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The marginal impact of cash flow information on bank failure prediction: An empirical investigation

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THE MARGINAL IMPACT OF CASH FLOW INFORMATION ON BANK FAILURE PREDICTION: AN EMPIRICAL INVESTIGATION

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by

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Chapter One

Introduction

In the 1980s the United States banking industry entered a new era. Passage of the Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn-St Germain Act of 1982 precipitated extensive changes in the industry. By eliminating interest rate ceilings and expanding allowable bank activities, these acts substantially changed the competitive structure and nature of the banking industry. The net result was the generation of intense competition both within the banking industry itself and between the industry and other depository and nondepository financial institutions.

Banks were thrust into this dynamic environment at the same time the economy was experiencing an economic recession. High and volatile interest rates strained interest margins and ultimately bank performance. Unable to adapt to the changing competitive and economic environment, many banks sought and received Federal Deposit Insurance Corporation (FDIC) assistance or failed outright. Forty-two banks closed in 1982 setting a post-Depression annual record. Commenting on developments at the time, the FDIC noted, "There is a greater sense of bank exposure and risk of failure that exists not just among those who regulate and follow banks, but among the general public as well." (FDIC, 1985, p. 9)

The economic and competitive conditions surrounding the banking industry are less volatile than those of the early 1980s, but the banking industry is still in turmoil. Today banks are failing at a rate far surpassing the record experience of 1982, severely straining FDIC resources. In 1991, 124 insured banks closed because of financial difficulties resulting in an FDIC insurance fund outlay of $12.329 billion. Table 1.1 provides an overview of FDIC insured bank failures since 1982. Table 1.2 documents the FDIC problem bank experience for the same period.

If a troubled bank can be identified in advance of failure, remedial action may be taken to avert failure and avoid unnecessary economic consequences. Much research has been directed toward discovering the factors that identify or signal bank failure. In this body of research, financial ratios selected to mimic the FDIC's bank monitoring system have been shown to provide reliable signals for predicting financial distress. This monitoring system and the variables used as proxies for the system do not incorporate cash flow analysis. However, it is possible that cash flow information may also provide signals of a bank's financial

TABLE 1.1

FDIC INSURED BANK FAILURES
1982-1991

	1982	1983	1984	1985	1986
Total Failures	42	48	79	120	138
Deposit pay-outs	7	9	4	22	21
Deposit transfers	--	--	12	7	19
Deposit assumptions	35	39	63	91	98
Small bank failures*	29	36	67	109	110
As % of total failures	69%	75%	85%	91%	78%
Deposit pay-outs	6	9	2	22	19
Deposit transfers	--	--	10	6	14
Deposit assumptions	23	27	55	81	77

	1987	1988	1989	1990	1991
Total Failures	184	200	206	168	124
Deposit pay-outs	11	6	9	8	4
Deposit transfers	40	30	23	12	17
Deposit assumptions	133	164	174	148	103
Small bank failures	157	144	133	131	63
As % of total failures	85%	72%	65%	78%	51%
Deposit pay-outs	29	6	8	4	4
Deposit transfers	33	26	15	5	12
Deposit assumptions	115	112	110	122	47

*Total assets $50 million or less.
Source: FDIC Annual Report, 1982-1991.

health or lack thereof.

Currently there are conflicting views as to the usefulness of a bank's cash flows as indicators of performance and/or financial health. A related controversy

TABLE 1.2

FDIC INSURED PROBLEM BANK EXPERIENCE
1982-1991

	1982	1983	1984	1985	1985
FDIC insured banks	14,767	14,759	14,825	14,906	14,837
Problem banks	369	642	848	1,140	1,484
As % of insured banks	2.5%	4.4%	5.7%	7.7%	10.0%
% change in problem banks	65.5%	74.0%	32.1%	34.4%	30.2%

	1987	1988	1989	1990	1991
FDIC insured banks	14,289	13,606	13,293	12,788	NA
Problem banks	1,575	1,406	1,109	1,406	NA
As % of insured banks	11.0%	10.3%	8.4%	8.2%	NA
% change in problem banks	6.1%	-10.7%	-21.1%	-5.7%	NA

Source: FDIC Annual Report, 1982-1990.

surrounds the relevancy of cash flow reporting by banks. The banking community, bankers and bank regulators, generally argue that cash flow analysis is not meaningful for assessing bank performance. Others, including the accounting profession in general and the Financial Accounting Standards Board (FASB) in particular, hold an opposing view.

Turning first to the accounting view, interest in cash flow information began in the early 1970s. (Financial Executives Institute, 1985: Perry, 1982) The FASB responded to this interest and in 1981 issued the first of several exposure drafts related to the cash flow issue. Three subsequent drafts were issued before Statement no. 95, "Statement of Cash Flows," was adopted in 1987. Throughout the process, nearly all respondents to these various Exposure Drafts supported a statement of cash flow in some form. The general consensus of the respondents was that "important uses of information about an entity's current cash receipts and payments include helping to assess factors such as the entity's liquidity, financial flexibility, profitability, risk and solvency." (FASB, 1983, paragraph 32.) To the extent that the FASB standard and the attendant responses elicited prior to its adoption reflect the views of the accounting community, it is appropriate to assume that the accounting community values and supports cash flow information and the usefulness of this information for the users of financial statements. It is important to note that the FASB arguments and standards for cash flow reporting apply equally to commercial banks and other financial institutions.

The banking community holds a different view. This community generally contends that the type of information needed to assess a bank's financial health and solvency is not contained in an analysis of cash flow. Solvency, they argue, depends mainly on maintaining an adequate spread between the cost of funds and interest received. Assessing risk exposure requires information regarding interest rate sensitivities and maturity schedules of loans. Analyzing cash flow does not lend insight into these areas of performance.

Specific to Statement no. 95, bank regulators do not officially acknowledge FASB standards. However, the Securities and Exchange Commission recognizes FASB rules and enforces financial accounting standards for publicly held companies, including commercial banks. Bankers feel that Statement no. 95 is not meaningful when applied to a bank. They argue that cash is the main product of a bank's operating activity and any store of cash a bank may maintain resembles an inventory of this product. For example, as cash is loaned or deposits withdrawn, a bank's inventory is depleted, and as loans are repaid or deposits accepted, a bank's inventory is enhanced. As such, a bank's Statement of Cash Flow merely represents a report of inventory activity and volume, not liquidity. The inventory nature of the report coupled with its failure to include information needed to assess risk and solvency yield the Statement of Cash Flow irrelevant for "assessing the ability of a commercial bank to generate future cash flow." (Valenza,

1989) The impact of cash flow-based information on bank failure and the separate but related issue of the relevancy of bank cash flow reporting are the subjects of this study.

PURPOSE OF THE STUDY

The primary purpose of this study is to assess empirically whether cash flow-based information enhances the predictive accuracy of traditional accrual-based CAMEL commercial bank failure prediction models. Since 1978 the FDIC has used a rating system, popularly known as CAMEL, to assess and monitor bank performance. In this system, CAMEL is an acronym for Capital adequacy, Asset quality, Management, Earnings and Liquidity. The finance literature is replete with financial distress and failure prediction models estimated with explanatory variables selected to represent the various CAMEL categories.

Traditionally these CAMEL variables are constructed using accounting information contained in a bank's Report of Condition and Income Statements. By accounting convention these reports are compiled using accrual accounting methods. While ratio analysis employing these statements and their respective accounts has been useful for identifying and predicting failing or troubled banks, the traditional CAMEL measures constructed from accrual-based accounting information may not capture all the relevant aspects of bank performance.

Cash flow protagonists hold the view that a firm's cash flows yield a better measure of operating performance than do accounting profits. Accounting profits, which are based on accrual accounting methods, are subject to inflationary distortions and differing accounting practices. Cash flow, on the other hand, reflects the actual dollar receipts and disbursements of a firm. Cash flow provides the funds needed to repay borrowings and meet other obligations and cash flow, not accounting profits, allows the firm to withstand adverse operating conditions. As such cash flow is a better measure of a firm's financial flexibility and solvency.

While the primary functions of banking and nonbanking firms differ substantially, the firms share a common requirement for the maintenance of financial health. Both types of firms need cash to pay bills and employee wages, repay borrowings, meet interest and lease obligations, invest for future growth and reward owners. If this cash is not available on a timely basis both firms are threatened with insolvency in the short-run and failure in the long-run. Therefore, cash flow may be no less important in determining the health of the banking firm.

The FASB supports this view. It also recognizes the uniqueness of banking activities but notes that

> "...a bank needs cash for essentially the same reasons a manufacturer does, and...a bank - like a manufacturer - must generate positive (or at least neutral) cash flows from its operating, investing and financing activities over the long run." (FASB 95, 1987, p.24)

The Board further notes that a bank's cash flow from operating activities may differ significantly from its net income. These differences may arise from noncash revenue and noncash expense items. For example, noncash bank expense items may include amortization of good-will, depreciation and provisions for probable loan losses (FASB, 1987). In calculating net income, these items are charged against revenue along with cash expense items. Because these noncash expense items do not involve actual cash outlays, cash flow from operations can differ from net income in a positive direction. Conversely, because noncash revenue items (such as accrued interest) involve no cash inflows, cash flow from operations can differ from net income in a negative direction.

To date cash flow analysis (CFA) as reflected in cash flow-based (CFB) variables has not been used in modeling bank failure. To integrate CFA in the failure prediction model, this study incorporates a CFA model developed by Lawson (1985). The Lawson model is a cash flow identity which explicitly details the firm's total cash flows, internal and external. In Lawson's model cash flows are generated internally from the firm's operations. The cash flows thus generated are applied to operating expenses and other obligations and used to finance investment activities. Any surpluses or shortages flow to or from the shareholders. Lawson and Aziz (1989) subsequently applied the identity in a failure prediction study of nonbanking firms.

A secondary purpose of this study is to assess the impact of CFB information on small bank failure. A small bank is defined as one with total assets of $50 million or less. This secondary focus is adopted for two reasons.

First, it is reasonable to assume that small banks, because of the size and range of their operations, may be more susceptible to cash flow imbalances and less likely to respond to critical cash shortages. Small banks tend to serve smaller, local geographic markets. Deposits originate within their local market area and loans are made to local borrowers. Both the sources and uses of funds available to the small bank are tied to the economic conditions prevailing in its local market. Without the diversification opportunities available to banks serving broader markets, these small banks are more susceptible to the vicissitudes of their local economies. A local economic downturn, simultaneously affecting the majority of the bank's borrowers, could generate critical cash flow imbalances as the bank is deprived of the interest income needed to pay bills and meet other obligations.

Cash shortages from temporary economic set-backs may be relieved by cash infusions from outside borrowing. If the cash imbalance is of a more permanent nature, additional capital may be required. However, obtaining these funds can be problematic for the small bank which may not have the financial flexibility available to its larger counterpart. This flexibility derives from the larger bank's more ready access to inter-bank lending networks and external capital markets combined with more experienced management. Because of these differences in small bank environmental and operating characteristics, it is possible that cash flow measures may yield more accurate distress signals for these banks.

Second, the majority of banks that fail are small. In 1989, for example, 78 percent of the 206 bank closings occurred in banks with total assets of $50 million or less. Furthermore, small banks fail at a rate substantially greater than their larger counterparts. The 1989 failure rate for the small bank segment was 1.85 percent. The comparable rate for banks with total assets greater than $50 million was 1.20 percent. In view of the fact that the majority of banks that fail are small, it is important to know if failure in this important bank group can be predicted.

RESEARCH PROBLEM

The basic research problem is to assess the marginal impact, if any, of cash flow information on predicting bank failure. As previously noted, traditional failure prediction models rely predominantly on accrual-based CAMEL measures as predictors of bank failure. This study asks the question, "If CFB information is added to a traditional CAMEL model, will the predictive ability of the model improve?"

Investigation of this problem requires developing and then comparing the predictive results of two models. One model, the CAMEL version, is based solely on selected CAMEL measures as explanatory variables. The other model, the mixed version or MM, is based on these same CAMEL variables but in combination with CFB variables. Since the only difference between the models is the CFB information, differences between the predictive abilities of the models may be attributed to the cash flow information.

Development of a model to investigate the failure problem typically proceeds in three phases or steps: estimation, validation and prediction. Estimation involves specifying the model and estimating the model parameters.

Validation involves confirming the relationships between failure and the independent variables discovered in the estimation phase. Prediction involves assessing whether these relationships are relevant for forecasting future failures. Each phase involves a separate analysis.

While the phases are sequential, the research goal rather than intermediate findings dictates whether the investigation proceeds through all three phases. For example, the researcher may be interested in identifying those factors that contribute to poor bank performance with a view toward explaining why banks fail. Or the research goal may be the development of a theory of the underlying causes of bank failure. In these instances the analysis would center on identifying an optimum set of factors which individually or collectively explain as much as possible the variation in bank performance. Only the first or estimation phase is relevant in these analyses.

If the researcher is interested in determining the model's ability to identify accurately failed and nonfailed banks, then validation and prediction procedures are performed. The distinction between validation and prediction is based on Joy and Tollefson's argument (1978). Validation does not imply prediction. Validation merely establishes the model's ability to identify failure after the fact. Claims of prediction require inter-temporal validation. To claim prediction, the model's ability to identify future or potential failures must be established. Therefore, if the research goal is a simple classification of banks into failed and nonfailed groups, only the validation step is required. If forecasting is the goal, both steps are required.

Validation and prediction both involve classification procedures, i. e., use the estimated model coefficients to sort a bank sample into failed and nonfailed groups. The single, important distinction between the validation and prediction steps is the bank sample that is classified. In validation, the target sample is a bank group drawn from the same time period as the bank group used to estimate the model. In prediction, the target sample is a bank group drawn from a different or future time period.

Since failure prediction is the goal of this study, the research proceeded through all three phases. The hypotheses tested in each phase of the analysis are presented and discussed below.

The hypothesis tested in the estimation phase is:

H_{01}: no difference can be found between the explanatory ability of the CAMEL and MM models.

The analysis in this phase centered on investigating the usefulness of CFB variables for explaining bank failure. This was accomplished by comparing the CAMEL and MM estimated discriminating functions and assessing to what extent, if any, the addition of the CFB variables improved the MM model's discriminant function.

Bank researchers and other interested parties are constantly searching for the factors which describe or explain bank failure. When these factors are identified, they are used to develop a financial profile of a troubled institution. This profile, once established, can serve as a guide to bank managers and regulators who can learn from other's successes or failures. The empirical evidence generated in the estimation phase provides a contribution to this profile.

The hypothesis tested in the validation phase is:

H_{02}: no difference can be found between the validation ability of the CAMEL and MM models.

The validation step addressed the issue of cross-validation. In this phase the CAMEL and MM model coefficients were applied to the control sample. Classification accuracy rates were calculated and compared to assess the marginal impact of CFB information on identifying failed banks. As noted, successful classification at this point did not impart predictive ability. It merely provided a clue as to the usefulness of the model for predicting potential bank failure.

The hypothesis tested in the prediction phase is:

H_{03}: no difference can be found between the predictive ability of the CAMEL and MM models.

In this phase the CAMEL and MM models were applied to a new group of banks to determine their respective ability to identify troubled banks in which failure subsequently occurred. Comparison of resultant accuracy rates determined if either model was the superior performer.

Phase three established the utility of cash flow information for predicting bank failure. A superior performance of the CAMEL model would indicate that CFB measures do not enhance the predictive ability of the accrual-based CAMEL measures. This finding would imply that parties interested in predicting bank failure would not benefit from any effort or expense directed at collecting, analyzing or incorporating cash flow data in their forecasting activities. The empirical evidence regarding predictive ability suggests that this is, in fact, the case. While the CAMEL and MM models predicted failed and nonfailed banks at different rates, the differences in classification accuracy rates were not strong enough to establish statistically significant differences between the models.

This finding contradicts the empirical evidence regarding nonfinancial firm failure and cash flow. In most firm failure prediction studies, including CFB information enhances a model's predictive ability. It is possible that bank failure and firm failure are different phenomena. Firm failure is typically characterized by an historical and a continuing inability to meet contractual financial obligations. The failing firm's financial data most likely reflect these extreme circumstances.

A bank failure is an arbitrary event, the result of regulators acting to protect the safety and soundness of the financial system. Since regulators close a bank when they perceive it to be a threat to the system, a bank's cash flow imbalances may not be as critical as those of its nonfinancial failing counterpart. Furthermore, regulators' assessment of the viability of a bank is based primarily on the quality of the bank's asset portfolio, not its cash flows. If bad loans, not cash flow problems, are the primary reason for closing the institution, it is not likely that cash flow imbalances would be evidenced in the bank's financial data.

Small bank failure, the secondary focus of this study, was the final research problem. Small banks comprise the greater portion of total bank failures. Intuition suggests that cash flows may play a significant role in these small bank failures because, as noted, small banks are more likely to experience cash flow imbalances. If so, it is possible that cash flow based-information may be a more useful signal for this particular bank group. The research problem was to determine if CFB information is capable of predicting small bank failure at a rate significantly different from overall bank failure.

The final hypothesis tested was:

H_{04}: no difference can be found between the ability of the MM model to predict small bank failure versus total bank failure.

The problem here was not to determine the precise relationship between small bank failure and cash flow. No inferences can or should be made regarding the degree to which cash flow contributes to explaining small bank failure. The problem was merely to explore the marginal predictive ability of this information for that group of banks that exhibits the higher failure rate and assess if cash flow is a better predictor for this group than the population at large. The empirical evidence relative to small bank prediction was mixed.

POTENTIAL CONTRIBUTIONS

The finance literature is replete with financial distress and failure prediction models for banks. This study enhances this literature in several ways. The first contribution relates to this study's emphasis on cash flow as a predictor of bank failure. The importance of cash flow analysis is widely recognized by financial analysts.

Commenting on the emphasis on cash flow and citing a 1981 Financial Executive Institute study, Casey and Bartczak (1984, p.61) report, "according to recent surveys, corporate and government officials have accepted this: they rate cash flow data as the most important piece of information contained in published financial statements."

The Financial Accounting Standards Board has also confirmed the important of cash flow analysis. After a series of exposure drafts, the Board issued the Statement of Financial Accounting Standards No. 95 (1987) entitled Statement of Cash Flows. FASB 95 requires all corporate entities (including financial institutions) to present a statement of cash flows along with an income and balance sheet for the accounting period.

Several researchers have incorporated this cash flow information in financial distress models for nonbanking firms. The information has been found to have varying degrees of predictive ability. No previous empirical work addresses the role of cash flow in financial distress models for the banking firm. This study takes a first step in that direction. The empirical evidence of this study has implications both for bank failure prediction and the related issues of bank cash flow reporting.

Another contribution relates to this study's secondary focus on small banks. The vast majority of previous bank failure research centers on large banks. However, the majority of banks that fail are small.

The large bank focus is typically justified on the basis of data availability and/or the potential magnitude of the consequences of these failures. Data availability is no longer a reasonable justification. Bank data are readily available for all banks regardless of size. With regard to consequences, FDIC Insurance fund disbursements provide one measure. In 1988, $3.893 billion was disbursed to aid failing or troubled banks. Forty-seven percent of these funds was disbursed to small banks, a sizable consequence. In view of these facts, it is now possible and necessary to direct research attention to the small bank group. By providing empirical evidence on the impact of cash flow information on small bank failure, this study addresses a gap in the existing literature.

Furthermore, existing bank failure studies are dated. Much of the failure prediction research was sponsored by regulatory agencies as a part of early warning systems. The major portion of this research was completed prior to 1980. Changes since 1980 have profoundly altered the structure of the financial services industry and the nature of banking operations. A changing regulatory environment relaxed or eliminated constraints on bank pricing, allowable activities and the geographic scope of bank operations. Economic factors, such as high and volatile interest rates, inflation, and other economic conditions, also contributed. Some change was driven by the emergence and application of new technology and the demands of more sophisticated customers. The environment in which the banking firm operates today is vastly different and far more competitive than that in existence in the early 1980s and before. Consequently, current empirical evidence provided by this study is needed by various publics.

Finally, the model developed in this study is potentially useful as a guide to bank regulators, managers and investors. The data used to estimate the model are regularly available to bank regulators and examiners. A failure prediction model based on this data could serve as a tool for monitoring bank performance. The model is not intended as a replacement for current monitoring and examination procedures. It could be used by regulators as a supplemental tool or screening device to alert them to potential problems evidenced in Call Report data.

An individual bank's data are obviously available to its managers. For these managers, the model could serve as a check of their own bank's performance. Investors and lenders also have access to similar data via published annual reports which must now include Statements of Cash Flow. This study offers these parties some insight as to the efficacy of incorporating CFA into their investment and lending decision-making processes.

ORGANIZATION OF THE STUDY

Chapter 2 reviews the relevant bank failure prediction literature. Special attention is given throughout to variable selection and statistical methodology. Accordingly, the reviewed studies are grouped by the research methodology adopted by the author.

The research methodology used in this study is presented in Chapter 3. The research hypotheses are presented first, followed by the formal research design adopted to test these hypotheses. The rationale for selecting logit analysis is presented along with a description of the logit technique. A discussion of the Lawson Cash Flow Model and the rationale for the selection of specific variables concludes the chapter.

Chapter 4 presents the empirical results. Total bank population results are discussed first. Small bank results follow.

The study is concluded in Chapter 5. The research methodology and results are reviewed and summarized. Implications of the research findings and limitations of the study are discussed. Finally, suggestions for refinements and extensions of the study are offered.

Chapter Two

Review of the Relevant Literature

This chapter presents a review of the failure prediction literature relevant to commercial banks. Various government agencies have a collective mandate to protect the "safety and soundness" of the banking system. As a means to that end, individual agencies have sponsored research, internally or via consultants, aimed at developing early-warning systems (EWS) as part of their oversight function. Other independent researchers in the academic community have also addressed the issue of commercial bank failure. The collective results of these research efforts constitute the body of literature reviewed in this chapter.

While the central issue addressed in each of the studies reviewed here is singular, the methodology adopted by individual researchers is not. An array of analytical techniques and statistical methodologies has been used to examine and predict potentially troubled banks. These various methodologies provide the organizational basis for this chapter.

Early Work, ANOVA Analysis and Linear Probability Models

In the early 1970's the Office of Management of the

Federal Deposit Insurance Corporation (FDIC) initiated efforts to develop a system for distinguishing between problem and healthy banks under its jurisdiction. The FDIC had in mind a project in which Report of Condition and Report of Income data, Call Report data, could be massaged and packaged so as to be more useful to the Division of Bank Supervision. (Sinkey, 1975) The Research division of the FDIC provided much of the analytical input to the project. The project lasted several years and involved the efforts of several researchers. Several of the studies discussed below are results of these efforts. These studies represent inputs toward a larger research effort which had as its goal the development of an EWS.

Meyer and Pifer (1970) conducted the first FDIC failure prediction study. Exploratory in nature, the study examines 39 banks that closed between 1928 and 1965. The closed banks are paired with solvent banks based on age, size, location, time period and regulatory requirements. A linear probability model (LPM) is used to test 32 financial variables selected to measure managerial ability and employee honesty. Each of the 32 variables is expressed in five forms to measure level, trend, variability and unexpected deviation. Of the initial 160 variables, 15 are included in the final models.

The significant variables included in the final model

TABLE 2.1

COMMONLY USED ABBREVIATIONS

CAMEL	Capital adequacy, Asset quality, Management, Earnings, Liquidity
A	Assets
CAP	Capital
CD	Certificate of deposit
DD	Demand deposits
EQ	Equity
INV	Investments
L	Loans
LIA	Liabilities
NI	Net income
NW	Net Worth
OE	Operating expense
OI	Operating income
OR	Operating revenue
RES	Reserves
REV	Revenue
SEC	Securities
T	Total
TA	Total assets
TD	Total deposits
TL	Total Loans
TR	Total Revenue

are classified in their CAMEL categories and summarized in Table 2.2. CAMEL is an acronym representing the five categories of the federal bank examiners' rating system. The categories are Capital adequacy, Asset quality, Management, Earnings and Liquidity. Table 2.1 provides definitions of commonly used abbreviations.

