Troubled Banks: Why Don't They All Fail?

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October 7, 2004

Abstract

In this paper we examine troubled banks—those that receive a poor safety and soundness rating when examined—to model future bank state. Besides failure, we see three alternative outcomes for these banks: recovery, acquisition, or remaining a problem. The determinants of bank failure along with failure prediction have been much researched. Most of this research uses a binary approach, dividing banks into two groups—those that fail and those that do not—or predicting one of two states—failure or non-failure. Because our sample includes troubled banks, we can go beyond a two-state approach.

First we use univariate trend analysis to determine whether financial variables differ among this group of banks, depending on future state. This analysis suggests that meaningful relationships exist between these future states and prior period financial conditions. We then use financial ratios as explanatory variables in a unified model of bank states with the goal of improving predictions of future bank condition.

We gauge the model's effectiveness by testing the out-of-sample forecasting accuracy. Our results show that our model compares favorably with the standard bivariate failure prediction model and, yet, has the added feature of predicting recovery, merger or remaining a problem bank.

1. Introduction

The determinants of bank failure along with failure prediction have been much researched. Most of this research uses a binary approach, dividing banks into two groups—those that fail and those that do not—or predicting one of two states—failure or non-failure. However, for troubled banks, failure is but one possible outcome. There three alternative outcomes: recovery, acquisition or remaining a problem.

Recognizing these three alternatives, we develop a multi-state model for recovery, merger, remaining a problem, and failure. We use a sample of troubled commercial banks—banks rated a composite CAMELS rating of either 4 or 5 when examined—during the period 1990 through 2002.[1] Knowing the future state of banks in our sample, we construct financial profiles for each group. These profiles are then used to develop a multinomial logit estimating procedure that predicts the likelihood of a bank's future state: recovery, acquisition, remaining a problem, or failure.

Our research differs from previous research on bank failure in two ways. First, we study troubled banks only. Second, this sample allows us to develop a multi-state model that identifies financial characteristics that contribute to recovery as well as failure.

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[1] CAMELS is an acronym for the five components of the regulatory rating system: **C**apital adequacy , **A**sset quality, **M**anagement, **E**arnings, **L**iquidity and market **S**ensitivity. Examiners have rated sensitivity only since 1998. Banks with a rating of 4 or 5 are considered problem banks. Four-rated banks generally exhibit unsafe or unsound practices or condition while 5-rated banks exhibit extremely unsafe or unsound practices of condition.

Accurate predictions of the future state of problem banks are particularly important for long-term strategic planning of the Federal Deposit Insurance Corporation—the independent deposit insurance corporation created by the Congress in 1933 to maintain stability and public confidence in the nation's banking system. When a bank goes on the problem list, a number of actions transpire (see Curry, et al., 1999, for an example of some such actions.) Predictions of future state would affect resources applied to these banks.

Reasons that problem banks may not fail are:

1. Recovery because of a good economy:

A good economy allows banks with inefficiencies and problems to survive. DeYoung (1999) notes that established banks are more prone to failure during recessionary periods, and almost completely unlikely to fail during expansionary periods. He cites the large number of bank failures from the mid-1980s through the early 1990s and their causes, a series of substantial economic disruptions, including a general recession in the early 1990s and a number of regional recessions in the mid- to late 1980s. FDIC (1997) finds a strong connection between participation in regional real estate booms during the 1980s and bank failure. Total real estate loans of banks more than tripled, and commercial real estate lending quadrupled, all with much looser bank underwriting standards. When the bubble burst in the late 1980s, banks heavily exposed to real estate lending suffered a significant deterioration in loan quality that eventually caused many banks to fail.

2. Recovery through capital injections:

When a bank is a subsidiary of a holding company, the parent has a vested interest in keeping the subsidiary viable. French (1991) presents evidence that shows that banks with increasingly weaker CAMELS ratings have increasingly larger capital injections.[2] He notes that this correlation is intuitive since supervisors probably put greater pressure on undercapitalized banks to seek outside capital.

3. Acquisition:

Piloff and Santomero (1998) point out that one traditional view for acquisitions is that cost efficiency may be improved if the management of the acquirer is more skilled at holding down expenses for any level of activity than that of the target. However, they note that most studies fail to find a positive relationship between merger activity and gains in performance. Hannan and Rhoades (1987) and Hunter and Wall (1989) note one theory for the likelihood of acquisition is that the acquirer's management may be better than the target's and could turn around the troubled bank. However, using four different measures of bank rates of return as proxies for firm and managerial performance, Hannan and Rhoades found no support for the notion that poorly managed firms are more likely acquisitions targets than other firms. Hunter and Wall did not find that banks which acquire other banks improve the efficiency of the target bank. Ely and Song (2000) note that purchasing out-of-state banks was another common way for banking organizations to expand into new markets before the passage of the Riegle-Neal

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[2] Defined as the sum of capital stock transactions, capital contributions through mergers, and capital transactions with the parent holding company.

Interstate Banking and Branching Efficiency Act of 1994, which permitted banks and bank holding companies to purchase banks or establish subsidiary banks in any state.

4. Remain a Problem:

A bank may languish. Curry, et al (1999) note that banks are in a retrenchment mode as they approach the problem bank status; they reduce growth or shrink assets, generate new equity capital, charge-off bad loans, and increase loan-loss provisions.

The following section of this study describes previous empirical studies of bank failures, mergers and financial distress. Section three discusses our methodology; section four our data and sample; section five our results; and section six concludes.

