure.

The achieved result of the study was the derivation of a linear Discriminant Function (or Predictive Model) for commercial banks failing in the year 1991, together with a decision rule. The combination of the two will provide all interested persons (depositors, stockholders, bondholders, management, financial services companies, etc.) with an easy-to-use tool or model to determine whether a commercial bank is apt to fail within one, two or three years before failure or closure by their chartering authority.

CHAPTER IV

ANALYSIS AND PRESENTATION OF FINDINGS

In this section, three linear predictive models that identify commercial banks that are likely to be categorized as either FAILED or NON-FAILED are discussed, along with a test of the null hypothesis and an interpretation of the variables selected in the three models.

Next, the models' accuracy in classifying the 1991 sample used to develop the models, and the 1993 sample used for Validation, are compared.

Afterwards, the z-scores of the Commercial Banks in the 1991 samples used to develop the three models are examined and decision rules for each are discussed.

Finally the tests for accuracy of the three 1991 Models on the samples for 1994 and 1995 are discussed and compared.

Failed Commercial Bank Prediction Models

Using the categorical (dependent) variables FAILED and NON-FAILED, and the twenty-five metric (independent) variables described in Chart 3-1, and using the SPSS Professional Statistics 6.1 software for development of a predictive model, three linear discriminant functions were derived from the 1991 sample. The best 1991 Linear Predictive Model had seven discriminant variables, while the second and third best models had five and four variables respectively. Tables 4-3, 4-4 and 4-5 depict the discriminant variables and the coefficients for each of the three models.

Test of the Null Hypothesis

Acknowledging Wilks' Lambda as a Test of the Null Hypothesis (Norusis, 1988), the observed values of Lambda for each of the models and their associated chi-square values, the degrees of freedom, significance levels, and the group means (group centroids) for the seven, five and four variable models are depicted in Table 4-1.

Since the observed significance level is .0000 for each of the three discriminant predictive models, it appears unlikely that the banks which FAIL, and those which survive and are designated NON-FAILED, have the same means in any of the three discriminant functions, therefore, the Null Hypothesis that the means of both functions (FAILED and NON-FAILED) are equal in the population is rejected.

Table 4-1

Data Used to Test the Null Hypothesis

		7 VAR MODEL	5 VAR MODEL	4 VAR MODEL
Wilks' Lambda	=	.365406	.384279	.395480
Chi-square	=	184.738	176.453	171.616
df	=	7	5	4
Significance	=	.0000	.0000	.0000
Group Mean (F)	=	-1.37482	-1.32055	-1.28982
Group Mean (NF)	=	1.24984	1.20050	1.17256

Interpretation of the Variables

Even though the Wilks' Lambdas in this study are statistically significant, they provide little knowledge of the effectiveness of the Discriminant Function in classification. They only provides a test of the Null Hypothesis that the means of the populations are equal (Norusis, 1988).

The importance of individual variables in the function cannot be assessed, since the variables are correlated. Therefore, the value of the coefficient for a particular variable will depend on the other variables in the function. Variables with large coefficients contribute more to the overall discriminant function, except that the magnitude of the unstandardized coefficients is not a good index of relative importance unless they differ in the units measuring them, which is not the case here. Also, the actual signs of the coefficients may be either positive or negative. For instance, negative signs for certain coefficients could just as easily be positive, if other coefficient signs were reversed (Norusis, 1988).

It is possible to determine which variable values result in large and small function values by studying the groups of variables that have coefficients of different signs. The larger weights increase the function. The unstandardized coefficients (Tables 4-3, 4-4, and 4-5) are the multipliers of the variables used in the discriminant function (Norusis, 1988).

The standardized canonical discriminant function coefficients (weights), the pooled within-group correlations between discriminant variables and canonical discriminant functions (loadings), and the partial F values for the variables in the three models are all depicted in Table 4-2.

Table 4-2

Data Used in Interpreting the Variables in Each Model

	7 VAR MODEL	5 VAR MODEL	4 VAR MODEL
Standardized Coefficients			
X13 (NPLOTL) =	-.62356	-.66081	-.66622
X04 (T1CRBA) =	.60544	.54326	.55478
X07 (NIAA) =	.52015	.49161	.50729
X25 (MVBVS) =	.25161		
X06 (DDNI) =	.22883	.22982	.23198
X24 (PSTS) =	-.20653		
X21 (BDTDD) =	-.20197	-.21477	
Pooled Within-Groups Correlations Between Discriminating Variables and Canonical Discriminant Functions			
X13 (NPLOTL) =	-.73771	-.76802	-.78632
X04 (T1CRBA) =	.42971	.44737	.45802
X07 (NIAA) =	.33516	.34893	.35724
X21 (BDTDD) =	-.17183	-.17889	
X06 (DDNI) =	.16504	.17182	.17592
X24 (PSTS) =	-.08531		
X25 (MVBVS) =	.06126		
Partial F Values			
X13 (NPLOTL) =	54.3778	61.6943	62.0333
X04 (T1CRBA) =	37.9440	31.3036	32.3599
X07 (NIAA) =	29.0110	25.6158	27.1066
X25 (MVBVS) =	6.6841		
X06 (DDNI) =	6.1217	6.0657	6.1024
X21 (BDTDD) =	4.7636	5.3342	
X24 (PSTS) =	4.6373		

Note:SPSS Professional Statistics 6.1, SPSS Inc. Chicago

For the interpretation process, the variables were ranked in terms of both their loadings and Partial F values shown in

Table 4-2. Weights were not used in this comparison, since loadings are thought to be more valid than weights (Hair, et al., 1987). As can be noted in Table 4-2, variable X13, Nonperformance Loans Plus ORE to Total Loans plus ORE (NPLOTL), an Asset Quality indicator (CAMEL "A") was ranked number 1 as the best discriminating variable, while variable X04, Tier 1 Capital to Risk Based Assets (T1CRBA), a Capital indicator (CAMEL "C") was ranked number two. The third best discriminating variable was variable X07, Net Income to Average Assets, a Profitability indicator (CAMEL "E").

The loadings and F values for the remaining four variables were smaller and less clear as to their positioning with and within one another. Based on the data in Table 4-2, the numbered entry of each variable into the discriminant function, and considering the fact that variable X06 (DDNI) appeared in all three models, the remaining four variables in the order of their importance would be:

4-X06-Dividends Declared to Net Income (DDNI) a Capital indicator (CAMEL "C").

5-X21-Brokered Deposits to Total Domestic Deposits (BDTDD), a Liquidity indicator (CAMEL "L").

6-X25-Market Value to Book Value Securities (MVBVS), a Liquidity indicator (CAMEL "L").

7-X24-Pledged Securities to Total Securities (PSTS), a Liquidity indicator (CAMEL "L").

Clearly the liquidity indicators X21, X24 and X25 are helpful in discriminating between FAILED and NON-FAILED banks, since they all appear in the seven variable model (Table 4-3). Two of the three liquidity indicators (X24 and X25) drop out of the five variable model, while the other (X21) drops out with the four variable model.

Seven Variable Model

In Table 4-3 the seven variable linear model is depicted. The variables (in Table 4-3) inversely associated with a commercial bank being classified as a NON-FAILED bank are:

1. Nonperforming Loans plus Other Real Estate (ORE) to Total Loans plus ORE (NPLOTL).
2. Brokered Deposits to Total Domestic Deposits (BDTDD).
3. Pledged Securities to Total Securities (PSTS).

Table 4-3

Linear Discriminant Function Identifying Commercial Banks Likely to Experience Failure Within Two years (Best 1991 Model)

SEVEN VARIABLES		COEFFICIENTS	RATIOS	SCORE
Constant		-0.2555729		= ______
CAPITAL (CAMEL "C")				
X4 (T1CRBA)	Tier 1 Capital / Risk Based Assets	0.0430741 X	______	= ______
X6 (DDNI)	Dividends Declared / Net Income	0.0030480 X	______	= ______
PROFITABILITY (CAMEL "E")				
X7 (NIAA)	Net Income / Average Assets	0.1748788 X	______	= ______
ASSET QUALITY (CAMEL "A")				
X13 (NPLOTL)	Nonperforming Loans + ORE / Total Loans + ORE	-0.1043449 X	______	= ______
LIQUIDITY (CAMEL "L")				
X21 (BDTDD)	Brokered Deposits / Total Domestic Deposits	-0.0264608 X	______	= ______
X24 (PSTS)	Pledged Securities / Total Securities	-0.0064131 X	______	= ______
X25 (MVBVS)	Market Value / Book Value Securities	0.0154799 X	______	= ______
			z-Score Total	= ______

The Nonperforming Loans plus ORE to Total Loans plus ORE ratio is associated with loan quality problems of Failed banks and is indicative of Asset Quality, the "A" in the CAMEL rating.

The Brokered Deposits to Total Domestic Deposits ratio reveals a bank's dependence on high risk, higher cost Jumbo CDs and is associated with Liquidity, the "L" in the CAMEL rating.

The Pledged Securities to Total Securities ratio reflects a bank's reliance on borrowing to increase liabilities, rather than obtain core deposits at lower costs, and is associated with Liquidity, the "L" in the CAMEL rating.

The variables (in Table 4-3) positively associated with commercial banks that are apt to be classified as NON-FAILED are:

1. Tier 1 Capital to Total Risk Based Assets (T1CRBA).
2. Dividends Declared to Net Income (DDNI).
3. Net Income to Average Assets (NIAA).
4. Market Value to Book Value of Securities (MVBVS).

Tier 1 Capital to Total Risk Based Assets reveals the level of a bank's required capital to its risk weighted assets as illustrated in Table 1-2. The ratio is associated with Capital, the "C" in the CAMEL rating.

Dividends Declared to Net Income reveals the percentage of Net Income earned by a bank that is distributed to its stockholders, and can be considered a sign of strength. The ratio is associated with Capital, the "C" in the CAMEL rating, since undistributed income accumulates as capital.

Net Income to Average Assets indicates that the NON-FAILED banks are generally more profitable than FAILED banks, and the ratio is associated with Profitability, the "E" or earnings of the CAMEL rating.

Market Value to Book Value of Securities reveals the premium paid by purchasers of the banks' stock and the ratio is generally indicative of Liquidity, the "L" in the CAMEL rating.

Five Variable Model

The five variable linear model is shown in Table 4-4. The variables (in Table 4-4) inversely associated with a commercial bank being classified as a NON-FAILED bank are:

1. Non-performing Loans plus Other Real Estate (ORE) to Total Loans plus ORE (NPLOTL).
2- Brokered Deposits to Total Domestic Deposits (BDTDD).