Estimation, classification and predictive results are reported for one- and two-year prior models. Classification improves as more variables are added but deteriorates as the

TABLE 2.2

FDIC STUDIES

SIGNIFICANT EXPLANATORY VARIABLES BY CAMEL CATAGORY

Study	Capital Adequacy	Asset Quality	Management	Earnings	Liquidity
Meyer and Pifer (1970)		Consumer L /TA TL Real estate L/ TA Fixed A/TA Questionable A/ TA	TD/DD OR/OE Interest paid on TD Indebtedness of directors/TA	OI/TA	(Cash + Securities)/ TA
Sinkey and Walker (1975)	CAP/TA Excess CAP/ risk A L/(CAP +RES) CAP/risk A	L/TA (Commercial + industrial L)/ TL Interest + fees on loans	OE/OI	NI/TA NI/CAP	U.S. treasury SEC/TA
Sinkey (1975)	L/(CAP + RES)	L REV/TR TL/TA	OE/OI OE/TR	REV from state and local obligations /TR	
Sinkey (1978)	ACR NCR	Substandard L/TL T classified L/TL T classified A + SEC)/TA		NI/TA	
Boveni, Marino and McFadden (1983)	T LIA/EQ CAP	Gross charge-offs/TL Overdue L/TA	OE/TA		

lead time to failure increases. At a cutoff value of 0.5, overall classification accuracy ranges from 78.5 percent to 88.5 percent. With regard to predictive abilities, classification accuracy deteriorates as the time before failure increases. The one-year prior model correctly predicts at least 83.5 percent of the holdout sample. Predictive accuracy falls to 61 percent for the two-year prior model.

Meyer and Pifer offer two main conclusions. First, even though failure frequently results from embezzlement and other financial irregularities, financial measures can evaluate the relative strength of the banking firm. Second, since several of the variables measure trends, variation, unexpected changes and values two years prior to failure, much more than just the current financial position of the firm is needed to discriminate among bank groups.

Much of the early-warning research sponsored by the FDIC was conducted by Joseph Sinkey during his tenure as a financial economist at the agency. Sinkey's research centered primarily on problem and failed banks, the bank examination process and the development of an EWS for the identification of problem commercial banks. Only his efforts in the latter area are reviewed here.

The FDIC identifies three classes of problem banks based on bank examinations. These classes are: (1) serious problem-potential payoff (PPO), banks with a 50 percent chance of requiring FDIC assistance; (2) serious problems (SP), banks headed for PPO status unless serious action is taken; and (3) other problem (OP), banks with serious problems but less vulnerable than PPO or SP banks. A bank designated as a problem bank by the above criteria is placed on the FDIC's problem bank list.

In a preliminary study to examine differences between problem and nonproblem banks, Sinkey and Walker (1975) apply ANOVA analysis to a matched sample of 62 banks. Pairings are based on deposit size, geographic market area, number of banking offices and federal examining agency. Financial measures representing each of the five CAMEL categories are generated from 1969-1972 Call Report data. Significant differences between the two groups are found for all measures at least one year prior to a bank's appearance on the problem bank list. One measure of capital adequacy--loans to capital plus reserves--is significant in all three years prior to problem bank list appearance. See again Tables 2.1 and 2.2 for a presentation of the significant variables and associated abbreviations.

Discriminant Analysis

Encouraged by the preliminary findings generated from the ANOVA analysis, Sinkey (1975) extends the research and applies discriminant analysis (DA) to a larger paired sample of 220 problem/nonproblem banks. The matching criteria and data period parallel the earlier Sinkey and Walker (1975) study. In this subsequent Sinkey study, the initial variable set of 100 financial ratios "include those that have been meaningful in previous banking studies...some popular measures found in the nonbanking literature...and ratios thought to be particularly relevant to the identification of problem banks" (p. 26). Ten of the original 100 variables are ultimately included in the DA model.

To determine the importance of specific variables, Sinkey applies four ranking methods. For 1969 loan to revenue, operating expense to operating income, and other expense to total revenue appear to be the important variables regardless of the ranking method used. Efficiency and other expense to revenue are found to be important in 1969-1971 and loan volume and loan quality are more important in 1972. Overall results indicate that six variables account for most of the discriminatory power in the set. The six variables are presented in Table 2.2.

Sinkey uses a quadratic discriminant function to reclassify the sample and validates using the Lachenbruch holdout technique. Lachenbruch classifications are 5 to 10 percent less accurate than simple reclassification results. Lackenbruch results correctly classify 53, 57, 62 and 72 percent of the problem banks in 1969, 1970, 1971, and 1972, respectively. Accuracy rates of both classification models increase as the time before failure decreases. Both the Sinkey (1975) and Sinkey and Walker (1975) studies suggest predicting problem status can be fairly accurate in the short run, one to two years lead time.

Sinkey proposes an alternative DA model in his contribution to Financial Crisis (Altman and Sametz, 1977). His sample consists of 208 randomly selected nonproblem banks and 204 banks from the 1975 FDIC problem bank list. The model is estimated using 1974 year-end Call Report data. With the exception of the inclusion of a liquidity variable, the seven variables in this study roughly parallel those in Sinkey's 1975 study. Sinkey again uses DA and the Lachenbruch holdout technique. One hundred thirty seven problem banks and 174 nonproblem banks are correctly classified. However statistical tests find substantial overlap between the means and covariance matrices leading Sinkey to conclude that no substitute exists for the judgment and analysis of the examination staff when identifying problem banks. He further emphasizes:

> There is nothing magical about these particular (sic) seven variables. If certain dimensionalities are captured, the form that the individual variables take is relatively unimportant. Moreover using only

the loan revenue and operating efficiency variables, the classification results were quite comparable with those using all seven variables (p. 37).

Sinkey's (1978) final reported FDIC study uses 1973 bank examination data and a quadratic DA model to identify problem banks. A group of 143 problem banks from the 1974 problem bank list is compared with a random sample of 163 nonproblem banks. Twenty-one variables are tested and the results of a six variable model are reported. The included variables again reflect the various CAMEL categories. See Table 2.2. This Sinkey study focuses on two capital adequacy measures, the adjusted capital ratio (ACR) and the net capital ratio (NCR).

ACR and NCR are standard FDIC capital ratios and depend critically upon an FDIC examiner's loan evaluations. The numerator of ACR is formed by subtracting assets classified as loss and 50 percent of those classified as doubtful from a bank's total capital accounts. The numerator of NCR is formed by subtracting all loss, substandard and doubtful assets from a bank's capital. The denominator of both ratios is the same, a bank's quarterly average of gross assets. The difference between ACR and NCR is the 50 percent of doubtful and all substandard assets.

Sinkey finds NCR is the most significant variable and the most important discriminator between the groups. NCR for the average problem bank is -2.3 compared with 7.6 for the average non-problem bank. Again validating with the Lachenbruch technique, 306 banks are correctly reclassified for overall classification accuracy of 95.4 percent. Classification accuracy cannot be improved by adding other examination variables. Sinkey (1978, p.190) concludes that "it is clear that a bank's volume of 'substandard' loans is the kicker in the NCR formula."

During the same time economists at the FDIC were focusing research efforts on the development of an EWS, almost parallel efforts were in progress in the banking studies department of the Federal Reserve Bank of New York (FRBNY). The ultimate goal of the FRBNY was the efficient allocation of supervisory resources. The thrust of the research was to develop a procedure for identifying banks potentially vulnerable to financial difficulty. Early identification of such banks could permit more efficient deployment of supervisory personnel. FDIC and FRBNY studies are generally similar in that both employed statistical methodologies to predict and/or classify commercial banks. However, the studies differ in several respects. The primary difference is the shift in definition from problem or closed banks to banks "vulnerable to failure." The vulnerability definition is in keeping with the FRBNY's research objective of determining allocative efficiency. Other differences will become apparent below.

Preliminary FRBNY work focuses on the 350 state and national banks in the Second Federal Reserve district. Call Report and examination data for the period 1969-1974 are used to estimate and test several models. Results are reported in a series of articles culminating in "A Nationwide Test of Early Warning Research in Banking." (Korobow, Stuhr and Martin, 1977)

In the beginning phase of the project Stuhr and Van Wicken (1974) use DA to discriminate between banks with high and low supervisory ratings. At the time, FRBNY supervisory personnel assigned banks a summary rating based on asset quality, capital adequacy and management quality. Ratings ranged from 1 for financially sound to 4 for weak. In the study, banks rated 1 are considered high-rated and banks rated 3 or 4 are considered low-rated. Banks rated 2 are excluded. The variables included in the DA models are total deposits, a proxy for bank size, and seven CAMEL measures. See Tables 2.1 and 2.3.

Separate functions are estimated for 63 state and 151 national banks in the Second Federal Reserve District for the period 1967 and 1968. Results are validated with holdout samples of 46 and 19, respectively. The models correctly classify all the weak State banks in both the original and holdout samples. For the national group, three

TABLE 2.3

FEDERAL RESERVE BANK OF NEW YORK STUDIES

SIGNIFICANT EXPLANATORY VARIABLES BY CAMEL CATAGORY

Study	Capital Adequacy	Asset Quality	Management	Earnings	Liquidity
Stuhr and Van Wicken (1974)	CAP/TA	(Classified A + 1\2 specially mentioned L/ (TL + SEC)	Borrowings/ CAP	Pre-tax Income/ CAP DIV/CAP	
Korobow and Stuhr (1975)		L/TA			
Korobow, Stuhr and Martin (1976)	Gross CAP/ Risk A Provision for Loss/(TL +INV)	TL/TA (Commercial + Industrial L)/ TL	OR/OE		Net Liquid A/ TA
Korobow, Stuhr and Martin (1977)	EQ CAP/ Adjusted Risk A	L + Leases/T Sources of Funds (Commercial and Industrial L/TL Gross Charge-offs/ (NI + Provision for Losses)	OR/OE		
Martin (1977)	Gross CAP/ Risk A	L/TA Commercial L/TL Loss Provision/ (L + SEC) Gross Charge-offs/ Net OI	OR/OE	NI/TA	Net Liquid A/ TA

weak banks in the original sample are misclassified. Upon follow-up, the authors find a number of apparent misclassifications were suggestive of future changes leading the authors to conclude that the model appears to have moderate predictive ability.

Korobow and Stuhr (1975) retest the 1967 and 1968 estimated functions and coefficients but use instead 1974 data for state chartered banks in the Second Federal Reserve District. The re-estimated functions successfully distinguish between banks with high and low ratings in 1974. Encouraged by the classification results, the authors shiftthe research focus to the problem of anticipating a bank's potential deterioration.

Korobow and Stuhr acknowledge that much of the work in this phase is preliminary and exploratory. Their ultimate goal is to identify banks that are vulnerable to a weakening in their financial condition. Furthermore, they want to identify these particular banks without the use of information gathered from on-site examinations. Korobow and Stuhr experiment with various sampling techniques, ratio combinations, sources of data, procedures and functions. The procedure, for which results are reported, involves ranking all banks in the sample using an index procedure based on a combination of 12 financial variables. Several functions are then estimated based on the multivariant rankings. Each estimated function yields a rank score for each bank. Cutoff scores, calculated to minimize the cost of misclassifications, serve as the basis for dividing the sample intc two groups, resistent and vulnerable. Discriminant scores are also estimated based on the supervisory rating criteria. The functions are estimated and tested using various samples drawn from the 350 bank sample.

Test results are reported for four functions, EXAM I, EXAM II, MISR and MISF. EXAM I and II are both discriminant functions. EXAM I uses only examination data and EXAM II excludes examination data in favor of regularly reported Call Report data. MISR, multivariate index standard ranking, is based on the index procedure described above. This technique assigns equal weights to the 12 variables. This MISR function is then used in conjunction with discriminant techniques to yield a function called MISF, multivariate standard index function. All functions are able to identify banks subsequently receiving low supervisory ratings with classification accuracies ranging from 89.7 to 97.4 percent. Best results are achieved with MISF and MISR. The authors conclude that these two approaches merit further attention and direct subsequent research efforts to that end.

Arctangent Regression Analysis

Further refinements in the Korobow and Stuhr model are presented in the next article in the series (Korobow, Stuhr and Martin, 1976). Incorporating a cost function which minimizes the two types of errors, for example examining more banks than necessary and failing to identify potentially weak banks, the authors narrow the variable set to six CAMEL measures. See Table 2.1 and 2.3 for a summary.

Since the goal was to maximize efficiency of supervisory personnel, the authors seek to determine the likelihood a bank might experience financial distress and require supervisory resources. Probabilities are incorporated in the model and the model's forecasting ability tested using the same Second Federal Reserve District, 1969-1974, data set. The probability function is estimated using dummy regression analysis and an arctangent regression function. Based on preliminary results, the authors conclude that the early warning function has a significant capability for identifying vulnerable banks in years subsequent to the estimating period.

The completed model is tested using a nationwide universe of Federal Reserve member banks. Korobow, Stuhr and Martin (1977) report the findings. Again the objective test employed is the "incidence of low supervisory ratings among member banks that have been ranked according to an index of vulnerability which is comprised of key financial ratios" (p. 39). The authors select five financial ratios as explanatory variables. Their selection is based on the historical ability of these ratios to proxy the causes of bank weakness. The hypothesized causes of weakness are: poor management, erosion of earnings and capital, poor internal control of expenses, and unanticipated loan losses.

Banks are grouped by size and region and separate functions estimated for each group. Previous FRBNY studies use standardized deviations to calculate bank scores. In this study the probability of receiving a low rating is estimated directly using dummy regression analysis and an arctangent regression function. This methodology yields separate estimates of the contribution of each independent variable.

Using various base and forecast periods, the regional functions come reasonably close to correctly predicting the number of banks which eventually receive low ratings. For example, with 1970-1972 as the base period, the model predicts 96 of the 117 Northwest region banks which received low ratings over the 1973-1975 forecast period. Forecast results are similar for the other regions. In all four regions, the operating expense ratio has the highest elasticity, ranging from 1.4 in the West to 1.0 in the Midwest. Loans and leases has the next highest elasticity coefficient.

Results are similar for the size groupings. The best results are in the $50-100 million asset group where the model predicts 37 of 38 vulnerable banks. Predictive ability decreases as asset size increases. In the $300 million plus group, the model predicts only 28 of 65 vulnerable banks. Overall, in the 1973-1975 forecast period, the model predicts 475 of the 525 banks which ultimately receive low ratings. For all size groupings, the expense ratio again has the largest impact on potential weakness.

To summarize, Korobow, Stuhr and Martin find forecast results of early-warning models generally useful for predicting the incidence of low supervisory ratings. Results are similar regardless of forecast period and grouping. For their purposes, efficient allocation of agency resources, they conclude use of their model could potentially generate substantial gains in efficiency.

Logit Analysis

Martin (1977) conducted the final published FRBNY early warning study. Martin's study differs from previous FRBNY studies in two ways. First, Martin abandons the vulnerability concept. He specifically defines failure as "failure, supervisory merger or other emergency measure to resolve an imminent failure situation within two years of the statement year to which financial ratio data apply" (p. 262). Second, Martin's study is the first to use logit analysis. For comparative purposes, Martin also estimates two discriminant models, linear (LDA) and quadratic (QDA).

Martin's models are estimated using financial data from a population of Federal Reserve member banks. Ratios are derived from Call Report data for the period 1970-1978. Fifty-eight of approximately 5,700 banks met Martin's definition of failure. Various periods and various ratio combinations are tested including Korobow, Stuhr and Martin's (1976) six variable combination. The best logit model is estimated using 1974 data and incidence of failure in 1975-1976. Twenty-three failed and 5,575 nonfailed banks are examined. In its final four variable form, the model includes four of the six Korobow, Stuhr and Martin (1977) variables. The excluded variables are net liquid assets and loss provisions/loans plus securities. See Table 2.3 for a summary.

Estimation results are reported and compared for each of the three techniques. In all instances, Martin finds the logit functions yield better probability estimates. However, when comparing classification ability, Martin finds the classification accuracy of the logit and discriminant models virtually the same. Accuracy rates (failed/nonfailed) for logit, LDA and QDA were 91.3/91.1, 82.6/96.2 and 91.3/92.0 percent, respectively. Martin (1977) states:

> The relative merits of logit vs. discriminant analysis...appear to depend on the intended use of the results. If a dichotomous classification into 'sound' and 'unsound' banks is the goal, then we may be indifferent between discriminant and logit models. On the other hand, the user may be capable of varying levels of response to risk of failure: a supervisory agency can choose between more and less urgent measures to deal with a problem situation. In that case, probability estimates can be of greater interest that (sic) a simple classification, and the quality of these estimates is an important issue, favoring the logit approach. (p. 267)

West (1985) notes what he considers a weakness in bank regulatory agencies' monitoring/examination processes. These bodies develop and use early warning systems to predict problem banks. They also develop and use examination systems to rate a bank's actual performance. West argues that no direct relationship exists between the inputs of these two systems. His study provides the link.

Like Martin (1977), West uses a form of ratio analysis and a logit regression (LR) model. However West's study is the first reported bank study which uses classical factor analysis (FA) to identify the common characteristics of bank performance. The goal of FA is to reduce a large number of observed variables to a smaller set of subgroups which summarize the data. Factor scores are calculated for each factor and these factor scores serve as the independent variables in the logit estimation.

West's sample includes 1,900 banks located predominantly in the Tenth Federal Reserve District and some surrounding states. Both Call Report and examination data for 1980-1981 are used to generate the 19 variables included in the study. With the exception of total assets, all variables are in ratio form. West's FA finds eight identical common factors in 1980 and 1981 and seven factors in 1982. West identifies these factors by the variables they contain and characterizes them as representative of capital adequacy, asset quality, earnings, liquidity, various loan categories, and source of deposits. He is quick to note that the first four factors are similar to the CAMEL ratings used by regulatory agencies. Factor scores for 1980 and 1981 are used as variables in the logit estimation. Banks with CAMEL ratings of 2,3 or 4 are considered problems and banks with ratings of 1 and 2 are considered sound. Table 2.4 presents the factors and variable groups.

Signs on the estimated coefficients are as expected FA/logit analysis combination "holds a good deal of promise as an early warning system." Furthermore, because the

TABLE 2.4

FACTOR GROUPINS AND ASSOICATED CAMEL CATEGORIES

			Loan Categories
F-1	**Capital Adequacy** EQ CAP/TA TL/(EQ CAP +RES) TA	F-5	**Commercial** (Commercial + Industrial L)/TL (CDs + federal funds + repos)/ /TA
F-2	**Asset Quality** Substandard L/ T CAP Doubtful L/T CAP Uncollectible L /T CAP	F-6	**Real Estate (RE)** Residential RE L/TL Non-farm, non-residential RE L /TL Agricultural L/TL
F-3	**Earnings** NI/TA NI/EQ CAP T OE/TA	F-7	**Consumer** Consumer L/TL
F-4	**Liquidity** TL/TA Liquid A/TA	F-8	**Sources** (Time + savings deposits)/TD Interest paid on deposits/TD

Source: West (1985).

indicating banks with good capital, earnings and liquidity will receive lower probabilities of failure. The model correctly identifies 89.6 and 90.4 percent of the problem banks and 89.2 and 90.4 percent of the sound banks in 1981 and 1982, respectively. In other tests not reported, West finds the model stable over time and geographic area. Based on these results, West (1977, p. 264) concludes that explanatory variables in his model bear a strong resemblance to CAMEL ratings inputs, West concludes that his model provides support for regulatory agencies' use of these ratings.

Probit Analysis

While serving as an economist in the Financial Studies Section of the Federal Reserve System, Gerald Hanweck provided another contribution toward the development of an EWS. Hanweck suggests that studies conducted prior to his writing are not based on theoretical principles or empirically validated relationships. Because these studies are merely descriptive, he contends that screening programs based on their results provide only a shotgun approach to bank monitoring. Hanweck develops and empirically tests a theoretical model of bank failure.

In developing the theoretical model, Hanweck (1977) distinguishes between technical insolvency and insolvency leading to failure. Technical insolvency occurs when the book value of bank liabilities plus accrued interest on debt exceeds the market value of bank assets. Technical insolvency may be temporary and does not necessarily lead to failure. In the state of technical insolvency, failure results only if the present value of bank future income is insufficient to cover bank expenses. In the Hanweck model, the probability of failure is less the greater are the present value of future income, the market value of bank assets, the bank's capital base and the bank's ability to raise new equity capital.

To test the model, Hanweck applies probit analysis to a randomly selected sample of 177 FDIC insured banks. Data are taken from Call Reports for the period 1971-1975. The model is validated with a hold-out sample of 12 failed banks.

Of the six variables included in the model, only net income to total assets and loans to capital are significant. Hanweck interprets this result as supportive of regulators' emphasis on bank capital, loan quality and earnings performance. Classification procedures correctly identify eight of the 12 failed banks and 176 of the 177 non-failed banks. Hanweck considers these results remarkable given the random selection of the nonfailed sample. He concludes that the model can provide a basis for an EWS.

Continuing earlier FDIC failure prediction research, Bovenzi, Marino and McFadden (1983) adopt a probit model and a somewhat different focus. The impetus of their work came from the FDIC's desire to explore a risk-based deposit insurance premium system. This shift in focus is reflected in the authors' definition of failure, variable set and statistical methodology. Failure is defined as all commercial banks that required cash outlays from the Deposit

Insurance Fund. In addition to the standard CAMEL measures, the authors include variables to measure credit risk, interest rate risk and diversification risk. Call Report and examination data for the period 1979-1984 are used to estimate a probit model. Seventy-two banks failed during this period.

The authors explore many issues. First, to compare the classification and predictive abilities of Call Report data versus examination data, they estimate three models, CALL A, EXAM A, and EXAM B. CALL A is based solely on call report data. EXAM A incorporates both call report and examination data. EXAM B is essentially the same as CALL A but incorporates one examination based variable. Results based on these models are also compared with Martin's (1977) logit analysis and the FDIC's CAMEL rating scheme. Second, to examine the impact of lead time, they estimate three versions of each of these models, one-, two- and three-year prior models. Finally, to examine the impact of sampling techniques, they estimate two additional versions of each of the models. One version is estimated using the universe of all insured commercial banks, approximately 14,300 banks at the time. The other is based on a random sample of 150 nonfailed banks drawn from this universe. Comparative results are presented for various models, lead times and sampling techniques. The variables included in the final form of each of the probit models are listed in Table 2.2.

With regard to comparative results of alternative data sources, inclusion of exam data tends to improve classification accuracy. EXAM A is the best predictor with one- and two-year lead times. However, with three year lead time, CALL A is the best performer. Classification accuracy of all models decreases over time. Comparing Call A with Martin's model with a probit specification, Martin's model is the better performer one and two years prior to failure. With a three-year lead time, CALL A is superior. The authors suggest that these results are a result of difference in variables. Martin's variables focus on capital adequacy and bank earnings which may be better predictors when lead time is short. When comparing the classification abilities of CALL A and EXAM A with the FDIC's CAMEL rating system, the authors conclude, "The results substantiate that models based upon financial ratios can classify failures as well as or better than a scheme based solely on examiner's ratings (Boveni, Marino and McFadden, 1983, p.22)."

Finally, with regard to the alternative sampling techniques, results are mixed. While the estimated coefficients are similar for both the universe and random samples, only the universe generated estimates precise enough to establish the significance of the variables. The authors conclude that the financial variables may be useful for comparing differences between failed and nonfailed banks, but the predictive ability of these variables is questionable.

Abrams and Huang (1987) also use a probit model to explain bank failure. In addition to the usual bank operating and risk characteristics, Abrams and Huang incorporate additional variables to assess how bank structure influences the probability of failure. The authors model bank failure as a function of three factors: net worth, expected earnings and variability of earnings. They assume that a bank's risk and other problems a bank might experience would impact through one or more of these factors and in turn affect the probability of failure. Several financial ratios representing the CAMEL categories are used to measure the effects of the three factors.

Three models are estimated for the period 1981-1982. In general a higher probability of failure is associated with a bank that is small in size, is unaffiliated with a holding company, is a unit bank, has relatively lower net worth and earnings, and operates in a relatively growing market. The use of probit analysis allows the calculation of elasticities of the probability of failure with respect to each variable. The highest elasticities are found for loan losses and net worth. The smallest elasticities are

TABLE 2.5

OTHER STUDIES

SIGNIFICANT EXPLANATORY VARIABLES BY CAMEL CATAGORY

Study	Capital Adequacy	Asset Quality	Management	Earnings	Liquidity
Abrams and Huang (1978)	NW/TA	CD/TA L/TA Provision for Loan Loss/TL		NI/TA	
Lane, Looney and Wansley (1986)	TC/TA	(Commercial + Industrial L) /TL TL/TD Municipal SEC/ TA TL/TA	OE/OI	NI/TC	

found for size, long-term securities holdings and holding company affiliation. The authors conclude that the finding of most significance is the fact that banks that affiliate with holding companies or are large in total asset size have a lower probability of failure.

