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Predicting Small Bank Failure

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There are many studies of bank performance and bank failure in the literature. Most of these studies used banking ratios as variables in their models without giving consideration to their appropriateness, nor was much consideration given to the stability of those ratios through time and across asset size. Many studies also failed to recognize that bank structure may differ by asset size. This study evaluates a large number of banking variables in order to identify stable ratios. These ratios are then used in disaggregated logistic models to predict bank failure. The study finds that the disaggregated models with stable variables were better predictors of bank failure than aggregated models used in earlier studies.

INTRODUCTION

Studies of bank performance have used a myriad of bank financial ratios as measures of performance [3, 5, 6, 9, 14, 16, 22]. Other studies which used banking ratios were more concerned with predicting bank failures [13, 19, 21]. While these ratios may have been adequate in making cross-sectional and comparative analyses, it has yet to be shown that bank financial ratios are adequate measures of bank performance through time. In order to use these measures to compare bank performance through time, it is necessary to first show that they are stable through time. Ratios which are found to be intertemporally stable may also have better predictive properties, when used in various forecasting techniques, to predict bank behavior or bank failure.

The question of the stability of banking ratios is even more pertinent since the initiation of the deregulation process in the early 1980s. This may have encouraged bank managers to change the structure of their balance sheets and the decision strategies of commercial banks. Consequently, the results of studies and predictive models using historically popular ratios may now be questionable. The purpose of this study was to evaluate the stability, through time, of 43 banking ratios popularly

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used in the analysis of bank performance and bank behavior. A second purpose was to determine whether stable ratios were better predictors of banking conditions. The banking data used in this study are for small banks with total assets of $500 million or less.

A factor analysis technique which extracted factors by the principal component method was used in this study to evaluate the stability of each ratio and to identify stable ratios. The predictive power of the ratios chosen was then evaluated in logit regression models. This study departed from previous studies in that it evaluated banking ratios by asset class or size and then used those ratios to build predictive models in each asset class. This approach was chosen because there were evidences in the literature which suggested that bank structures differ significantly across asset class. Therefore, it should be expected that models which used data that were disaggregated by asset size should perform better than models which use data that were aggregated across asset classes. The results of this study seem to bear this out.

PREVIOUS STUDIES

A review of the literature has not revealed any studies on the stability of banking ratios. However, there were some studies on the stability of financial ratios in general. These studies were done by Johnson [7], Pinches, Mingo, and Caruthers [18], and Libby [11]. The Johnson study used cross-sectional analysis across industries; neither study adjusted for the effects of firm size on ratio stability. However, Pinches, Mingo, and Caruthers did an intertemporal factor analytic study across industries. These earlier studies implicitly suggested that financial ratios were stable across time and industries. A notable exception to the notion of ratio stability was a study by Dambolena and Khoury [4]. Their study provided evidence that some of the ratios used in earlier models to predict corporate failure were unstable. Some of those ratios were also used in models to evaluate corporate performance.

Banking ratios were used in a study by Meyer and Pifer [15] to predict bank failures. They used 10 ratios in a discriminant analysis model, and their study indicated only one of the ratios had predictive power. A more recent study by West [21] used 19 variables to estimate bank failures in a logit-factor analytic framework. The regression variables in the West study were the factor loadings of the 19 banking ratios. The West study was criticized by Korobow and Stuhr [8] for its lack of predictive power. A possible reason for the poor predictive power of the West models was that the factor analysis results suggested some of his variables were unstable. The instability of variables is suspected because the factor loadings of the variables were not consistently ranked in each of the three consecutive years for which the study was conducted.

In a recent study, Lane, Looney and Wansley (LLW) [10] used 20 banking variables in the Cox Proportional Hazard Model to estimate bank failure. They admitted that the predictive ability of their model depended on the stability of the variables used but they did not evaluate the stability of their variables. Despite this potential problem, the LLW technique proved to be adequate, at least for the data used. In a subsequent article Looney, Wansley and Lane (LWL) [12] used eight variables to study the misclassification problem of bank failure models. The misclassification problem was one of identifying a bank as belonging to the group with a low probability of failure, when, in fact, the bank belonged to the group of potential failures, a Type II error. The misclassification study ignored the stability even though it could be hypothesized that some of the misclassification errors were the result of the use of unstable ratios as variables in model building. Since classification errors can be costly to investors, regulatory agencies, and eventually, to the taxpaying public more accurate models are needed for effective public monitoring, efficient government regulations and bank management.