2. Empirical Studies

Research on determinants of bank failures and merger activity are numerous. Also numerous are studies on early warning systems that alert regulators of potential deterioration in banks' financial condition since the last examination.[6]

Previous research differs from ours in two ways. First, statistical methods used in this research include discriminant analysis, discrete-response regression techniques, or proportional hazard techniques for two-state prediction models: failure or non-failure,

[6] See Demirguc-Kunt, 1989, Jagtiani, et al., (2003), and King, et al., (forthcoming) for reviews of the literature.

problem or non-problem, acquirer or target. We use multi-state logistic regression. Second for predictions of future bank state, the sample used in previous research is failed banks versus non-failed banks or problem banks versus non-problem banks. We use only troubled banks—those already a problem—as our sample.

Most previous studies use bank financial ratios that are similar to those that bank examiners review at on-site examinations: capital, asset quality, management, earnings and liquidity. Sinkey (1975) uses multiple discriminant analysis to identify financial characteristics that distinguish between problem and nonproblem banks.[7] Stuhr and Van Wicklen (1974) also use multiple discriminant analysis to identify how financial characteristics differ between banks rated high or low (during examinations) to develop a scoring technique that provides a measure of the condition of each bank relative to other banks. Korobow, Stuhr, and Martin (1976) develop early-warning indicators from financial ratios and also a scoring technique to rank banks' resistance to adverse economic or financial developments. They use these indicators to divide banks into two groups: banks vulnerable to potential financial deterioration versus banks not vulnerable.

Research on failure prediction includes Martin (1977); Bovenzi, Marino, and McFadden (1983); Avery and Hanweck (1984); Barth, Brumbaugh, Sauerhaft (1985); Short, et al. (1985); and Thomson (1991) who use two-state prediction models, usually with a sample of failed banks and non-failed banks.[8] Kolari, et al. (2002) develop failure prediction models using both logit and trait recognition, again a two-state model, again

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[7] Sinkey defines a problem bank as one whose present or future solvency is in question, and therefore poses a risk to the FDIC insurance fund.

[8] Barth, et al. studied failed and non-failed thrifts.

using failed and non-failed banks. Jagtiani, et al. (2003) also develops a two-state prediction model for bank failure, but the states predicted were capital adequacy versus capital inadequacy—where the latter state represented capital levels that fall below a minimum threshold. In a prior study in 2000, Estrella, Park, and Peristiani use three types of capital ratios to predict bank failure. Again both studies use all banks.

Whalen (1991) adds to the binary state failure literature by using a proportional hazard model to estimate the probability that a bank with a given set of characteristics will survive longer than some specified length of time into the future. Fissel (1994) uses a similar approach to estimate actuarially-fair insurance premiums based on econometric estimates of expected time-to-failure. And DeYoung (1999) puts a twist on the approach by estimating separate hazard functions for newly-charted banks and established banks to predict time-to-failure.

Cole and Gunther (1998) use a probit model to estimate the relationship between a set of financial ratios and the likelihood of bank failure to develop an early warning system. Collier, et al. (2003) describe the FDIC's major off-site monitoring tool that supplements the current system of on-site examinations to identify institutions that have experienced noticeable financial deterioration since the last examination. This tool also uses financial ratios from previous literature on bank failures in its ordered logit prediction model of CAMELS ratings. O'Keefe, et al. (2003) add bank loan underwriting practices as an explanatory variable in predicting banks' financial deterioration since the last examination. In addition, O'Keefe, et al. use ordered logit to predict CAMELS ratings.

As with much of the literature on bank failure, the literature for acquisitions and mergers also uses binary state prediction models. Using mean difference and logit regression models, Rose (1988) identifies significant differences between acquirers and non-acquiring banks and acquired banks and non-acquired banks. O'Keefe (1996) uses logit estimations in a study for similar purposes. Again, each of these studies uses a binary state model.

Three studies, one recent on bank failure, one recent on failure and acquisitions, and one less recent on mergers deviate from the studies above by predicting a three-state outcome. DeYoung (2003) estimates the long-run probability of failure and acquisition in de novo banks by defining three states: (1) Failure, (2) Merger by acquisition and (3) Conversion of whole bank affiliate of a bank holding company to a branch bank of that bank holding company. Wheelock and Wilson (2000) use a competing-risks model to consider explicitly the joint determination of the probability of being acquired, failing or survival. Hannan and Rhoades (1987) predict that a bank may experience one of three outcomes: (1) Not be acquired, (2) Be acquired by a firm operating within its market, or (3) Be acquired by a firm operating outside its market. DeYoung expects that including the other two exit states (merger by acquisition and conversion) would improve the accuracy of the failure estimates. Wheelock and Wilson find that inefficiency increases the risk of failure while reducing the probability of a bank's being acquired. And Hannan and Rhoades find that adding the third state (distinguishing between merger types) yields a number of firm and market characteristics which significantly influence the likelihood of acquisitions that earlier studies did not.

3. Methodology

Referencing previous studies, we select certain financial variables proven to be useful in determining future bank state. We use univariate trend analysis to determine whether banks that recover have different prior-period financial characteristics from banks in one of three alternative states: mergers, remaining a problem, and failure.

Prior literature on bank performance suggests a number of reasons for failure: low earnings, low liquidity, risky asset portfolios, and poor management, to name a few. Thus, we select financial variables from the same broad categories used to explain or predict binary bank states—capital adequacy, asset quality, management, earnings, and liquidity. In addition, we run a one-way analysis of variance to examine the financial characteristics of recovered banks versus banks in the remaining three states.