Gambler's Ruin Model

Santomero and Vinso (1977) examine the cross-sectional riskiness of the then present banking structure. The study focuses on capital adequacy issues for the banking system as a whole. However in the concluding section, the authors propose a problem bank screen which they suggest could be useful as part of an EWS. After developing a theoretical framework, the authors estimate a Gambler's Ruin model. Information developed with this model is then used as input in a discriminant model to develop the problem bank screen.

Santomero and Vinso challenge regulators' practice of using ratio forms of capital accounts for assessing the risk position of banks in particular and the banking system in general. They argue that the static nature of these devices "rather than obtaining evidence concerning the bank's likely exposure to failure in its operations, these ratios question the ability of the bank to avoid present failure with its present asset characteristics" (p. 187). If the concern is future bank exposure, they argue, it is essential to consider the dynamics of banking operations.

Given these arguments, the authors abandon simple ratio methods in favor of first passage time or Gambler's Ruin and maximum risk exposure models. Similar in approach, both methods perceive the movement of the total capital account as a stochastic time series that must be specified. The total capital account, the system's buffer stock to prevent failure, is defined as reserve for bad debts and security losses plus total capital (debt and equity).

Data are compiled from weekly Report of Condition statements filed by the banks. The sample includes 224 Federal Reserve member banks for which consistent data are available over the period 1968-1974. To adjust for seasonality, weekly data are transformed to monthly data and first differences used to generate changes in the total capital account. Safety indices for each bank are generated using capital and loan reserve accounts as of January 1974. A frequency distribution of these safety indices provides the information for assessment of banking system risk and sensitivity of the system to changes in bank capital. The relative risk posture of an individual bank is given by the bank's position in the distribution. To investigate the system's sensitivity to changes in bank capital, alternative additions and reductions in the initial total capital account are tested.

The authors find "that at its riskiest point the safety index ... suggests a very low average risk exposure for the banking system as a whole" (p. 197). Results also indicate that changes in bank capital have a negligible impact on the safety index or risk. However soundness of the marginal or problem bank is affected by variation in capital prompting the authors to investigate an early warning system.

To develop the problem bank screen, Santomero and Vinso use an arbitrary safety index score to divide the sample into 37 risky and 187 nonrisky banks. They select five variables and test for significance between the groups. Significant differences exist only in the capital asset ratio and coefficient of variation of capital. The authors then estimate and test a discriminant screen comprised of these two ratios. Two alternative decision rules are used to reclassify the sample.

The more stringent decision rule correctly classifies all risky and 208 of 214 nonrisky banks. The weaker decision rule correctly classifies 60 percent of the risky banks. The authors conclude that the simple two-dimensional screen could be useful for isolating potentially troubled banks. Furthermore, both a bank's capital asset ratio and variability of capital are equally important indicators of bank soundness.

Bi-Plot Technique

Cheva and Sokoler (1982) studied problem banks in Israel. They argue that bank failure is the end result of a process of excessive risk taking by a bank. Basic to their analysis is the assumption that the banking system as a whole does not engage in this behavior. An individual bank in the system could, however, be characterized by its own risk structure. Healthy banks would exhibit risk structures which are not significantly different one from another but problem banks would be characterized by risk structures significantly different from those of healthy banks. A bank's risk structure consists of three components: (1) operating risk, (2) financial risk, and (3) liquidity and capital risk. To test their hypothesis the authors apply a bi-plot technique to a set of financial ratios arbitrarily selected to capture these risk components. Cheva and Sokolor are the first to apply the bi-plot technique to the study of bank failures.

The model is developed and tested using a sample of 23 Israeli banks which failed over the period 1959-1972. The ratios employed as proxies for the three risk components are traditional CAMEL measures. When both components of the classification criteria are used, the model correctly classifies four of the five failed banks and 17 of 18 non-failed banks.

Cheva and Sokolor's study, while interesting for its methodology, has several drawbacks. The model is not validated with a hold-out sample or other technique because of the small sample size. The size of the sample itself also raises a question of validity. Finally, the technique itself would most likely prove untenable for a regulatory agency supervising thousands of banks.

Proportional Hazard Model

In a 1986 study, Lane, Looney and Wansley apply the Cox proportional hazard model to the prediction of bank failures. This model, used predominantly in biomedical research, had not been previously employed in the bank literature. The authors give two arguments for their model selection. First, the model has the ability to explicitly incorporate a bank's expected time to failure. A model estimating not only the probability of a bank's failure but also the expected time of such an event could greatly enhance regulatory agencies' allocation of on-site examination resources. Second, on the technical side, the Cox model does not require any assumptions regarding underlying probability distributions. DA, logit and probit analyses assume multivariate normal, logistic and cumulative normal distributions, respectively.

The sample consists of 133 failed banks identified from FDIC annual reports for the period 1978-1984. The failed banks are matched with 334 nonfailed banks for the same period based on age, size, geographic location, structure and charter. An initial set of 21 financial ratios, chosen to represent the five categories in the CAMEL rating system, is constructed from Call Report data. For comparative purposes, two similar MDA models are estimated using the same sample and data. For classification purposes, proportional priors are used to establish the critical value. The included variables for the four versions are listed in Table 2.5.

No significant difference is found between the classification ability of the Cox and MDA models. Type I error rates for the Cox model are less than those of the MDA model indicating the Cox model's superior ability to classify failed banks. With regard to the Cox model's ability to predict time to failure, results are mixed. When one-year prior survival curves are plotted for the holdout sample, the average curve for the failed bank group quickly diverges from that of the nonfailed group and rapidly decreases over time. However, the model tends to classify banks as failures sooner than the actual failure occurred. The model predicts 38 holdout banks will fail in the first month of 1984. Of the 38 only two actually fail by January 31. Another 28 failed within six months. The authors view this phenomenon as an advantage since early identification of a problem bank allows more time for remedial action. They conclude that the Cox model is a viable alternative for inclusion in an early warning system and use of the model provides valuable information without sacrificing classification accuracy.

Marcus and Shaked (1984) suggest a novel approach to failure prediction. They first calculate insolvency probabilities for individual banks within a bank group. Then selected financial ratios are calculated and examined to determine if these ratios are correlated with estimated insolvency risk. Their approach is the opposite of the usual approach which typically conditions the failure of probability on a set of preselected financial ratios. Their sample consists of 40 large banks included on the Compustat and CRSP data tapes for 1979 and 1980.

In the Marcus and Shaked model, failure is a function of bank asset returns. Central to their analysis is the assumption that the asset returns of the sample bank group are lognormally distributed. An individual bank's probability of failure is a direct estimate of the parameters of the lognormal distribution for that particular bank. Asset values, returns and all other parameter inputs are estimated using market data.

Examination of the estimated frequency distribution reveals that the probability of failure for most sample banks is small: 32 banks faced failure probabilities of less than one in a thousand. However, the distribution is extremely skewed implying a few banks have relatively large probabilities of financial distress.

Of the 23 ratios examined, several CAMEL type ratios are significantly correlated with insolvency risk. These are loans to deposits, operating revenue to operating expense, net income to capital, and provision for bad debt losses to operating expense. These results are consistent with Sinkey and Walker (1975), Sinkey (1975) and Meyer and Pifer (1970). Two ratios, capital to liabilities and loans to capital plus reserves, are significantly correlated but of the wrong sign. The authors interpret their findings as supporting the validity of traditional ratio analysis. However, because of the incorrect sign on some significant variables, they suggest that "the relevant assessment of financial strength must be based on the interaction of a set of ratios" (p. 80).

Descriptive Study

A study sponsored by the Office of the Comptroller of the Currency (OCC) provides the most recent contribution toward an understanding of bank performance. The OCC study identifies several difficulties and conditions that contribute to problem and failed banks. Although the study is more descriptive than empirical, it is included in this review because it offers useful insights for modeling bank failure.

The purpose of the OCC study (Graham and Horner, 1988) is to identify the factors, internal and external, that contribute to the failure of national banks. To assess these factors, the OCC examines 260 FDIC insured, national banks in operation through the period 1979-1987. The sample includes 38 healthy, 171 failed and 51 rehabilitated banks. A rehabilitated bank is one which experienced significant difficulty sometime in the period but subsequently returned to healthy status. Two types of data are used. Factual information concerning a bank's asset size, location, type of ownership and change in control is gathered from examiners' reports. Subjective data include the OCC's assessment of each bank's performance in eight broad categories representing both internal bank characteristics and external local economic conditions.

With regard to internal factors and failure, the OCC study finds deficiencies in the Board of Directors and management practices are the primary contributing factors. The Board of Directors of failed banks are typically passive, lacking in bank knowledge, and uninformed about bank activities. They are lax in exercising oversight responsibilities and implementing control procedures. Management deficiencies include poor lending policies, inadequate problem loan identification systems, weak or non-existent asset and liability management policies, and inadequate compliance systems. Boards and/or management of failed banks also tend to engage in overly aggressive behavior as evidenced by excessive loan growth, inadequate liquidity and liberal repayment and collection policies.

Another major cause of bank failure can be traced to the Chief Executive Officer. In 63 percent of the failed banks, the OCC judged this officer as lacking the capacity, experience or integrity needed to ensure bank success. Insider abuse is present in 35 percent of the failures and material fraud is present in 11 percent. The OCC finds problems of insider abuse and fraud are often related to other deficiencies in management or Board oversight and control procedures and suggests that these deficiencies provide the opportunity for abuse and fraud to occur.

The OCC holds the view that banks' management and Board are ultimately responsible for performance of the institution. While local economic conditions can strain bank performance, the policies and procedures of management and the Board have the greater influence on whether a bank will succeed or fail in a local economic downturn. The OCC study supports this view. A depressed economy is the sole cause of failure in only seven percent of the cases. This finding combined with the fact that 59 percent of rehabilitated and 50 percent of healthy banks operated in significantly depressed local economies, prompts the OCC to conclude "poor management and other internal problems are the common denominator of failed and problem banks." (Graham and Horner, 1988)

Event Studies

A common thread in the studies reviewed above is their dependence on accounting and financial information as predictors of bank failures. The studies reviewed below employ an alternative approach which investigates the use of market information in the form of bank stock prices and rates of return. The logic behind this approach is derived from the efficient market hypothesis (EMH). EMH states that common stock is continuously and fairly priced with respect to its intrinsic value and new information which might influence this value is rapidly incorporated and reflected in the stock's price. If markets for bank securities are efficient, then changes in a bank's position will be reflected in the price behavior of the bank's equity securities. Thus regulators could gain valuable information regarding a bank's condition by monitoring this price behavior.

The methodology employed in these studies is generally similar. The market model, developed by Sharp (1963) and refined and expanded by Sharp (1964), Litner (1968) and others, is estimated. Residuals are analyzed using a methodology similar to that developed by Fama, Fisher, Jensen and Roll (1969). This involves constructing an event study in which the average residuals are cumulated and plotted for a specific period before and after the event. An event or critical date is variously defined depending on the specific relationship being examined. Inferences regarding changes in investor perceptions, as reflected in changes in equity prices and returns, are drawn based on the pattern of the cumulative average residuals.

Shick and Sherman (1980) examine the historical relationship between stock prices and changes in bank condition. A bank's condition is taken as the composite rating assigned to the bank as a result of a regulatory agency's examination process. A change in the assigned rating is taken as a change in bank condition, and the date the change was recognized by the regulatory agency serves as the event date. Their sample consists of 25 banks which experience ratings decreases over the period 1967-1976. Because only large banks have actively traded stock, all banks in the sample had total assets in excess of $200,000,000.

Parameters are estimated using 72 months of data, 36 prior to the event and 36 after the event. Bank price data are taken from COMPUSTAT data tapes and ratings information is gathered from the Office of the Comptroller of the Currency. Market and industry data are taken from the Standard and Poor's (S&P) 500 Stock index and S&P non-New York City bank index, respectively. Residuals, forecasted minus actual returns, are calculated for 20 months prior to and nine months after the event. The cumulative average residuals for this period are computed and presented graphically.

Examination of the cumulative residuals supports the authors' hypothesis that bank stock prices do reflect changes in bank condition. Moreover, the decline in the residual pattern predates the beginning of the examination by an average of nine months implying that bank capital markets respond to changes in bank condition before examiners are aware of financial problems. Acknowledging the small sample and non-random selection, they are quick to note that the study is only a first step toward an early warning system.

Pettway (1980) conducts a similar study. According to Pettway, bank regulators believe that the market for bank equities is inefficient. The market is inefficient because regulators have unique information, on-site examination results and subsequent bank ratings, which they do not make available to the public. Because investors are unable to incorporate this unique information in their pricing decisions, bank equity returns do not reflect any increased potential for bankruptcy. Hence regulator's tend to discount the role that markets can play in bank regulation. Pettway tests this belief and investigates what value, if any, market information may have for an early warning system.

Pettway's failed bank sample includes five large banks that failed and two that reorganized to avoid failure during the period 1973-1976. Problem bank lists and failure dates are obtained from the FDIC. The market model is estimated for a portfolio of 24 non-failed banks over the same period. The pattern of residuals, return on the failed bank minus return on the portfolio of non-failed banks, is examined around three critical dates. Critical dates are: (a) examination date, the beginning date of the exam which led to classification as a problem bank; (b) classification date, the date of the bank's appearance on the problem bank list; (c) failure date, the date authorities officially closed the institution.

Pettway finds no support for the hypothesis that the market for large bank stocks is inefficient. In all three event studies the market adjusts to the potential of bankruptcy sooner than regulators acknowledge the possibility of such an event. Cumulative residuals around the exam date, classification date and failure date begin declining 38 weeks, 36 weeks, and two years prior to the respective event. Pettway concludes that "because of this lead in changing risk perceptions, it may be possible to develop an EWS employing market return data which might be beneficial to regulators in identifying and thereby treating the increased potential of bankruptcy of large commercial banks" (p.235).

Pettway joins with Sinkey (Pettway and Sinkey, 1980) to develop and test an early warning technique which incorporates both accounting and market information. Their model uses two filters, an accounting filter and a market filter. The dual screening technique yields four possible outcomes: no flag, an accounting flag, a market flag, and an accounting and market flag. A flag is an adverse classification by the filtering mechanism. The condition of a bank triggering two flags is considered critical and in need of immediate remedial action. One flag denotes a less serious situation and no flag implies a safe situation.

The market filter is based on Pettway's 1980 study. The market model is again estimated for a portfolio of 24 large banks using S&P 500 weekly returns. Firm-specific error, the difference between a bank's total error and estimated error, measures the impact of new information and/or change in market perceptions about the potential failure of the bank. Six weeks of successive reduced cumulative residuals is interpreted as an increase in the probability of a bank's failure. The critical date, for both screens, is the date of the beginning of the on-site examination which results in designation as a problem bank.

The accounting filter is based on Sinkey's (1979) two variable, DA failure prediction model. Again the variables are total operating expense to total operating income and investments to total assets. The model is estimated using a matched sample of 33 banks that failed over the period 1970 to 1975 and validated with a holdout sample of 16 banks that failed in 1976. The model correctly classifies 15 of the 16 banks one year prior to failure and 14 of the 16 banks two years prior to failure.

When reporting results the authors focus on six of the nine failed banks. Lead time is the number of weeks by which an accounting or market flag precedes the critical date, beginning of the on-site examination. Accounting lead times range from a maximum 103 weeks to a minimum 51 weeks with an average of 66 weeks. Market lead times range from 140 weeks to seven weeks with an average of 53 weeks. Accounting flags generally precede market flags but the appearance of the accounting flag and the downturn in cumulative firm-specific error are close. Given these findings, the authors offer two main conclusions. First, large bank equity markets are efficient. Second, the dual screening technique could provide substantial benefits to regulators when establishing on-site examination priorities.

Simpson (1983) argues that it is possible that insider information indicating financial distress may reach capital markets before regulators are aware of a bank's financial problems. This is possible because bank examinations are conducted only periodically. In the interim between examinations, proxies for the insider information eventually gathered by examiners may become publicly available. Simpson tests this hypothesis using the same bank group, six large bank failures and a portfolio of 24 non-failed banks, and the same data employed in the Pettway 1980 study.

Simpson first estimates a transfer function model which incorporates an intervention variable. The intervention variable is structured to allow for evaluation of individual bank returns in four specific time periods. Time periods range from one year prior to regulatory awareness of financial problems to some time after awareness but six months prior to failure. Intervention analysis for each of the six failed banks gives no support to Simpson's hypothesis that capital market returns are better indicators of financial failure than on-site examination procedures. This finding is inconsistent with previous market study findings in general and Pettway and Sinkey (1980) in particular.

To explain the inconsistencies with Pettway and Sinkey, Simpson replicates their study but incorporates risk differentials for each bank relative to the non-failed bank portfolio. Cumulative residual analysis results are mixed. First, indication of financial distress occurs in the market in two cases and in on-site examination in one. In the three remaining cases, market awareness and examination awareness are close. Given his results, Simpson concludes that capital market ability to predict commercial bank failure prior to on-site examinations must be questioned.

The failure prediction ability of bank capital market information remains an empirical question. Some of the findings discussed above suggest that inclusion of capital market information can enhance EWS and aid regulators in early identification of problem banks. Simpson's findings do not support these conclusions. In any case, capital market failure prediction is only relevant for those banks which have publicly (and actively) traded securities. In the studies reviewed and in general, this description applies predominantly to large banks. However, most commercial banks that fail are small in asset size. Therefore, it is difficult, if not impossible, to examine small bank failure in the capital market context.

Summary

The discussion above reviews and summarizes the failure prediction literature relevant to commercial banks. The review reveals several facts. First, many of the existing studies are dated. The passage of the Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn-St Germain Act of 1982 precipitated extensive changes in the operating and competitive environment of the banking industry. Since the banking environment today is vastly different from the pre-reform banking environment, it is likely that the factors contributing to failure today are also different. However only three studies examine failure in this new environment. The most recent period examined in the two empirical studies is 1984. The 1988 OCC study is more recent but is descriptive and subjective and no attempt is made to empirically validate the relationships discovered in the survey.

Second, the existing literature examines failure either in the banking industry as a whole or in the large bank segment in particular. Recent history shows that most banks that fail are small in asset size. No study specifically addresses this particular, important segment. Consequently it has not yet been determined if it is possible to predict the failure of those particular banks which account for the greater portion of total bank failure.

Third, with the exception of market studies, bank failure prediction studies rely almost exclusively on CAMEL type measures as explanatory variables. CAMEL variables are constructed using accounting information contained in a bank's report of Income and Condition Statements. By accounting convention these reports are constructed using accrual accounting methods. While ratio analysis employing these statements and their respective accounts has been useful in identifying and predicting potentially failed banks, traditional measures using accrual-based information may not capture all the relevant aspects of bank performance.

Since the 1970s financial analysts and other interested parties have shown an increasing interest in the use of cash flow analysis for assessing firm performance.

(Financial Executives Institute, 1985; Perry, 1983) This interest stems from the generally accepted view that a firm's cash flows and the timing of these cash flows are a more critical factor in determining firm solvency than are accrual-based accounting profits. By traditional accounting standards, a firm is profitable if sales revenues exceed costs. In a profitable firm, cash inflows will eventually exceed cash outflows. However the timing of these cash flows is critical. If cash inflows are not sufficient to meet required cash outlays during the operating cycle, a firm faces potential insolvency. If these cash imbalances are severe and/or persist, even a profitable firm (by accounting standards) may face bankruptcy. (Brigham, 1989)

Until recently the presumption that cash flow is an important factor in firm financial health has been largely intuitive. Beginning in the 1980s several researchers have empirically investigated the usefulness of cash flow information for predicting firm failure. Gombola, Haskins, Ketz and Williams (1987) provide a comprehensive overview of these studies. The empirical evidence is mixed, but the bulk of the evidence supports cash flow as an important predictor of failure. Banks, however, have not been included in these studies.

The function of the banking firm differs from that of the nonbanking firm. The primary output of the banking firm is loans. The primary output of the nonbanking firm is a good or service. While the output of these firms differs substantially, generating this output gives rise to similar needs. Both types of firms require resources, human and capital. Both firms borrow funds and strive to achieve future growth. Consequently both firms need cash to pay bills and employee wages, meet interest and lease obligations, repay borrowings and reward owners and take advantage of investment and growth opportunities. If cash is not available on a timely basis, both firms may face insolvency or bankruptcy. Based on these similarities, cash flow is no less important to the financial health of a bank than it is to the financial health of a nonbanking firm. As such cash flow information may also be an important predictor of bank failure.

This study empirically examines the usefulness of cash flow variables in predicting bank failure by incorporating a cash flow identity developed by Lawson (1985). The Lawson cash flow model is an accounting identity which incorporates both internal cash flows and external capital flows. Lawson and Aziz (1989) have applied the model in the failure prediction context to a sample of industrial firms. This study presents the first application of the identity to the banking firm.

Second, many of the existing studies are dated. The bulk of the bank failure prediction research was conducted prior to the deregulation of the early 1980s. (Altman and Sametz, 1977; Hanweck, 1977; Korobow, Stuhr and Martin, 1976; Martin, 1977; Sinkey and Walker, 1975) The few studies conducted since deregulations use data for banks operating either prior to the implementation of the acts (Boveni, Marino and McFadden, 1983) or in the turbulent period immediately following. (Lane, Looney and Wansley, 1986; Marcus and Shaked, 1984; West, 1985) The OCC study (Graham and Horner, 1988) is more recent but is descriptive and no attempt was made to empirically validate the relationships discovered in the survey.

Passage of the Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn-St Germain Act of 1982 precipitated extensive changes in the operating and competitive environment of the banking industry. The acts authorized depository institutions to offer interest bearing transactions accounts and to expand their deposit offerings and servicing capabilities. Changes in banking activity initiated by the acts have affected the sources of bank funds, the cost of these funds, allocation patterns across bank assets and the growth and profitability of banking institutions. (Fortier and Phillis, 1985) The financial statements of banks, the traditional source of data for failure prediction studies, will ultimately reflect these changes.

Third, the existing literature examines failure either in the banking industry as a whole ore in the large bank segment in particular. Recent history shows that most banks that fail are small in asset size. No study specifically addresses this particular, important segment. Consequently it has not been determined if it is possible to predict the failure of those particular banks which account for the greater portion of total bank failure.

To summarize, this study enhances the current failure prediction literature in several ways. Investigating the marginal impact of cash flow information and examining small bank failure as a separate issue enhances and expands the current bank failure literature. Estimating the models with the most currently available data updates the existing literature. The following chapter presents the formal hypotheses and the research design adopted to test these hypotheses.

Chapter Three

Research Methodology

This chapter presents the methodology adopted in this study. It is divided into two sections. The first section presents the research design. Included in this section is a formal statement of the hypotheses, the research models proposed to test the hypotheses, a discussion of logit analysis and the procedures proposed to evaluate the logit models. The rationale for the selection of the variables that will be used is presented in the second section along with an explanation of the Lawson Cash Flow Identity and its application in this study.

Research Design

The primary purpose of this study is to assess the marginal impact, if any, of cash flow-based information on predicting bank failure. Many of the failure prediction studies reviewed in the literature survey rely predominantly on accrual-based CAMEL measures as explanatory variables. This study is designed to investigate the marginal impact of cash flow-based information (CFB) on modeling bank failure.

Exploring this issue requires developing two models: (1) a CAMEL model employing only accrual-based CAMEL measures as explanatory variables, and (2) a mixed model (MM) combining these same CAMEL variables with CFB variables. The analysis then proceeds in four phases: estimation, validation, prediction and small bank failure analysis. In the first three phases, the CAMEL and MM models are compared to assess the impact, if any, of CFB information on the failure prediction models. In the final phase, the effects of CFB information on predicting small bank failure is analyzed.

This study tests four hypotheses. They are:

H_{01}: No difference can be found between the explanatory ability of CAMEL and MM models.

H_{02}: No difference can be found between the validation ability of CAMEL and MM models.

H_{03}: No difference can be found between the predictive ability of CAMEL and MM models.