No studies were found which evaluated the intertemporal stability of popular banking ratios used by analysts to evaluate bank performance and to predict bank failures. This study used some of the variables which were included in the studies mentioned above. Other variables, which we believe are important, were added and then evaluated in four asset categories. The first objective was to find a number of variables in each asset class which were stable through time. Since the reliability of predictive models depends on the stability of the variables used, the second objective of this study was to develop models which may reduce both Type I and Type II errors.

DATA AND METHODOLOGY

The financial data for the factor analysis part of this study was obtained from the Federal Reserve Call and Income Reports for the base year 1981 and for the

Table 1
Frequency of 10% Sample of Commercial Banks
In Factor Analysis

Asset Class	←——*Number of Sample Banks*	——→	
(Millions of dollars)	*1981*	*1984*	*1988*
0–25	668	587	440*
25–50	329*	348	333
50–100	223*	265	264
100–500	155*	209	220

Note: *Represents the sample size actually used in the factor analysis comparison years 1984 and 1988. The research design followed the Pinches, Mingo, and Caruthers factor analysis approach in their evaluation of the stability of the accounting ratios of industrial firms. This study, however, stratified banks by asset size and covered the period 1981–1989 for both the factor and logit analyses. The study was done by asset class because studies have shown that the asset structure of commercial banks may have changed significantly since 1980 [1, 6, 16, 20].

A 10% random sample of four asset-size groups from all banks in the Federal Reserve data base for years 1981, 1984, and 1988 was obtained for the factor analysis. The factor analysis technique used in this study required identical sample sizes for each asset class in each study year. Therefore, the smallest 10% sample in a class was chosen as the sample for that class in each year of the study. The frequencies of the samples by size-group for the years 1981, 1984 and 1988 are given in Table 1.

Statistical *t*-tests were done on 54 variables identifying statistically significant changes for different bank sizes between 1981 and 1984, 1984 and 1988, and 1981 and 1988. Variables which did not have data for each class and time period were eliminated from further analysis. Forty-three variables were identified as significant and were eventually used in the factor analysis. The advantage of this approach was the number of ratios it provided in each group.

Factor analyses were done on 1981, 1984, and 1988 data. Factor analyses were also done on the differences of the ratios for study years for the between years period; 1981–1984, 1984–1988, and 1981–1988. This was the differential (dR) technique described by Catell [2] and used by Pinches, Mingo, and Caruthers [18]. Thus, the criteria for stable ratios were: (i) Ratios were consistently loaded on the same factor for each of the study years, and (ii) When the dR technique was used, ratios remained loaded on the same factor on which they were consistently loaded for each of the study years. The exception was when a ratio had a dR factor loading of less than 0.5 and was, therefore, insignificant. Inter-class stability of ratios was assumed if an intertemporally stable ratio had consistent factor loadings across asset classes.

The hypothesis was that intertemporally stable ratios were better predictors of banking conditions than those ratios which were not classified as stable by our factor analysis criterion. This hypothesis was evaluated by the use of logit models to predict bank failure. The relative strength of the hypothesis was assessed by comparing the predictive abilities of two kinds of logit models; (i) disaggregated models in which the stable ratios of each asset class were used, and (ii) models which aggregated banks across asset class. The idea was to compare those models which contained only stable ratios with models which included both stable and non stable ratios. The expectation was that stable variables would include the variables in each of the CAMEL groupings; capital adequacy, asset quality, management efficiency, earnings; and liquidity.

The data set for the logit regression sets included the 1981–1983 yearly data for banks which failed in 1984 and a matched sample of healthy banks. The matched sample of healthy banks was selected from those banks which were in existence before 1978 and continued in operation for at least up to 1988. The objective was to predict bank failure one to three years prior to actual failure for each of the four asset classes and for all banks as a single asset class. The basic logit model adapted for this study was

$$\text{Prob}[\text{Fail}_{1984} = 1] = 1/(1 + e^{z_{it}})$$

where
$$z_{it} = B_{0t} + B_{1t}X_{it} + \ldots + B_{Nt}X_{Nt}$$

and X_{it} represented the ith banking ratio at time (t).