Table 4-4

Linear Discriminant Function Identifying Commercial Banks Likely to Experience Failure Within Two years (Second Best 1991 Model)

FIVE VARIABLES		COEFFICIENTS	RATIOS	SCORE
Constant		1.0969820		= ______
CAPITAL (CAMEL "C")				
X4 (T1CRBA)	Tier 1 Capital / Risk Based Assets	0.0386504 X	______	= ______
X6 (DDNI)	Dividends Declared / Net Income	0.0030612 X	______	= ______
PROFITABILITY (CAMEL "E")				
X7 (NIAA)	Net Income / Average Assets	0.1652832 X	______	= ______
ASSET QUALITY (CAMEL "A")				
X13 (NPLOTL)	Nonperforming Loans + ORE / Total Loans + ORE	-0.1105779 X	______	= ______
LIQUIDITY (CAMEL "L")				
X21 (BDTDD)	Brokered Deposits / Total Domestic Deposits	-0.0281370 X	______	= ______
			z-Score Total	= ______

The variables (in Table 4-4) positively associated with commercial banks that are apt to be classified as NON-FAILED are:

1. Tier 1 Capital to Risk Based Assets (T1CRBA).
2. Dividends Declared to Net Income (DDNI).
3. Net Income to Average Assets (NIAA).

Note that the second best five variable model (Table 4-4) contains all of the variables found in the seven variable model (Table 4-3) except two Liquidity indicators:

1. Pledged Securities to Total Securities (PSTS).
2. Market Value to Book Value Securities (MVBVS).

The explanations of the variables for Table 4-4 are the same as those used in Table 4-3 and will not be repeated here.

Four Variable Model

The four variable linear model is shown in Table 4-5. The only variable (in Table 4-5) associated with a commercial bank being classified as a NON-FAILED bank is:

1. Nonperforming Loans plus Other Real Estate (ORE) to Total Loans plus ORE (NPLOTL).

The variables (in Table 4-5) positively associated with commercial banks that are apt to be classified as NON-FAILED are:

1. Tier 1 Capital to Risk Based Assets (T1CRBA).
2. Dividends Declared to Net Income (DDNI).
3. Net Income to Average Assets (NIAA).

Table 4-5

Linear Discriminant Function Identifying Commercial Banks Likely to Experience Failure Within Two years (Third Best 1991 Model)

FOUR VARIABLES		COEFFICIENTS	RATIOS		SCORE
Constant		1.0490377		=	________
CAPITAL (CAMEL "C")					
X4 (T1CRBA)	Tier 1 Capital / Risk Based Assets	0.0394699 X	________	=	________
X6 (DDNI)	Dividends Declared / Net Income	0.0030900 X	________	=	________
PROFITABILITY (CAMEL "E")					
X7 (NIAA)	Net Income / Average Assets	0.1705546 X	________	=	________
ASSET QUALITY (CAMEL "A")					
X13 (NPLOTL)	Nonperforming Loans + ORE / Total Loans + ORE	-0.1114830 X	________	=	________
LIQUIDITY (CAMEL "L")					
NONE					
			z-Score Total	=	________

Note that this third best four variable model contains all the variables found in the seven variable model except the three Liquidity indicators (CAMEL "L"):

1. Brokered Deposits to Total Domestic Deposits (BDTDD).
2. Pledged Securities to Total Securities (PSTS).
3. Market Value to Book Value Securities (MVBVS).

Development Model Accuracy

Table 4-6 illustrates the accuracy of the linear models in classifying the sample of 198 banks used for its development.

As shown in Table 4-6, the development model, using the seven variables, had Type I errors of 10.1% and Type II errors of 6.1%. It correctly identified 89.9% of the FAILED banks and 93.9% of the NON-FAILED banks. Its overall accuracy for 198 banks was 91.9%

By contrast with the seven variables (in Table 4-6), the development model, using only five variables, had Type I errors of 13.1% (vs. 10.1%) and Type II errors of 5.1% (vs. 6.1%). It correctly identified 86.9% (vs. 89.9%) of the FAILED banks and 94.9% (vs. 93.9%) of the NON-FAILED banks. Its overall accuracy for 198 banks was 90.9% (vs. 91.9%).

Similarly, by contrast with the seven variables (Table 4-6), the development model using only four variables had Type I errors of 14.1% (vs. 10.1%) and Type II errors of 7.1% (vs. 6.1%). It correctly identified 85.9% (vs. 89.9%) of the FAILED banks and 92.9% (vs. 93.9%) of the NON-FAILED banks. Its overall accuracy for 198 banks was 89.4% (vs. 91.9%).

Table 4-6

Classification Matrices (Accuracy) of 1991 Sample Used to Develop 1991 Model, and 1993 Sample Used for Verification and Cutoffs

	1991 MODEL (Development)		1993 SAMPLE (Validation)		1993 SAMPLE (w/cutoffs)	
	#	%	#	%	#	%
SEVEN VARIABLES (Best)						
FAIL					.30 CUTOFF	
Correct	89	89.9%	31	79.5%	35	89.7%
Type I	10	10.1%	8	20.5%	4	10.3%
Total	99	100.0%	39	100.0%	39	100.0%
NON-FAIL						
Correct	93	93.9%	35	89.7%	35	89.7%
Type II	6	6.1%	4	10.3%	4	10.3%
Total	99	100.0%	39	100.0%	39	100.0%
Overall Accuracy	198	91.9%	78	84.6%	78	89.7%
FIVE VARIABLES (Next Best)						
FAIL					.50 CUTOFF	
Correct	86	86.9%	31	79.5%	35	89.7%
Type I	13	13.1%	8	20.5%	4	10.3%
Total	99	100.0%	39	100.0%	39	100.0%
NON-FAIL						
Correct	94	94.9%	35	89.7%	33	84.6%
Type II	5	5.1%	4	10.3%	6	15.4%
Total	99	100.0%	39	100.0%	39	100.0%
Overall Accuracy	198	90.9%	78	84.6%	78	87.2%
FOUR VARIABLES (Third Best)						
FAIL					.40 CUTOFF	
Correct	85	85.9%	32	82.0%	35	89.7%
Type I	14	14.1%	7	18.0%	4	10.3%
Total	99	100.0%	39	100.0%	39	100.0%
NON-FAIL						
Correct	92	92.9%	36	92.3%	33	84.6%
Type II	7	7.1%	3	7.7%	6	15.4%
Total	99	100.0%	39	100.0%	39	100.0%
Overall Accuracy	198	89.4%	78	87.2%	78	87.2%

Validation of the Models

Seventy eight (78) banks of the 1993 sample were used to validate the 1991 development model. By using the seven variable model with the 1993 sample (1992 data), and contrasting with its development counterpart (Table 4-6), Type I errors were 20.5% (vs. 10.1%) and Type II errors were 10.3% (vs. 6.1%). It correctly identified 79.5% (vs. 89.9%) of the FAILED banks and 89.7% (vs. 93.9%) of the NON-FAILED banks. Its overall accuracy was 84.6% (vs. 91.9%).

Similarly, by using the five variable model with the 1993 sample (1992 data), and contrasting with it's development counterpart (Table 4-6), Type I errors were 20.5% (vs. 13.1%) and Type II errors were 10.3% (vs. 5.1%). It correctly identified 79.5% (vs. 86.9%) of the FAILED banks and 89.7% (vs. 94.9%) of the NON-FAILED banks. Its overall accuracy was 84.6% (vs 90.9%).

Also, in a similar manner, by using the four variable model with the 1993 sample (1992 data), and contrasting with its development counterpart (Table 4-6), Type I errors were 18.0% (vs. 14.1%) and Type II errors were 7.7% (vs. 7.1%). It correctly identified 82.0% (vs. 85.9%) of the FAILED banks and 92.3% (vs. 92.9%) of the NON-FAILED banks. Its overall accuracy was 87.2% (vs. 89.4%).

Decision Rules

Misclassification costs are those that are incurred as a result of incorrectly identifying the category to which a commercial bank belongs. Rudolph and Hamdan (1988) reported that misclassifying a failed S & L as a non-problem cost 100 times more than misclassifying a non-problem S & L as failed. For this reason, a decision rule was established to increase the efficiency of the predictive ability of the 1991 models by limiting the misclassification costs.

Tables 4-7, 4-8, and 4-9 provide information about the three 1991 models (seven, five and four variables respectively) at different z-score cutoff values. By way of illustration, if a commercial bank's z-score is less than the cutoff value, the bank will be classified as FAILED. If it is more than the cutoff value, the bank will be classified as NON-FAILED. Tables 4-7, 4-8 and 4-9 indicate how accurate the models are at z-score cutoff values from 1.00 to .10 decreasing in increments of .10.

Table 4-7

Incremental Changes in the Predicted Number of Banks

Classified as Failed

	z-score Cutoff Values									
	.00 to .10	.11 to .20	.21 to .30	.31 to .40	.41 to .50	.51 to .60	.61 to .70	.71 to .80	.81 to .90	.91 to 1.00
Failed Banks (a) Predicted as Failed	2	4	6	7	7	8	8	8	8	10
Non-Failed Banks (a) Predicted as Failed	4	8	9	13	13	13	15	27	30	35
Trade-off between Failed & Non-Failed Banks (b)	2.0	2.0	1.5	1.9	1.9	1.6	1.9	3.4	3.8	3.5
Failed Banks (a) Percent Accurate	92	94	96	97	97	98	98	98	98	1.00
Non-Failed Banks (a) Percent Accurate	90	86	85	81	81	81	79	67	64	59
Overall % Accuracy	91	90	90	89	89	89	88	82	81	79

a) Best 1991 Model using seven discriminant variables.

b) The trade-off is calculated by dividing the number of additional banks incorrectly identified by the additional banks correctly identified.

Note: Idea for trade-off from Fuller, P.R. (1991). Predicting the financial distress and failure of savings and loan associations (Doctoral dissertation, Mississippi State University, 1990). Dissertation AbstractInternational, 51(11), 3853A

To illustrate the interpretation of Table 4-7 (seven variable model), refer to the column of z-score cutoff values between .21 to .30. In that column, six additional FAILED banks were predicted as FAILED, while nine more NON-FAILED banks were predicted as FAILED. Since the cost of classifying a FAILED bank as NON-FAILED is greater than misclassifying a NON-FAILED bank, the trade-off between the two figures needs to be determined.

Trade-off was calculated by dividing the number of additional banks incorrectly identified by the additional banks correctly identified. A lower trade-off figure, such as 1.5 in this case, is desirable when combined with an enhancement to the development model's ability to predict FAILED banks without too great a loss in the model's predictive ability of the other two areas (ie: NON-FAILED and overall accuracy). As the z-score cutoff is increased in increments of .10, the accuracy in predicting FAILED banks increases minimally, while the accuracy for NON-FAILED banks decreases significantly.

In this case, FAILED bank accuracy increased from 90% in the development model to 96%, while NON-FAILED bank accuracy decreased from 94% in the development model to 85%. At the same time, overall accuracy only decreased from 92% to 90%. For the reasons outlined, .30 was determined to be the z-score cutoff for the seven variable 1991 model.