H_{04}: No difference can be found between the ability of the MM model to predict small bank versus total bank failure.

As stated, H_{01} implies that CFB information does not contribute to explaining bank failure. Explanatory ability is used here in a technical context. Specifically it refers to the "goodness-of-fit" of the estimated discriminating function. The "goodness-of-fit" is a measure of the collective impact of the independent variables on the dependent variable. If the fit of the MM model, which includes CFB measures, is not significantly different from the CAMEL model, the null hypothesis is maintained. Such a finding would imply that cash flow analysis, as embodied in the CFB measures taken together, does not significantly contribute to explaining the causes of bank failure.

It is expected that cash flow problems would be a significant factor for explaining bank failure. However a contradictory finding does not preclude further analysis. When prediction is the goal it is necessary to ascertain if the variables are capable of signaling future failures. It is possible that even though the explanatory variables, individually or collectively, are insignificant in the explanatory sense, they may still be useful in the predictive sense. Establishment of predictive ability requires further investigation. This investigation is the subject of the validation and prediction phases.

It is important to distinguish between validation and prediction. Both involve classification procedures. According to Joy and Tollefson (1978) validation ability merely relates to the model's ability to classify a sample drawn from the same time period as that used to estimate the model. This is cross-validation (alternatively referred to as *ex post* discrimination) and should be interpreted as confirmation only. Prediction, they claim, requires inter-temporal validation. That is, predictive ability is imparted to a model based on results obtained when the model is applied to a sample drawn from a time period subsequent to that used to estimate the model. Only these inter-temporal results (alternatively referred to as *ex ante* predictive) should be used to claim predictive ability.

For example, if a model is estimated using a sample of banks for the year 1988, validation results are established by using the estimated model coefficients to classify another sample of banks drawn from the same 1988 period. Prediction results, on the other hand, are established by using the 1987 estimated model coefficients to classify a sample of banks from 1988. The 1989 classification would establish the ability of the 1988 model to predict future bank failures.

Joy and Tollefson's view is adopted in this study. H_{02} addresses only validation. It is evaluated by comparing the hit rates (classification accuracy rates) of the MM and CAMEL models when the models are applied to a control sample. If the MM model outperforms the CAMEL model in this classification task, it is appropriate to assume that CFB measures add information useful for identifying failed banks after the fact. But, if early warning is the goal so that failure can be avoided, the real issue is whether information identified after the fact is capable of foretelling impending financial distress.

H_{03} addresses prediction, the essence of the study. CAMEL and MM model ex ante hit rates are compared to determine if either model is the superior performer. A superior performance of the MM model would imply that CFB measures as a group can signal financial distress. If this is the case, bank regulators and other interested parties would have preliminary empirical justification for incorporating cash flow analysis in their bank monitoring procedures.

H_{04} addresses the issue of small bank failure. Based on arguments presented earlier, intuition suggests that small banks are more likely to experience cash imbalances. If this is the case, the CFB information embodied in the MM model may render it more efficient for predicting the failure of a small bank group. To evaluate H_{04}, ex ante classification procedures are performed with the MM model on a subset of banks with total assets of $50 million or less. These results are compared with the MM ex ante hit rates derived when evaluating H_{03} above.

Research Models

The hypotheses stated above will be evaluated in the context of a dichotomous choice, probability model. The model links a set of independent variables to a dependent variable which can take on only two values. Adopting Gujarati's notation (1988, p. 481), a logit model is specified as

$$P_i = E(Y=1\ X_i) = 1/(1+e^{-z}). \qquad (3.1)$$

In equation 3.1, P_i denotes the probability of failure given knowledge of the X_i, e represents the base of the natural logarithm, and

$$Z_i = \alpha + \beta X_i \qquad (3.2)$$

where α = the intercept term,

β = the vector of unknown parameters to be estimated,

X_i = the vector of financial ratios for the i^{th} observation.

The Variables

Logit analysis requires assigning the dependent variable, a bank, a value of 1 if failure occurred and 0 if it did not. A bank is considered failed if it received a disbursement from the FDIC Insurance fund in one of three forms: deposit pay-off, deposit transfer, deposit assumption. In a deposit pay-off, the FDIC pays off the insured depositors of the failed or failing bank and the institution is closed. In a deposit transfer, the FDIC transfers insured and secured deposits to another healthy bank. Uninsured depositors, the FDIC and other general creditors share in any proceeds realized from the sale of the failed bank's assets. In a deposit assumption, the failed or failing bank's assets are purchased or assumed by a healthy bank. The FDIC disbursement is the amount paid to facilitate the assumption. In all three cases the failed or failing bank is considered closed and ceases to exist. (FDIC, 1988)

The independent variables employed in this analysis are listed in Tables 3.1 and 3.2. The CFB variables are based on the Lawson Cash Flow Identity. The CAMEL variables are proxies for the various categories in the FDIC CAMEL rating system. The rationale for the selection of these particular variables is discussed later in this chapter.

Sample Design and Data Source

The sample consists of all U.S. FDIC insured commercial banks for the periods 1988 and 1989. The sample includes both failed and nonfailed banks. To test the fourth hypothesis, a subset of small banks (total assets less than $50 million) is derived from the 1989 total bank population. Data for all banks are taken from annual financial statements filed during the period 1986-1989.

The 1988 sample is comprised of 13,221 banks, 177 of which closed or ceased to exist in 1988. This sample is split into two groups, an analysis sample and a control sample. The analysis sample is used to estimate the model. The control sample is used to validate the model. Since failure occurred sometime in 1988, the last period for which annual statement data is available for the 1888 group is year-end 1987. CAMEL variables are constructed from year-end 1987 data. Construction of CFB variables requires calculating the change in various accounts over the reporting period. Thus CFB variables are constructed using year-end 1986 and 1987 data.

The 1989 bank group, comprised of 12,700 insured banks, constitutes the prediction sample. Two hundred and six banks closed in 1989. The last available statement date for this group is year-end 1988. CAMEL variables are constructed using year-end 1988 data and CFB variables are constructed using year-end 1987 and 1988 data. The models estimated with the 1988 analysis sample are applied to this prediction sample to establish the predictive ability of the estimated models.

Constructing the variables needed to test the hypotheses requires data for both failed and nonfailed banks. The primary source of data for all banks is the Report of Condition and Income for Commercial Banks and Selected Financial Institutions magnetic data tapes for the years 1986-1989. Commonly referred to as Call and Income reports, the data base contains balance sheet and income statement data for insured commercial banks, mutual savings banks, Banking Edge Act and Agreement Corporations, U.S. branches and agencies of foreign banks and New York state Investment Companies. The data are collected by the FDIC, the U.S. Federal Reserve System and the Office of the Comptroller of the Currency. Collection of the data is supervised by the Federal Financial Institutions Examinations Council (FFIEC), an inter-agency body charged with the task of establishing and maintaining uniform reporting standards and systems for federally supervised financial institutions. The data tapes are distributed by the Department of Commerce via the National Technical Information Service.

Call and Income reports are filed by reporting institutions in one of four alternative formats. These are:

FFIEC 031	banks with domestic and foreign offices;
FFIEC 032	banks with domestic offices only and total assets of $300 million or more;
FFIEC 033	banks with domestic offices only and total assets of $100 million but less than $300 million;

FFIEC 034 banks with domestic offices only and total assets less than $100 million.

In order to be included in the research population, the reporting institution must satisfy three additional criteria. First, it must possess a bank entity code equal to one which designates the institution as a traditional banking operation. Second, it must possess a bank type code equal to one which classifies the institution as a commercial bank. Third, it must possess an insurance status code equal to one signifying FDIC insurance coverage. Fulfillment of these criteria establish the institution as a FDIC insured, U.S. commercial bank.

Failed banks are identified from FDIC annual reports. These reports contain an annual listing of all FDIC insured banks which receive any form of FDIC insurance assistance during the reporting period. Included in the listing are the name and location of the failed bank, class (National, State and Federal Reserve status), asset and deposit size, number of insured accounts, amount and type of the FDIC disbursement, date of closing and the receiving bank in the case of a deposit transfer or assumption.

Insurance assistance is provided in one of four forms: deposit pay-off, deposit transfer, purchase and assumption, and transaction assistance. Transaction assistance is a temporary infusion of cash to an institution experiencing liquidity problems. Because banks receiving this form of assistance do not close, they do not meet the definition of failure established in this study and are, therefore, excluded.

A small bank sample is drawn from this total research population. Therefore, small banks also satisfy the three criteria established above. Small banks are separated from the total population based on filing format. Only those institutions reporting under filing format FFEIC 034 are included in the small bank population. Small bank failures are also identified from FDIC annual reports. Here again the additional criterion of total assets of $50 million or less is imposed.

Logit Regression Analysis

This study compares the results of two models estimated using logit regression techniques. The discussion to follow establishes the reasons for selecting the logit procedure. The shortcomings of DA and LPM are presented to justify their exclusion as possible candidates for estimating the failure prediction models.

In the early phase of failure prediction, DA and LPM were the techniques of choice. Both techniques have been criticized on various grounds. The strongest criticisms of DA are: (1) lack of adherence of the data to two underlying assumptions of the analysis, and (2) difficulty of interpreting the meaning of the estimated coefficients. DA assumes that the discriminating (independent) variables are normally distributed and the covariance matrices of the two groups under investigation are approximately equal. Bedingfeld, Reckers and Stagliano (1985) have shown that many of the commonly used financial ratios in the banking industry do not follow the normal distribution, violating the former assumption. Collins and Green (1981) argue that it is likely that the variability of the financial ratios of failed firms are substantially different from those of successful firms, violating the latter assumption.

With regard to interpretation of DA estimated coefficients, DA, unlike regression analysis, is not designed to determine the independent contribution of each of the explanatory variables. Eisenbeis (1977) has shown that only the ratios of the coefficients, not the coefficients themselves, are unique. Several alternative methods have been suggested to evaluate DA coefficients. (Altman, Avery, Eisenbeis and Sinkey, 1981; Eisenbeis, 1977; Joy and Tollefson, 1975) All, however, have been criticized on various grounds. Zavgren (1983) concludes that, "Based on the conflicting conclusions of various researchers, the coefficients are impossible to interpret in any unambiguous manner." (pp. 14-15)

The major criticism of the LPM centers on the linearity assumption implicit in the model. (Aldrich and Nelson, 1984) LPM assumes the relationship between the independent and dependent variables is linear in its parameters but not necessarily in the variables. Specification of a linear relationship implies the marginal effect on the dependent variable, probability of failure, of a change in the independent variable, financial ratio, is constant. For example, assume that one of the independent variables is the delinquent loan rate. The LPM implies that a change in this rate has an impact on the probability of failure that is the same for all banks. An increase in this rate, say 10 percent, increases the probability of failure for each bank by 10 percent regardless of each individual bank's existing delinquent loan rate. This is an unrealistic assumption.

The incorrect assumption of linearity also presents other statistical problems. According to Aldrich and Nelson (1984) the least squares estimates have (1) no known distribution properties, (2) may grossly overstate the magnitude of true effects, (3) systematically yield probability estimates outside the 0,1 range, and (4) become worse as the standard statistical practices to improve them are employed.

Logit analysis offers several advantages over DA and LPM. Logit analysis does not require the assumption of normality implicit in the DA analysis and, because logit is a special form of regression analysis, interpretation of the estimated coefficients proceeds in a straight forward manner. Relative to LPM, also a special form of regression analysis, logit offers two main advantages rendering it more appealing in the failure prediction context. This appeal stems from the behavior of the specified expectation, or distribution, function.

Logit specifies a logistic distribution function which is cumulative and sigmoid or s-shaped. Specification of a cumulative function versus the linear specification of the LPM, has two implications for the failure prediction problem. First, logit analysis is more theoretically appealing. Take the simple case of a probability, P_i, conditioned on one independent variable, X_i. Logit posits the relationship between P_i and X_i as "one which approaches zero at slower and slower rates as X_i gets small and approaches 1 at slower and slower rates as X_i gets very large." (Gujarati, 1988, p. 480.) In other words, the marginal effects of changes in the independent variable are not constant.

This is a reasonable assumption in the bank failure context. For example, if a bank has a small delinquent loan rate (X_i), say 5 percent, a 10 percent increase in this rate would not substantially increase the bank's likelihood of failure, (P_i). But for a bank with an already high delinquent loan rate, say 40 percent, a 10 percent increase in this rate would substantially increase this bank's likelihood of failure. This is not the case in the LPM which posits a linear relationship such that the marginal effects are constant. As previously noted, a 10 percent increase in the delinquent loan rate would increase the probability of failure for both banks by 10 percent in the LPM.

Second, because the distribution function specified in a logit model is cumulative, logit analysis is more logically appealing. In logit analysis the conditional probabilities are constrained to be between 0 and 1 as probabilities should be. This is not always the case in the LPM. In fact, in the LPM the estimated probabilities may be outside the 0,1 range. This leads to interpretation problems. Negative probabilities and probabilities greater than 1 have no meaning. Various estimation techniques have been suggested to deal with this particular problem of the LPM but each technique has statistical drawbacks arguing against its use. (Altman, Avery, Eisenbeis and Sinkey, 1981)

Probit analysis has also been used in bank failure prediction. The only difference between logit and probit models is the thickness of the tails in their respective cumulative distribution functions. The normal distribution specified in a probit model has the thinner tail implying the curve approaches the extreme 0,1 values more quickly. The logit and probit curves and their associated density functions are so similar as to yield essentially the same results. (Nelson and Aldrich, 1984) The similarity between the two models has led several authors to conclude that the choice between them is inconsequential. (Nelson and Aldrich, 1984; Gujarati, 1988) These authors suggest the choice between models revolves around the practical concerns of availability and flexibility of computer programs, mathematical convenience and personal preference and experience.

In summary, DA, LPM logit and probit analyses are all capable of performing the research task required in this study. Each of the procedures and their respective models can be used to classify a bank into a failed or nonfailed group depending on the characteristics of that bank. Because of the advantages of logit and probit over DA and LPM and in view of the inconsequential differences between logit and probit analyses, logit analysis is adopted in this study.

Estimation and Evaluation of the Research Models

In this study two logit models will be estimated using the LOGIST regression program. LOGIST produces maximum likelihood estimates. (Harrell, 1986) The principle of maximum likelihood estimation is to choose as an estimate of the β_ks that set of K numbers which would make the likelihood of having observed a particular Y as large as possible. (Aldrich and Nelson, 1984)

The discussion below outlines the procedure used for evaluating the models and testing the four null hypotheses. The first hypothesis is tested in the estimation phase of the analysis. The second and third hypotheses are tested using classification procedures in the validation and prediction phase of the analysis. Testing the fourth hypothesis involves only the MM model. The MM predictive results of small bank failure are compared with the MM predictive results of total bank failure in the final phase of the analysis.

Estimation, H_{01}. In LR analysis, evaluation of the discriminating function and interpretations of the estimated coefficients are similar to that of standard regression analysis. The logit equivalent to the overall goodness-of-fit, F-test, in regression analysis is based on the likelihood ratio principle. The statistic is computed as

$$c = -2\log(L0/L1) = -2(\log L0 - \log L1)$$

where L1 is the value of the likelihood function for the full model and L0 is the likelihood function if all coefficients are zero. The statistic follows a chi-square distribution when the null hypothesis is true. (Aldrich and

Nelson, 1984)

A procedure suggested by Aldrich and Nelson (1984, pp. 56-61) is used to test H_{01}. In this procedure the fitted L1 value of the estimated MM model, CAMEL and CFB combined, is compared with the fitted likelihood value, L2, obtained when the subset of CFB variables is deleted. The test statistic is

$$c = -2\log(L2/L1)$$

which follows a chi-square distribution if the null hypothesis is not rejected.

Interpretation of the estimated coefficients in the LR analysis is also similar to that of standard regression analysis. The estimated coefficient of each variable can be interpreted as the effect of a unit change in an independent variable on the probability of the dichotomous dependent variable. The t statistic is used to test the null hypothesis that the coefficient is zero. The standard, more conservative approach is to use the Student's t rather than the z score test, even though the coefficient estimates are asymptotically normally distributed. (Aldrich and Nelson, 1984)

Classification, H_{02}, H_{03}. To evaluate the efficiency of the CAMEL and MM models, each model is tested for its ability to classify a bank sample into failed and nonfailed banks. Following Joy and Tollefson (1978), each model is first estimated with the 1988 analysis sample. The ex post validation results are used to test H_{02}. Next both the 1988 estimated models are applied to the 1989 prediction sample. The ex ante predictive results are used to test H_{03}.

Typically, classification results are reported in a matrix which contains the information needed to evaluate the individual models. Various criteria have been used for evaluation purposes. Some researchers focus on correct classifications (hit rates), either overall accuracy rates and/or the percentage of correctly classified failed and nonfailed firms. (Ketz, 1988; Lawson and Aziz, 1989; Meyer and Pifer, 1970; Stuhr and VanWicken, 1974) Others focus on misclassification or error rates which are the complements of the accuracy rates. (Boveni, Marino and McFadden, 1983; Hanweck, 1977; Korobow, Stuhr and Martin, 1977; Mensah, 1983; Norton and Smith, 1979)

To compare the validation and predictive abilities of the CAMEL and MM models, this study follows the procedure adopted by Elam (1975) and Mensah (1983). These authors examine bankruptcy in nonbank firms. Both authors compare results of failure prediction models estimated with alternative accounting information. The procedure uses both the overall classification accuracy and misclassification error rates generated from the validation procedures.

A statistic developed by Conover (1971, p. 142) is used to test H_{02} and H_{03}. Adopting Elam's notation, the test statistic is expressed as

$$T = N(O_{11}O_{22}-O_{12}O_{21})^2/n_1n_2(O_{11}+O_{21})(O_{12}+O_{22}),$$

where O_{ij} represents the cells in a classification matrix defined as

O_{11} Number of banks correctly classified by the CAMEL Model	O_{12} Number of banks incorrectly classified by the CAMEL Model
O_{21} Number of banks correctly classified by the MM Model	O_{22} Number of banks incorrectly classified by the MM Model

and,

$$n_1 = O_{11} + O_{12},$$

$$n_2 = O_{21} + O_{22},$$

$$N = n_1 + n_2.$$

The large sample distribution of the T-statistic is approximately a chi-square with one degree of freedom. For a one-tailed test, the null hypothesis of no difference in the models may be rejected at the approximate level of $\alpha/2$ if T exceeds the critical chi-square at $1-\alpha$. (Mensah, 1983, p. 234)

In total, four classifications are performed, two on the ex post data and two on the ex ante data. H_{02} is tested by comparing the *ex post* CAMEL and MM classification results. H_{03}, comparative predictive ability, is tested using *ex ante* classification results.

Small bank prediction, H_{04}. Based on arguments presented earlier, it is hypothesized that cash flow may play a more critical role in the viability of a small bank. Cash flow problems may, therefore, provide better distress signals for a small bank versus its larger counterpart. If this is the case, the cash flow information embodied in the MM model may render it more efficient for predicting failure in small banks.

To test this H_{04}, the estimated MM model is applied to a subset of banks with total assets less than $50 million. *Ex ante* classification procedures are performed. These small bank *ex ante* classification results are compared with the MM total bank *ex ante* classification results generated when testing H_{03} above. Comparative classification results are evaluated in the framework described above and Conover's T (1971) is again the test statistic.

Rationale for Selection of the Variables

CAMEL Variables

Martin (1977) posits a simple theory of the causes of bank failure. He states that "Banks are typically threatened with failure because of losses on assets; and capital adequacy, liquidity and earnings measure the bank's ability to remain open in spite of these losses" (p. 263). Assets in the form of loans are of primary importance to banks. Loans comprise the greater portion (over 50 percent) of a bank's asset base and provide a bank's primary source of income. Principal and interest are lost when borrowers default affecting the bank in several ways. First, operating income, net income and the returns to owners are all reduced. Second, non-performing loans must be written off and bank assets reduced. With the erosion of its asset base, the bank's potential to generate future income is reduced. Finally, when borrowers are not repaying as expected, the bank may encounter cash shortages threatening liquidity in the short-run and solvency in the long-run as would be the case for any firm. In the face of these asset losses, banks, as are all economic firms, are threatened with failure.

Loan defaults are an inevitable fact of life for lending institutions. To the extent that bank managers anticipate and plan for this eventuality, bank viability need not be threatened. Careful screening of borrowers and diversification across different types of borrowers enhance the quality of a bank's loan portfolio by reducing the risk associated with the lending function. If, however, loan losses are greater than anticipated, the three measures suggested above by Martin will mitigate the effects of these losses.

With regard to the first measure, capital adequacy, banks are required by statute to hold reserves against losses equal to a prescribed percent of total assets. In addition to these reserves, banks may choose to retain a portion of earnings from previous periods. Together, these reserves and undistributed earnings provide a capital base. In the short-run, the greater a bank's capital and reserve base, the greater a bank's ability to absorb losses and the lesser the potential for failure in the long-run. The importance of bank capital adequacy is well-known to bank regulators and has been well-documented in the literature.

Typically, capital adequacy is measured by relating a bank's capital and/or reserve base to the bank's risk or total assets. The literature review documents various measures of capital adequacy significant in previous studies. In all cases, the greater the capital and reserve base, the less the potential for failure.

The quality of a bank's loan portfolio also has implications for risk and ultimate success or failure. In addition to loans, banks invest in other income earning assets. Loan revenue is generally considered to be riskier than revenue generated from other investment sources. As such the greater the bank's investment in loans relative to its overall asset investment, the greater the risk exposure of the bank. Additionally, risk characteristics vary across different types of loans. In theory diversification of the loan portfolio can potentially reduce risk for the bank and, conversely, loan portfolios concentrated in any one type of loan are potentially riskier.

Almost all bank studies have included a variable capturing this aspect of bank behavior. As documented in the literature review, various measures of loan concentration and loan volume have been useful in explaining bank failure. These measures also serve as proxies for asset risk. In general banks with loan portfolios concentrated in higher risk assets are more prone to failure.

With regard to the second measure suggested by Martin, liquidity provides another protection against loan losses. Banks may maintain a stock of liquid assets. Liquid assets and access to other short-term borrowings allow a bank to generate cash flow if loan repayments are less than expected. Depository institutions have obligations to both creditors and depositors. If loan repayments are slow or other cash inflows fall short of expectations, a bank with a stock of liquid assets is in a better position to meet its obligations. If depositors make larger than expected withdrawals, liquid assets again provide the flexibility to meet depositors' needs. Banks maintaining sufficient liquidity in their asset portfolios are more able to respond to unexpected cash flows and banks possessing this ability are less prone to failure. On the other hand, excess liquidity can be a detriment to a firm's performance.

Conventionally, liquidity is measured by examining a firm's investment in liquid assets relative to its total asset investment. By definition liquid assets include cash and other investments which, because of their maturities and ease and cost of convertibility, are similar to cash. Permissible investments of this type for banks include U. S. government securities (bonds, notes and bills) and government agency securities, municipal bonds, federal funds and repos. As documented in the literature review, the importance of bank liquidity for explaining or predicting bank failure is uncertain.

With regard to the last measure, current income or earnings can help absorb loan losses in the short-run. The greater is management's ability to generate income, the greater would be the bank's ability to absorb losses. However, when loans are in default, interest is lost and revenues depressed. If revenues are insufficient to cover expenses, immediate losses occur. Even under the best cost control conditions, depressed revenue and loan losses translate to depressed earnings. Depressed earnings affect management's ability to provide returns to owners. Managerial ability to generate earnings and ultimately returns for the bank's owners is essential to the survival and growth of the bank.

Typically, this aspect of bank performance is measured in two ways: (1) examining bank profitability and returns and, (2) examining management efficiency. Invariably profitability measures have been found to be highly significant discriminators and predictors of bank failure. In all cases, low profitability is positively related to troubled or potentially troubled banks.

Management efficiency or inefficiency is difficult to measure directly. It is generally assumed that efficient managers strive to streamline internal operations such that costs and expenses incurred in generating revenue are minimized. Traditionally this aspect of managerial quality is proxied by relating operating expenses to operating revenues generated. Most bank failure studies cited in the review employ this proxy as a measure of management quality. In all cases this expense ratio is negatively and significantly related to bank failure.