We use a multinomial logistic estimating procedure to model future bank state. As Long (1997) points out, a multinomial logit model is the most frequently used model for nominal outcomes.[9] This model simultaneously estimates binary logits for pairwise comparisons among the outcome categories to a specified reference outcome. These

[9] Dependent variable may take multiple outcomes that cannot be ordered. In our case: Recovery, Merge, Still a problem, or Failure.

binary logits are recover relative to failure, merge relative to failure and still a problem relative to failure.

A general form of the model tested is shown in equation 1, where *Probability of State* (k)$_{i,t}$ is the probability that bank i will be in state k at time t.

$$(1)\qquad \textit{Probability of State}\ (k)_{i,t} = F(\textit{Financial condition}_{i,t,t-1} + \textit{Economic conditions}_{t})$$

We gauge the model's effectiveness by testing the out-of-sample forecasting accuracy. Further, we also use bivariate bank failure models for comparisons to our multinomial model. These additional comparisons allow us to test whether including additional alternative states improves the accuracy of failure estimates over binary models.

Two versions of the bivariate failure model are tested, one using the same explanatory variables as used in Jarrow, et al. (2002), referred to as the loss distribution model (LDM), and a second that uses the same variables as are used in our multi-state model.

We also check to determine that the banks with the highest predicted probability of failure from our model are the ones that actually fail. And we check to determine the economic significance of the explanatory variables.

4. Sample and Data

Our sample consists of 3,747 occurrences of BIF-insured banks on the FDIC problem-bank list from 1990 through 2002. We divide this sample of problem banks into annual cohorts to allow us to implicitly control for the effects of economic conditions and banking legislation. Each bank has a first event and second event. The first event occurs when a bank is examined and receives a CAMELS-rating of 4 or 5. The second event occurs when the bank (1) recovers—improves to a CAMELS rating of 1, 2 or 3 at the next examination, (2) merges with a bank either outside of its multibank holding company or consolidates within its multi-bank holding company[11], (3) remains a problem bank—continues to have a CAMELS-rating of 4 or 5 at the next examination, or (4) fails.[12] Problem banks that have no second event are not included in the analysis. To allow for enough time to pass for changes in condition, second events are measured in the interval of 6 to 24 months after first events.

A bank can be in several cohorts depending on when it first receives a CAMELS-rating of 4 or 5 and its outcome at the second event. If the bank still exists after the second event, its future state may be either recovered (if the CAMELS-rating improves to a 1, 2, or 3) or still a problem (if the CAMELS-rating remains a 4 or 5). When the bank goes from the problem status to the recovered status, we count it as a recovery. If it does

[11] We recognize that characteristics differ between mergers and consolidations. However, during this period, the number of consolidations is small (39). Because of the small number, we combined both events into one state.

[12] In this paper, failure is defined as a closing resulting from an action by a regulator or an assisted merger by the FDIC.

not recover, we count it as still a problem. But the bank enters this new cohort (based on the second event) as already a problem, and we must wait until the next event to determine its future state for a second observation.

Our sample has the following characteristics. The number of problem banks declines drastically during the 1990s as the banking crisis that began in the mid-1980s and lasted through the early 1990s subsided. As Figure 1 shows, the 1991 cohort has the highest number of problem banks, 897; the 1997 cohort has the lowest number, 62. Both the 1990 and 1998 cohorts have the highest percentage of failures, 5 percent. No problem banks fail before the second event in the 1997 or 2002 cohorts. (See Figure 2.) Most banks remain a problem at the second event, ranging from a high of 69 percent in the 1990 cohort to a low of 40 percent in the 1997 cohort, with an average of 49 percent. The proportion of banks that merge by the second event is small, ranging from 3 percent in the 1990 cohort to 20 percent in the 1998 cohort. The proportion that recovers by the second event ranges from a low of 23 percent in the 1990 cohort to a high of 53 percent in the 1997 cohort. Figure 3 shows that most problem banks that remain a problem at the second event ultimately recover.[13]

Jones and Critchfield (2004) note three reasons that might explain the 1997 and 1998 peak years noted above for merger activity and recoveries: (1) Banks were highly profitable, liquid, and operating in favorable economic and interest-rate environments, (2) The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 removed the

[13] The decline in the percent of still a problem banks the ultimately recover beginning in 2001 is because the second event has not yet occurred.

remaining barriers to interstate banking and branching, and (3) A record-breaking bull market in stocks pushed market valuations of banks and thrifts to unprecedented levels, encouraging many banking firms to use their stock as currency to purchase other firms. The Nasdaq Bank Stock Index reached a high in mid-1996.

In looking at capital injections as a percentage of average assets 12-months prior to recovery, we found large increases in external injections for banks that recover peaking in 1996. Internal capital injections increased sharply from 1994 to 1995 but did not peak until 1999. (See Figure 4.)

We use data from the Consolidated Reports of Condition and Income (Call Reports) that banks file quarterly with their lead supervisory agency. We calculate beginning and ending periods of data for each bank from these Call Reports. The beginning period is calculated from the Call Report filed just before the first event and the one filed twelve months previously.[14] Balance sheet items are averaged for the two reporting periods and taken as a ratio of average assets for the same two periods; income items are summed over the 12-month period and taken as a percent of average assets for the two periods. Similar calculations are made for the ending period of data, using the Call Report filed immediately prior to the second event and the one filed twelve months previously.

[14] Gunther and Moore (2000) find atypical movements in call report data for the quarters in which banks are downgraded by examiners. These call reports are more subject to revisions. For that reason, we also did our univariate analysis on the Call Reports filed prior to the ones specified in this paper. The resulting trends in data were similar to the ones reported in this paper.