Z-score cutoff values for the five and four variable development models (Tables 4-8 and 4-9 respectively) were derived in the same manner.

Table 4-8

Incremental Changes in the Predicted Number of Banks Classified as Failed

	z-score cutoff Values									
	.00 to .10	.11 to .20	.21 to .30	.31 to .40	.41 to .50	.51 to .60	.61 to .70	.71 to .80	.81 to .90	.91 to 1.00
Failed Banks (a) Predicted as Failed	1	2	4	6	9	10	12	12	12	12
Non-Failed Banks (a) Predicted as Failed	4	6	7	8	11	14	19	23	28	32
Trade-off between Failed & Non-Failed Banks (b)	4.0	3.0	1.8	1.3	1.2	1.4	1.6	1.9	2.3	2.7
Failed Banks (a) Percent Accurate	87	88	90	92	95	96	98	98	98	98
Non-Failed Banks (a) Percent Accurate	90	88	87	86	83	80	76	71	67	62
Overall % Accuracy	90	89	89	90	90	89	88	85	83	81

a) Second Best 1991 Model using five discriminant variables.

b) The trade-off is calculated by dividing the number of additional banks incorrectly identified by the additional banks correctly identified.

Note: Idea for trade-off from Fuller, P.R. (1991). Predicting the financial distress and failure of savings and loan associations (Doctoral dissertation, Mississippi State University, 1990). Dissertation AbstractInternational, 51(11), 3853A

For illustration purposes, in Table 4-8, refer to the column with z-score cutoff values from .41 to .50. Note that the trade-off was only 1.2, and the accuracy in predicting FAILED banks was 95%, up significantly from the 87% derived in the development model. At the same time the overall accuracy was 90%, only slightly under the 91% of the development model. The most significant decrease was in the accuracy of the NON-FAILED banks which dropped from 95% to 83%. For the reasons stated .50 was the z-score cutoff value selected for the five variable model (Table 4-8).

The z-score cutoff value for the four variable development model (Table 4-9) was selected in the same manner. By referring to the column of z-score cutoff values between .31 to .40, it was determined that the trade-off between failed banks predicted as FAILED and non-Failed banks predicted as FAILED was 1.2. By doing so, the accuracy in predicting failed banks as FAILED was 91%, up from 86% in the development model. Simultaneously the percentage of non-failed banks predicted as FAILED was 85%, down slightly from 93% in the development model, while the overall development model accuracy of 89% was maintained. For these reasons, .40 was selected as the z-score cutoff value for the four variable model (Table 4-9).

Table 4-9

Incremental Changes in the Predicted Number of Banks

Classified as Failed

	z-score Cutoff Values									
	.00 to .10	.11 to .20	.21 to .30	.31 to .40	.41 to .50	.51 to .60	.61 to .70	.71 to .80	.81 to .90	.91 to 1.00
Failed Banks (a) Predicted as Failed	1	2	4	6	8	11	11	11	11	13
Non-Failed Banks (a) Predicted as Failed	2	4	5	7	13	15	19	22	27	31
Trade-off between Failed & Non-Failed Banks (b)	2.0	2.0	1.3	1.2	1.6	1.4	1.7	2.0	2.5	2.4
Failed Banks (a) Percent Accurate	86	87	89	91	93	96	96	96	96	97
Non-Failed Banks (a) Percent Accurate	90	88	87	85	79	77	73	70	65	61
Overall % Accuracy	89	88	89	89	87	87	85	84	81	80

a) Third Best 1991 Model using four discriminant variables.

b) The trade-off is calculated by dividing the number of additional banks incorrectly identified by the additional banks correctly identified.

Note: Idea for trade-off from Fuller, P.R. (1991). Predicting the financial distress and failure of savings and loan associations (Doctoral dissertation, Mississippi State University, 1990). Dissertation AbstractInternational, 51(11), 3853A

Test of the 1994 Sample of Failed and Non-Failed banks

In Table 4-10, the predictive ability of the three 1991 Models were tested for accuracy by using the 1994 sample of 22 FAILED and NON-FAILED banks. All models tested the 1993 as well as the 1992 data for the 1994 sample, and contrasted the results against similar results using the appropriate cutoff values.

Table 4-10

Classification Matrices (Accuracy) of 1991 Model in Testing 1994 Banks for Failure with 1993 and 1992 Data and Using Cutoffs

	1993 DATA		1993 DATA W/CUTOFFS		1992 DATA		1992 DATA W/CUTOFFS	
	#	%	#	%	#	%	#	%
SEVEN VARIABLES			.30 CUTOFFS				.30 CUTOFFS	
FAIL								
Correct	9	81.8%	10	90.9%	8	72.7%	8	72.7%
Type I	2	18.2%	1	9.1%	3	27.3%	3	27.3%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
NON-FAIL								
Correct	10	90.9%	10	90.9%	10	90.9%	10	90.9%
Type II	1	9.1%	1	9.1%	1	9.1%	1	9.1%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
Overall Accuracy	22	86.4%	22	90.9%	22	81.9%	22	81.9%
FIVE VARIABLES			.50 CUTOFFS				.50 CUTOFFS	
FAIL								
Correct	9	81.8%	10	90.9%	7	63.6%	10	90.9%
Type I	2	18.2%	1	9.1%	4	36.4%	1	9.1%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
NON-FAIL								
Correct	10	90.9%	9	81.8%	10	90.9%	9	81.8%
Type II	1	9.1%	2	18.2%	1	9.1%	2	18.8%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
Overall Accuracy	22	86.4%	22	86.4%	22	77.3%	22	86.4%
FOUR VARIABLES			.40 CUTOFFS				.40 CUTOFFS	
FAIL								
Correct	9	81.8%	10	90.9%	7	63.6%	10	90.9%
Type I	2	18.2%	1	9.1%	4	36.4%	1	9.1%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
NON-FAIL								
Correct	10	90.9%	9	81.8%	10	90.9%	10	90.9%
Type II	1	9.1%	2	18.2%	1	9.1%	1	9.1%
Total	11	100.0%	11	100.0%	11	100.0%	11	100.0%
Overall Accuracy	22	86.4%	22	86.4%	22	77.3%	22	90.9%

Seven Variable Model

Using the 1993 data (Table 4-10), the seven variable or best model correctly identified 81.8% of the FAILED banks as FAILED. Using the .30 cutoff value, the accuracy increased to a 90.9%. Concurrently, there were 90.9% NON-FAILED banks correctly identified as NON-FAILED and overall accuracy was 86.4%. Oddly, by using the .30 cutoff value, overall accuracy increased to 90.9%, but NON-FAILED bank accuracy remained constant at 90.9%.

Similarly, when using the 1992 data (Table 4-10), the seven variable model correctly identified only 72.7% (vs. 82.8% for 1993 data) of the FAILED banks. Again the percent of NON-FAILED banks classified as NON-FAILED was 90.9%, while overall accuracy was lower than 1993 at 81.9%.

Five Variable Model

In testing the 1993 data (Table 4-10) and using the five variable or second best model, 81.8% of the FAILED banks were predicted to FAIL, 90.9% of the NON-FAILED were predicted to be NON-FAILED, and the overall accuracy was 86.4%. Each of these figures were the same as those for the seven variable model for 1993 data. By using the .50 cutoff value, FAILED bank accuracy increased to 90.9%, while NON-FAILED bank accuracy decreased to 81.8%, and overall accuracy remained the same as the 1993 data.

When testing the 1992 data (Table 4-10) with the five variable model, 63.6% (vs. 81.8% in 1993) of the FAILED banks were predicted to fail, while the accuracy in predicting NON-FAILED banks as NON-FAILED was 90.9% (identical to 1993). Unfortunately the overall accuracy dropped to 77.3% (vs. 86.4% for 1993 data). By using the .50 cutoff value. FAILED bank accuracy increased to 90.9% (vs. 72.7% for the seven variable model). Simultaneously, NON-FAILED bank accuracy decreased to 81.8%, (vs. 90.9% without the cutoff), and overall accuracy increased to 86.4% (identical to 1993 data).

Four Variable Model

Using the four variable model with the 1993 data (Table 4-10), the same figures from the seven and five variable models emerged: 81.8% of the FAILED banks were predicted to fail, 90.9% of the NON-FAILED banks were predicted not to fail, and overall accuracy was 86.4%. By utilizing the .40 cutoff value, FAILED bank accuracy increased to 90.9% (identical to the seven and five variable models), NON-FAILED bank accuracy decreased to 81.8% (vs. 90.9%), and overall accuracy remained constant just as it had in the five variable comparison.

In evaluating the 1992 data (Table 4-10) with the four variable model, only 63.6% (vs. 81.8% in 1993) of the FAILED banks were predicted to fail, while 90.9% (identical to 1993) of the NON-FAILED banks were predicted not to fail. Unfortunately, overall accuracy decreased to 77.3% (vs. 86.4% in 1993). This overall accuracy figure was identical to the five variable figure. When cutoff values were utilized at .40, there was an increase in FAILED bank accuracy to 90.9% (vs. 63.6%), similar to the increase derived by using the five variable model. There was no change in the percentages of NON-FAILED banks predicted to fail (90.9%), but overall accuracy increased to 90.9% (vs. 77.3%), which was higher than either the seven variable model (81.9%) or the five variable model (86.4%).

Test of the 1995 Sample of Failed and Non-Failed Banks

Table 4-11 shows the predictive ability of the three 1991 models, (and their cutoff values) on the sample of twelve 1995 FAILED and NON-FAILED banks using data from the years 1992, 1993 and 1994.