Another aspect of management quality and ongoing decision making is reflected in a bank's loan loss and delinquent loan experience. When management exercises skill, prudence and sound diversification practices in

TAELE 3.1

CAMEL VARIABLES

Variable	Proxy
Capital Adequacy	Net Worth/Total Assets Total Loans/(Capital + Reserves)
Asset Quality	
Loan Volume	Total Loans/Total Assets
Loan Composition	Commercial Loans/Total Loans Loans Charged Off/(Operating Income + Loss Provisions)
Management	Operating Expense/Operating Revenue Loans Past Due/Total Assets
Earnings	Net Income/Total Assets Net Income/Equity Captial
Liquidity	(Cash + Securities)/Total Assets

screening borrowers and assessing borrowers' capacity to repay, loan losses will be minimized. If, however, management's lending and collection policies are inadequate or poorly implemented, loan repayments may be slow or fail to materialize. These management deficiencies will be reflected in a higher loan loss experience and/or a higher delinquent loan rate for the bank. Various bank researchers have found this aspect of management capacity significantly related to failure.

In theory each of the considerations discussed above could potentially influence bank failure. These factors are well known to regulators who have incorporated them in a system, called CAMEL, to monitor and rank bank performance. As noted, these same factors have been used extensively in bank failure studies and similar measures are used in this study. The CAMEL variables included in this study are summarized in Table 3.1.

Cash flow Based (CFB) Variables and the Lawson Identity

To integrate cash flow analysis (CFA) in the failure prediction model, this study incorporates a CFA model developed by Lawson (1985) and applied by Lawson and Aziz (1989). The Lawson CFA model is an accounting identity which incorporates both internal cash flows and external capital flows.

In the 1985 article, Lawson demonstrates the relationship between his CFA model and the normative corporate valuation model used by Modigliani and Miller (MM) to illustrate the debt irrelevance hypothesis (Modigliani and Miller, 1958) and the dividend irrelevance proposition (Modigliani and Miller, 1961). In the MM context the valuation model distinguishes only between entity cash flows and proprietor cash flows such that

Entity Cash flows = Shareholder Cash Flows + Lender Cash Flows.

The Lawson CFA identity explicitly details the firm's total cash flows. In Lawson's model cash flow is generated internally from the firm's operations. The cash flow thus generated is applied to operating expenses, taxes, capital investment and liquidity changes. Any surpluses or shortages flow to or from the firm's lenders or shareholders in the form of debt repayment or dividends. A firm's total cash flow for a year is expressed as the identity

$$(k - h) - (A + R - Y) - H - t = (D - B) + (F - N - M),$$

where:

$(k - h)$ = operating cash flow represented by cash collected from customers, k and operating payments, h,

$(A + R - Y)$ = net capital investment represented by replacement investment, A, growth investment, R, and the proceeds from assets displaced, Y,

H = liquidity changes,

t = taxes paid,

$(D - B)$ = shareholder cash flow represented by D, dividends paid to shareholders, and equity capital raised or repaid, B, (F - N - M) = lender cash flows represented by interest paid, F, medium and long term debt raised or retired, N, and short term debt, M.

In a multiperiod context, the left hand side of the Lawson identity is concerned with economic performance and the right hand side with financial policy. The identity directly reflects management's operating, investing and financing activities and indirectly reflects management's resource allocation decisions.

Because of the unique nature of banking activities, applying Lawson's Identity to the banking firm requires some explanation. Interpretation of the identity for the banking firm differs from that of the nonbanking firm with respect to the terms: net capital investment, (A + R - Y); lender cash flow, (F - N - M); and operating cash flow (k - h).

In Lawson's Identity, net capital investment is specified as that portion of the firm's cash flow directed to new and replacement capital investment less any cash flow received when assets are displaced. Implicitly these cash flows reflect the firm's cash committed to earning assets for the period. The earning assets in a banking firm are loans and securities. These investments generate the major source of earnings for a bank in the form of interest income. Changes in a bank's investment portfolios may be interpreted as contributing to net capital investment. The associated cash flows result as loans are collected (disbursed) and investment securities sold (purchased). For the banking firm, the net effect of these cash flows are included with other capital investment cash flows.

With regard to lender cash flow, a nonbanking firm's liabilities typically stem from debt-related transactions. The associated cash flows are the proceeds from the sale of new debt, the repayment of existing debt and payment of associated interest obligations. While banking firms engage in similar transactions, the major portion of a bank's liabilities stem from demand and time deposits of customers. Cash flows associated with these deposits result when depositors withdraw cash or increase cash in deposit accounts. For the banking firm, deposit-related cash flows are included in lender cash flow along with other short-, medium-, and long-term credit flows. Because interest payments associated with lender cash flow, deposit and other credit flows, are a major operating expense for a bank, interest paid is excluded from lender cash flow and is included instead in operating cash flow.

With regard to bank operating cash flow, the operating cash disbursements for a banking firm involve a combination of cash flows associated with maintaining and supporting the bank's earning assets and cash flows associated with servicing deposits. The former cash flows are comprised

TABLE 3.2

CASH FLOW BASED VARIABLES
LAWSON'S CASH FLOW IDENTITY

Lawson's Identity	Variable
(k - h)	Operating Cash Flow*
Less	
(A + R -Y)	Net Capital Investment
Less	
H	Change in Liquidity
Less	
T	Taxes
Equals	
(F - N - M)	Change in Liabilities
Plus	
(D - B)	Change in Equity Capital

*Operating cash flow = net income adjusted for non-cash items.

of employee compensation and benefits and other operating costs: the latter are interest payments to depositors and other creditors. Cash collected is interest collected from loans and investments and cash inflows generated from other income sources.

The remaining terms, H, t and (D - B), are interpreted as discussed by Lawson. Taxes, t, are a bank's actual dollar disbursements to meet all tax obligations in the period. The change in liquidity, H, reflects the combined result of purchasing and selling marketable securities and changes in the bank's cash position. Shareholder cash flow, (D - B), reflects dividend cash flows to investors and equity capital raised or retired. Cash flow associated with transfers to or from reserves are also reflected in this term.

The above discussions of the factors comprising the CAMEL rating system and the dimensions of cash flow provide the basis for selecting the variables included in this study. The CFB variables are summarized in Figure 3.2.

Summary

The proposed research methodology is presented in this chapter. The study is designed to assess the marginal impact of CFB information on predicting bank failure. Two models will be developed. The CAMEL model contains only accrual based accounting information. The MM model is the same as the CAMEL model except for the addition of CFB information. Since the only difference between the models is the CFB information, any difference between the empirical performance of the models may be attributed to this information.

Four hypotheses will be tested. Three of these hypotheses relate specifically to the marginal impact of the CFB information on modeling and predicting bank failure. Since most bank failures occur in banks that are small in asset size, a fourth hypothesis will be tested to ascertain if CFB information is more useful for predicting failure in that group.

Logit techniques will be used to estimate the models. Logit analysis is proposed because it offers two advantages in the failure prediction context. Specifically, logit analysis assumes that the marginal effect of changes in the independent variable are not constant and logit analysis constrains the estimated probabilities to the 0,1 range.

The accrual based CAMEL variables that will be used in this study parallel the categories in the FDIC bank monitoring system. Martin's (1977) theory of the causes of bank failure justifies selection of these measures as explanatory variables. To incorporate cash flow analysis in the failure prediction model, Laswon's (1985) Cash Flow Identity will be adapted to the banking firm. The Lawson Identity will serve as the basis for the derivation of the CFB measures.

Chapter Four

Research Results and Analysis

The purpose of this study was to provide empirical evidence concerning the marginal impact of cash flow-based information on predicting bank failure. The presentation of the research results is divided into seven sections. The first section describes the source and composition of the data and presents the research design. The procedure used to develop the CAMEL model is discussed in the second section followed by discussion and intertrepation of the CAMEL logit analysis in section three. CFB and MM logit analyses are the focus of sections four and five, respectively. Contingency table analysis of validation and prediction results is the subject of section six. The usefulness of CFB information in predicting small bank failure is analyzed in the last section.

Sample Selection and Design

As stated in Chapter 3, the sample consists of all FDIC insured commercial banks for the period 1988-1989. Failed banks were identified from FDIC annual reports for the same years. The source of data for both failed and non-failed banks is the Report of Income and Condition for Commercial Banks and Selected Financial Institutions magnetic data tapes for the years 1986-1989. This data base contains annual bank balance sheet and income statement information (Call Report data) collected jointly by the FDIC, Federal Reserves System and Comptroller of the Currency for use in their regulatory and oversight functions. All financial ratios used in the study were constructed from data extracted from this comprehensive data base.

Throughout this study, the research is designed to distinguish between validation and prediction. Both validation and prediction relate to the classification procedures used to sort a sample into groups, i. e., failed and nonfailed banks. The distinction between the two procedures is based on Joy and Tollefson's (1978) definition of the two concepts. According to these authors, validation relates to a model's ability to classify a sample drawn from the same period as the sample used to estimate the model. Prediction relates to a model's ability to classify a sample drawn from a time period subsequent to that used to estimate the model. Establishing validation and predictive ability, therefore, requires two sets of sample data: an estimation sample corresponding to the 1988 failed bank group and a prediction sample corresponding to the 1989 failed bank group.

The FDIC reported 200 banks that closed or ceased to exist in 1988. Since failure occurred sometime in 1988, the last period for which annual statement data are available for the 1988 failed bank group is year-end 1987. Therefore, 1987 data for these banks and their ongoing counterparts is used to estimate and validate the models. Of the 200 failed banks, only 177 are included on the 1987 data base. The 23 excluded banks officially closed in 1988 but began liquidation procedures in 1987. Consequently, year-end 1987 data are unavailable for these banks. The 1987 data base includes 13,044 successful banks which resulted in a total sample size of 13,221 failed and nonfailed banks.

Joy and Tollefson (1978) also recommend using the split/holdout technique for developing and validating the model. This technique requires randomly splitting the 1988 estimation sample data into two sample groups: analysis and control. Analysis sample data are used to develop and estimate a preliminary model: control sample data are used to validate the relationships discovered in the preliminary estimation. Given successful validation results, i. e., ex post classification, the analysis and control sample data are recombined. The model coefficients are then estimated from the combined sample data. Randomly splitting the 1988 estimation sample data yielded an analysis sample comprised of 6,441 nonfailed and 86 failed banks. The validation sample is comprised of 6,610 nonfailed and 91 failed banks.

The prediction sample data corresponds to the 1989 bank group. The FDIC reported 206 failed banks in 1989. Again, 19 failed banks are excluded from the data base because of liquidation procedures initiated earlier in the year. Year-end 1988 data for the remaining 187 failed banks and 12,513 nonfailed banks constitutes the 1989 prediction sample which totaled 12,700.

CAMEL variables are calculated using the appropriate year-end data: 1987 for the analysis and control samples and 1988 for the prediction sample. Constructing CFB variables required calculating changes in various accounts over the reporting period. Thus CFB ratios are calculated using year-end 1986 and 1987 data for the analysis and control samples and year-end 1987 and 1988 for data for the prediction sample. Finally, a small bank subset was drawn from the 1989 prediction sample. Only those banks, failed and nonfailed, with total assets of $50 million or less are included in the small bank sample.

Development of the CAMEL Model

In bank failure studies, the capture of certain dimensionalities is more important than the choice of individual ratios (Sinkey, 1977). The literature review reveals that variable sets vary across studies. Each study, however, focuses on capturing the dimensions of bank operation and performance embodied in the CAMEL rating system which in turn is based on Martin's (1975) simple theory of bank failure.

Two factors were considered in selecting the financial ratios used in this study: theoretical justification and past performance. First, ratios used in previous failure studies were identified and grouped by CAMEL category. Grouping by CAMEL categories insured that the dimensions of failure suggested by Martin's theory are represented. This process revealed that several ratios within each CAMEL grouping were repeatedly used by various researchers. These ratios became the initial candidates.

Ratios were then selected from the initial candidates in each CAMEL grouping based on the ratio's previous empirical performance. Only those ratios that were proven consistent, statistically significant predictors of failure from past studies were retained for this study. The final candidates are listed by CAMEL category in Exhibit 4.1 along with their hypothesized relationship to failure. These ratios have repeatedly and consistently captured the dimensions of bank failure theorized by Martin. The reader is referred to Tables 2.2, 2.3, 2.4 and 2.5 in Chapter 2 for summaries of previous ratio specifications and Chapter 3 for an in-depth discussion of the rationale for variable

EXHIBIT 4.1

CAMEL VARIALBLES

VARIABLE NAME	RATIO CALCULATION*	EXPECTED SIGN FOR FAILED BANK
Capital Adequacy		
CAPAD1	(Equity Capital -Preferred Stock)/Total Assets	-
CAPAD2	Total Loans/(Equity Capital + Allowance for Loan Loss	+
Asset Quality		
AQ1	Total Loans/Total Assets	-
AQ2	Loans Charged-off/(Operating Revenue + Loan Loss Provision	+
AQ3	Allowance for Loan Loss/Total Loans	+
Management		
MGT	Operating Expense/Operating Revenue	+
GPM	(Operating Revenue - Operating Expense)/ Operating Revenue	-
Earnings		
ROE	Earnings after Tax/Equity Capital	-
ROA	Earnings after Tax/Total Assets	-
Liquidity		
LIQ1	(Cash + U.S. Government Securities)/Total Assets	-

*See Appendix A for the precise definition of the accounts used to calcualate the ratios.

selection.

Note from Exhibit 4.1 that two, and in one case three, different ratios appear as measures of a particular CAMEL dimension. The ratios within these categories, therefore, measure the same dimension of failure. Since multicollinearity is a frequent problem in failure prediction studies, avoidance of redundant measures is desired. The task is to determine if any of the multiple measures within a category is redundant, and if so, which ratio by itself provides the better empirical measure.

The use of ratios representing the CAMEL variables is justified if the ratios' group means take on significantly different values between the failed and nonfailed bank groups. As a preliminary step, ratio group means of the analysis sample were compared using univariate t tests. Group means, standard deviations, univariate t test results and p-values are presented in Table 4.1.

Hosmer and Lemeshow suggest that any variable whose univariate test has a p-value less than 0.25 should be considered as a candidate for the multivariate model (1989, p. 86). Comparison of the ratio group means produces significant differences for all ratios except CAPAD2 and ROE. The differences are significant at the 0.05 level or better. Most differences are significant with a probability of 0.0002. Preliminary analysis suggests that CAPAD1, AQ1, AQ2, AQ3, MGT, GPM, ROA and LIQ1 may be significant predictors of failure. Ratio mean comparisons for CAPAD2 and ROE, with p-values of 0.3552 and 0.4526, respectively, do not meet the 0.25 criterion. However, since these two ratios are theoretically important measures of performance, they are not eliminated as candidates based solely on their univariate performance.

TABLE 4.1

CAMEL RATIO GROUP MEANS AND STANDARD DEVIATIONS

Variable	Failed		Nonfailed		T* (p-Value)
	Mean	SD	Mean	SD	
CAPAD1	0.0164	0.0445	0.0858	0.0450	14.22** (0.0000)
CAPAD2	52.9719	319.8774	6.0842	3.0690	-1.36 (0.3552)
AQ1	0.5549	0.1544	0.5124	0.1560	-2.60** (0.0188)
AQ2	0.2369	0.1575	0.0636	0.0750	-10.18** (0.0002)
AQ3	0.0433	0.0330	0.0181	0.0150	-7.09** (0.0002)
MGT	1.0580	0.1894	0.8690	1.1024	-7.6840** (0.0002)
GPM	-0.0580	0.1894	0.1310	1.1024	7.68** (0.0002)
ROE	-5.8930	44.8680	0.0038	1.5784	1.22 (0.4526)
ROA	-0.0457	0.0454	0.0053	0.0161	10.42** (0.0002)
LIQ1	0.2100	0.1215	0.3845	0.1531	13.18** (0.0002)

*Significance levels are based on univariate t-tests using pooled variance estimates.
**Significant at 0.05 level of significance.

In an effort to determine which of the ratios within a specific CAMEL category is the better regressor, several statistical versions of the CAMEL model were estimated and compared. Analysis sample logit estimation results are reported in Table 4.2. Version I is a full model containing all the ratios listed in Exhibit 4.1. Versions II-VI are reduced versions of the full model where various ratios are

TABLE 4.2

CAMEL LOGIT ESTIMATES
1988 ANALYSIS SAMPLE

Variable	Version I	II	III	IV	V	VI
CONSTANT	-4.3685	-4.3697	-4.7348	-5.5238	-5.0140	-1.2690
	(-5.62)*	(-5.63)*	(-6.41)*	(-4.06)*	(-6.82)*	(-2.19)*
CAPAD1	48.3116	47.7347	49.4412	49.4412	63.1238	
	(7.42)*	(7.43)*	(7.67)*	(7.67)*	(11.99)*	
CAPAD2	-0.0009					-0.0011
	(-0.52)					(-0.65)
AQ1	5.8969	5.9222	5.9304	5.9304	5.0413	5.3537
	(6.33)*	(6.35)*	(6.44)*	(6.44)*	(5.89)*	(6.25)*
AQ2	-2.1901	-2.0808				
	(-1.63)	(-1.55)				
AQ3	28.0272	29.0813	32.7879	32.7879	20.1716	16.0328
	(4.50)*	(4.47)*	(5.68)*	(5.68)*	(3.02)*	(3.28)*
MGT	-853.E-13			0.7890		
	-			(0.80)		
GPM	- 0.7067	- 0.7945	- 0.7890		-0.0141	- 0.0608
	(-0.80)	(-0.81)	(-0.80)		(-0.13)	(-0.36)
ROE	0.0060					
	(0.65)					
ROA	18.3759	21.0457	27.8203	27.8203		52.8482
	(2.20)*	(2.67)*	(4.08)*	(4.08)*		(10.35)*
LIQ1	8.7683	8.7629	8.6730	8.6730	8.7050	9.4926
	(7.97)*	(7.97)*	(7.92)*	(7.92)*	(7.96)*	(9.20)*
Model X^2	424.320*	423.236*	420.949*	420.949*	402.026*	344.344*
D_f	9	7	6	6	5	5
p-value	(0.0001)*	(0.0001)*	(0.0001)*	(0.0001)*	(0.0001)*	(0.0001)*

T-values in parentheses.
*Significant at 0.05 level of confidence.

deleted for the reasons given below. All results are evaluated at the 0.05 level of significance.

A note on the signs on the estimated coefficients reported in Table 4.2 is in order here. In dichotomous logit analysis, the dependent variable is assigned a value of 1 if the event (failure) occurs and 0 if it does not. The SAS Logist program used to estimate all models is written to solve for the P(Y=0 X), the probability of non-failure (or success). Since the program estimates P(Y=0), the signs on the coefficients reported in Table 4.2 reflect the relationship between the variable and a bank's likelihood of success, not failure. For interpretive purposes, the expected signs on the coefficients reported in Table 4.2 are the reverse of those indicated in Exhibit 4.1. (Recall that the expected relationship to failure is given in that table.) Standard errors, covariances and goodness of fit measures are unaffected. (Hosmer and Lemeshow, 1989, p. 90)

With regard to the measure of capital adequacy, CAPAD1 is chosen over CAPAD2. Both ratio coefficients have the expected sign in all versions in which they are included. CAPAD2, with *t*-values of -0.52 and -0.65 in Versions I and II, respectively, is not statistically significant. The CAPAD1 coefficient is statistically significant in all estimates and in only one instance, Version V when ROA is excluded) does the coefficient change substantially from the 47 to 49 range.

Asset quality relates to both loan volume, sometimes interpreted as loan concentration, and the quality of a bank's loan portfolio. AQ1 is a singular measure of the former as it reflects a bank's ability to book loans and ultimately generate loan revenue. However, since loan revenue is generally considered riskier than revenue generated from other sources, a measure of loan quality, or asset risk, is also needed. AQ2 and AQ3 are two measures of loan quality. In Version I and II estimates, AQ2 has the correct sign but is not statistically significant. Since AQ3 is consistently significant in all estimates, AQ3 is selected over AQ2 as the empirical measure of loan quality.

Analysis of simple correlation coefficients for MGT and GPM, two measures of management ability, revealed that the two ratios are nearly perfectly negatively correlated. When both are included in the full version of the model, almost perfect multicollinearity results accounting for the estimated coefficient of -853E-13 on the MGT variable. MGT is removed in Version II and replaces GPM in Version IV. The choice between GPM and MGT is obviously inconsequential, which is confirmed by comparing Versions III and IV. The only difference between these versions is the interchange of GPM and MGT. Coefficients on the other variables and the model X^2 are identical for both estimates.

ROA is selected over ROE as the measure of earnings ability. ROE is rejected for two reasons, First, a review of analysis sample failed bank data reveals that most failed banks reported both negative net income and negative stockholder's equity resulting in a positive ROE for those observations. Clearly a positive ROE is not a true representation of a bank which is both technically insolvent and incurring losses. Furthermore many failed banks reported very small equity bases relative to earnings which yielded unusually large (greater than one) ROEs. Failed bank ROEs ranged from rates of return of 2,824 percent to -40,500 percent. Again rates of return over 100 percent exhibited by many failed banks do not truly reflect the earnings records of those banks. Second, the estimated ROE coefficient is not significant in Version I confirming the univariate _t_ test

result for this ratio. Since ROA is both consistently significant and of the theoretically expected sign, ROA is selected as the measure of earnings ability.

Version III contains the variable set ultimately designated as the CAMEL model. The CAMEL model provides the basis for examining the impact of CFB information. The ratios included in the model as respective measures of the CAMEL dimensions are CAPAD1, AQ1, AQ3, GPM, ROA and LIQ1.

CAMEL Model Logit Estimation Results and Analysis

Following the procedures suggested by Joy and Tollefson and given the successful validation results reported below, the analysis and control samples were combined and the coefficients reestimated. Results of the final logit version of the CAMEL model estimated with the combined sample are reported in Exhibit 4.2. Evaluation of the explanatory significance of the independent variables is based on the results of this combined estimate.

The usual $\underline{t}$ statistic is used to test the null hypothesis that the individual slope coefficient is less than or equal to zero. Since the sample is large (n = 13,221), the critical value for a 95 percent confidence level is 1.645. All coefficients except GPM are significant at the 0.05 level. In fact, the $\underline{t}$ values of the significant coefficients far exceed the 3.291 critical value required for a 99.95 percent confidence level. However, one significant coefficient, AQ3, does not have the sign normally expected for a successful bank.

In logit analysis, the likelihood ratio test is used to test for the overall significance of the variables in the model. This test is analogous to the F test in linear regression (Aldrich and Nelson, 1984). Under the null hypothesis that all slope coefficients for the covariates are equal to zero, the distribution of the likelihood ratio statistic follows a chi-square distribution.

The logistic procedure in the SAS statistical program computes and reports this statistic and the model $\underline{X}^2$ along

Exhibit 4.2

CAMEL Model

VARIABLE	COEFFICIENT	T-VALUE
Constant	- 3.3412	6.75*
CAPAD1	39.7432	10.09*
AQ1	4.4686	7.47*
AQ3	21.8753	4.88*
GPM	- 0.2745	.40
ROA	24.3822	5.82*
LIQ1	8.8508	11.37*

Model X^2 = 789.075*
D_f = 6
(p-value = 0.0001)

* Significant at the 0.05 level or better.

with the degrees of freedom and p-value. The CAMEL model X^2, 789.075, with six degrees of freedom far exceeds the critical value of 18.55 required for a 99.5 percent confidence level. Rejection of the null hypothesis implies that at least one, and perhaps all, slope coefficients are significantly different from zero.

The observed signs on CAPAD1, AQ1, ROA and LIQ1 are as expected. Bank equity provides a buffer against losses. The larger a bank's equity base relative to its assets, CAPAD1, the greater its ability to absorb losses and avoid failure. Loans are a bank's major sources of revenue. The positive sign on AQ1 suggests that a bank which concentrates its investments in these earning assets enhances its chance of success. Bank profitability is a strong indicator of success as indicated by the positive sign on ROA. Holding cash, U. S. government securities and other short-term securities provides protection against unanticipated loan losses and other unexpected withdrawals. Larger holdings of these liquid assets also enhance a bank's likelihood of success. These findings support the relationships suggested by Martin's (1977) simple theory and are consistent with previous empirical findings documented in the literature.