We group banks by future state to compare their condition and performance. We then compare data reported at the second event to that reported for the first. We compute the percentage of banks with an increase between the two events for each of the measures. We expect to see that the percentages of banks with increases in performance ratios such as net income and net non-interest income that recover will be greater than the percentages in any alternative state. For expense items, we expect the opposite. In addition we expect that the percentages of banks with increases in any of the risky asset measures, high liquidity measures, and bad management that recover will be less than the percentages in any alternative state. We also expect that the percentages of banks that fail will be the greatest in these four measures. We have no expectations for the ranking of banks that merge or are still a problem except that the percentages that increase will fall between the percentages for banks that recover and those that fail.

We compare the percentages of banks in each state with increases in: Net interest income, provision for loan losses, and net non-interest income as measures of earnings; average allowance for loan and lease losses, average loans and leases past due 30-89 days, average loans and leases past due 90 days or greater, average nonaccrual loans and leases, and average other real estate owned as measures of risky asset portfolios; average risk-based capital and average tangible equity capital as measures of capital adequacy; average volatile liabilities and loans and securities with maturities greater than or equal to 5 years as measures for liquidity; and for the management measure, we use the efficiency ratio (noninterest expense as a percent of net interest income plus noninterest income). A lower efficiency ratio is better.

To model future bank states, we select almost the same financial variables as were used in the univariate trend analysis.[15] We added capital injections from a bank holding company and capital injections from outside as measures of the economy. From the univariate trend analysis we are able to form expectations concerning the sign that coefficients on these variables will take when estimated using logit analysis. A negative coefficient implies that an increase in the variable will result in the future state's becoming less likely relative to failure. A positive coefficient implies the opposite.

Table 1 shows the expected sign of explanatory variables used in the multi-state model. As Table 1 shows, financial ratios associated with not failing are: capital, capital injections, allowance for loan losses, interest income, non-interest income, and longer-term assets (assets and securities with maturities equal to or great than 5 years). Although we expect a negative sign for the efficiency ratio's coefficient (because lower is better), we also associate this ratio with not failing. The financial ratios associated with failure are those measuring poor asset quality (past due loans, non-accruing loans, real estate owned and loan charge-offs), expense items (interest expense, loss provision, salaries, expenses on premises, and other non interest expense), and volatile liquidity as measured by volatile liabilities.[16]

5. Results

[15] For the logits we used the total income and expense items instead of netting them as we did in the univariate analysis. In addition, we also estimated the model using Call Report data from the quarter prior to the quarter before the examination, as in the univariate. There was little difference in the results from those reported in this paper.

[16] Federal funds purchased and sold under agreements to repurchase, demand notes issued to the U.S. Treasury and other borrowed money, time deposits over $100,000 held in domestic offices, foreign office deposits, trading liabilities less trading liabilities revaluation losses on interest rate, foreign exchange rate, and other commodity and equity contracts.

Our results from both the univariate trend analysis and multi-state logit estimating procedure are generally in agreement with prior expectations. Banks with increases in performance ratios such as net income and net non-interest income that recover are greater than the percentages in any alternative state. For expense items, the opposite occurs. In addition, the percentages of banks with increases in any of the risky asset measures that recover are less than the percentages in any alternative state.

In the logit analysis, we find that increases in financial ratios associated with non-failure have positive coefficients and those associated with failure have negative.

5.1 Univariate Trend Analysis

For all three earnings measures, the relative position of banks that recover is the best; the position of banks that fail is the worst for two of the three. As shown in Figure 5, 62 percent of banks that recover (825 banks) have an increase in net interest income between the first and second events, compared with 28 percent of banks that fail (33 banks). The percentages for banks that merge or are still a problem is also greater than the percentage for those that fail, but less than that for those that recover. Figures 6 and 7 show that a smaller percentage of banks that recover have an increase in expenses between the two events: Twenty-eight percent of banks that recover (372 banks) experience an increase in provision for loan losses at the second event, compared with 46 percent of banks that fail (53 banks). The percentages for banks that merge or are still a problem is less than the percentage for those that fail but greater than that for banks that recover. And, a larger percentage of banks that recover have an increase in net non-interest income between the two events: Fifty-two percent of banks (689 banks) that recover experience an increase in net non-interest income compared with 32 percent of banks that fail (37 banks).

Our results agree with our expectations for all five assets quality measures. The relative position of banks that recover is the best; the position for those that fail is the worst. A smaller percentage of banks that recover experience increases in loan loss reserves, average loans and leases past due 30-89 days, average loans and leases past due 90 days or greater, average nonaccrual loans and leases, and average other real estate owned between the first and second events than banks that merge, remain a problem or fail. As shown in Figure 8, 50 percent of banks that recover (667 banks) experience an increase in loan loss reserves, compared with 72 percent of banks that fail (84 banks). The percentages for banks that merge or remain a problem are less than the percentage for those that fail but greater than that for banks that recover. Figure 9 shows that 36 percent of banks that recover (476 banks) experience an increase in average loans and leases past due 30-89 days, compared with 56 percent of banks that fail (65 banks). Forty-one percent of banks that recover (543 banks) experience an increase in average loans and leases past due 90 days or greater, compared with 56 percent of banks that fail (65 banks), as shown in Figure 10. Figure 11 shows that 38 percent of banks that recover (509 banks) experience an increase in nonaccrual loans and leases, compared with 61 percent of banks that fail (71 banks). Forty-four percent of banks that recover (585 banks) experience an increase in other real estate owned, compared with 76 percent of banks that fail (88 banks), as shown in Figure 12.