Table 4-11

Classification Matrices (Accuracy) of 1991 Model in Testing 1995 Banks for Failure with 1994, 1993 and 1992 Data and Using Cutoffs

	1994 DATA		1994 DATA W/CUTOFFS		1993 DATA		1993 DATA W/CUTOFFS		1992 DATA		1992 DATA W/CUTOFFS	
	#	%	#	%	#	%	#	%	#	%	#	%
SEVEN VARIABLES			.30 CUTOFFS				.30 CUTOFFS				.30 CUTOFFS	
FAIL												
Correct	6	100.0%	6	100.0%	6	100.0%	6	100.0%	1	16.7%	3	50.0%
Type I	0	0.0%	0	0.0%	0	0.0%	0	0.0%	5	83.3%	3	50.0%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
NON-FAIL												
Correct	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Type II	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Overall Accuracy	12	100.0%	12	100.0%	12	100.0%	12	100.0%	12	58.3%	12	75.0%
FIVE VARIABLES			.50 CUTOFFS				.50 CUTOFFS				.50 CUTOFFS	
FAIL												
Correct	6	100.0%	6	100.0%	5	83.3%	5	83.3%	1	16.7%	4	66.7%
Type I	0	0.0%	0	0.0%	1	16.7%	1	16.7%	5	83.3%	2	33.3%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
NON-FAIL												
Correct	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Type II	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Overall Accuracy	12	100.0%	12	100.0%	12	91.7%	12	91.7%	12	58.3%	12	83.3%
FOUR VARIABLES			.40 CUTOFFS				.40 CUTOFFS				.40 CUTOFFS	
FAIL												
Correct	6	100.0%	6	100.0%	5	83.3%	5	83.3%	1	16.7%	4	66.7%
Type I	0	0.0%	0	0.0%	1	16.7%	1	16.7%	5	83.3%	2	33.3%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
NON-FAIL												
Correct	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Type II	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Total	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%	6	100.0%
Overall Accuracy	12	100.0%	12	100.0%	12	91.7%	12	91.7%	12	58.3%	12	83.3%

Seven Variable Model

The seven variable or best 1991 model, using 1994 and 1993 data (Table 4-11), had zero percent Type I and Type II errors for both FAILED and NON-FAILED banks with overall accuracy at 100.0% for two straight years with and without using the .30 cutoff value. Unfortunately there was a severe drop in the Type I error percentage when the 1992 data was used. Type I errors were at 83.3% with FAILED bank accuracy at only 16.7%. By using the cutoff value, Type I errors were decreased to 50%, with FAILED bank accuracy being only 50% (vs. 16.7%). Concurrently, Type II errors for NON-FAILED banks remained at zero percent just as it had for the first two years (1993 and 1994). Overall accuracy was reduced to 58.3% without using the cutoff value, and 75.0% when using it.

Five Variable Model

The five variable model (Table 4-11) also had zero Type I and Type II errors for the 1994 data with 100% accuracy in predicting FAILED and NON-FAILED banks and overall accuracy of 100%, but the same was not true with the 1993 data. For 1993 data the five variable model had 16.7% Type I error and 83.3% accuracy in predicting FAILED banks as FAILED. Concurrently, Type II errors remained zero percent, and overall accuracy decreased to 91.7%. The .30 cutoff value generated no improvement in the figures. For 1992 data, the Type I errors remained the same as with 1993 data (83.3%), causing 16.7% accuracy in predicting FAILED banks as FAILED, just as with 1993 data. Again Type II errors remained zero, and NON-FAILED bank accuracy continued to be 100%, but overall accuracy decreased to 58.3%, the same as with the seven variable model. By using the cutoff value of .50, Type I errors were decreased to 33.3% causing 66.7% of the FAILED banks to be accurately predicted as FAILED. Type II errors remained zero, but overall accuracy increased to 83.3% (vs. 75%) for seven variables.

Four Variable Model

Similarly, the four variable model (Table 4-11) using 1994 data had zero Type I and Type II errors with 100% overall accuracy just as the seven and five variable models did. Just as with the five variables, however, the 1993 data produced 16.7% Type I errors and 83.3% accuracy in predicting FAILED banks as FAILED. Also for 1993 data, Type II errors remained at zero and overall accuracy decreased to 91.7%, just as it did with the five variables. The .40 cutoff generated no differences in the figures. The 1992 data produced the same figures as were derived in the five variables, which, of course, was still better than those figures derived for the seven variable model.

CHAPTER V

SUMMARY AND CONCLUSIONS

This study has attempted to develop a Discriminant Function, or simple to use model, for predicting the failure of commercial banks in the nineties, either one, two, or three years before failure occurs. Three models (seven, five and four variables) were derived from the 1991 bank sample of 99 FAILED banks and 99 NON-FAILED banks.

As indicated in Table 4-6 the most discriminating function (best) in the development phase (with Type I error of only 10.1% and overall accuracy of 91.9%) had seven variables (shown in Table 4-3), The next best function (Table 4-4) had five variables with Type I error of 13.1% and overall accuracy of 90.9%, while the third best function (Table 4-5) had only four variables with Type I error of 14.1% and overall accuracy of 89.4%

In the validation test, the same relative results occurred with the seven variable discriminant function rendering the most predictive accuracy (Type I error of 10.3% and overall accuracy of 89.7% with cutoffs) of the three models.

All of the variables appearing in the five and four variable models also appeared in the seven variable model. The differences in the three models were the uses of the three liquidity variables, two of which (PSTS and MVBVS) were not used in the five variable model, and three of which (BDTDD, PSTS, and MVBVS) were not used in the four variable model.

The resulting comparative figures in Table 4-6 indicate that fewer variables do not provide a more efficient discriminant function. Rather it indicates the importance of the three liquidity factors (BDTDD, PSTS, and MVBVS) in providing a more accurate discriminant function.

Tables 4-7, 4-8. and 4-9 show that misclassifications in the predicted number of FAILED banks classified as FAILED can be improved as the z-score values are moved incrementally from .00 to 1.00. By doing so, only one position on the incremental scale provides the least trade-off between FAILED banks predicted as FAILED, and NON-FAILED banks predicted as FAILED. In Table 4-7 (seven variable model) the derived cutoff figure is .30. It means that on any scale between -1.37482 (Group mean for F) and 1.24984 (Group mean for NF), any bank whose z-score is either a negative figure, or less than a positive .30 should be classified as FAILED. Those banks having positive scores above .30 should be classified as NON-FAILED.

Model's Usefulness to Stakeholders

Using only the seven variable model (depicted in Table 4-3) and applying it with its .30 z-score cutoff figure, Table 4-10 shows that 1994 FAILED banks could be predicted at a 90.9% rate one year prior to failure, while dropping to a 72.7% rate two years prior to failure. Overall accuracy was 90.9% for one year, and 81.9% for two years before failure.

More intriguing are the results in the testing of 1995 banks for failure using data from the years 1994, 1993 and 1992. The results show that the accuracy in predicting FAILED banks as FAILED and NON-FAILED BANKS as NON-FAILED was 100% for the first two years prior to failure. Unfortunately results for three years prior to failure, using 1992 data, were far less impressive with accuracy of 50% for predicting FAILED banks as FAILED and 75% overall accuracy.

An interesting development occurred in the testing of the five and four variable models three years prior to failure. The accuracy of both models in predicting FAILED banks as FAILED exceeded the seven variable (best) model in the third year with accuracy of 66.9% (vs. 50.0%) and overall accuracy of 83.3% (vs. 75.0%). One reason for the differences may be that two of the three liquidity variables (PSTS and MVBVS) found in the seven variable model are less accurate three years prior to a bank's failure. Hence the five and four variable models, having excluded the liquidity variables, may be more accurate than the seven variable model for testing banks three years before failure.

By way of summary and for best results, stakeholders should use the three models as recommended below:

1-For predictive accuracy ONE or TWO years prior to failure-use the Seven Variable Model (Table 4-3).

2-For predictive accuracy THREE years prior to failure-use either the Five (Table 4-4) or Four (Table 4-5) Variable Models. (CAUTION: Predictive accuracy with these models is only 66.6% for FAILED banks and 83.3% overall-not much better than chance).

<u>Model Limitations</u>

The difference between the predictive accuracy of the seven variable model (Table 4-3) in testing the 1994 and 1995 samples of FAILED and NON-FAILED banks indicates an inconsistency in the model, which is predicated on the financial data (ratios) used for the three specific 1994 banks which were inaccurately classified.

To recap, the 1995 test involved twelve banks (six FAILED and six NON-FAILED). They were all classified accurately two years prior to bank failure. The 1994 test involved twenty-two banks (eleven FAILED and eleven NON-FAILED). The model inaccurately classified two FAILED banks and one NON-FAILED bank. By using the .30 z-score cutoff, the model's accuracy improved to one FAILED and one NON-FAILED bank. Why did the model not accurately classify the three banks?

To ascertain the answer, the study scrutinized the bank data for the twenty-two banks used in the 1994 test, and averages for each of the seven variables were determined. The differences between the specific bank data (Banks #5, #9, and #24) are depicted in Table 5-1. For FAILED banks, it appears that the two improperly classified banks had abnormal data for their group (FAILED) in the following areas:

X4	(T1CRBA)	Capital
X7	(NIAA)	Profitability
X13	(NPLOTL)	Asset Quality
X24	(PSTS)	Liquidity

Table 5-1

Review of 1994 Misclassified FAILED & NON-FAILED Banks

FAILED BANKS	GROUP AVERAGES	BANK #5	DIFF	BANK #9	DIFF
X04 (T1CRBA)	4.7	8.5	3.8	202.4	197.7
X06 (DDNI)	0.0	0.0	0.0	0.0	0.0
X07 (NIAA)	-3.4	-1.1	-2.3	4.7	8.1
X13 (NPLOTL)	17.3	9.8	7.5	0.0	17.3
X21 (BDTDD)	0.0	0.0	0.0	0.0	0.0
X24 (PSTS)	53.9	26.1	27.8	0.0	53.9
X25 (MVBVS)	100.0	100.2	0.2	99.3	0.7

NON-FAILED BANKS	GROUP AVERAGES	BANK #24	DIFF
X04 (T1CRBA)	13.8	11.1	2.7
X06 (DDNI)	0.0	0.0	0.0
X07 (NIAA)	0.8	-0.1	0.9
X13 (NPLOTL)	5.7	19.4	13.7
X21 (BDTDD)	0.0	1.7	1.7
X24 (PSTS)	26.0	16.6	9.4
X25 (MVBVS)	100.6	99.9	0.7

The differences for FAILED bank # 5 are not as pronounced as those for bank # 9. At least, by using the .30 z-score cutoff, bank # 5 was accurately classified. Unfortunately, the figures for bank #9 were extremely skewed. For this reason, it is the conclusion of this study that a FAILED bank with extremely abnormal variable data cannot be accurately classified with the derived seven variable model.

As for the misclassified NON-FAILED bank (#24), it had higher than average data for at least four of the seven variables: T1CRBA, NIAA, NPLOTL, and BDTDD, The study must conclude that NON-FAILED banks which have lower than normal Tier 1 Capital, negative profitability, and higher than normal Non-Performing Loans and Brokered Deposits may appear in the seven variable model as FAILED banks, when in fact they have not failed. Even so, any bank whose figures cause it to be classified in this manner, is still a questionable investment, and should be scrutinized carefully.

Areas for Further Study

This study developed a model with 1991 FAILED banks and data from the year 1990, a year after the highest point in bank failure history. Even though the resulting group means from the comparative data showed differences of a statistical significance, the data for many of the NON-FAILED sample banks still showed signs of financial distress such as (1) negative profitability, (2) low tier 1 Capital, (3) high Non-Performing Loans, and (4) high amounts of Brokered Deposits. Perhaps the development of a model with data from a prosperous financial period might provide more predictive accuracy, whereby FAILED bank ratios and NON-FAILED bank ratios are more distinctive, so that the resulting model might have a clearcut linear z-score for both target groups (FAILED & NON-FAILED.