AQ3, calculated as allowance for loan losses as a percent of loans outstanding, is a measure of the quality of a bank's lending portfolio. Allowance for loan losses reflects management's assessment of the riskiness of its borrowers. It is management's estimate of loans and other credits which they believe may ultimately prove to be uncollectible by the bank. The higher the percentage of potential losses (either uncollectible interest, principal default or both), the greater the risk to a bank. Since higher risk has a potentially adverse impact on bank success, a negative sign is expected on the AQ3 coefficient.

The positive coefficient is puzzling and difficult to explain. Perhaps the managers of successful banks included in this sample have greater skill in assessing loan risk or are more conservative when evaluating loan portfolios, thereby overstating the loan loss allowance. Another possible explanation is that high risk loans generally carry higher than average interest rates. Perhaps during the data period covered in this study, these loans were performing, enhancing bank earnings and ultimately a bank's likelihood of success.

In summary, CAMEL logit results are encouraging. Both the model and all individual variable coefficients except GPM are statistically significant. With the exception of AQ3, all variable coefficients have the signs expected for a failed bank and are consistent with both the relationships posited by Martin and previous empirical work. These findings suggest that the CAMEL model provides a sound empirical base for examining the role of cash flow-based information.

Cash flow-Based Analysis

Cash flow-based (CFB) variables used to examine the impact of cash flow information on predicting bank failure follow the previous work of Lawson and Aziz (1989). Refer to Chapter III for a thorough discussion of the Lawson Cash Flow Model and how it is applied to the banking institution. Components of Lawson's Model as they are applied to the banking firm, the associated variable names and their hypothesized relationship to failure are presented in Exhibit 4.3.

EXHIBIT 4.3

CASH FLOW-BASED VARIABLES

LAWSON CASH FLOW COMPONENT	VARIABLE NAME*	EXPECTED SIGN FOR FAILED BANK
Operating Cash Flow		
Before Tax	CFFO	-
After Tax	CFAT	-
Investment Cash Flow	GRVCF	-
Loan-related	CLNSN	-
Investment-related	NETVCF	-
Taxes Paid	TAX	-
Liquidity Cash Flow	CLQ	-
Shareholder Cash Flow	SHRCF	-
Lender Cash Flow	LENDCF	-
Deposit-related	DEPCF	-
Debt-related	DEBTCF	-

*See Appendix for ratio calculations and the precise definitions of the accounts used to calculate the ratios.

Results of the preliminary CFB univariate analysis for the analysis sample are reported in Table 4.3. In calculating CFB group means, and in all CFB ratio calculations throughout the study, the value of total assets is used as a scale factor. Univariate *t*-tests comparing failed and nonfailed group means for each CFB variable finds statistically significant differences between group means for all CFB variables except CLQ. This preliminary analysis

TABLE 4.3

CFB RATIO GROUP MEANS AND STANDARD DEVIATIONS
1988 ANALYSIS SAMPLE

Variable	Failed		Nonfailed		T* (p-value)
	Mean	SD	Mean	SD	
CFFO	-0.0008	0.0186	0.0163	0.0185	8.46** (0.0001)
CFAT	-0.0004	0.0178	0.0141	0.0130	7.51** (0.0001)
GRVCF	-0.0982	0.1805	0.0285	0.3243	6.37** (0.0001)
CLNSN	-0.1087	0.1716	0.0281	0.3032	7.24** (0.0001)
NETVCF	0.0105	0.0325	0.0004	0.0230	-3.10** (0.0001)
TAX	-0.0004	0.0037	0.0023	0.0073	6.48** (0.0001)
CLQ	-0.0120	0.1401	0.0021	0.1634	0.80 (0.4247)
SHRCF	-0.0433	0.0528	0.0061	0.0307	8.68** (0.0001)
LENDCF	-0.0656	0.2232	0.0280	0.4240	3.80** (0.0001)
DEPCF	-0.0774	0.2114	0.0276	0.4066	4.50** (0.0001)
DEBTCF	0.0118	0.0603	0.0004	0.0493	-2.11** (0.0001)

*Significance levels are based on univarite t-tests using pooled variance estimates.
**Significant at 0.05 level of significance.

implies that CFFO, CFAT, GRVCF, NETVCF, CLNSN, TAX, SHRCF, LENDCF, DEPCF and DEBTCF are potentially capable of differentiating between the failed and nonfailed bank groups. With a p-value = 0.4247, CLQ is not a good candidate for the multivariate model based on Hosmer and Lemeshow's (1989) criterion of a p-value less than 0.25.

A review of group means reveals that all nonfailed CFB variable means are positive. On average, a successful bank generates positive cash flows from its operating and financing activities. The average successful bank diverts cash inflows to capital investment, the majority of this investment committed to its loan portfolio. The major portion of cash inflow generated from lenders comes from increases in deposits. The remaining lender cash flow comes from other lenders in the form of increased short- and/or long-term borrowings.

The average failed bank had negative operating cash flow, before and after tax, and also experienced net cash outflows related to both shareholder and lender activities. The shrinking equity base implies a draw down of capital to cover losses. Examination of the separate lender components reveals that deposit transactions account for the net outflow as deposit withdrawals exceed deposit inflows. Borrowing activities provided a net cash inflow. To offset the outflows, the average failed bank sold both liquid and earning assets to generate cash. This is reflected in the net reduction in both its liquidity and earning assets. Examination of the separate components of GRVCF reveals that the draw down of its loan portfolio, CLNSN, provided the net inflow.

As a preliminary step to combining the CFB and CAMEL variable sets, CFB only models were estimated and evaluated for goodness of fit and significance of the CFB variable coefficients. Logit results of various CFB model specifications estimated with analysis sample data are reported in Table 4.4. All Model X^2 and estimated coefficients except TAX in CFB1 and NETVCF in CFB6 are statistically significant at the 0.05 level or better.

Note from Exhibit 4.3 that the hypothesized relationship to failure for all CFB variables is negative. Because the Logist procedure estimates the probability of success, positive signs are expected on the estimated coefficients. In the Logit estimate a bank's probability of success is given by $e^{f(x)}/(1+e^{f(x)})$: a higher f(x) indicates a higher success potential. In Lawson's Model (operating cash flow - net capital investment - taxes - liquidity requirements - shareholder cash flow - lender cash flow = 0) all cash flows, inflows or outflows, are assumed positive (Lawson and Aziz, 1989). For example, a successful bank is expected to generate higher operating cash flows, pay out more in taxes and invest more in assets, both earning and liquid. A successful bank is also more capable of generating cash from equity transactions, increased borrowings and deposit activity and hence all the CFB variables for this bank would have positive values. Thus positive signs on the coefficients of these positive values

TABLE 4.4

CFB LOGIT ESTIMATES
1988 ANALYSIS

Variable	Version					
	CFB1	CFB2	CFB3	CFB4	CFB5	CFB6
Constant	4.2854	4.3463	4.2941	4.3430	4.3365	4.3847
	(26.37)*	(26.53)*	(27.01)*	(28.63)*	(28.67)*	(26.51)*
CFFO	39.8997					
	(4.95)					
CFAT		40.1161	36.8007	34.9865	37.2067	35.2577
		(4.74)*	(4.23)*	(4.02)*	(4.32)*	(4.07)*
TAX	9.7543					
	(0.45)					
GRVCF	34.4155	36.2780	3.7715		4.5295	
	(8.46)*	(8.82)*	(2.97)*		(4.10)*	
CLNSN				5.1041		5.8168
				(3.53)*		(4.00)*
NETVCF				-7.0227		-5.9661
				(-2.03)*		(-1.63)
CLQ	30.5941	32.3092				
	(7.34)*	(7.64)*				
SHRCF			32.9993	31.0285	32.5229	30.6145
			(7.86)*	(7.32)*	(7.81)*	(7.26)*
LENDCF	-35.4172	-37.3635	- 4.9370	- 5.1935		
	(-8.20)*	(-8.54)*	(-4.81)*	(-4.97)*		
DEPCF					-4.9854	-5.2417
					(-4.90)*	(-5.04)*
DEBTCF					-12.5016	-12.6500
					(-5.34)*	(-5.61)*
Model X^2	206.014*	201.674*	205.715*	215.898*	219.355*	228.903*
D_f	5	4	4	5	4	6
p-value	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

T-value in parentheses.
*Significant at 0.05 level of significance.

would result in a higher value of f(x) and hence a higher probability of success. On the other hand, for a less successful or failing bank, the individual values of the cash flows would be lower and/or negative resulting in a lower f(x) and increased probability of failure if the coefficient is positive.

Recall from the discussion in Chapter 3 that Lawson and Aziz compute the investment cash flow component as the net change in capital asset investment over the period. GRVCF is the comparable measure for a bank. Recall also that loans comprise the major portion of bank asset investment. To allow for examination of the individual effect of this important bank cash flow, GRVCF is divided into two components, loan cash flow (CLNSN) and other investment cash flow (NETVCF).

A similar treatment is applied to the lender cash flow component. Lawson and Aziz compute lender cash flow as the net change in total liabilities over the period plus interest paid in the period. LENDCF, a roughly comparable bank measure, excludes interest paid. Interest paid or received by a bank is considered operating cash flow and included in either CFFO or CFAT. LENDCF is also separated into two components to enable examination of the effects of unique bank cash flows. DEPCF represents cash flow associated with deposit-related activities: DEBTCF relates to cash flow generated from or paid to bank creditors, both short- and long-term.

CFB1 conforms to the Lawson and Aziz specification. Their specification includes all but one of the cash flow components. According to the authors, "using different combinations suggested that shareholder cash flow should be excluded in order to avoid statistical over-identification." (Lawson and Aziz, 1989, p. 56) CFB1 and CFB2 differ only with respect to the operating cash flow component. In CFB1, operating cash flow, CFFO, is calculated on a before tax basis and taxes paid in the period, TAX, is included as a separate cash flow. In CFB2, taxes paid are included as a deduction from operating cash flow. In CFB2 and all other CFB versions, CFAT, cash flow after tax, replaces CFFO. The signs on these variable coefficients are as expected.

To avoid statistical over-identification referred to above, CLQ is replaced by SHRCF in versions CFB3 through CFB6. CLQ is the most likely candidate for exclusion based on its univariate performance and potential redundancy with LIQ1, a similar liquidity measure in the CAMEL model. This exchange allows for examination of the effects of shareholder related cash flows. SHRCF represents the net effect of bank equity transactions, raising or retiring equity capital and dividend payments. As expected a potentially successful bank generates higher shareholder cash flow.

CFB4, CFB5 and CFB6 highlight the investment and lender cash flows unique to a banking firm. In CFB4, CLNSN and NETVCF replace GRVCF, their associated aggregate investment cash flow component. In CFB5, DEPCF and DEBTCF replace LENDCF, their associated aggregate cash flow component. Finally CFB6 includes the separate components of both GRVCF and LENDCF.

While the sign on GRVCF is as expected for a successful bank in all versions, the sign on its component NETVCF is not. The negative sign on NETVCF suggests that a bank which diverts cash flow to long-term investments, such as buildings, equipment and real estate, inhibits its potential for success. On the other hand, cash flow committed to lending activities as represented by CLNSN, the primary function of a bank, would enhance success potential.

LENDCF and both its components do not have the sign normally expected for a successful bank. As noted, positive signs were expected on these coefficients. Turning first to DEBTCF, this variable is positive if the amount of new funds raised by borrowing exceeds the amount of existing debt retired over the period. Thus a positive value for DEBTCF represents a net cash inflow. At the same time, a positive DEBTCF represents an increase in total bank indebtedness with its accompanying interest obligation and risk.

Possibly the interest payments required to service the higher debt level strains bank cash flow and solvency, ultimately decreasing a bank's likelihood of success.

The negative coefficient on DEPCF does not make economic sense for a successful bank. A positive value of DEPCF reflects a net increase in a bank's deposit base. Such an increase may be interpreted in two ways. First, a positive DEPCF gives rise to a net cash inflow as deposit inflows exceed deposit withdrawals. One would expect these inflows to enhance bank success not detract from it. Alternatively, increasing deposit bases reflect a bank's growth and ability to attract funds, both favorable indicators of bank performance. The observed negative sign on DEPCF suggests the converse of both interpretations: a negative coefficient when DEPCF is positive decreases a bank's likelihood of success.

CFB6 estimation results are generally consistent with CFB4 and CFB5 results with one notable exception. NETVCF, significant in the CFB4 version, is not statistically significant in the CFB6 version.

In summary, both the preliminary univariate and logit analyses suggest that CFB information may be an important factor in explaining and/or predicting failure. Univariate analysis finds statistically significant differences between failed and nonfailed bank group means. Multivariate Logit analysis further reveals that the variable coefficients are generally significant and, in most cases, the observed coefficients signs confirm the variables' hypothesized relationship to failure. Noted exceptions are NETVCF, which is also insignificant in CFB6, and the lender related cash flow components. These preliminary results are encouraging and support further investigation of the role of cash flow information in bank failure analysis.

MM Logit Analysis

To investigate the marginal impact of the CFB information, CFB variables are combined with the CAMEL variable set. Models including both CAMEL and CFB variables are hereafter referred to as MM models. The combined MM model estimation results are subsequently evaluated relative to the stand alone CAMEL model. Six versions of the MM model, paralleling the six versions of the CFB models discussed above, were estimated. Estimation results are reported and discussed for versions MM1, MM3 and MM6 only. Recall that CFB1 and CFB2 differ only with respect to the treatment of taxes. MM1 and MM2 estimation, validation and prediction results for these versions were essentially the same. Since CFB1 and its MM version conform to the Lawson and Aziz specification, MM1 results are reported for comparative discussion purposes. CFB4 and CFB5, and their companion MM versions, differ only with respect to the treatment of the investment and lender cash flow components: CFB4 includes the separate components of GRVCF and CFB5 includes the separate components of LENDCF. Logit estimations of MM4 and MM5 yielded results that were essentially similar to the MM6 version which includes the separate components of both cash flows. MM3 is unique in that SHRCF replaces CLQ.

Based on the MM validation results reported and discussed below, coefficients on the MM model variables were estimated from the combined 1988 sample data. The MM logit results are reported in Table 4.5. All model χ^2's are significant with p-values of 0.0001. Turning first to the CAMEL variables, CAMEL variable coefficients are stable, i.e., values of the estimated CAMEL coefficients are essentially the same in all MM versions and these values are essentially the same as their estimated values in the CAMEL model. The *t*-values of all CAMEL coefficients are slightly less in the MM models but all coefficients except GPM are statistically significant. GPM, insignificant in the CAMEL model, remains so in all MM versions. Signs on the CAMEL variable coefficients in the MM models are consistent with those in the CAMEL model. Thus, interpretation of the observed signs follows the discussion above relative to the CAMEL only estimate.

TABLE 4.5

MM LOGIT ESTIMATES
1988 ESTIMATION SAMPLE

Variable	MM1	MM2	MM6
Constant	-3.0365	-3.0167	-2.8781
	(-5.66)*	(-5.65)*	(-5.18)*
CAPAD1	40.1021	39.8648	40.4797
	(9.82)*	(9.78)*	(9.54)*
AQ1	3.9969	3.9690	3.8176
	(5.88)*	(5.95)*	(5.45)*
AQ3	22.3890	22.2732	23.2313
	(4.98)*	(5.00)	(5.23)*
GPM	-0.0161	-0.0232	-0.2686
	(0.11)	(-0.12)	(-0.34)
ROA	25.8150	25.2333	23.9877
	(5.76)*	(5.86)*	(4.83)*
LIQ1	8.7117	8.7176	8.4867
	(11.12)*	(11.13)*	(10.16)*
CFFO	-5.2725		
	(-0.78)		
CFAT		-3.7525	-3.5293
		(-1.04)	(-0.86)
GRVCF	-1.2151	1.7353	
	(0.31)	(1.67)	
CLNSN			2.3423
			(2.09)*
NETVCF			-1.9866
			(0.79)
TAX	3.0623		
	(0.58)		
CLQ	-2.9294		
	(-0.74)		
SHRCF		-2.4647	-1.8257
		(-0.61)	(-0.41)
LENDCF	1.8902	-1.0929	
	(0.45)	(-1.40)	
DEPCF			-1.0580
			(-0.67)
DEBTCF			-5.2275
			(-2.98)*
Model X^2	792.964*	792.702*	801.307
D_f	11	10	12
p-value	(0.0001)	(0.0001)	(0.0001)

T-values in parentheses.
*Significant at 0.05 level of significance.

Turning to the CFB variable coefficients, most CFB coefficients do not retain the significance observed in the CFB only model versions. When combined with the CAMEL variable set, only two CFB variables retain their statistical significance. Operating cash flow, taxes paid, liquidity and shareholder-related cash flow components are insignificant in all versions in which they are included. The broader measures of investment and lender related cash flows, GRVCF and LENDCF respectively, are both insignificant in MM1 and MM3. However, substitution of their separate components in MM6 yields significant results for CLNSN and DEBTCF.

The positive sign on CLNSN affirms the relationship posited in Lawson's model: the negative sign on DEBTCF does not. CLNSN measures the net change in a bank's loan portfolio. As such CLNSN is a proxy for bank cash flow diverted to investment in these earning assets. Committing cash flow to these investments enhances a bank's likelihood of success. Lawson's model also assumes that a more successful bank would be capable of carrying more debt. The negative sign in DEBTCF suggests otherwise. A bank generating positive cash inflow from borrowing activities decreases its chance for success. Since the signs on CLNSN and DEBTCF in the MM models are the same as those in the CFB models, the reader is referred to the discussion of the CFB models for interpretation and explanation of these findings.

The first hypothesis tested in this study is:

H_{01}: No significant difference can be found between the explanatory ability of the CAMEL and MM models.

Explanatory ability as used in this study refers to the "goodness-of-fit" of the estimated discriminating function. Goodness-of-fit is a measure of the collective impact of the independent variables on failure. If this collective impact is not significantly different when the independent variables include the subset of CFB variables, the null hypothesis is maintained.

The procedure testing the collective or joint impact of the CFB variables is a variant on the likelihood ratio test used above to assess the overall fit of the individual models. The test is analogous to the *F* test in regression analysis for testing the joint significance of a subset of all the regression coefficients. (Pindyke and Rubinfeld, 1991) The test requires comparing the fitted likelihood value of the full MM model with the fitted likelihood value of the CAMEL model which excludes the CFB variables (Aldrich and Nelson, 1984). Excluding the CFB variables is tantamount to constraining the CFB variable coefficients to be zero. The likelihood values of the two models would be equal only if the CFB variable coefficients are also zero in the full MM model. The test statistic is given as

$$C = -2\log(L2/L1) = (-2\log L2) - (-2\log L1),$$

where: L1 = the fitted likelihood value of the full MM model,

L2 = the fitted likelihood value of the CAMEL model where all CFB coefficients are constrained to equal zero.

The test statistic follows a chi-square distribution when the null hypothesis is true. Degrees of freedom correspond to the number of constraints, the number of CFB variables excluded from the full MM model to yield the constrained CAMEL model.

Calculated C statistics are reported in Exhibit 4.5 along with critical χ^2 values at the 0.05 significance level. For each MM model, the calculated C value exceeds the critical χ^2 value. For each MM model, one can reject the null hypothesis that the CFB variables are all zero. The test indicates that, jointly considered, one or more of the CFB variables are significantly different from zero. Therefore, H_{01} is rejected for each model.

This finding may seem surprising in the context of the MM estimation results previously discussed. In those results only two variables, CLNSN and DEBTCF in MM6, had significant coefficients. All CFB variable coefficients were insignificant in MM1 and MM3. The reader is reminded

Exhibit 4.5

D_f	X^2
4	0.711
5	1.145
6	1.640

		Calculated C Values		
Model	D_f	(-2LogL2)	(-2LogL1)	C
CAMEL		1089.492		
MM1	5		1085.549	3.943*
MM3	4		1085.812	3.680*
MM6	6		1077.207	12.285*

*Significant at the 0.05 level.

that H_{01} relates to the complete subset of CFB variables. The only difference between the CAMEL and MM models is the presence of this variable subset. The test of H_{01} is to ascertain the collective impact of the subset, not the significance of the individual coefficients. Pindyke and Rubinfeld (1991, p. 111) state that, "It is not unlikely that all *t* tests will be insignificant, yet the joint F will be significant." This is apparently the case for the CFB group. Taken together, the group of CFB variables does have a significant impact on failure. Taken individually, only CLNSN and DEBTCF are significant factors.

In summary, it appears that the traditional CAMEL measures of bank performance tend to dominate in the MM models. With the exception of GPM, the CAMEL variable coefficients are stable and consistently significant in the three MM versions. The CFB information, as embodied in the group of CFB variables, has a significant impact on failure. However, only those cash flows associated with bank lending and borrowing activities are individually significant. When included with the traditional CAMEL measures, cash flow from operating activities and cash flow generated from liquidity, shareholder- and deposit-related transactions are not significant indicators of failure.

Classification Efficiencies: Validation and Prediction

The CAMEL and MM models were validated in conformance with the procedures suggested by Joy and Tollefson (1978). As noted earlier, application of the split/holdout technique to the estimation sample resulted in two samples, analysis and control, for the 1988 bank group. The analysis sample was used to develop and estimate the CAMEL and MM models. The estimated model coefficients were then applied to the control sample to classify banks in that sample. More specifically, coefficients estimated from analysis sample data were used to calculate the logits, probabilities of failure, for each bank in the control sample. Each bank in the control sample was then classified as failed or nonfailed based on the bank's calculated probability of failure.

The validation procedure is an intermediate step. It tests the estimated model coefficients' ability to identify other failed and nonfailed banks. It is merely a means to verify or confirm the relationships discovered in the estimation phase. If these relationships do not hold for other banks which operated in the same time period, the validity and usefulness of these relationships for discovering future failed banks is questionable. Successful validation, on the other hand, implies that these relationships may hold for banks outside the estimation sample and suggests that the model may have a more general application.

Prediction procedures parallel validation procedures with one essential difference. In prediction, the 1988 combined data estimated coefficients are used to calculate the logits and classify the 1989 bank group. Since the 1989 bank group operated in a period subsequent to that of the operating period of the banks used to estimate the models, prediction results indicate the model's ability to identify troubled banks before failure actually occurred. Essentially, prediction procedures examine the stability of the estimated coefficients over time. If the coefficients are stable as evidenced in successful prediction results, this stability imparts predictive ability to the model.

The respective CAMEL and MM model validation and prediction results are reported in Table 4.6 and 4.7, respectively, along with other commonly used evaluative criteria. Following Joy and Tollefson (1978), population priors were used to determine the cut-off point for these and all other classifications performed in this study. That is, the cut-off point assumes a priori probabilities of group membership equal to the sample frequencies and equal cost of misclassification. Given successful validation as evidenced in the classification accuracy rates, the analysis and control sample data were combined and the coefficients re-estimated yielding the CAMEL and MM model estimation results reported and discussed above.

Classification accuracy rates (alternatively called hit rates) refer to the percentage of banks correctly classified by the model, either overall correct classification and/or correct nonfailed and failed classifications, respectively. Misclassification error rates refer to incorrect classifications and are of two types. A Type I error occurs when a model misclassifies a nonfailed bank, incorrectly places a bank that did not fail in the failed bank group. A Type II error occurs when a model misclassifies a failed bank or incorrectly places a bank that did fail in the successful bank group. Type I and Type II error rates are the complements of the nonfailed and

TABLE 4.6

VALIDATION RESULTS

NF Banks	6,610
F Banks	91
Total Banks	6,701

Contingency Tables

	Classified as	
Actual	NF	F
NF		
F		

CAMEL		MM1		MM3		MM6	
6,049	561	6,062	548	6,065	545	6,068	542
8	83	7	84	8	83	10	81

Classification Accuracy Rates

CAMEL	MM1		MM3	MM6
91.51%	91.72%	Overall	91.75%	91.76%
91.51	91.71	NF	91.75	91.80
91.21	92.31	F	91.21	81.01

Error Rates

CAMEL	MM1		MM3	MM6
8.49%	8.29%	Type I	8.25%	8.20%
8.79	7.69	Type II	8.79	10.99

failed accuracy rates.