In 1984, there were 65 banks with assets of $500 million or less which failed. Of these 65 failed banks as many as 10 were not included in some models because of missing data. The distributions of failed banks by asset class were: 38 in the less

Table 2
Consistent Ratios Across Years and Asset Class

	←——— *Variable Asset Class* ———→			
	$0–25	*$25–$50*	*$50–$100*	*$100–$500*
Equity/Risk Assets (AVERQ/RA)*	2**	1	1	1
Real Estate Loans/Total Assets (REL/ASS)	1	0	0	0
Total Securities/Total Assets (SC/A)	1	1	1	0
U.S. Govt. Securities/Total Assets (US)*	1	1	1	1
Total Loans/Total Assets (LA)*	2	2	1	1
Total Expense/Total Assets(EX/TA)*	1	2	1	1
Net Interest Expense/Total Assets (NIEXP/A)*	1	1	1	1
Overhead (OHD)	0	1	1	1
Wages/Total Assets (WG/TA)	1	1	1	0
Other Expenses/Operating Expenses (OOE)	1	1	0	0
Total Assets/Employee (TA/MPL)	1	1	0	0
Loan Lease Income/Interest Income (LLI/II)*	2	1	1	1
Interest Income/Net Loans (II/NL)	1	1	1	0
Loan Lease Income/Operating Inc. (LLI/OI)	2	2	0	0
Net Income/Total Assets (ROA)	0	0	2	0
Net Loan/Total Deposit (LOAN/DEP)	1–2	1–2	1	0
Liquid Assets/Total Assets (LIQ)	1–2	1	1	0
Net Interest Income/Interest Income (NII/II)	0	1	1	1
Allowance Loan Loss/Net Charge-off (ALL/NCO)	8	0	6	6

Notes: * Indicates variables which are both stable across years and asset class
** Represents factors on which ratios are loaded

than $25 million class, 13 in the $25 million to $50 million asset class, 7 were in the $50 million to $100 million asset class, and 7 in the $100 million to $500 million asset class. Each class of failed banks was matched with healthy banks in their asset class. There were 427, 329, 234, and 181 healthy banks in each of the respective asset classes.

EMPIRICAL RESULTS

The results of the *t*-tests for the 1981–1988 variables are included in the unrotated factor analysis results which are in an Appendix.[1] The *t*-tests showed that there were significant changes in the banking ratios in every asset class for the period 1981–1988. These results were consistent with the results obtained by Wall [20], Meinster and Elyasiani [14], and others. The issue here was whether these changes represented changes in banking structure and, if so, were the structural changes stable. The factor analysis results sought to answer these two questions.

Factor Analysis

The results of the unrotated factor analysis are summarized in Table 2. Only factor loadings greater than 0.5 are reported. Loadings below 0.5 were considered to have weak correlation with the factor on which they were loaded. Although 20 factors were identified in each of the asset classes for each year, the first eight factors explained approximately 70% of the variance in each of the data sets. Each of the other factors explained less than 3% of the variance.

An inspection of the results revealed most of the banking ratios did not have consistent correlations with any factor and were probably unstable. However, there were 16 ratios which were consistently loaded for each year in the less than $25 million asset class. In the $25 million to $50 million asset class, 16 ratios were consistently loaded. Two ratios were different from the first asset class; overhead became a stable ratio and real estate loans/total assets lost its stability. Fifteen ratios were consistently loaded for the $50 million to $100 million asset class; ROA was stable in this group and not in the other groups. Nine ratios were consistent across years in the $100 million to $500 million asset class (See Table 2).

Six ratios were constant across years and across classes. These ratios were equity/risk-assets, loan and lease income/interest income, United States securities/total assets, total expenses/total assets, total loans/total assets, and net-interest expenses/total assets. Risk measures, such as loan-loss and charge-off ratios, were conspicuously absent from the sets of stable and constant variables. However, one liquidity ratio, liquid assets/total assets, was stable across years for the first three asset classes. The United States securities/total assets ratio could also be considered as a liquidity ratio. All of the variables which were consistently loaded across both years and asset class were loaded on the first two factors. The total average equity/

risk assets, total assets/employees, and total loans/total assets ratios were consistently loaded across years but not across asset classes. It seemed from the factor analysis that liquid assets/total assets and United States securities/total assets may have been the indicators of relative risk in the smaller asset size groups.