APPENDIX A

COMMERCIAL BANK FAILURE

1991
(Dollar amounts in thousands)

DOF	NAME	CITY	ST	1990 ASSETS
Aug 16	Northwest National Bank	Fayetteville	AR	$33,451
Apr 12	Arizona Commerce Bank	Tucson	AZ	$80,832
Mar 8	Manilabank California	Los Angeles	CA	$20,775
Jan 25	Alvarado Bank	Richmond	CA	$33,480
Oct 18	Mission Valley Bank, N.A.	San Clemente	CA	$45,103
Jul 12	Landmark Thrift and Loan Assoc	San Diego	CA	$17,484
Apr 26	Columbine Valley Bank & Trust	Jefferson Cty	CO	$9,458
Mar 29	Citizens National Bank	Limon	CO	$11,414
Oct 25	The Citizens Bk of Pagosa Springs	Pagosa Sprgs	CO	$19,677
Jul 26	The Housatonic Bank & Trust Co.	Ansonia	CT	$69,492
Oct 3	Harbor National Bk of Connecticut	Branford	CT	$24,346
Aug 9	Citytrust	Bridgeport	CT	$2,107,777
Oct 18	Connecticut Valley Bank	Cromwell	CT	$32,591
Dec 13	Bank of East Hartford	East Hartford	CT	$47,694
Aug 16	Enfield National Bank	Enfield	CT	$23,114
Apr 12	Whitney Bank and Trust	Hamden	CT	$49,724
Jan 6	Connecticut Bk & Trust Co, N.A.	Hartford	CT	$7,210,748
Mar 28	The Landmark Bank	Hartford	CT	$227,859
Feb 1	The Merchants Bk & Trust Company	Norwalk	CT	$269,867
Dec 6	Saybrook Bank & Trust Co.	Old Saybrook	CT	$89,263
May 10	Madison National Bank	Washington	DC	$528,607
May 24	Florida State Bank	Holiday	FL	$94,033
Aug 9	Bank of South Palm Beaches	Hypoluxo	FL	$75,285
Nov 26	First National Bank of Miami	Miami	FL	$50,136
Sep 19	Southeast Bank, N.A.	Miami	FL	$13,063,547
Dec 20	North Ridge Bank	Oakland Park	FL	$116,900
Mar 8	First Marine Bank of Florida	Palm City	FL	$17,165
Sep 19	Southeast Bank of West Florida	Pensacola	FL	$102,094
Mar 8	SeaFirst Bank	Port St. Luci	FL	$11,521
Aug 9	Southcoast Bank Corporation	West Palm Bch	FL	$29,342
Dec 13	Federal Finance & Mortgage, LTD	Honolulu	HI	$9,413
Jan 29	Citizens Nat'l Bk & Tr Co-Chicago	Chicago	IL	$18,776
Nov 14	Worthington State Bank	Worthington	IN	$49,109
Jun 13	The Bank of Horton	Horton	KS	$200,315
Oct 30	Bank of the South	Baton Rouge	LA	$45,632
Feb 14	Merchants Trust & Savings Bank	Kenner	LA	$43,848
Jul 19	Pontchartrain State Bank	Metairie	LA	$149,560
May 17	First City Bank	New Orleans	LA	$57,843
Apr 11	American Bank & Trust Co.	Shreveport	LA	$60,928
May 3	Boston Trade Bank	Boston	MA	$338,021
Oct 25	Coolidge Bank & Trust Co.	Boston	MA	$341,895
Mar 15	The Blackstone Bank & Trust Co.	Boston	MA	$49,258
Dec 13	Merchants National Bank	Leominster	MA	$170,262
May 31	University Bank, N.A.	Newton	MA	$341,467
Sep 27	MidCounty Bank & Trust Co.	Norwood	MA	$61,591
May 10	The Washington Bank (of MD.)	Baltimore	MD	$44,078
Jan 6	Maine National Bank	Portland	ME	$1,045,658
Oct 25	First Hanover Bank	Wilmington	NC	$68,608

(appendix A continues)

APPENDIX A (continued)

DOF	NAME	CITY	ST	1990 ASSETS
Sep 6	The Family Bank & Trust	Allenstown	NH	$42,005
Mar 29	City Bank and Trust	Claremont	NH	$116,044
Nov 15	Durham Trust Company	Durham	NH	$73,051
Oct 10	Bank Meridian, N.A.	Hampton	NH	$129,351
Oct 10	BankEast	Manchester	NH	$877,899
Aug 30	Hillsborough Bank & Trust Co.	Milford,	NH	$59,027
Oct 10	Nashua Trust Company	Nashua	NH	$469,733
Jul 19	Community Guardian Bank	Elmwood Park	NJ	$59,347
Jul 26	Suburban National Bank	Hillsborough	NJ	$94,752
Sep 20	Mid-Jersey National Bank	Somerville	NJ	$30,908
May 22	First National Bank of Toms River	Toms River	NJ	$1,646,875
Feb 21	Southwest National Bank	Albuquerque	NM	$37,236
May 23	Liberty National Bank	Lovington	NM	$55,029
Nov 8	Community Nat'l Bk & Trust of NY	New York	NY	$404,608
Feb 22	The McKinley Bank	Niles	OH	$70,565
Aug 29	First National Bank & Trust Co.	Blackwell	OK	$34,074
Aug 30	Hilton Head Bank & Trust Co., N.A.	Hilton Head	SC	$72,441
Nov 14	Alvarado National Bank	Alvarado	TX	$9,798
Jun 13	Tascosa National Bank of Amarillo	Amarillo	TX	$91,041
Jan 31	Rockport Bank, N.A.	Rockport	TX	$17,796
Jan 31	Bank of the Hills	Austin	TX	$255,108
Oct 24	First National Bank, Bedford	Bedford	TX	$22,129
Oct 3	Reagan State Bank	Big Lake	TX	$26,343
May 16	First National Bank of Cedar Hill	Cedar Hill	TX	$11,777
May 9	Chireno State Bank	Chireno	TX	$12,991
Feb 28	United Citizens Bank, N.A.	College Stat	TX	$44,906
Aug 22	Buchel Bank & Trust Co.	Cuero	TX	$33,881
May 16	Capital Bank	Dallas	TX	$124,939
Jul 12	Drippings Springs National Bank	Dripping Sprg	TX	$22,019
Jun 13	Peoples Bank	Hewitt	TX	$18,702
May 9	Village Green National Bank	Jersey Vill	TX	$34,155
Feb 7	First National Bank in Kaufman	Kaufman	TX	$20,351
Jul 25	The Kerens Bank	Kerens	TX	$21,196
Feb 7	Lockhart State Bank	Lockhart	TX	$24,316
Aug 22	First Mexia Bank	Mexia	TX	$24,169
May 9	The First National Bank of Poth	Poth	TX	$20,038
Mar 21	Sabinal Bank	Sabinal	TX	$24,822
Oct 31	Union Bank	San Antonio	TX	$114,492
Jun 6	Northwest Bank, N.A.	San Antonio	TX	$8,046
Aug 29	The San Saba National Bank	San Saba	TX	$17,239
Apr 18	Community National Bank	Sherman	TX	$19,048
May 9	Texas Bank and Trust of Temple	Temple	TX	$49,165
Mar 14	Crossroads Bank	Victoria	TX	$22,416
Jun 13	Texas Premier Bk of Victoria, N.A.	Victoria	TX	$16,651
Apr 4	First State Bank	Weimar	TX	$26,023
Mar 21	Citadel Bank	Willis	TX	$21,874
Feb 14	The First National Bk of Wortham	Wortham	TX	$7,282
Sep 13	Valley Bank	White River J	UT	$39,045
May 10	Madison National Bank	McLean	VA	$190,194
May 24	First Security Bank	Roanoke	VA	$17,996
Apr 5	The Blueville Bank of Grafton	Grafton	WV	$48,118

NOTE: From: FDIC, Washington, D.C.

APPENDIX B

COMMERCIAL BANK NON-FAILURES

1991
(Dollar amounts in thousands)

NAME	CITY	ST	1990 ASSETS
The Endora Bank	Eudora	AR	$22,476
Southern Arizona Bank	Yuma	AZ	$58,211
Sun Country Bank	Apple Valley	CA	$6,798
Redlands Centenniel Bank	Redlands	CA	$10,114
Rancho Bank	San Dimas	CA	$36,929
Bank of Grand Junction	Grand Junction	CO	$15,528
First National Bk of Leedville	Leedsville	CO	$9,067
Equitable Bk of Littleton N.A.	Littleton	CO	$10,736
Peoples Bank	Bridgeport	CT	$6,917,710
The Canaan National Bank	Canaan	CT	$51,160
Liberty National Bank	Danbury	CT	$14,359
The Bank of Hartford, Inc.	Hartford	CT	$405,703
Fleet Bank, N.A.	Hartford	CT	$2,364,015
Prime Bank	Orange	CT	$21,701
National Iron Bk of Salisbury	Salisbury	CT	$60,969
Shelton Savings Bank	Shelton	CT	$176,687
Bank of Waterbury	Waterbury	CT	$61,256
Nationsbank of DC, N.A.	Washington	DC	$1,093,698
Apalachicola State Bank	Apalachicola	FL	$22,657
First National Bk of Pasco	Dade City	FL	$23,060
BankFirst	Eustis	FL	$20,547
Homosassa Springs Bank	Homosassa Springs	FL	$65,117
Great Southern Bank	Lantana	FL	$39,951
Barnett Bk of South Fl, N.A.	Miami	FL	$6,467,260
Helm Bank	Miami	FL	$13,163
Bank of Boston-Florida, N.A.	Palm Beach	FL	$56,290
Florida Bank of Commerce	Palm Harbor	FL	$45,762
First American Bk of Pensacola	Pensacola	FL	$48,898
Charlotte State Bank	Port Charlotte	FL	$17,635
Realty Finance, Inc.	Hilo	HI	$13,904
Burling Bank	Chicago	IL	$17,790
Bank of Wolcott	Wolcott	IN	$30,810
The Home Nat'l Bk of Arkansas	Arkansas City	KS	$138,315
Bank of Commerce	Baton Rouge	LA	$47,354
Bank of LaPlace of St John Bapt	La Place	LA	$39,992
Minden Bank & Trust Company	Minden	LA	$113,707
Gulf Coast Bk & Trust Co	New Orleans	LA	$49,892
City Bk & Trust of Shreveport	Shreveport	LA	$32,883
The Beverly National Bank	Beverly	MA	$130,379
Atlantic Bank & Trust Company	Boston	MA	$55,056
Grove Bank	Boston	MA	$215,968
Wainwright Bank & Trust Co	Boston	MA	$346,478
Cambridge Trust Company	Cambridge	MA	$266,522
First & Ocean National Bank	Newburyport	MA	$64,925
The Harbor Bank of Maryland	Baltimore	MD	$37,531
Maryland Permanent Bk & Trust	Baltimore	MD	$15,051
Casco Northern Bank	Portland	ME	$1,626,394
Enterprise NB Piedmont	Winston-Salem	NC	$18,790
Centerpoint Bank	Bedford	NH	$19,915