Using the CAMEL validation results in Table 4.6 as an example, the CAMEL model's overall accuracy is 91.51 percent ([6,049 + 83]/6,701). Nonfailed and failed accuracy rates are 91.51 percent (6,049/6,610) and 91.21 percent (83/91), respectively. CAMEL Type I error rate is 8.49 percent

TABLE 4.7

PREDICTION RESULTS

NF Banks	12,513
F Banks	187
Total Banks	12,700

Contingency Tables

	Classified as	
Actual	NF	F
NF		
F		

CAMEL		MM1		MM3		MM6	
11,548	965	11,531	982	11,513	1,000	11,516	997
6	181	7	180	7	180	6	181

Classification Accuracy Rates

92.35%	92.21%	Overall	92.07%	92.10%
92.29	92.15	NF	92.01	92.03
96.79	96.26	F	96.26	96.79

Error Rates

7.21%	7.85%	Type I	7.99%	7.97%
3.21	3.74	Type II	3.74	3.21

(561/6,610), alternatively calculated as 100 percent minus 91.51 percent. Type II error rate is 8.79 percent (8/91) or 100 percent minus 91.21 percent.

Korobow and Stuhr (1984) caution against using the overall accuracy rate as the primary evaluative criteria.

The ultimate goal in failure prediction is to identify troubled banks so that remedial action may be initiated. Since it is possible for a model to exhibit high overall accuracy yet fail to correctly classify a large percentage of failed banks, overall accuracy rates may be misleading. For example, take 100 banks ten of which fail. If a particular model correctly classifies all the nonfailed banks (90) and none of the failed banks (10), its accuracy is 90 percent even though it failed to identify any of the failed banks. This problem is magnified when the portion of failures is low relative to the total bank population, such as in this study. An efficient model, according to these authors, is one which would identify failed banks with a high degree of accuracy. They argue Type II error or its compliment is a more meaningful criterion since it focuses the analysis on a model's ability to identify the critical failed bank.

When assessing comparative performance, a model's intended use is also at issue. If the purpose is to avert failure, then, as Korobow and Stuhr suggest, a model which predicts failures at the highest rate may be preferred. If, on the other hand, the intended use is as an input to establishing insurance premiums, the focus may change. Under this circumstance, predicting successes may be the goal especially if an incorrect prediction of failure results in a higher insurance premium. In this case, Type 1 error rates would be of primary importance.

Turning first to relative validative classification results, simple review of the data in Table 4.6 reveals that all models classify banks at different rates. Overall classification rates are high, exceeding 90 percent for all models, and the differences between these rates is slight. MM6 has a slight edge with the highest overall accuracy of 91.76 percent. Its edge in overall accuracy is derived from its ability to classify nonfailed banks more accurately but is at the expense of a higher Type II error rate, 10.99 percent, the highest of all models. Applying Korobow and Stuhr's criterion, MM1 with the lowest Type II error is the better performer. MM1's superiority is minor and also not without cost. It classifies only one more actual failure than does either MM3 or CAMEL, but it misclassifies nonfailures at a rate slightly higher than MM3 and MM6. CAMEL is inferior by all measures: it exhibits lowest overall accuracy, highest Type I error and higher Type II error than MM3. Thus no clear cut superior performer emerges in validative accuracy.

As noted validation procedures are an intermediate step. Validation results do not impart predictive ability but merely provide a clue as to a model's potential in that regard. The successful validation results exhibited above were sufficiently encouraging to justify further investigation. Predictive classification accuracies are reported in Table 4.7.

Simple review of the data in Table 4.7 reveals that the CAMEL model is slightly more accurate. The CAMEL model exhibits the highest overall accuracy, 92.35 percent, and the lowest Type I error, 7.71 percent. Imposing Korobow and Stuhr's criterion, CAMEL and MM6 are equally accurate with a common Type II error rate of 3.21 percent. Therefore, since the CAMEL model is the most accurate overall, exhibits the lowest Type I error and is equal to MM6 in Type II error, the CAMEL model appears to be a slightly better predictor of both failed and nonfailed banks.

The second and third hypotheses tested in this study relate to the comparative validative and predictive ability of the CAMEL model _vis a vis_ the MM models. These hypotheses are:

H_{02}: No significant difference exists between the validation ability of the CAMEL and MM models.

H_{03}: No significant difference exists between the predictive ability of the CAMEL and MM models.

Conover's T, a chi square test for differences in probabilities, is used to ascertain if these differences are statistically significant. (Conover, 1971, p. 142) The test statistic is expressed as

$$T = N(O_{11}O_{22}-O_{12}O_{21})^2/n_1n_2(O_{11}+O_{21})(O_{12}+O_{22}),$$

where O_{ij} represent cells in a classification matrix defined below

O_{11} Number of banks correctly classified by the CAMEL Model	O_{12} Number of banks incorrectly classified by the CAMEL Model
O_{21} Number of banks correctly classified by the MM Model	O_{22} Number of banks incorrectly classified by the MM Model

and,

$$n_1 = O_{11} + O_{12},$$

$$n_2 = O_{21} + O_{22},$$

$$N = n_1 + n_2.$$

The large sample distribution of the T statistic is approximately a Chi-square with one degree of freedom. For a one-tailed test, the null hypothesis of no difference in the models may be rejected at the approximate level of $\alpha/2$ if T exceeds the critical Chi-square at $1-\alpha$.

The values for Conover's matrix and, ultimately, the test statistic, are taken from the contingency tables in Tables 4.6 and 4.7. Take the CAMEL and MM1 validation results as an example. The appropriate cell values for the

Conover matrix taken from Table 4.7 are then:

O_{11} 6,123	O_{21} 569
O_{21} 6,164	O_{22} 555

$$\text{and } n_1 = 6{,}701,$$
$$n_2 = 6{,}701,$$
$$N = 13{,}402.$$

The calculated T values reported in Exhibit 4.7 comparing CAMEL with each MM model versions' validation and prediction results do not exceed the critical T=3.841. Therefore, since no statistically significant differences are found between either the validative or predictive ability of the CAMEL model relative to each of the MM model versions, it is not possible to reject either hypotheses, H_{02} or H_{03}.

In summary, the CAMEL and MM models classify failed and nonfailed banks at different rates as evidenced in their respective validative and predictive accuracy and error rates. The CAMEL model is a slightly more accurate predictor than any of the MM models. It predicts failed banks at the same rate as MM6 and nonfailed banks at a higher rate than either MM1 or MM3. While the CAMEL model appears to have a slight edge in predictive ability, its higher accuracy rates are not strong enough to establish

Exhibit 4.7

Conover's T Test

Critical Chi-Square Value = 3.841

Comparing CAMEL to:	Validation T	Prediction T
MM1	0.1903	0.1791
MM2	0.2490	0.7105
MM3	0.2620	0.5652

statistical difference between it and its MM counterparts.

CFB Information and Small Bank Failure

Roughly 55 to 60 percent of FDIC insured commercial banks are small in asset size with total assets of $50 million or less. Arguments presented earlier suggested that a small bank, because of the size and range of its operations, may be more susceptible to cash flow imbalances than its larger counterpart. At the same time, a small bank may not possess the same degree of financial flexibility available to a larger bank for adapting and/or responding to these imbalances. It is possible, therefore, that cash flow may play a more critical role in the viability of this small bank.

The purpose here is to determine if cash flow information yields more accurate distress signals for a small bank. If cash flow is more critical for small bank survival, the CFB information embodied in the MM model may render that model more efficient at predicting failures and successes in the small bank group. The focus is the predictive classification accuracies of the three MM model versions. The comparison of interest is the small bank versus total bank predictive classification accuracy rates for each of the respective MM1, MM3, and MM6 model versions. Total bank predictive classification results are reported above for these versions. Small bank predictive classification results follow.

The sample design and procedures used to develop small bank predictive classifications follow those discussed above for the total bank group except that only small bank data are used. MM model versions estimated from small bank data and their related predictive classifications are hereafter referred to as small bank model and small bank results, respectively. MM model versions previously estimated from all bank data and their related predictive classifications are hereafter referred to as general model and general model results, respectively.

Small bank samples were segmented from both the total bank estimation and prediction samples by imposing the criterion of total assets less than or equal to $50 million. This yielded small bank estimation and prediction samples of 7,696 and 7,174, respectively. The small bank estimation sample consists of the relevant data for the 117 small banks failing in 1988 and their 7,579 ongoing counterparts. The small bank prediction sample consists of the relevant data for the 119 small banks failing in 1989 and their 7,055 ongoing counterparts. Model coefficients for three small MM versions paralleling general models MM1, MM3 and MM6 above were estimated from the 1988 estimation sample data. These 1988 estimated model coefficients were then used to calculate the logits, probabilities of failure, for each bank in the 1989 prediction sample. Again, these calculated probabilities provide the basis for classifying the 1989 small bank prediction sample into failed and nonfailed bank groups. Small bank predictive classifications are reported in Table 4.8.

Simple comparison of the accuracy and error rates reported in Tables 4.7 and 4.8 reveals that the general and small bank models predict failures and nonfailures at different rates, However, the observed differences in these rates for all versions is slight. With both smaller Type I and Type II error rates and superior overall accuracy rates, the general MM3 and MM6 versions outperform their small bank counterparts. Small MM1, with smaller Type II error than the general MM1 model, satisfies the Korobow and Stuhr criteria for superior performance. Since the differences in overall accuracy and error rates for the small versus

TABLE 4.8

MM SMALL BANK PREDICTION RESULTS

NF Banks	7,055
F Banks	119
Total Banks	7,174

Contingency Tables

Actual	Classified as NF	Classified as F
NF		
F		

MM1		MM3		MM6	
6,443	612	6,455	610	6,461	594
4	115	5	114	5	114

Classification Accuracy Rates

	MM1	MM3	MM6
Overall	91.41%	91.43%	91.65%
NF	91.33	91.35	91.58
F	96.64	95.80	95.80

Error Rates

	MM1	MM3	MM6
Type I	8.67%	8.65%	8.42%
Type II	3.36	4.20	4.20

general models is slight, it is not possible to conclude which, if any, model is a better performer.

The fourth and final hypothesis tested in this study is:

H_{04}: No difference can be found between the ability of the MM model to predict small versus total bank failure.

This hypothesis is tested for each of the three MM model versions. The relevant comparison is the predictive accuracy rates of a particular general MM model vis a vis its small bank counterpart. For example, general MM1 predictive results are compared with small MM1 predictive results. Conover's T for differences in probabilities is again the test statistic.

Continuing with the MM1 example, the appropriate cell values for the Conover matrix are calculated from the data in the contingency tables: Table 4.7 for general MM1 and and Table 4.8 for small MM1. These are:

O_{11}	O_{12}
11,711	982
O_{21}	O_{22}
6,558	616

and n_1 = 12,700,

n_2 = 7,714,

N = 19,874.

The calculated T-values are reported in Exhibit 4.8. The MM1 calculated T-value exceeds the critical T=3.841. Statistically significant differences are found between the predictive accuracy rates of the small MM1 and general MM1 models and the null hypothesis relative to MM1 is not

Exhibit 4.8

Conover's T

Comparing General MM Model Results with
Small Bank Model Results

	T
MM1	3.944*
MM3	2.533
MM6	1.264

*Statistically Significant at 0.05 level of significance.

maintained. However, with calculated T-values of 2.533 and 1.264 for MM3 and MM6, respectively, it is not possible to reject H_{04} relative to these models. Significant differences are not established between the small versus general model predictive accuracy rates for MM3 and MM6.

In summary, the CFB information in the MM models does not yield more accurate distress signals for this particular small bank group. Predictive accuracy differences between total bank and small bank classifications are slight but the general MM3 and MM6 models, with higher overall accuracy and smaller misclassification rates, appear to have a slight edge over their comparable small bank counterparts. Only the CFB information as specified in MM1 yields statistically significant differences between predictive classificationaccuracy rates. When failure prediction is the goal, small MM1 with the lower Type II error rate, is a significantly, slightly superior performer.

Summary

The purpose of this chapter was to present the research results of this study. All research results were evaluated at the 0.05 level of significance. In the first section, the source and composition of the data was described and the sample design was presented. The sample was designed to insure conformity with the Joy and Tollefson (1978) distinction between validation and prediction, a distinction applied throughout the study. This required dividing the bank data into two sample groups, estimation and prediction, both containing data for failed and nonfailed banks. The 1988 estimation sample was used to develop and estimate the logit models. The 1989 prediction sample was used to ascertain if the estimated models could predict failed and nonfailed banks outside the estimation sample data.

The second section relates entirely to the development of the CAMEL model. Univariate analysis was presented and discussed for all potential CAMEL ratios followed by a description of the procedure used to select the CAMEL variable set. Logit estimation results of various versions of the CAMEL model were presented in Table 4.2. The variable set in Version III was ultimately designated as the CAMEL model. This section also included a discussion of the expected signs of the coefficients of the various ratios.

CAMEL model estimation results were the focus of the next section. Logit results of the CAMEL model estimated with combined analysis and control sample data were presented. Signs on the estimated coefficients were as expected except for AQ3 and GPM. The *t*-test was used to test the null hypothesis that the individual slope coefficient was equal to zero. With the exception of GPM, variable coefficients were statistically significant. The model Chi-square was used to test the hypothesis that all slope coefficients for the covariates were equal to zero. The model Chi-square far exceeded that required for a 99.5 percent confidence level. The CAMEL model summarized in Exhibit 4.2 provided the basis for examining the marginal impact of CFB information.

The fourth section was devoted to the results of the CFB analysis. Preliminary CFB variable univariate analysis was summarized in Table 4.3. Results of logit estimations for six CFB model versions were presented in Table 4.4. In most cases the observed coefficient signs confirmed the relationship to failure posited in the Lawson Cash Flow Model. *T*-test and model Chi-squares were again used to test hypotheses regarding individual slop coefficients and the joint significance of the CFB variables, respectively. All but two variables, TAX and NETVCF, had slope coefficients not significantly different from zero and all model Chi-squares were significant for all CFB model versions. The CFB results and analysis supported further investigation of the role of CFB information in bank failure. CFB information was combined with the CAMEL model yielding the MM model results discussed in the next section.

In section five, the results of logit analysis were reported and evaluated for each of the three MM model versions: MM1, MM3 and MM6. T-tests and model Chi-squares again provided the basis for evaluation individual slope coefficients and the joint significance of the MM model variables. All MM model Chi-squares were statistically significant. However, the CAMEL variable set appeared to dominate in the MM models. The t-test results of the CAMEL variables were consistent with t-test results for these variables in the stand alone CAMEL mode. The t-tests on the CFB variables revealed that only two CFB variables, CLNSN and DEBTCF, had slope coefficients significantly different from zero.

The first hypothesis was also tested in section five. The c statistic, a variant on the likelihood ratio test, was used to test for the joint significance of the CFB variables in the MM model. Since the CFB information embodied in the MM model had a significant impact on the "goodness-of-fit" of all three MM model versions, H_{01} was not maintained.

The discussion in section six focused on validative and predictive classification results. Details of the classification procedure as it related to validation and prediction were described. Various criteria, all relating to the number of banks classified as failed or non-failed, were defined and their appropriateness in failure prediction noted. Since failure prediction was the goal in this study, Korobow and Stuhr's criterion, based on Type II error rates, was selected as the primary evaluation criterion for assessing classification efficiency. MM1 exhibited a slight edge in validative efficiency. In general all validation classification accuracy rates were high justifying further investigation of predictive ability.

Prediction results reported in Table 4.7 revealed that CAMEL and MM6 shared the lowest Type II error rate. CAMEL, with the slightly higher overall accuracy, was deemed the slightly superior performer in predictive accuracy. As in validation, the observed differences in predictive classification accuracies were slight. No model, CAMEL or any of the three MM versions, emerged as an unequivocally, superior performer.

Both H_{02} and H_{03} were tested in section six. These hypotheses related to the comparative validative and predictive abilities of the CAMEL model and each MM model version. Conover's T, a Chi-square test for differences in probabilities, was used to test both hypotheses. In no case were the observed differences in validative or predictive accuracies of the CAMEL model vis-a-vis each respective MM model version strong enough to establish statistical differences in either validative or predictive classification abilities.

The last section presents the comparative general MM and small bank MM predictive results. A small bank was defined as one with total assets of $50 million or less. Procedures used to generate the small bank predictive classifications were described and the results presented in Table 4.8. The final hypothesis, tested in this section, relates only to MM model predictive accuracies. General bank MM predictive accuracies are compared with small bank MM predictive accuracies. Conover's T was again used to test for significant differences between each respective MM general model and its small bank counterpart. In one case, MM1, the differences in predictive accuracy rates was strong enough to establish statistical differences. Therefore, H_{04} was rejected for MM1 but was maintained for MM3 and MM6.

The empirical evidence provided by this study is mixed. The evidence appears to point to the conclusion that CFB information collectively provides useful signals of bank distress. Of the individual cash flow components, only CLNSN and DEBTCF are significant distress signals. Including

CFB information does not significantly improve either validative or predictive accuracy rates for the total bank group. In one case, MM1, the CFB information did generate statistically different classification accuracies for the small bank group relative to the total bank group. Small MM1 was a slightly superior performer than its general MM counterpart.

Chapter Five

Summary and Conclusions

This chapter presents a summary of all phases of the research. The first section contains a review of the importance of the study. The research methodology is reviewed in section two and the empirical research results are summarized. Implications of the research findings are also discussed in this section. Contributions and limitations of the study are discussed in the last section and suggestions for further study are offered.

Importance of the Study

Since the early 1980s, U. S. commercial banks have been failing at an alarming pace. Initially, the unprecedented turmoil in the banking industry was generally attributed to the combined impact of a changing regulatory environment and the economic recession present when the prescribed regulatory changes were implemented. In the 12 years since, many banks have responded to the challenges in their competitive environment. Economic conditions, while still uncertain in some sectors, have stabilized substantially relative to the banking industry. Today, however, banks continue to fail at a pace far surpassing the record 1982 experience.

A bank failure has far reaching and unpleasant economic consequences for many parties. If the bank is insured, the FDIC Bank Insurance Fund and perhaps U. S. taxpayers bear the cost. In 1991 alone, troubled banks cost the already strained fund roughly $12.329 billion. Other costs are more difficult to quantify. Depositors are inconvenienced, at a minimum, and if their deposits are uninsured or in excess of the $100,000 FDIC ceiling, they face an additional direct loss. Bank shareholders may lose their investment outright and other bank creditors may encounter slow or nonexistent repayment of the failing bank's outstanding debt. Communities lose the resources and services of a closed institution, and employees of a closed or merged bank lose jobs and income. If a troubled bank can be identified in advance of failure, remedial actions may be taken to avoid these unpleasant consequences.

Bank failure has been the subject of much research. Identification of factors, distress signals capable of foretelling banks with financial difficulties, has been the primary thrust of this research. Traditionally, the research framework for identifying distress signals has been based on the FDIC's system for assessing and reviewing bank performance, commonly referred to as the CAMEL rating system. The usual distress signals are financial ratios constructed from accrual-based accounting information.

With the ongoing bank failure experience, it is more important than ever to identify bank distress signals. To date, minimal research has looked beyond the traditional CAMEL indicators of distress. This study took a step in that direction by incorporating bank cash flow analysis with the traditional accrual-based CAMEL measures. The primary purpose of the study was to provide evidence concerning the usefulness of bank cash flows as predictors of bank failure. A secondary purpose of this study was to assess the impact of cash flow-based information on predicting failure of small banks.

Research Results

The purpose of this study was to provide empirical evidence concerning the marginal impact of cash flow-based (CFB) information on predicting bank failure. Prior empirical studies rely predominantly on accrual-based CAMEL measures to predict bank failure. In this study, CFB variables were combined with the traditional CAMEL measures. The study was designed to ascertain if including the CFB information in the CAMEL model significantly enhanced the explanatory and/or predictive accuracy of the stand-alone

CAMEL model.

Assessing the marginal impact of CFB information required developing two models: (1) the CAMEL model includes only accrual-based CAMEL variables, and (2) the mixed model, MM, contains these same CAMEL variables and CFB measures. The CAMEL model was developed first and provided the basis for examining the marginal impact of the CFB information. Ultimately three MM model versions were estimated and evaluated relative to the CAMEL only model. The basic hypothesis was that no difference exists between a failure model using accrual-based CAMEL information only and a failure model using combined CAMEL and CFB information.

Failed banks and their ongoing counterparts for the years 1988 and 1989 comprise the study sample. Failed banks were identified from FDIC annual reports for the same years. A bank was considered failed if it received FDIC assistance in any of three forms: deposit pay-off, deposit transfer or purchase and assumption. A bank receiving any of these types of assistance ceases to operate as a separate identity and is considered closed by the FDIC. The primary source of data for all banks is the <u>Report of Condition and Income for Commercial Banks and Other Selected Financial Institutions</u> magnetic data tapes for the years 1986-1989. These data are collected by the FDIC, Federal Reserve System and the Office of the Comptroller of the Currency. The data tapes contain the balance sheet and income statement accounting data required to calculate both the CAMEL and CFB financial ratios for all banks.

Joy and Tollefson's (1978) distinction between validation and prediction is applied throughout the study. This required separating the sample data into two groups, the 1988 estimation and the 1989 prediction samples. The 1988 estimation sample was further divided (and later recombined) into two groups, an analysis and a control sample. To test one hypothesis, a small bank subset was segmented from both the 1988 estimation and 1989 prediction samples by imposing the criterion of total assets of $50 million or less.

Logit models were used to test the hypotheses of the study. Logit analysis was selected over other commonly used failure prediction analyses (discriminant, linear probability and probit analyses) because of the advantages inherent in the logit technique. Logit analysis does not require the assumption of normality implicit in discriminant analysis, and unlike linear probability analysis, logit analysis constrains the values of the conditional probabilities to a zero to one range. Also, logit analysis specifies a cumulative distribution function which is more theoretically appealing in the failure prediction context than is the linear specification of linear probability analysis. Several authors have found that logit and probit analysis yield essentially the same results and have, therefore, concluded that the choice between logit and probit analysis is inconsequential and at the discretion of the researcher.

Several logit models were estimated in the study. Since the CAMEL model was considered the basis for assessing the impact of CFB information, it was developed first. CFB information was analyzed separately prior to combining it with the CAMEL information. Given encouraging CFB analysis results, CFB variables and CAMEL variables were combined yielding the MM model. In all logit estimates, the usual *t*-test and a Chi-square likelihood ratio test were used to evaluate hypotheses relevant to individual variable coefficients and the joint significance of the explanatory variables, respectively. All research results were evaluated at the 0.05 level of significance.

In developing the CAMEL model, six different versions were estimated and compared to determine which group of financial ratios collectively representing the CAMEL categories provided the better set of empirical measures. The version ultimately designated the CAMEL model included CAPAD1, AQ1, AQ3, GPM, ROA and LIQ1. The model and all individual variable coefficients except GPM were statistically significant. With the exception of AQ3, all variable coefficients had the sign expected for a successful bank. The CAMEL results were generally consistent with Martin's simple theory of bank failure and previous empirical work.

Six separate versions of CFB only models using various specifications of Lawson's cash flow components were also estimated and compared. All CFB model versions and most cash flow components were statistically significant. Coefficients on TAX in CFB1 and NETVCF in CFB6 were not significant. Some coefficients did not have the sign Lawson hypothesized for a successful bank. The aggregate measure of lender-related cash flow and both its separate components, debt-related and deposit-related cash flows, had negative signs. Lawson and Aziz (1989) argued that a successful institution would be able to carry higher levels of borrowing. The negative signs on the lender related cash flow components suggests otherwise. Overall, the CFB results and analysis were encouraging and supported including CFB information in the failure prediction models.

Three MM model versions were estimated, evaluated and ultimately compared with the stand-alone CAMEL model. All model Chi-squares were statistically significant but only two CFB variables, measuring loan and debt cash flows, retained the significance exhibited in the CFB models. With statistically significant coefficients on all CAMEL variables except GPM, the CAMEL variable set dominated in all MM versions.

The usefulness of CFB information for predicting small bank failure was investigated in the final phase of the study. The purpose here was to ascertain if CFB information was more useful for predicting failure for that group of banks which historically are more susceptible to financial difficulties and failure. Small bank predictive classification accuracies were compared with general bank group predictive accuracies to ascertain if CFB information was more useful for predicting failure in the small bank group.

Four hypotheses were tested in the study. Three hypotheses concerned the respective comparative explanatory, validative and predictive ability of the CAMEL and MM models. The fourth hypothesis concerned the comparative small bank versus total bank predictive ability of only the MM model. A Chi-square statistic comparing the fitted likelihood values of the CAMEL model with each of the three MM model versions was used to test the first hypothesis. Conover's T, a Chi-square statistic comparing differences in probabilities, was used to test the remaining three null hypotheses. The values for the T statistic were taken from the classification contingency tables generated with the validation and prediction procedures.