In line with our expectations, a larger percentage of banks that recover experience increases in average risk-based capital and average tangible equity capital between the first and second events than any alternative state. The smallest percentage of banks experiencing increases are those that fail. Figure 13 shows that 72 percent of banks that recover (952 banks) experience an increase in average risk-based capital, compared with 14 percent of banks that fail (16 banks). And Figure 14 shows that 70 percent of banks that recover (926 banks) experience an increase in average tangible equity capital, compared with 13 percent of banks that fail (15 banks).

In its 1988 study of bank failures, the Office of the Comptroller of the Currency lists over-reliance on volatile liabilities as one of the root causes of failure. Further, O'Keefe, et al.(2003) find that the percent of volatile liabilities to average assets is positively related to a CAMELS downgrade. We find, however, that banks that fail have the smallest percentage of banks with an increase in volatile liabilities between the first and second events. This result could be because management has reduced brokered deposits as required by more recent legislation. (The Federal Deposit Insurance Corporation Improvement Act of 1991 restricts activities of critically undercapitalized institutions. One such restriction is these institutions cannot pay an exceptionally large amount of interest on new or renewed liabilities.)

Also, given that low liquidity is associated with failure, we expect a larger percentage of banks that recover to experience an increase in loans and securities with maturities of greater than or equal to 5 years between the first and second events than those that fail. However, our data do not support this expectation. One explanation for this trend may be that banks that fail were more likely to take on loans that were more risky (construction loans, commercial real estate loans) than banks that recover.

Twenty-six percent of banks that recover (351 banks) experience an increase in volatile liabilities compared with only 19 percent of banks that fail (22 banks), as shown in Figure 15. Figure 16 shows that 37 percent of banks that recover (492 banks) experience an increase in loans and securities of longer maturities compared with 40 percent of banks that fail (46 banks).

A larger percentage of recovering banks experience improvements in the efficiency ratio between the first and second events than banks that merge, remain a problem or fail. Forty percent of banks that recover (832 banks) experience an increase in the efficiency ratio compared with 22 percent of banks that fail (25 banks), as shown in Figure 16.

5.2 Analysis of Variance

Tables 2 and 3 show results from the analysis of variance that complement the above results. Table 2 shows the mean and standard errors for each financial characteristic by state. Table 3 shows the differences in means and statistical significances for six pairings: (1) recovery versus merger, (2) recovery versus still a problem, (3) recovery versus failure, (4) still a problem versus merger, (5) still a problem versus failure, and (6) merger versus failure. The beginning period data are used in these tables.

The results reported in Table 2 show that the mean values for each financial variable are statistically different from zero at the first event. Further, it shows that the mean values in financial ratios associated with not failing generally are most often larger for banks that recover, merge or remain a problem than they are for banks that fail. The opposite is true for the mean values in financial ratios associated with failing.

There are three exceptions, however: the mean values for total interest income, total non-interest income, and loans and securities with maturities greater than or equal to 5 years are largest for banks that fail. These results seem counter-intuitive until we considered that banks with a future state of fail probably take on riskier assets that would have higher yields than banks in the alternative states. Banks with riskier assets have a higher probability of failure. Fee income from these riskier assets may have resulted in higher non-interest income. And, in banks with a future state of fail, the ratio between loans and securities in the longer term assets may be geared toward loans which are usually considered more risky than more-liquid securities.

The results reported in Table 3 show that except for two variables (capital injections from the bank holding company and capital injections from outside), the difference in means between banks that recover and those that fail are significantly different from one another. The difference in means between banks that merge and those that fail and the difference in means between banks that are still a problem and banks that fail are also significant for most variables.

The results from Table 3 also indicate that the difference in means between banks that remain a problem and banks that merge and also in the pairing between recovery versus still a problem are statistically significant. For the pairing of recovery versus merger, fewer variables are statistically different from one another. And for the pairing of still a problem versus merger, still fewer variables are statistically different from one another.

5.3 Logit Analysis

For our multivariate analysis, we rely on a multinomial unordered logit probability model that takes into account all four future bank states. Equation 2 shows the model tested:

$$\text{(2)} \qquad \textit{Probability of State } (k)_{i,t} = F(\textit{Financial condition}_{i,t,t-1})$$

We did not include variables for economic condition in our model for a number of reasons. First, we found no significance in the variables we selected as measures of the economy: a ratio of the number of problem banks to total number by state and a ratio of

[18] We ran the model using these variables separately.

the assets of problem banks to total assets by state.[18] We also included the percentage change in state housing permits with no success. Nuxoll, et al. (2003) did not find that state-local economic data contributed to the performance of standard offsite models. Second, much of the literature theorizes that the economy is subsumed in the balance sheet. Thus, any effect of the economy has already shown up in the financial data. Third, we included capital injections (from the bank holding company and also from outside) as a measure of the economy. And, finally, we divided the sample into cohorts which obviates the need to include national economic variables.

A stepwise logit estimation procedure is used to identify those terms that have a significant relationship in predicting the likelihood that a bank will end up in one of the states: recover, merge, still a problem or failure. The stepwise estimation procedure allows us to include several measure of the same attribute in the logit model yet isolates the most important factors in terms of predicting state.

Table 4 shows summary statistics for the variables used in the logistic regressions. The beginning period data, as explained in Section 4, are used in this table.

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We estimate the logits for each of our cohorts, 1990 through 2002. However, because of the small number of failures, beginning with the 1994 logit, we combine cohorts. The 1994 model is a combination of the 1993 and 1994 cohorts, and the 1995 model combines 1993 through 1995. We continue combining cohorts up to 5 years (the

1993 through 1997 cohorts for the 1997 logit). For the 1998 models through 2002 we use a panel of the most recent previous 5 years.