(Appendix B continues)

APPENDIX B (Continued)

NAME	CITY	ST	1990 ASSETS
Cornerstone Bank	Derry	NH	$145,601
Valley Bank	Hillsboro	NH	$39,654
The Monadnock Bank	Jeffrey	NH	$158,968
Peoples Bank	Littleton	NH	$51,482
Bank of New Hamshire	Manchester	NH	$759,602
First Nat'l Bk of Portsmouth	Portsmouth	NH	$213,082
First Southern State Bank	Avalon	NJ	$10,142
United Jersey Bk/South, N.A.	Cherry Hill	NJ	$1,109,433
West Jersey Community Bank	Fairfield	NJ	$32,220
New Era Bank	Somerset	NJ	$73,913
Bank of the Rio Grande, N.A.	Las Cruces	NM	$33,218
The Peoples National Bank	Portales	NM	$63,766
Glens Falls Nat'l Bk & Trust	Glens Falls	NY	$454,890
Farmers Savings Bank	Northwood	OH	$65,009
Security Bank & Trust Company	Blackwell	OK	$47,026
Greenville National Bank	Greenville	SC	$62,033
Security State Bank	Abilene	TX	$57,088
Alvarado State Bank	Alvarado	TX	$21,653
First State Bank	Austin	TX	$233,141
Texas National Bk of Baytown	Baytown	TX	$10,583
First National Bank-Big Lake	Big Lake	TX	$16,873
State Nat'l Bk of Caddo Mills	Caddo Mills	TX	$16,302
The First State Bank	Celina	TX	$19,881
Commerce National Bank	College Station	TX	$28,846
The Bank of Crowley	Crowley	TX	$21,110
First Texas Bank	Dallas	TX	$99,783
First National Bank of Dublin	Dublin	TX	$25,765
The First National Bk of Hico	Hico	TX	$19,545
Alief Alamo Bank	Houston	TX	$31,470
First State Bank	Keene	TX	$19,447
The Farmers Guaranty Bk	Kennard	TX	$11,464
The Citizens State Bank	Lometa	TX	$28,188
Texas Bank	Mont Belvieu	TX	$30,080
Powell State Bank	Powell	TX	$13,556
Home State Bank	Rochester	TX	$11,742
Bank of San Antonio	San Antonio	TX	$79,149
Sanderson State Bank	Sanderson	TX	$17,783
Peoples State Bank	Shepherd	TX	$14,739
First State Bank	Temple	TX	$33,390
The Bank of Vernon	Vernon	TX	$19,021
First Texas Bank	Vidor	TX	$25,670
Wallis State Bank	Wallis	TX	$26,490
First State Bank	Waskom	TX	$23,151
Peoples National Bank	Winters	TX	$9,938
First State Bank	Danville	VA	$24,732
Fairfax Bank & Trust Company	Fairfax	VA	$95,441
First Brandon National Bank	Brandon	VT	$50,941
The Calhoun County Bank	Grantsville	WV	$49,145

APPENDIX C

COMMERCIAL BANK FAILURES

1993
(Dollar amounts in thousands)

DOF	NAME	CITY	ST	1992 ASSETS
Apr 30	American Commerce National Bank	Anaheim	CA	$128,867
Oct 21	Mid City Bank, N.A.	Brea	CA	$114,232
Jul 9	First California Bank	La Mesa	CA	$87,935
Mar 4	First American Capital Bank, N.A.	Laguna Beach	CA	$28,451
Oct 15	Brentwood Thrift & Loan Assoc	Los Angeles	CA	$14,362
Jun 18	Capital Bank of California	Los Angeles	CA	$244,127
Nov 5	Century Thrift & Loan	Los Angeles	CA	$28,403
Jul 9	City Thrift & Loan Association	Los Angeles	CA	$41,088
Aug 27	Maritime Bank of California	Los Angeles	CA	$39,494
Apr 2	Olympic National Bank	Los Angeles	CA	$105,747
Sep 24	Western United National Bank	Los Angeles	CA	$25,797
May 6	Wilshire Center Bank, N.A.	Los Angeles	CA	$10,358
Apr 8	Premier Bank	Northridge	CA	$73,024
May 21	Palos Verdes National Bank	Rolling Hills	CA	$45,355
Oct 29	The Bank of San Diego	San Diego	CA	$400,433
Apr 15	First Western Bank, N.A.	San Diego	CA	$16,235
Sep 17	Regent Thrift & Loan Assoc	San Francisco	CA	$8,335
Jun 18	American Bank & Trust Company	San Jose	CA	$38,556
Jan 22	Columbia National Bank	Santa Monica	CA	$47,618
Jul 2	Jefferson Bank & Trust	Lakewood	CO	$121,456
Jun 25	City National Bank of Washington	Washington	DC	$27,375
Apr 29	Valley National Bank of Fremont Co	Hamburg	IA	$7,689
Jul 1	Eagle Bank of Champaign County,N.A.	Rantoul	IL	$20,459
Apr 2	Midland Bank of Kansas	Mission	KS	$124,262
Apr 2	College Boulevard National Bank	Overland Park	KS	$202,754
May 20	Crown National Bank	Charlotte	NC	$25,103
Feb 26	Jefferson National Bank	Watertown	NY	$256,014
Jun 10	Banc Central Amarillo	Amarillo	TX	$37,799
Aug 25	Tarrant Bank	Fort Worth	TX	$66,267
Feb 5	American Bank of Haltom City	Haltom City	TX	$99,525
Jul 22	Fidelity National Bank	Houston	TX	$58,253
Jul 1	Westheimer National Bank	Houston	TX	$35,696
Mar 18	United Bank, National Association	Lancaster	TX	$49,268
Oct 14	Plaza Bank, N.A. of New Braunfeis	New Braunfeis	TX	$70,061
Feb 25	Planters National Bk of Rosebud	Rosebud	TX	$13,728
Apr 1	First State Bank	Vega	TX	$21,444
Jul 29	Wolfe City National Bank	Wolfe City	TX	$44,998
Aug 12	New Atlantic Bank, N.A.	Norfolk	VA	$16,394
Jul 2	Emerald City Bank	Seattle	WA	$10,477

NOTE: From: FDIC, Washington, D.C.

APPENDIX D

COMMERCIAL BANK NON-FAILURES

1993
(Dollar amounts in thousands)

NAME	CITY	ST	1992 ASSETS
Southern California Bank	Anaheim	CA	$464,229
San Joaquin Bank	Bakersfield	CA	$93,784
Frontier Bank, N.A.	La Palma	CA	$111,184
Monarch Bank	Laquna Niguel	CA	$68,863
First Valley National Bank	Lancaster	CA	$22,706
California Center Bank	Los Angeles	CA	$211,281
Founders Bank	Los Angeles	CA	$74,301
Gilmore Bank	Los Angeles	CA	$76,584
Saehan Bank	Los Angeles	CA	$39,547
National Bank of California	Los Angeles	CA	$111,398
Royal Trust & Loan Company	Los Angeles	CA	$45,678
Pan American Bank	Los Angeles	CA	$35,635
Cerritos Valley Bank	Norwalk	CA	$61,425
First Continental Bank	Rosemead	CA	$63,521
Peninsula Bank of San Diego	San Diego	CA	$242,722
San Diego First Bank	San Diego	CA	$22,106
California National Bank	San Francisco	CA	$62,679
First Bk of San Luis Obispo	San Luis Obispo	CA	$67,352
Mariners Bank	San Clemente	CA	$89,568
FirstBank of Lakewood, N.A.	Lakewood	CA	$78,185
First Liberty National Bank	Washington	DC	$20,483
Iowa State Bank	Hamberg	IA	$32,478
Raritan State Bank	Raritan	IL	$42,296
Mission Bank	Mission	KS	$383,532
Boatmens Bank	Overland Park	KS	$185,520
Park Meridian Bank	Charlotte	NC	$31,101
Watertown Savings Bank	Watertown	NY	$183,112
Western National Bank	Amarillo	TX	$32,724
Bank of Commerce	Fort Worth	TX	$90,483
Hamlin National Bank	Hamlin	TX	$80,556
Bank of Almeda	Houston	TX	$53,908
First Bank	Houston	TX	$63,254
NBC Bank of Laredo	Laredo	TX	$46,476
Citizens Bank	New Braunfels	TX	$36,829
Lakeside National Bank	Rockwall	TX	$25,744
Bank of Vernon	Vernon	TX	$17,202
Citizens State Bank	Woodville	TX	$49,435
Heritage Bank & Trust Company	Norfolk	VA	$49,013
Viking Community Bank	Seattle	WA	$11,852

APPENDIX E

COMMERCIAL BANK FAILURES

1994

(Dollar amounts in thousands)

DOF	NAME	CITY	ST	1993 ASSETS
July 29	Western Community	Corona	CA	$58,759
Aug 26	Capital Bank	Downey	CA	$82,024
July 8	Pioneer Bank	Fullerton	CA	$144,657
July 15	Bank of San Pedro	Los Angeles	CA	$134,128
Aug 12	Bank of Newport	Newport Beach	CA	$218,341
July 29	Commerce Bank	Newport Beach	CA	$188,121
April 1	Mechanics National Bank	Paramount	CA	$152,473
May 19	Barbary Coast National Bank	San Francisco	CA	$11,147
July 7	Meriden Trust & Safe Co	Meriden	CT	$3,345
May 6	Commercial Bank & Trust Co	Lowell	MA	$32,341
April 14	Superior National Bank	Kansas City	MO	$19,970

NOTE: From: FDIC, Washington, D.C.

APPENDIX F

COMMERCIAL BANK NON-FAILURES

1994
(Dollar amounts in thousands)

NAME	CITY	ST	1993 ASSETS
Concord Commercial Bank	Concord	CA	$54,245
Downey National Bank	Downey	CA	$39,547
Foothill Independent Bank	Glendora	CA	$279,306
Century Bank	Los Angeles	CA	$152,320
Orange National Bank	Orange	CA	$193,073
National Bank of Southern Cal	Newport Beach	CA	$324,200
Citizens Comm Trust & Sav Bk	Pasadena	CA	$146,103
Mission National Bank	San Francisco	CA	$37,512
Moodus Savings Bank	Moodus	CT	$36,954
Butler Bank	Lowell	MA	$22,140
Hillcrest Bank	Kansas City	MO	$42,420

APPENDIX G

COMMERCIAL BANK FAILURES

1995

(Dollar amounts in thousands)

DOF	NAME	CITY	ST	1994 ASSETS
Jan 20	Guardian Bank	Los Angeles	CA	$316,944
Mar 31	Los Angeles Thrift & Loan Co	Los Angeles	CA	$23,388
Mar 3	First Trust Bank	Ontario	CA	$227,695
Jul 28	Pacific Heritage Bank	Torrance	CA	$155,662
Jul 28	Founders Bank	New Haven	CT	$79,022
May 19	Bank USA, N.A.	Kihel	HI	$8,817

NOTE: From: FDIC, Washington, D.C.