The first null hypothesis was rejected for each of the three MM model versions. The test indicated that jointly considered, one or more CFB variable coefficients was different from zero. As a group, the CFB information had a significant impact on failure. However, considered individually, only two cash flow components, those measuring loan and debt cash flows, were significant failure indicators.

Both null hypotheses H_{02} and H_{03} were maintained. When validation and prediction procedures were performed, the CAMEL and MM model versions classified failed and nonfailed banks at different rates. However, the differences in classification accuracies generated from either procedure were not strong enough to establish statistically significant differences between the CAMEL model and any MM model version.

Korobow and Stuhr's (1984) criterion of lowest Type II error rate was used to determine which if any model was the better performer. This criterion is appropriate in the failure prediction context because it focuses on misclassifications of failed banks (banks which actually failed but were classified as nonfailed by the model). MM1 exhibited the lowest Type II error in validative accuracy but its superiority was minor. It correctly classified one more failed bank than the next best performer but at the expense of greater misclassifications of nonfailed banks.

Prediction is the more important of the two classifications. Successful prediction results imply that a model may be useful for identifying a bank likely to fail before failure actually occurs. CAMEL and MM6, sharing the lowest Type II error rate of 3.21 percent, were the better predictors of failed banks. However, because CAMEL was also able to predict successful banks more accurately, it was deemed a slightly superior overall predictor.

The last hypothesis tested was rejected for MM1 but maintained for MM3 and MM6. Small bank MM models classified failed and nonfailed banks at rates slightly different from their general model counterparts. Only the predictive classification differences between small MM1 and its general MM1 counterpart were strong enough to establish statistical significance. With smaller Type II error than general MM1, small MM1 was the better predictor of failed banks.

Arguments offered earlier suggested that cash flow may be as important for the banking firm as it is for the nonbanking firm. Essentially, both types of firms need cash on a timely basis to maintain financial health, i. e., pay bills and wages, repay borrowings, meet interest and other fixed obligations, and invest for growth. The empirical evidence regarding cash flow and nonfinancial firm failure prediction is mixed. However, with 11 of 16 studies finding superior predictive results with CFB variables (alone or in combination with traditional accrual-based accounting ratios), the preponderance of evidence supports cash flow as a predictor of firm failure. Given the empirical findings of this study, the same cannot be said for cash flow as a predictor of bank failure.

Several explanations for these findings come to mind. Nonfinancial firm failure and bank failure are two different phenomena. In nonfinancial firm failure studies, the filing of Chapter 11 bankruptcy defines the incident of failure. The bankruptcy filing may be initiated by a firm or forced by a firm's creditors. In either case, the circumstances preceding the filing are characterized by a firm's historical and continuing inability to meet its contractual financial obligations. Also, filing for bankruptcy is usually a firm's final resort, the only recourse available when all resources, particularly cash, are exhausted. It is appropriate to assume that the financial data of such a firm reflect these extreme conditions.

In this and most other bank failure studies, a bank closing serves as the incident of bank failure. A bank closure is an arbitrary event, the result of the actions of bank regulators. The primary goal of these regulators is protection of the safety and soundness of the banking system, and they are empowered to close a bank if they feel it poses a threat to this goal. To determine if a bank is a threat, regulators review the bank's operations and assets, particularly its loan portfolio. Ultimately, the bank's fate depends primarily on regulators' assessment of the probability that the bank will receive interest from and principle repayment on its outstanding loans. Two implications follow.

First, since regulators close a bank when they perceive it to be a threat to the system, the bank may or may not be suffering the same degree of financial distress experienced by a nonfinancial firm when it files for bankruptcy. If it is not, it is possible that bank cash flow imbalances have not yet reached the critical stage and will, therefore, not be reflected in the data of the closed institution. Second, regulators' assessment of the viability of a bank is based primarily on the quality of the bank's asset portfolio, not necessarily its cash flow. If bad loans, not cash flow problems, are the reason for closing the institution, it is not likely that cash flow imbalances would be evidenced in the bank's financial data.

The respective firm and bank data sources may provide another possible explanation. In most successful nonbank failure prediction studies, CFB variables are constructed with data taken directly from a firm's reported Statement of

Cash Flow. The data used in this study were extracted from Call Report data regularly collected by various federal agencies. These agencies require reporting of condition and income only. Since cash flow reporting consistent with Statement no. 95 is not required by these agencies, the cash flow components had to be constructed from the available data. Essentially, this involved using the balance sheet and income statement data to simulate a Statement of Cash Flow. The information thus created served as the basis for constructing the CFB ratios representing Lawson's components. Great care was taken to insure that the simulated statement mirrored the actual Statement of Cash Flow. It is possible that data taken directly from bank Statements of Cash Flow, had they been available, may have been more revealing and generated results more consistent with firm failure prediction studies.

Furthermore, banks are very liquid institutions. Cash flows into and out of the bank with regularity and in volumes most likely in excess of those experienced by the nonbanking firm. Bank cash flows also are highly interrelated, i.e., a withdrawal from a deposit account at a bank (outflow) for repayment of a loan at the same bank (inflow). The CFB variables were specified to measure the net effects of these types of transactions over a bank's operating period. Perhaps because of the complexity and interrelated nature of bank cash flows, the CFB variables are not able to capture the nuances of cash flow patterns particular to banks.

Finally, creation of cash via the lending function is the primary product of banking activities. Any store of cash by the bank may be likened to the inventory a nonbank firm maintains to meet the needs of its customers. For example, as cash is loaned or deposits withdrawn, a bank's inventory of cash is depleted, and as loans are repaid and deposits received, a bank's inventory of cash is enhanced. Perhaps in this context, the CFB variables as applied to a banking institution are more representative of inventory fluctuations. As such, it is possible that the CFB variables and the Lawson Identity upon which they are based do not capture the type of cash flow patterns and imbalances critical to a bank's financial health and ultimate survival.

Implications

The results discussed above contain a number of implications for parties concerned with monitoring bank performance. These parties are many and varied. Included among them are bank regulators who seek to protect the safety and soundness of the banking system and in that capacity seek to avert bank failure. Also included are bank creditors and investors who use bank financial statements in their decision making processes. All these parties have access to the type of financial data (cash flow and otherwise) used in this study and regularly employ this information in their assessment activities.

The primary purpose of this study was to assess whether cash flow-based information enhances the predictive accuracy of traditional accrual-based bank failure prediction models. The empirical findings suggest that it does not. Both the traditional CAMEL model and the MM model are good predictors. Both have predictive accuracy rates consistent with or higher than those reported in previous studies. However, the additional CFB information in the MM model does not significantly enhance the predictive accuracy rates of the traditional CAMEL measures. In fact, the stand-alone CAMEL model more accurately forecasts both failed and ongoing concerns.

This finding contains several important implications for bank failure prediction in general and the CAMEL monitoring system in particular. With regard to failure prediction, regulators have little to gain from using cash flow information and/or cash flow analysis in early warning systems designed to predict failure before it occurs. While the MM model is a good predictor, the additional CFB variables in the model do not appear to add information capable of foretelling future failure. Since the readily available, historically proven CAMEL measures provide sufficient distress signals, regulators should carefully weigh any extra costs of committing agency resources to the collection and analysis of CFB information against the small gain in predictive accuracy.

With regard to the FDIC's monitoring system in particular, most previous failure prediction models have specified variables representing this system's various CAMEL categories. In general, these CAMEL-based models have been good predictors of failed banks. The successful CAMEL prediction results of this study are consistent with these earlier works. The repeated success of these traditional CAMEL models suggests that the FDIC's monitoring system does indeed capture those aspects of a bank's performance critical to its survival and supports continued use of the system as a monitoring and assessment tool.

Furthermore, the results of this study suggest that CAMEL variables are robust empirical failure predictors. Not only do these variables yield reliable distress signals when subjected to differing estimation techniques but also over time and through differing regulatory environments. Regulators' continued use of accrual-based CAMEL ratios is also affirmed and supported by the findings of this study.

Currently, a controversy surrounds the issue of bank cash flow reporting, in particular FASB Statement No. 95 requiring a "Statement of Cash Flow" as part of a complete set of financial statements. The banking community, bankers and bank regulators, generally argues that cash flow analysis is not meaningful for a bank and reporting of a bank's cash flows is, therefore, superfluous. The FASB and the accounting community in general hold an opposing view. The findings of this study contain implications for both views.

The accounting view gains mild support from the evidence in this study. The FASB contends that a statement of cash flow provides information not revealed in income or balance sheet statements. In this study, the CAMEL variables are constructed from balance sheet and income statement data. The CFB variables are representative of the cash flow components in Laswon's Model which closely parallels a statement of cash flow. Application of the Likelihood Ratio test, a powerful discriminating test to determine if the set of CFB ratios adds discriminating information to the balance sheet and income statement accrual-based CAMEL variable set, revealed an increase in explanatory power significant at the 5 percent level. This implies that a firm's statement of cash flow provides some information not contained in its balance sheet and income statement and lends some support to the FASB contention and argument that a statement of cash flow be part of a complete set of financial statements.

The evidence also implies that two bank cash flows are of particular importance the year prior to failure. Two cash flow components in MM6, CLNSN and DEBTCF, had significant coefficients. The significant coefficient on CLNSN suggests that cash committed to the loan portfolio enhances a bank's potential for success. Loans are the primary source of income for a bank. A bank unwilling or unable to divert cash to this activity may bear closer scrutiny. Similar to the nonbanking firm, increasing debt levels, DEBTCF, may have an adverse effect on bank performance. A bank generating high cash inflows from short- and long-term borrowing may also bear extra scrutiny.

However, support for the accounting position is limited. The FASB argument stresses the importance of cash flow information for assessing future cash flows. (FASB, 1987) The statistical test was applied only to the data of the analysis sample. No attempt was made to determine if this relationship existed in other samples, previous or future. Therefore, no inferences can or should be drawn regarding the marginal explanatory impact of CFB information in prior or subsequent years. Furthermore, as noted, the predictive value of the cash flow information is questionable. If the goal of financial reporting is to aid in assessing future performance, as FASB argues, then a statement of cash flow for a bank is not necessarily useful in this regard.

The banking view gains support from the classification results. The classification procedures were designed to ascertain if a model with CFB information (MM) could predict better that a model without CFB information (CAMEL). Application of the Conover T test revealed that the slight differences observed between CAMEL and MM model accuracy rates (validation and prediction) are not statistically significant. This evidence implies that when prediction is the goal, the marginal impact of CFB information is negligible and suggests that the information in a statement of cash flow is not useful for assessing future cash flow and potential insolvency.

The banking community has long contended that clues about a bank's financial health and future viability are not to be found in analyzing cash flow. Based on this view, they have argued that a separate statement of cash flow as required by FASB would be meaningless for banks. Since the CFB information was of questionable predictive value, the evidence in this study supports their view.

Contributions, Limitations and Suggestions for Further Study

Contributions

This study enhances and extends the bank failure prediction literature in several ways. The first and primary contribution relates to the study's investigation of the role of cash flow information in bank failure analysis. The general thrust of previous failure research has been a search for factors capable of explaining and/or foretelling banks in financial distress. In this search, most previous researchers use financial ratios constructed from accrual-based accounting data to represent those factors. This study took that search in a different and previously unexplored direction and provides the first empirical evidence regarding the usefulness of cash flows as signals of bank distress.

Most bank failure prediction studies are dated. The bulk of the Early Warning research was conducted prior to the deregulation of the early 1980s. (Altman and Sametz, 1977; Hanweck, 1977; Korobow, Stuhr and Martin, 1976; Martin, 1977; Sinkey and Walker, 1975) The few studies conducted since that time use data for banks operating either prior to the implementation of the regulatory changes (Bovenzi, Marino and McFadden, 1983) or in the turbulent period immediately following (Lane, Looney and Wansley, 1986; Marcus and Shaked, 1984; West, 1985). The empirical evidence provided by this study updates the existing failure prediction literature.

This study also enhances and extends the segment of the Accounting literature specific to the role of cash flow in failure prediction and the related issue of cash flow reporting. In 1987, the Financial Accounting Standards Board (FASB, 1987)) issued Statement no. 95 requiring a Statement of Cash Flow in a complete set of financial statements for all firms including banks. The banking industry was opposed to this requirement. The general argument was that the banking firm, whose primary output is the creation of money via the loan function, is so different from other nonbank firms as to render this type of information useless and without meaning. FASB acknowledged the uniqueness of bank operations but argued that a bank requires cash for essentially the same reasons as a nonbanking firm and that the information in a Statement of Cash Flow would be useful for forecasting future cash flows. This study is the first to provide any empirical evidence addressing the bank cash flow reporting controversy.

Finally, the empirical findings of this study affirm and support continued used of the traditional accrual-based CAMEL measures in bank regulators' failure forecasting activities. While the evidence on the role of cash flow information was mixed, the empirical evidence relative to the CAMEL variable set was not. In either the stand-alone version or the MM model version in which they dominated, these variables predicted failed banks at a rate consistent with or higher than those found in earlier studies. CAMEL type measures appear to maintain their predictive ability through time, even in differing regulatory and competitive environments.

Limitations

This study is subject to the same limitation found in other prediction studies: the assumptions regarding the cut-off point used to sort the observations into groups. The cut-off point directly determines the classification accuracies used to evaluate a model's predictive ability. Altering the cut-off point alters classifications results. Selection of an appropriate cut-off point is the subject of ongoing research. Several researchers have also suggested that the cost of misclassifying the observations be included in the analysis and have suggested methods for doing so. However, no method is without problems. (See Zavgren, 1983, for a review)

This study assumed a priori probabilities of group membership equal to the sample frequencies and equal cost of misclassification errors. These costs are of two types: (1) the direct and indirect costs associated with the failure to correctly predict a bank which ultimately fails, and (2) the direct and indirect costs associated with identifying an ultimately safe bank as a potential failure. It is not likely that these costs are equal. Furthermore, the direct costs of either error are difficult to estimate with any degree of accuracy. Regulators would be in the best position to assess these costs and any appraisal should be left to their expertise. The indirect costs are nearly impossible to forecast.

Suggestions for Further Research

The cash flow-based information used in this study was based on Lawson's Cash Flow Model. In applying the model to the banking firm, the primary assumption was that the Lawson components could be specified to capture the cash flows relevant to banking operations. Perhaps a different conceptual model, one which specifically considers the uniqueness of bank cash flow, would be more appropriate for examining bank cash flow.

Two amendments to Statement no. 95--FASB Statements no. 102 and no. 104--have clarified many issues related to classifying and reporting bank cash flow. The amendments have made it easier for banks to comply with the reporting requirements of FASB Statement No. 95 and purportedly provide information more relevant for bank performance. (Edwards and Heagy, 1991) Analysis of the impact of cash flow specified in accordance with these amendments could also be the focus of future research.

APPENDICES

APPENDIX A

COMPLETE SPECIFICATION OF CAMEL VARIABLES

CAPITAL ADEQUACY

Variable Label	Variable Calculation	Description (Element Number)*	
CAPAD1	(EQCAP-PSTOCK)/ TA	EQCAP:	Equity Capital (RCFD 3210)
		PSTOCK:	Preferred Stock (RCFD 3283)
		TA:	Total Assets (RCFD 2170)

Record Description*

RCFD 3210: The sum of perpetual preferred stock, common stock, surplus, undivided profits and capital reserves and cumulative foreign currency translation adjustments.

RCFD 3283: Includes the aggregate par value or stated value of outstanding perpetual preferred stock. Perpetual preferred stock is preferred stock that does not have a stated maturity date or that cannot be redeemed at the option of the holder. Includes those issues of preferred stock that automatically convert to common stock at a stated date.

RCFD 2170: The sum of all asset items.

APPENDIX A (Continued)

CAPAD2	LNSN/(EQCAP + ALLN)	LNSN:	Total Loans (RCFD 2125)
		EQCAP:	Equity Capital (RCFD 3210)
		ALLN:	Allowance for Loan Losses (RCFD 3123)

Record Description

RCFD 2125: Loans and leases, net of unearned income, allowance and reserves.

RCFD 3210: See above.

RCFD 3123: Includes the sum of allowance for loan and lease losses less beginning balance, recoveries in allowance for loan and lease losses, provisions for allowance for loan and lease losses and adjustments minus charge-offs in allowance for loan and lease losses.

APPENDIX A (Continued)

ASSET QUALITY

Variable Label	Variable Calculation	Description Element Number	
AQ1	LNSN/TA	LNSN:	Total Loans (RCFD 2125)
		TA:	Total Assets (RCFD 2170)

Record Description

RCFD 2125: See Above.

RCFD 2170: See Above.

Variable Label	Variable Calculation	Description Element Number	
AQ2	COINLNS/TA	COINLNS:	Commercial and Industrial Loans (RCFD 1766)
		TA:	Total Assets (RCFD 2170)

Record Description

RCFD 1766: The sum of commercial and industrial loans to U.S. addressees and commercial and industrial loans to non-U.S. addressees.

RCFD 2170: See above.

Variable Label	Variable Calculation	Description Element Number	
AQ3	ALLN/LNSN	ALLN:	Allowance for loan losses (RCFD 3123)
		LNSN:	Total Loans (RCFD 1766)

Record Description

RCFD 3123: See above.

RCFD 1766: See above.

APPENDIX A (Continued)

MANAGEMENT

Variable Label	Variable Calculation	Description (Element Number)
GPM	(OPREV-OPEXP)/ OPREV	OPREV: Operating Revenue (RIAD 4000) OPEXP: Operating Expense (RIAD 4130)

Record Description

RIAD 4000: Total interest and non-interest income. The amount of ordinary and recurring income during the year.

RIAD 4130: Total interest and non-interest expense. The amount of ordinary and recurring expenses of operation during the year.

MGT	OPEXP/OPREV	All items defined as above.

APPENDIX A (Continued)

EARNINGS

Variable Label	Variable Calculation	Description (Element Number)
ROE	NI/EQCAP	NI: Net Income (RIAD 4340) EQCAP: Equity Capital (RCFD 3210)

Record Description

RIAD 4340: Income (loss) before extraordinary items and other adjustments plus extraordinary items and other adjustments, net of income tax.

RCFD 3210: See above.

ROA	NI/TA	All items defined as above.

APPENDIX A (Continued)

LIQUIDITY

Variable Label	Variable Calculation	Description (Element Number)	
LIQ1	(CASH+SEC)/TA	CASH:	Cash items (RCFD 0071+ RCFD 0081)
		SEC:	U.S. Government securities (RCFD 0390)
		TA:	Total Assets (RCFD 2170)

Record Description

RCFD 0071: The amount of outstanding interest-bearing balances occurring in all cash items.

RCFD 0081: Non-interest bearing balances, currency and coin.

RCFD 0390: The total book value of securities and corporate stocks excluding trading account securities. This is the total of U.S. Government agency and corporation obligations, securities issued by states and political subdivisions in the U.S., other domestic securities (debt and equity) and foreign securities (debt and equity).

RCFD 2170: See above.

*Source: Call and Income Report tape documentation, 1985-1990.

APPENDIX B

COMPLETE SPECIFICATION OF CFB VARIABLES

OPERATING CASH FLOW

Variable Label	Ratio Calculation
CFFO	(EBT + XTRA - CUNCOL + CUNPD + LOSSPROV + TRANSPROV RECOV)/TA
	Where CUNCOL = EAUNCOL - lagEAUNCOL, CUNPD = EXUNPD - lagEXUNPD.

	Record Description* (Element Number)*
EBT: (RIAD 4301)	Income (loss) before income taxes and extraordinary items and other adjustments. Includes "Net interest income" (4704), minus "provision for loan and lease losses" (4230), and "provision for allocated transfer risk" (4243), plus total noninterest income" (4079), plus or minus "gains (losses) on securities not held in trading account" (4091), minus "total noninterest expense" (4093).
XTRA: (RIAD 4310)	Extraordinary items and other adjustments, gross of income taxes.
EAUNCOL: (RCON 2164)	Income earned but not collected on loans.
EXUNPD: (RCON 2933)	Expenses accrued and unpaid.
LOSSPROV: (RIAD 4230)	Provision for loan and lease losses.
TRANRPOV: (RIAD 4243)	Provision for allocated transfer risk.

APPENDIX B (Continued)

RECOV: (RIAD 4605)	Recoveries on allowance for loan and lease losses.
TA: (RCFD 2170)	Total assets. The sum of all asset items

Variable Label	Ratio Calculation
CFAT	CFFO - TAX/TA

	Record Description (Element Number)
CFFO:	See above.
TAX: (RIAD 4770)	Total applicable income tax paid in the period. Includes the sum of "Applicable federal income taxes" (4780), "Applicable state and local income taxes" (4790), and "Applicable foreign income taxes" (4795).
TA:	See above.

APPENDIX B (Continued)

TAX CASH FLOW

Variable Label	Ratio Calculation
TAX	TAX/TA
	All items defined as above.

APPENDIX B (Continued)

INVESTMENT CASH FLOW

Variable Label	Ratio Calculation
GRVCF	GRINV - lagGRINV/TA
	Where GRINV = TA - LIQ2

	Record Description (Element Number)
TA:	See above.
LIQ2:	All current asset items as defined below.

Variable Label	Ratio Calculation
CLNSN	LNSN - lagLNSN/TA

	Record Description (Element Number)
LNSN: (RCON 2125)	Loans and leases net of unearned income, allowance and reserve.
TA:	See above.

APPENDIX B (Continued)

Variable Label	Ratio Calculation
NETVCF	NETINV - lagNETINV/TA
	where NETINV = TA - LIQ2 - CLNSN

Record Description (Element Number)	
TA:	See above.
LIQ2:	Defined below.
CLNSN:	See above.

APPENDIX B (Continued)

LIQUIDITY CASH FLOW

Variable Label	Ratio Calculation
CLQ	LIQ2 - lagLIQ2/TA

where: LIQ2 = CASHNON + CASHINT + SEC + FEDFUNDS

	Record Description (Element Number)
CASHNON: (RCON 0081)	Noninterest bearing balances plus currency and coin. Includes the total of all noninterest-bearing balances due from depository institutions, currency and coin, cash items in process of collection, and unposted debits that are included in item RCON 0010.
CASHINT: (RCON 0071)	Interest bearing balances. The amount outstanding of interest-bearing balances occuring in all cash items.
SEC: (RCON 0390)	Total investment securities. The book value of securities and corporate stocks excluding trading account securities. This is the total of "U.S. Treasury securities" (0400), "U.S. government agency and corporation obligations" (0600), "Securities issued by state and political subdivisions in the U. S." (0402), "Other domestic securities (debt and Equity)" (0421), and "Foreign securities (debt and equity)" (0413).
FEDFUNDS: (RCON 1350)	Federal funds sold and securities purchased under agreements to resell in domestic offices of the bank.
TA:	See above.

APPENDIX B (Continued)

SHAREHOLDER CASH FLOW

Variable Label	Ratio Calculation
SHRCF	EQCF + DIVCF/TA
	where EQCF = EQCAP - lagEQCAP,
	DIVCF = CDIV + PDIV.

	Record Description (Element Number)
EQCAP: (RCFD 3210)	Equity capital. The sum of preferred stock, common stock, surplus, undivided profits and capital reserves and cummulative foreign currency translation adjustments.
CDIV: (RIAD 4460)	The amount of cash dividends paid during the calendar year-to-date.
PDIV: (RIAD 4470)	The amount of cash dividends paid limited-life preferred and perpetual preferred stock during the calendar year-to-date.
TA:	See above.

APPENDIX B (Continued)

LENDER CASH FLOW

Variable Label	Ratio Calcultion
DEBTCF	DEBT - lagDEBT/TA
	where DEBT = TA - TDEP - EQCAP

Record Description (Element Number)	
TA:	See above.
TDEP: (RCFD 2200)	Total deposits as defined by the FDIC Insurance act.
EQCAP:	See above.

Variable Label	Ratio Calculation
DEPCF	TDEP lag TDEP/TA
	All items defined as above.

Variable Label	Ratio Calculation
LENDCF	DEBTCF + DEPCF/TA
	All items as defined above.

*Source: Call and Income Report tape documentation, 1985-1990.

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