Logit Analysis

In the following analysis, Tables 3A through 3D show the logit regression coefficients for the models in each asset class. Table 3E shows the coefficients of an aggregate model for each of the three years prior to failure. Tables 4 and 5 show the classification results and misclassification errors, respectively. The logit regression results for the under $25 million asset class are shown in Table 3a. The variables, equity/risk assets, real estate loans/total assets, total securities/total assets, and U.S. securities/total assets, were the most predictive in the 1983 model. The variable, equity/risk assets, was also one of the most predictive variables in

Table 3a
Logistic Coefficients
(Asset Class $0–$25 Million)

Ratios	*1983*	*1982*	*1981*
Constant	14.671	14.470	28.393[a]
AVEQ/RA	–61.025[a]	–41.792[a]	–7.446
REL/TA	–13.350[a]	–7.366[b]	–6.159[b]
SC/TA	–20.129[c]	–35.622[a]	–41.510[a]
US/TA	27.100[c]	48.680[a]	41.855[a]
LA	–4.385	–2.867	35.267[b]
EX/TA	21.857	–24.224	–21.065
NIEXP/TA	268.348	262.721[b]	13.916
WG/TA	–253.662	–273.803[c]	–80.267
OOE	1.022	–2.430	6.787
TA/MPL	–.000	–0.000	0.001
LLI/II	15.630	5.508	–4.444
II/NL	40.847	4.549	9.669
LLI/OI	.000	0.000	0.000
LOAN/DEP	.860	–8.316	–48.697[a]
ALL/NCO	.033	0.036[b]	–.003
LIQ	–10.906	–24.121[b]	–34.099[a]
C	0.979	0.946	0.859
Somers *D*	0.959	0.892	0.719
Model Chi-Square	158.08	110.37	66.99
D.F.	16	16	16

Note: *a* = significant at 1%, *b* = significant at 5%, *c* = significant at 10%

Table 3b
Logistic Coefficients
(Asset Class $25–$50 Million)

Ratios	*1983**	*1982*	*1981*
Constant	64.897	16.522	–21.960
AVEQ-RA	–295.918	–53.772[c]	–59.361[c]
SC-TA	–307.292	–31.131	8.359
US-TA	506.427	20.927	–5.47
LA	520.511	–10.197	10.336
EX-TA	636.874	64.555	–6.729
NIEXP-TA	2341.821	–37.928	–86.804
WG-TA	–402.762	215.604	168.096
OOE	–59.555	–34.330[c]	–18.573
TA-MPL	–.019	.001	.002
OHD	2731.894	65.829	–182.813
LLI-II	156.547	0.844	20.450[c]
LLI-NL	–576.210	–49.912	–13.267
LLI-OI	–.023	.000	–.000
LOAN-DEP	–652.748	–2.798	–4.762
LIQ	–264.064	–2.453	14.438
C	1.0	0.967	0.944
Somers *D*	1.0	0.934	0.888
Model Chi-Square	97.05	67.56	42.28
D.F.	15	15	15

Notes: *a* = significant at 1%.
b = significant at 5%.
c = significant at 10%.
*All coefficients assumed to infinite in the SAS.

1982 model. The 1981 models had relatively weak predictive power. The signs for the regression coefficients for the most predictive variables were as expected. The signs for the regression coefficients were negative for average equity/risk-assets and positive for both interest income/net loans, and loans and lease income/interest income. However, the sign for the loans and lease income/interest income was negative for 1981. This indicated the positive role of capital in reducing bank failures. It also suggests the theoretical trade-offs between safety and profitability; banks with high loan and lease incomes may have achieved those income levels at the sacrifice of safety.

Only 78.1% of the banks in the under $25 million asset class which failed in 1984 were correctly classified as potential failures in the 1983 projection (See Table 4). The corresponding percentages for 1982 and 1981 were 43.0% and 15.0%, respectively. However, like all of the models in this study, the Type II errors were very small; they were only 2% in 1983, 4.0% in 1982, and 6.0% in 1981 (See Table 5).