APPENDIX H

COMMERCIAL BANK NON-FAILURES

1995

(Dollar amounts in thousands)

NAME	CITY	ST	1994 ASSETS
Citizens Comm. Trust & Sav Bk	Pasadena	CA	$138,432
Hanmi Bank	Los Angeles	CA	$360,752
Bank of Commerce	San Diego	CA	$188,770
Mission National Bank	San Francisco	CA	$37,548
Moodus Savings Bank	Moodus	CT	$46,232
Oahu Finance Co	Waipahu	HI	$4,449

REFERENCES CITED

Altman, E.I. (1968, September). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. _Journal of Finance_, 589-609.

Altman, E.I. (1983). _Corporate financial distress: A complete guide to predicting, avoiding, and dealing with bankruptcy_. New York: John Wiley & Sons.

Altman, E.I. (1993). _Corporate financial distress and bankruptcy: A complete guide to predicting and avoiding distress and profiting from bankruptcy_ 2nd Ed. New York: John Wiley & Sons.

Altman, E.I., Avery, R.B., Eisenbeis, R.A., and Sinkey, J.F. Jr. (1981). _Application of classification techniques in business, banking and finance_. Greenwich, Conn.: JAI Press Inc.

Altman, E.I., Haldeman, R.G. and Narayanan, P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. _Journal of Banking and Finance_, _1_, 29-54.

Beaver, W.H. (1966). Financial ratios as predictors of failure. _Empirical Research in Accounting: Selected Studies, Journal of Accounting Research_, (supplement), 77-111.

Benston, G.J., Eisenbeis, R.A., Horvitz, P.H., Kane, E.J., and Kaufman, G.J. (1986). _Perspectives on safe and sound banking_. Cambridge, MA: MIT Press.

Cates, D.C. (1985, Autumn). Bank risk and Predicting bank failure. _Issues in Bank Regulation_, 16-20.

Cole, R.A., Cornym, B.G., and Gunther, J.W. (1995, January). FIMS: A new monitoring system for banking institutions. _The Federal Reserve Bulletin_, 1-15.

Demirguc-Kunt, A. (1989, Fourth Quarter). Deposit-institution failures: A review of empirical literature. _Economic Review_, Federal Reserve Bank of Cleveland, _25_(4), 2-18.

Deposit Insurance Reform Committee. (March, 1990). _Federal deposit insurance: A program for reform_. Washington, DC: American Banker's Association.

Dimancescu, D. (1983). Deferred Future. Cambridge, Massachusetts: Ballinger Publishing Co.

Espahbodi, P. (1991, February). Identification of problem banks and binary choice models. Journal of Banking and Finance, 15(1), 53-71.

Federal Deposit Insurance Corporation. (1984). Federal deposit insurance corporation: The first fifty years. Washington, DC: Federal Deposit Insurance Corporation.

Federal Deposit Insurance Corporation. (1991). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1992). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1993). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1994). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Fuller, P.R. (1991). Predicting the financial distress and failure of savings and loan associations (Doctoral dissertation, Mississippi State University, 1990). Dissertation Abstract International, 51(11), 3853A.

Gart, A. (1994). Regulation, deregulation, reregulation: The future of the banking, insurance and securities industries. New York: John Wiley & Sons, Inc.

Hair, J.F. Jr., Anderson, R.E., Tatham, R.L., and Black, W.C. (1992). Multivariate data analysis. New York: Macmillan.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. Journal of Banking and Finance, 1, 249-276.

Meyer, P.A., and Pifer, H.W. (1970, September). Prediction of bank failures. Journal of Finance, 25, 853-868.

Moyer, R. C. (1977, Spring). Forecasting financial failure: A reexamination. Financial Management, 11-17.

Norusis, M. (1988). SPSS-X advanced statistics guide (3rd Ed.). Chicago: SPSS, Incorporated.

Rogers, D. (1993). The future of American banking: Managing for change. New York: McGraw-Hill.

Rudolph, P.M., and Hamdan, B. (1988). An analysis of post deregulation savings and loan failures. AREUEA Journal, 16(1), 17-32.

Secrist, H. (1938). National bank failures and non-failures. Bloomington, IN: The Principia Press.

Sinkey, J.F. Jr. (1979). Problem and failed institutions in the commercial banking industry. Greenwich, CT: JAI Press.

Sinkey, J.F. Jr. (1989). Commercial bank financial management: In the financial services industry (3rd ed.). New York: Macmillan.

Smith, R. and Winakor, A. (1935). Changes in financial structure of unsuccessful corporations. University of Illinois. Bureau of Business Research.

Sprague, I.H. (1986). Bailout: An insider's account of bank failures and rescues. New York: Basic Books.

Wang, G. et al. (1987. Thrift Institution Failure: Estimating the Regulator's Closure Rule (Washington, D.C.): The Office of Policy and Economic Research, Division of Federal Home Loan Bank Board, Research Working Paper No. 125.

White, L. J. (1991). The S & L debacle: Public policy lessons for bank and thrift regulation. New York: Oxford Press.

BIBLIOGRAPHY

Abrams, B.A. and Huang, C.J. (1987, October). Predicting bank failures: The role of structure in affecting recent failure experiences in the USA. Applied Economics, 19(10), 1291-1302.

Altman, E.I. (1968, September). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 589-609.

Altman, E.I. (1977). Predicting performance in the savings and loan association industry. Journal of Monetary Economics, 3, 443-466.

Altman, E.I. (1983). Corporate financial distress: A complete guide to predicting, avoiding, and dealing with bankruptcy. New York: John Wiley & Sons.

Altman, E.I. (1993). Corporate financial distress and bankruptcy: A complete guide to predicting and avoiding distress and profiting from bankruptcy 2nd Ed. New York: John Wiley & Sons.

Altman, E.I., Avery, R.B., Eisenbeis, R.A., and Sinkey, J.F. Jr. (1981). Application of classification techniques in business, banking and finance. Greenwich, Conn.: JAI Press Inc.

Altman, E.I., Haldeman, R.G. and Narayanan, P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. Journal of Banking and Finance, 1, 29-54.

Andrews, D.F., Gnanadesikan, R., and Warner, J.L. (1973). Methods for assessing multivariate normality. In: Multivariate Analysis III. ed. P.R. Krishnaiah. New York: Academic Press.

Avery, R.B., and Hanweck, G.A. (1984, May). A dynamic analysis of bank failures. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 380-395.

Bansal, A., Kauffman, R.J., and Weitz, R.R. (1993, Summer). Comparing the modeling performance of regression and neural networks as data quality varies: A business value approach. Journal of Management Information Sciences, 1(1), 11-32.

Barnes, P. (1987, Winter). The analysis and use of financial ratios: A review article. Journal of Business Finance and Accounting, 14(4), 449-461.

Barrow, J.M., and Horvitz, P.M. (1993, Autumn). Response of distressed firms to incentives: Thrift institution performance under the FSLIC management consignment program. Financial Management, 22(3), 176-184.

Barth, J.R., Brumbaugh, R.D., Sauerhaft, D., and Wang, G.H.K. (1985). Thrift institution failures: Causes and policy issues. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 184-216.

Beaver, W.H. (1966). Financial ratios as predictors of failure. Empirical Research in Accounting: Selected Studies, Journal of Accounting Research, (supplement), 77-111.

Benston, G.J. (1985). An analysis of the causes of savings and loan association failures. Monograph series in Finance and Economics, New York University.

Benston, G.J., Eisenbeis, R.A., Horvitz, P.H., Kane, E.J., and Kaufman, G.J. (1986). Perspectives on safe and sound banking. Cambridge, MA: MIT Press.

Berger, A.N., Hunter, W.C., and Timme, S.G. (1993, April). The efficiency of financial institutions: A review and preview of research past, present, and future. Journal of Banking and Finance, 17, 221-249.

Booker, I.O. (1983, November). Tracking banks from afar: A risk monitoring system. Economic Review, The Federal Reserve Bank of Atlanta, 68(11), 27-41.

Bovenzi, J.F., Marino, J.A., and McFadden, F.E. (1983, November). Commercial bank failure prediction models. Economic Review, Federal Reserve Bank of Atlanta, 68(11), 14-26.

Cates, D.C. (1985, Autumn). Bank risk and Predicting bank failure. Issues in Bank Regulation, 16-20.

Coats, P.K., and Fant, L.F. (1993, Autumn). Recognizing financial distress patterns using a neural network tool. Financial Management, 22(3), 142-155.

Cole, R.A., Cornym, B.G., and Gunther, J.W. (1995, January). FIMS: A new monitoring system for banking institutions. The Federal Reserve Bulletin, 1-15.

Cole, R.A, and Gunther, J.W. (1993, July). Separating the likelihood and timing of bank failure. Financial Industry Studies, Federal Reserve Bank of Dallas, 2, 1-21.

Collins, R.A. (1980, Summer). An empirical comparison of bankruptcy prediction models. Financial Management, 52-56.

Demirguc-Kunt, A. (1989, May). Modeling large commercial-bank failures: a simultaneous-equations analysis. Working Paper 8905, Federal Reserve Bank of Cleveland.

Demirguc-Kunt, A. (1989, Fourth Quarter). Deposit-institution failures: A review of empirical literature. Economic Review, Federal Reserve Bank of Cleveland, 25(4), 2-18.

Demirguc-Kunt, A. (1991). Modeling large commercial-bank failures: A simultaneous-equations analysis (Doctoral dissertation, The Ohio State University, 1990). Dissertation Abstracts International, 51(7), 2445A.

Demirguc-Kunt, A. (1991, April). Principal-agent problems in commercial bank failure decisions. Working Paper 9106, Federal Reserve Bank of Cleveland.

Deposit Insurance Reform Committee. (March, 1990). Federal deposit insurance: A program for reform. Washington, DC: American Banker's Association.

Dimancescu, D. (1983). Deferred Future. Cambridge, Massachusetts: Ballinger Publishing Co.

Espahbodi, P. (1991, February). Identification of problem banks and binary choice models. Journal of Banking and Finance, 15(1), 53-71.

Federal Deposit Insurance Corporation. (1984). Federal deposit insurance corporation: The first fifty years. Washington, DC: Federal Deposit Insurance Corporation.

Federal Deposit Insurance Corporation. (1991). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1992). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1993). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Federal Deposit Insurance Corporation. (1994). Annual Report. Washington, DC: Federal Deposit Insurance Corporation

Forsyth, T.B. (1991). A study of the ability of financial ratios to predict corporate failure and the relationship between bankruptcy model probability assessments and stock market behavior (Doctoral dissertation, The University of Alabama, 1991). Dissertation Abstracts International, 52(5), 1803A.