Tables 5 through 7 show the results. The reference state is failure so the coefficients are interpreted relative to failure. Asset quality variables, loan-loss provisioning, and capital are more often statistically significant at the 1 percent, 5 percent or 10 percent level than other variables. Further they have the right signs (as expected from Table 1). Remember that a negative coefficient means that an increase in a variable will result in the future state relative to failure becoming less likely. For example, in the 1990 model, loans past due 30 to 89 days is significant and has a negative sign for all three states versus failure. An increase in this variable will result in a future state of recovery, merger or still a problem becoming less likely relative to failure.

5.4 Prediction of State: Out-of-Sample Results

Whether the logit model is accurate in predicting out-of-sample forecasts is the true measure of its contribution. To test its accuracy, we forecast future bank states using prior-period estimations from our unordered logit model on the following year's cohort. All state predictions are determined by summing predicted state probabilities for the cohort, yielding the expected number of banks in each future state. Figures 18 through 20 show the results.

We use a standard bivariate bank failure model to compare binary forecasts against our multi-state model. The bivariate model tested uses our multi-state explanatory variables. Figure 21 shows very little difference in accuracy between the binary and multi-state logit.

The second comparison is shown in Figure 22. The LDM model uses variables found in conventional bank failure literature to predict bank failure within the second quarter after the Call Report is filed. The sample includes all banks and thrifts between December 1984 and December 2002. Instead, we run this model on all problem banks at year-end to predict the number of failures.[19] We then run our multi-state logit on the same set of banks to predict failures. Because a Call Report for any given cohort can extend up to 24 months beyond the year of the cohort, we use the predicted betas from one cohort to predict outcomes for troubled banks two years ahead. The LDM bivariate model, however only requires a one-year prediction horizon so one would expect an advantage for the bivariate model. As Figure 22 shows, the two models are comparable. The advantage to ours is that we can not only predict problem bank failure, but also recoveries, mergers and banks' remaining a problem.

5.5 Probabilities and economic significance

To determine whether banks with the highest probability of failure are the ones that actually fail, we rank banks that our model predicts to fail in each period by their

[19] Two variables of the binary model, examination interval and CAMEL ratings, were not used since our sample was troubled banks only.

probability of failure. We, then divide them into deciles to determine that the highest decile contains the largest number of banks that actually failed. Thirty-eight of the 65 failed banks in our cohorts from 1991 through 2002 were in the tenth decile.[20] An additional 8 banks were in the ninth decile.

To test the economic significance of the explanatory variables, we use a fairly standard approach—evaluating in-sample predicted state probabilities based on the mean values of explanatory variables and how they change with marginal changes in key explanatory variables.

Our basis for comparisons is the predicted in-sample state probabilities for 1990 based on the mean values for explanatory variables in 1990. The means for the sample of banks used in model estimation for 1990 are shown in Table 8.

The predicted state probabilities evaluated at the mean for banks in the 1990 cohort are 16.41 percent for recover, 1.82 percent for merger, 80.82 percent for still a problem, and 0.95 percent for failure. Both other real estate owned and tangible equity capital were statistically significant in 1990. Table 9 shows the effects on estimated state probabilities, ceteris paribus, should each of these ratios experience a one-percentage point increase (from 2.6808 percent to 3.6808 percent of bank assets for the former and from 5.3409 percent to 6.3409 percent of bank assets for the latter). When evaluated at the mean, we see that a one-percentage point increase in other real estate owned

[20] For the bivariate model, 39 of the 65 failed banks were in the tenth decile. Further a Pearson test of correlation between the unordered and bivariate models ranked all banks very closely (correlation of 92 percent.

decreases the probability of recovery by 3 percent, from 16.41 percent to 13.45 percent. Conversely, a one-percentage point increase in tangible equity capital increases the probability of recovery by 1.67 percent, from 16.41 percent to 18.08 percent. Interestingly, estimated merger probabilities are relatively unchanged in these cases, but there are compensating changes in the remaining state probabilities (since multinomial logit ensures estimated state probabilities sum to 100 percent).

6. Conclusions

We offer a different approach to previous failure prediction models. First, we recognize three possible future states that could be modeled as alternatives to bank failure: recovery, merging and remaining a problem. Most previous research uses a binary approach. Second, we focus on predicting outcomes for troubled banks only; other literature focuses on the universe of banks or thrifts.

Our results show that not only does our model compare favorably with the standard bivariate failure prediction model, it also gives banks that eventually will fail, the highest probability of failure. Further, the explanatory variables are economically significant.

Knowing these four predicted states is arguably more helpful to a deposit insurer than two-state failure forecasts: First, the FDIC's long-term strategic planning requires knowing the likely direction of all problem banks; and second, bank-regulatory policy often focuses on whether policy can affect the likelihood that troubled banks can successfully resolve their own problems.

This second point leads to possible future research: Can this model be used to determine whether certain policies helped or hurt the probability of recovery?

References

Avery, Robert B and Gerald A. Hanweck. September 1984. A Dynamic Analysis of Bank Failures. Working Paper Series, no. 74. Federal Reserve Bank.

Barth, James R., et al. 1985. Thrift Institution Failures: Causes and Policy Issues. In *Proceedings of the Conference on Bank Structure and Competition*. Federal Reserve Bank of Chicago.