Table 3c
Logistic Coefficients
(Asset Class $50–$100 Million)

Ratios	*1983*	*1982*	*1981*
Constant	224.899	–8.472	–39.500
AVEQ-RA	–53.423	–14.405	6.968
SC-TA	–243.960	–76.374	23.616
US-TA	256.890	55.352	–21.519
LA	178.581	–1.413	–15.732
EX-TA	–296.965	59.644	154.304
NIEXP-TA	–1103.723	–302.449	10.104
WG-TA	474.915	712.438	–83.331
NIEXP-TA	–1103.723	–302.449[b]	10.104
LLI-II	25.503[a]	17.846	31.006[b]
II-NL	95.578	71.039	–77.782
ROA	–649.685	–138.427	152.538
LOAN-DEP	–376.890	–9.060	12.447
LIQ	–264.798	–29.724	33.399
ALL-NCO	.064	–.068	–0.011
C	1.000	0.972	0.916
Somers *D*	1.000	0.944	0.831
Model Chi-Square	56.11	47.69	32.36
D.F.	14	14	14

Notes: *a* = significant at 1%, *b* = significant at 5%, *c* = significant at 10%

For banks in the $25 million to $50 million asset class, the models predicted quite well (See Table 3b). In 1983, all of the banks in the sample which eventually failed were correctly classified with a zero Type II error (See Table 5). The corresponding percentage was 57.0% for the 1982 model (See Table 4).[2]

The 1983 model correctly classified all of the banks which failed in 1984 in the $50 million to $100 million asset class, while the 1982 and 1981 models predicted 44.4% and 30% of the 1984 failures (See Table 3c). Again, Type II errors were small, 2% for 1983, 3% for 1982, and 3% for 1981 (See Table 5).

In the $100 million to $500 million asset class, the 1983 model correctly predicted 100% of banks which eventually failed in 1984 (See Table 3d). The 1982 predictions of 1984 banks failures were 16.7% correct. The model did not make any correct predictions in 1981 for 1984 failures. There were 1.1% Type II classification errors in the 1983 predictions, and 2% for 1981 (See Table 5).

The entire data set was also used to build two sets of aggregated logit models in this study. The first set of models included the six ratios in Table 2 which were stable across both time and asset class. This small aggregated 1983 model, correctly predicted the failure of 35 banks, or 53.8% of those banks in the study which

Table 3d
Logistic Coefficients
(Asset Class $100–$500 Million)

Ratios	*1983*	*1982*	*1981*
Constant	358.641	−1.193	−36.481
AVEQ-RA	−2721.364	−48.895	169.897
US-TA	−778.995	−20.589	36.037
LA	−216.257	3.611	−54.023
EX-TA	1586.891	38.008	6.447
NIEXP-TA	−1249.326	65.462	−817.640
OHD	7739.762	186.824	−910.145
LLI-II	−36.046	−1.732	96.038
ALL-NCO	−1.333	.008	−0.057
C	1.000	0.941	0.982
Somers *D*	1.000	0.881	0.965
Model Chi-Square	52.61	20.47	21.51
D.F.	8	8	8

Notes: *a* = significant at 1%, *b* = significant at 5%, *c* = significant at 10%

eventually failed in 1984. However, the predictions of two and three years prior to failure fell to 10% and 3%, respectively.

The other set of models contained all the ratios listed in Table 2. The results for this latter set of regressions are given in Table 3e. The 1983 logit model correctly predicted the failure of 72.7% of the banks in the entire sample (See Table 4). The 1982 and 1981 percentages were 28% and 7%, respectively. The Type II error was 2% for the 1983 model; 4% for the 1982 model and 5% for the 1981 model. In the 1983 and 1982 aggregated models, four variables were the most significant predictors of 1984 bank failures. These variables were, equity/risk assets, total securities/total assets, U.S. securities/total assets, and real estate loans/total assets. The total assets variable was significant in the 1983 aggregate model. The negative coefficients of this variable suggested that smaller banks were more likely to fail than larger ones.

The aggregated models were poorer predictors than the models for individual asset classes particularly as the time to failure increased. Their best predictions of failure, two years prior to failure, was 7.3%. This compared unfavorably with the 21.1% for the sum of the individual models. The actual numbers of failed banks predicted by the models for each year and in each asset class are summarized in Table 4.