Fuller, P.R. (1991). Predicting the financial distress and failure of savings and loan associations (Doctoral dissertation, Mississippi State University, 1990). Dissertation Abstract International, 51(11), 3853A.

Gajewski, G.R. (1989). Bank risk, regulator behavior, and bank closure in the mid-1980s: A two-step logit model. Dissertation Abstracts International, 49(7), 1872A.

Gajewski, G.R. (1989, May). Assessing the risk of bank failure. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 432-456.

Gajewski, G.R. (1990). Modeling bank closures in the 1980s: The roles of regulatory behavior, farm lending, and the local economy. Research in Financial Services, 2, 41-84

Gart, A. (1994). Regulation, deregulation, reregulation: The future of the banking, insurance and securities industries. New York: John Wiley & Sons, Inc.

Gilson, S.C. (1990, October). Bankruptcy, boards, banks, and blockholders: Evidence on changes in corporate ownership and control when firms default. Journal of Financial Economics, 27(2), 355-398.

Graham, F.C., and Horner, J.E. (1988, May). Bank failures: An evaluation of factors contributing to the failure of national banks. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of

Chicago, 405-435.

Hair, J.F. Jr., Anderson, R.E., Tatham, R.L., and Black, W.C. (1992). Multivariate data analysis. New York: Macmillan.

Hanke, J.E., and Reitsch, A.G. (1994). Understanding business statistics (2nd ed.). Homewood, Ill: Richard D. Irwin, Inc.

Hanweck, G.A. (1977, November). Predicting bank failure. Research Papers in Banking and Financial Economics. Division of Research and Statistics, Washington, DC: Board of Governors of the Federal Reserve System.

Hirschhorn, E. (1987, July/August). The information content of bank examination ratings. Banking and Economic Review, Federal Deposit Insurance Corporation.

Ho, T., and Saunders, A. (1980, December). A catastrophe model of bank failure. Journal of Finance, 35, 1188-1207.

Hooks, L.M. (1992, August). What do early warning models tell us about asset risk and bank failures. Financial Industry Studies, Federal Reserve Bank of Dallas, 1-13.

Hooks, L. (1992, September). A test of the stability of early warning models of bank failures. Financial Industry Studies, Federal Reserve Bank of Dallas, 2, 1-25.

Hough, K.A., and Woodliff, D.R. (1987, Winter). Financial ratios: The prediction of corporate "success" and failure. Journal of Business Finance and Accounting, 14(4), 537-554.

Joy, O.M., and Tollefson, J.O. (1975, December). On the financial application of discriminant analysis. Journal of Financial and Quantitative Analysis, 10, 723-739.

Korobow, L., and Stuhr, D.P. (1975, July). Toward early warning of changes in banks' financial conditions: A progress report. Monthly Review, Federal Reserve Bank of New York, 57(7), 157-165.

Korobow, L., Stuhr, D.P., and Martin, D. (1976, July). A probabilistic approach to early warning changes in bank financial conditions. Monthly Review, Federal Reserve Bank of New York, 58(7), 187-194.

Korobow, L., Stuhr, D.P., and Martin, D. (1977, Autumn). A nationwide test of early warning research in banking. Quarterly Review, Federal Reserve Bank of New York, 37-52.

Korobow, L., and Stuhr, D.P. (1983, November). The relevance of peer groups in early warning analysis. Economic Review, Federal Reserve Bank of Atlanta, 27-34.

Korobow, L., and Stuhr, D. (1985). Performance measurement of early warning models. Journal of Banking and Finance, 9, 267-273.

Lachenbruch, P.A. (1975). Discriminant Analysis. New York: Hafner Press.

Lane, W.R., Looney, S.W., and Wansley, J.W. (1986). An application of the Cox Proportional Hazards Model to bank failure. Journal of Banking and Finance, 10, 511-531.

Lane, W.R., Looney, S.W., and Wansley, J.W. (1987, May). An examination of bank failure misclassifications using the Cox Model. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 214-229.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. Journal of Banking and Finance, 1, 249-276.

Martinez, J.E., Courington, J.M. (1993, Spring). Bank performance and risk: Evidence from the energy-producing states. Journal of Applied Business Research, 9(2), 1-9.

Meyer, P.A., and Pifer, H.W. (1970, September). Prediction of bank failures. Journal of Finance, 25, 853-868.

Moyer, R. C. (1977, Spring). Forecasting financial failure: A reexamination. Financial Management, 11-17.

Norusis, M. (1988). SPSS-X introductory statistics guide for SPSS-X release 2. Chicago: SPSS, Incorporated.

Norusis, M. (1988). SPSS-X advanced statistics guide (3rd Ed.). Chicago: SPSS, Incorporated.

Office of the Comptroller of the Currency. (1988, June). Bank failure: An evaluation of the factors contributing to the failure of national banks. Washington, DC: U.S. Government Printing Office.

Pantalone, C.C., and Platt, W.B. (1987, July/August). Predicting commercial bank failure since deregulation. New England Economic Review, Federal Reserve bank of Boston, 37-47.

Peterson, R.L., and Scott, W.L. (1985). Major causes of bank failures. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 165-183.

Pettway, R.H. (1980, March). Potential insolvency, market efficiency, and bank regulation of large commercial banks. Journal of Financial and Quantitative Analysis, 15, 219-236.

Pettway, R.H., and Sinkey, J.F. (1980, March). Establishing on-site bank examination priorities: An early warning system using accounting and market information. Journal of Finance, 35(1), 137-150.

Putnam, B.H. (1983, November). Early warning systems and financial analysis in bank monitoring: Concepts of financial monitoring. Economic Review, The Federal Reserve Bank of Atlanta, 68(11), 6-13.

Rogers, D. (1993). The future of American banking: Managing for change. New York: McGraw-Hill.

Rose, P.S., and Kolari, J.W. (1985, Winter). Early warning systems as a monitoring device for bank condition. Quarterly Journal of Business and Economics, 24, 43-59.

Rose, P.S. and Scott, W. (1978, July). Risk in commercial banking: Evidence from postwar failures. Southern Economic Journal, 45(1), 90-106.

Rudolph, P.M., and Hamdan, B. (1988). An analysis of post deregulation savings and loan failures. AREUEA Journal, 16(1), 17-32.

Satchenberger, L.M., Cinar, E.M., and Lash, N.A. (1992, July/August). Neural networks: A new tool for predicting thrift failures. Decision Sciences, 23(4), 899-916.

Santalone, A.M., and Vinso, J.D. (1977). Estimating the probability of failure for commercial banks and the banking system. Journal of Banking and Finance, 1, 185-205.

Seballos, L.D., and Thomson, J.B. (1990, September). Underlying causes of commercial bank failures in the 1980s. Economic Commentary, Federal Reserve Bank of Cleveland.

Secrist, H. (1938). National bank failures and non-failures. Bloomington, IN: The Principia Press.

Shick, R.A., and Sherman, L.P. (1980, Autumn). Bank stock prices as an early warning system for changes in conditions. Journal of Bank Research, 11, 136-146.

Short, E.D., O'Driscoll, G.P., and Berger, F.D. (1985, May). Recent bank failures: Determinants and consequences. Proceedings from a Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 150-165.

Siems, T.F. (1992, First Quarter). Quantifying management's role in bank survival. Economic Review, The Federal Reserve Bank of Dallas, 29-41.

Sinkey, J.F. (1975, March). A multivariate statistical analysis of the characteristics of problem banks. Journal of Finance, 30, 21-36.

Sinkey, J.F. Jr. (1977, December). Identifying large problem/failed banks: The case of the Franklin National Bank of New York. Journal of Financial and Quantitative Analysis, 12, 779-791.

Sinkey, J.F. Jr. (1978, May). Identifying "problem " banks: How do the banking authorities measure a bank's risk exposure? Journal of Money, Credit and Banking, 10(2), 184-193.

Sinkey, J.F. Jr. (1979). Problem and failed institutions in the commercial banking industry. Greenwich, CT: JAI Press.

Sinkey, J.F. Jr. (1983, Summer). The performance of First Pennsylvania Bank prior to its bail out. Journal of Bank Research, 14(2), 119-133.

Sinkey, J.F. Jr. (1989). Commercial bank financial management: In the financial services industry (3rd ed.). New York: Macmillan.

Sinkey, J.F. Jr., Terza, J., and Dince, R. (1987, Autumn). A zeta analysis of failed commercial banks. Quarterly Journal of Business and Economics, 26(4), 35-49.

Sinkey, J.F. Jr., and Walker, D.A. (1975, Winter). Problem banks: Identification and characteristics. Journal of Bank Research, 5(4), 208-217.

Smith, R. and Winakor, A. (1935). Changes in financial structure of unsuccessful corporations. University of Illinois. Bureau of Business Research.

Sprague, I.H. (1986). Bailout: An insider's account of bank failures and rescues. New York: Basic Books.

Stuhr, D.P., and Van Wicklen, R. (1974, September). Rating the financial condition of banks: A statistical approach to aid bank supervision. Monthly Review, Federal Reserve Bank of New York, 56(9), 233-238.

Tam, K.Y., and Kiang, M.Y. (1992, July). Managerial applications of neural networks: The case of bank failure. Management Science, 38(7), 926-947.

Thomson, J.B. (1989, December). An analysis of bank failures 1984 to 1989. Working Paper 8916, Federal Reserve Bank of Cleveland.

Thomson, J.B. (1991, First Quarter). Predicting bank failures in the 1980s. Economic Review, Federal Reserve Bank of Cleveland, 27(1), 9-20.

Thomson, J.B. (1992). Modeling the bank regulator's closure option: A two-step logit regression approach. Journal of Financial Services Research, 6, 5-23.

Wang, G. et al. (1987. Thrift Institution Failure: Estimating the Regulator's Closure Rule (Washington, D.C.): The Office of Policy and Economic Research, Division of Federal Home Loan Bank Board, Research Working Paper No. 125.

West, R.C. (1985). A factor-analysis approach to bank condition. Journal of Banking and Finance, 9(2), 253-266.

Whalen, G.W. (1991, First Quarter). A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool. Economic Review, Federal Reserve Bank of Cleveland, 27(1), 21-31.

Whalen, G.W. and Thomson, J.B. (1988, Second Quarter). Using financial data to identify changes in bank condition. Economic Review, Federal Reserve Bank of Cleveland, 24(2), 17-26.

Wheelock, D.C. (1992, July). Deposit insurance and bank failures: New evidence from the 1920s. Economic Inquiry, 30(3), 530-543.

White, L. J. (1991). The S & L debacle: Public policy lessons for bank and thrift regulation. New York: Oxford Press.

Wilcox, J.W. (1971, Autumn). A simple theory of financial ratios as predictors of failure. Journal of Accounting Research, 389-395.