Bovenzi, John F., James A. Marino and Frank E. McFadden. November 1983. Commercial Bank Failure Prediction Models. Federal Reserve Bank of Atlanta *Economic Review* 68, no. 11:14–26.

Cole, Rebel A. and Jeffery W. Gunther. 1998. Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems. *Journal of Financial Services Research* 13, no. 2:103–117.

Collier, Charles, Sean Forbush, Daniel A. Nuxoll, and John O'Keefe. 2003. The SCOR System of Off-Site Monitoring. FDIC *Banking Review* 15, no. 3:17–32.

Office of the Comptroller of the Currency (OCC). 1988. *An Evaluation of the Factors Contributing to the Failure of National Banks*. OCC.

Curry, Timothy J., John P. O'Keefe, Jane Coburn, and Lynne Montgomery. 1999. Financially Distressed Banks: How Effective are Enforcement Actions in the Supervision Process? FDIC *Banking Review* 12, no. 2:1–18.

Demirguc-Kunt, Asli. 1989. Deposit-Institution Failures: A Review of the Empirical Literature. Federal Reserve Bank of Cleveland *Economic Review* (Quarter 4): 2–18.

DeYoung, Robert. 1999. Birth, Growth, and Life or Death of Newly Chartered Banks. Federal Reserve Bank of Chicago *Economic Perspectives* 23, no. 3:18–35.

____________. October 2003. De Novo Bank Exit. *Journal of Money, Credit, and Banking* 35, no. 5:711–728.

Ely, David P., and Moon H. Song. 2000. Acquisition Activity of Large Depository Institutions in the 1990s: An Empirical Analysis of Motives. *Quarterly Review of Economics and Finance* 40, (2000): 467–484.

Estrella, Arturo, Sangkyun Park, and Stavros Peristiani. 2000. Capital Ratios as Predictors of Bank Failure. Federal Reserve Bank of New York *Economic Policy Review* 6, no. 2:33–52.

Federal Deposit Insurance Corporation (FDIC). 1997. *History of the Eighties—Lessons for the Future: An Examination of the Banking Crises of the 1980s and Early 1990s.* 2 vols. FDIC.

____________. February 2002. Section 3. *DOS Manual of Examination Policies*. FDIC.

Fissel, Gary S. 1994. Risk Measurement, Actuarially-Fair Deposit Insurance Premiums and the FDIC's Risk-Related Premium System. FDIC *Banking Review* 7, no. 1:16–25.

French, George. 1991. Early Corrective Action for Trouble Banks. FDIC *Banking Review* 2, no. 2:1–12.

Gunther, Jeffery W. and Robert R. Moore. Third quarter 2000. Federal Reserve Bank of Dallas *Economic and Financial Review*.

Hannan, Timothy H. and Stephen A. Rhoades. February 1987. Acquisition Targets and Motives: The Case of the Banking Industry. *The Review of Economics and Statistics* 69, no. 1:67–74.

Hunter, William C. and Larry D. Wall. October 1989. Bank Merger Motivations: A Review of the Evidence and an Examination of Key Target Bank Characteristics. *Economic Review* 74, no. 5:2–19.

Jagtiani, Julapa, James Kolari, Catharine Lemieux, and Hwan Shin. 2003. Early Warning Models for Bank Supervision: Simpler Could Be Better. Federal Reserve Bank of Chicago *Economic Perspectives* (3rd Quarter): 49–60.

Jarrow, Robert A, Rosalind L. Bennett, Michael C. Fu, Daniel A. Nuxoll, and Huiju Zhang. 2003. A General Martingale Approach to Measuring and Valuing the Risk to the FDIC Deposit Insurance Funds. Unpublished paper, presented at the FDIC Conference on Finance and Banking: New Perspectives.

Jones, Kenneth D. and Tim Critchfield. 2004. The Declining Number of U.S. Banking Organizations: Will the Trend Continue?. FDIC.

Kennedy, Peter. 1992. Qualitative and Limited Dependent Variables. In *A Guide to Econometrics*, 228–246. MIT Press.

King, Thomas B., Andrew P. Meyer, Daniel A. Nuxoll and Timothy J. Yeager. (Forthcoming). Are the Causes of Bank Distress Changing? Can Researchers Keep Up? Working Paper Series. FDIC.

Kolari, James, Dennis Glennon, Hwan Shin and Michele Caputo. 2002. Predicting Large U.S. Commercial Bank failures. *Journal of Economic and Business* 54:361–387.

Korobow, Leon, David Stuhr and Daniel Martin. July 1976. A Probabilistic Approach to Early Warning Changes in Bank Financial Condition. Federal Reserve Bank of New York *Monthly Review*:187–194.

Long, J. Scott. 1997. Nominal Outcomes: Multinomial Logit and Related Models. In *Regression Models for Categorical and Limited Dependent Variables,* 148-154. Sage Publications.

Martin, Daniel. 1977. Early Warning of Bank Failure: A Logit Regression Approach. *Journal of Banking and Finance* 1, no. 3:229–276.

Nuxoll, Daniel A., John O'Keefe, and Katherine Samolyk. 2003. FDIC *Banking Review* 15, no. 2:39–53.

O'Keefe, John P. Predicting Merger Activity. 1996. FDIC *Banking Review* 9, no. 1:18–38.

____________, Virginia Olin and Christopher Richardson. 2003. Bank Loan Underwriting Practices: Can Supervisor's Risk Assessments Contribute to Early-Warning Systems? In *Market Discipline in Banking: Theory and Evidence*, edited by George G. Kaufman, 385–423. Elsevier.