The results in Table 4 also show that models for each asset class were better predictors than the models which used the entire data sets of banks under $500 million in assets. The numbers in parenthesis in the table show the percentage of correct predictions of bank failures in each model. Together, the models which were

Table 3e
Logistic Coefficients
(Asset Class-All)

Ratios	*1983*	*1982*	*1981*
Constant	4.025	1.228	7.694
AVEQ-RA	–45.626[a]	–32.469[a]	–8.776
SC-TA	–35.130[a]	–25.676[a]	–19.528[a]
US-TA	45.677[a]	32.728[a]	18.670[b]
LA	8.459	8.812	17.426[b]
EX-TA	45.770[c]	–28.361	–15.561
NIEXP-TA	–81.378	108.170	–37.557
WG-TA	134.063	–150.921	–81.236
OOE	–4.066	–2.006	2.625
TA-MPL	.000	.000	–.001[b]
OHD	–6.927	–38.812	–97.515[c]
LLI-II	2.159	4.317	1.092
II-NL	26.519[a]	13.402	8.475
LLI-OI	.000	.000	.000
LOAN-DEP	–15.745	–4.789	–16.555[c]
LIQ	–30.758[a]	–11.315	–13.015[c]
ALL-NCO	.015	.006	–.003
TOTAL ASSETS	0.000	.000	.000
REL/TA	–8.269[a]	–8.085[a]	–10.754[a]
ROA	–1.221	–51.734	–57.931[c]
C	0.984	0.939	0.894
Somers *D*	0.969	0.878	0.788
Model Chi-Square	312.58	196.04	127.27
D.F.	19	19	19

Notes:a = significant at 1%, *b* = significant at 5%, *c* = significant at 10%

disaggregated by asset class (those ratios in Tables 3a through 3d) correctly estimated the failure of 48 banks representing 87.0% of the sum of failed banks in the 1984 samples.

The aggregated 1983 model (all the ratios in Table 2 plus total assets with using full data set), correctly predicted the eventual failure of 72.7% or 40 out of the 55 banks in the aggregated sample of banks which failed in 1984. However, the actual percentage of correct prediction was 61.5% or 40 of the 65 failing banks in the study. The smaller aggregated 1983 model which used only those six variables which were stable across years and asset classes correctly predicted 35 banks, or 53.8% of those banks in the study which failed in 1984.

One of the problems with the models in which all the data were aggregated across asset classes was that the models contained many more variables, therefore,

Table 4
Correct Projections of 1984 Failed Banks
(Percentages of Sample in Parenthesis)

Asset Class (Millions)	*1981*	*1982*	*1983*
0–25	5 (15.0)	14 (43.8)	25 (78.0)
25–50	4 (10.0)	8 (57.1)	11 (100.0)
50–100	3 (30.0)	5 (55.6)	7 (100.0)
100–500	0 (00.0)	1 (16.7)	7 (100.0)
All[1]	12 (21.1)	28 (45.9)	48 (87.0)
All[2]	2 (3.0)	7 (10.4)	35 (53.8)
All[3]	4 (7.3)	17 (28.0)	40 (72.7)

Notes: [1]Sum over all four classes, and percentage of all banks correctly classified.
[2]Inter-class and inter-temporarily stable variables only. Variables with * in Table 2.
[3]All variables in Table 2.

there was a greater likelihood that some observations of banks which eventually failed would be dropped from the analysis because of missing values for some of the variables. Consequently, the results indicated that models with a smaller number of variables were in some cases not only more economical and more efficient, but also yielded better predictions.

Table 5 summarizes the Type I and Type II classification errors. Type I error is the error of classifying a failing bank as being sound, while the Type II error is the error of classifying a sound bank as failing. The Type I errors in this study were comparable to those of earlier studies in the literature, at least for the 1983 predictions. The Type I errors ranged from zero to 10% for the disaggregated models in 1983. The highest Type I errors were in both of the aggregated models;

Table 5
Type I and II Misclassification Errors
(in Percentages)

Asset Class	*<— 1983 —>*		*<—1982 —>*		*<—1981 —>*	
(Millions)	*I*	*II*	*I*	*II*	*I*	*II*
0–25	10.7	1.7	31.6	4.2	44.4	5.8
25–50	0.0	0.0	27.3	1.9	3.0	1.7
50–100	0.0	0.0	33.3	2.1	25.0	3.2
100–500	0.0	1.1	0.0	3.0	50.0	2.0
All[1]	14.0	2.2	55.6	4.6	33.3	4.6
All[2]	12.2	1.7	34.6	3.6	55.6	4.4

Notes: [1]Inter-class and inter-temporarily stable variables only. Variables with * in Table 2.
[2]All variables in Table 2.

the one with only variables which were stable across time and class, and the one which included all the variables used in the study including total assets. The model with variables which were stable across both time and class performed marginally better than the model with all the variables with respect to both Type I and Type II errors. The Type II errors in this study were also smaller than those in three models used by LWL [12]. They ranged from zero to 2.2% for 1983 and from 1.9% to 4.6% for 1982. Type I errors ranged from 0.0% to 14.0% in 1983 and 0.0% to 55.6% in 1982.

CONCLUSION

Our results suggest that significant structural differences existed across asset sizes of commercial banks. While this has long been recognized, the research also suggests that greater care should be taken when selecting ratios to analyze bank conditions. Our concern was that many earlier studies, which were designed to evaluate bank performance or to predict bank failure, may have used banking ratios which were inappropriate for each asset size. This was generally the case, because most of the analytic techniques used in earlier studies suggested the use of matched pairs data sets. Those banks were paired by asset class, and evaluated in models aggregated across asset classes. Most later studies used aggregated data without the paired matchings but used total assets as a variable to control for size. We suspect that much of the difficulty resulted from the use of models which were aggregated and ratios which were probably unstable.

Two of the ratios used by West [21] were found to be stable across years and asset class: total loans/total assets and total expenses/total assets. Also, two of the ratios, equity/total assets and total loans/total assets, used by Pantalone and Platt [17] , were found to be stable. We found these variables were both consistently correlated across class and across years, and they were good predictors in the logit models. We believe, by using the stable ratios identified in this study, the performance of earlier predictive models may be improved. The logit analysis in this study seemed to provide evidence to support this position because models with only stable variables did perform better than other models in this study.

The factor analysis results did not show any consistent groupings of ratios. The variables which were intertemporally stable did not load on the five CAMEL related factors. Six variables; equity/risk assets, loan and lease income/interest-income, U.S. securities/total assets, total expenses/total assets, total loans/total assets, and non-interest expenses/total assets dominated the factor and logit analyses. These variables were also stable across asset classes. They represented four of the CAMEL groups, but the traditional liquidity measures were not represented.

Models for the $25 million asset class were least successful in predicting bank failure. More variables were needed for predictions than in other classes and even then the logit models were still less predictive than those of the other asset classes. The t-test for the under $25 million asset class showed commercial and industrial loans to total assets, and agricultural loans to total assets were significantly higher, in 1983, for the banks which failed in 1984 than for the healthy sample. These differences were not present in the other asset classes in this study. Therefore, it may be possible to improve the logit models in this asset class if commercial and industrial loans to total assets, and agricultural loans to total assets were included as variables.

Variables such as bank age and primary market area, if included in the logit models, may also improve predictions of bank failure in the less than $25 million asset class. These variables, while important in the evaluation of the very small banks, may not be so important in the evaluation of larger banks because larger banks were more likely to be older and more institutionally entrenched than newer and smaller banks.

APPENDIX

Variable List and Abbreviations

ALL/NCO	Allowance Loan Losses/Net Charge-offs
AVEQ/RA	Equity/Risk Assets
EX/TA	Total Expenses/Total Assets
II/NL	Interest Income/Net Loans
LA	Total Loans/Total Assets
LIQ	Liquid Assets/Total Assets
LLI/II	Loan Lease Income/Interest Income
LLI/OI	Loan Lease Income/Operating Income
LOAN/DEP	Net Loans/Total Deposits
NIEXP/A	Non-Interest Expenses/Total Assets
NII/II	Net Interest Income/Interest Income
OHD	Overhead Expenses/Total Assets
OOE	Other Expenses/Operating Expenses
REL/TA	Real Estate Loans/Total Assets
ROA	Net Income/Total Assets
SC/TA	Total Securities/Total Assets
TA/MPL	Total Assets/Employees
US	U.S. Government Securities/Total Assets
WG/TA	Wages/Total Assets

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NOTES

1. The factor analysis and *t*-test results for the ratios used in this study may be obtained from the authors.
2. When the SAS Logit procedure was unable to calculate the marginal probabilities, the most predictive variables were by using the stepwise logit regression. In the $25 million to $50 million asset class, the equity/risk assets and loan and lease income/interest income ratios were very predictive with the latter being most predictive in 1983 and the former most predictive in 1982. Return on assets was the single most predictive variable in 1983 for the $50 million to $100 million asset class.

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