Piloff, Steven J. and Anthony M. Santomero. 1998. In *Bank Mergers & Acquisitions*. Kluwer Academic Publishers.

Rose, Peter S. Fall 1988. Characteristics of Merging Banks in the United States: Theory, Empirical Results, and Implications for Public Policy. *Review of Business and Economic Research* 24, no. 1:1–19.

Short, Eugenie D., Gerald P. O'Driscoll, Jr., and Franklin D. Berger. 1985. Recent Bank Failures: Determinants and Consequences. In *Proceedings of the Conference on Bank Structure and Competition*. Federal Reserve Bank of Chicago.

Sinkey, Joseph. March 1975. A Multivariate Statistical Analysis of the Characteristics of Problem Banks. *Journal of Finance* :21–38.

Stuhr, David P. and Robert Van Wicklen. September 1974. Rating and Financial Condition of Banks: A Statistical Approach to Aid Bank Supervision. Federal Reserve Bank of New York *Monthly Review* 56, :233–38.

Thomson, J. 1991. Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland *Economic Review* 27, no. 1:9–20.

Whalen, Gary. 1991. A Proportional Hazard Model of Bank Failure: An Examination of Its Usefulness as an Early Warning Tool. Federal Reserve Bank of Cleveland

Economic Review 27, no. 1:21–31.

Wheelock, David C. and Paul W. Wilson. February 2000. Why do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions. *Review of Economics and Statistics* 82, no. 1:127–138.

Figure 1

Number of Banks by Cohort

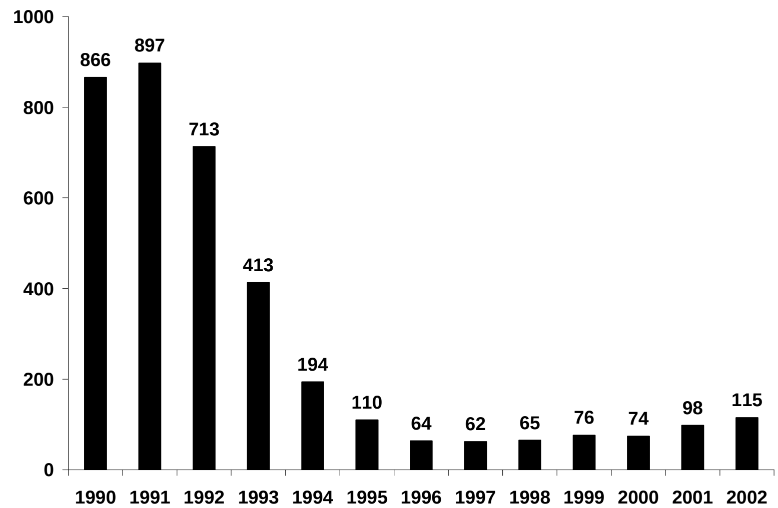


Figure 2
Cohort Composition at Second Event

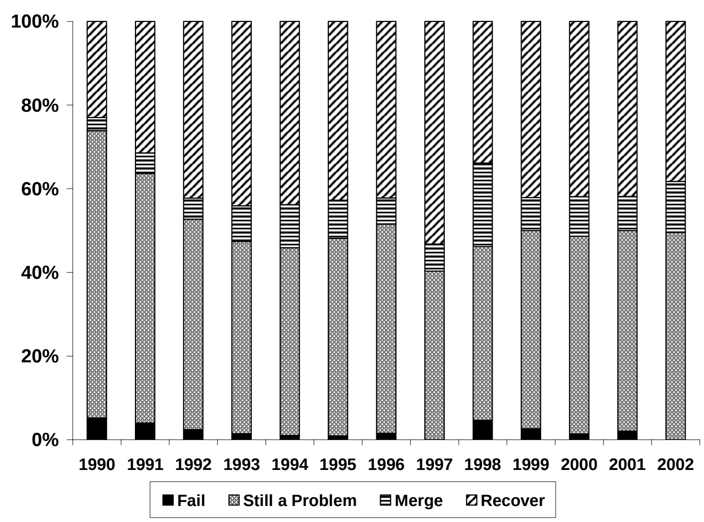


Figure 3
Number of Banks “Still a Problem” that Ultimately Recover

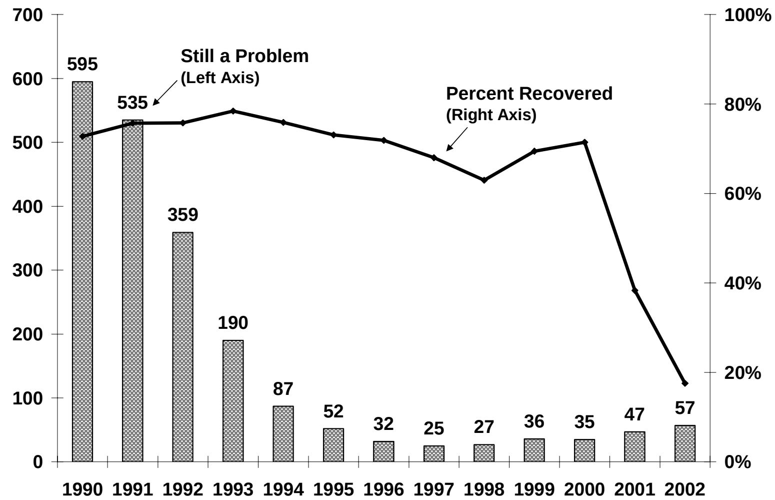


Figure 4
External and Internal Capital Injections in Banks that
Received Injections and Recovered, 1990 – 2002
(12 months prior to recovery)

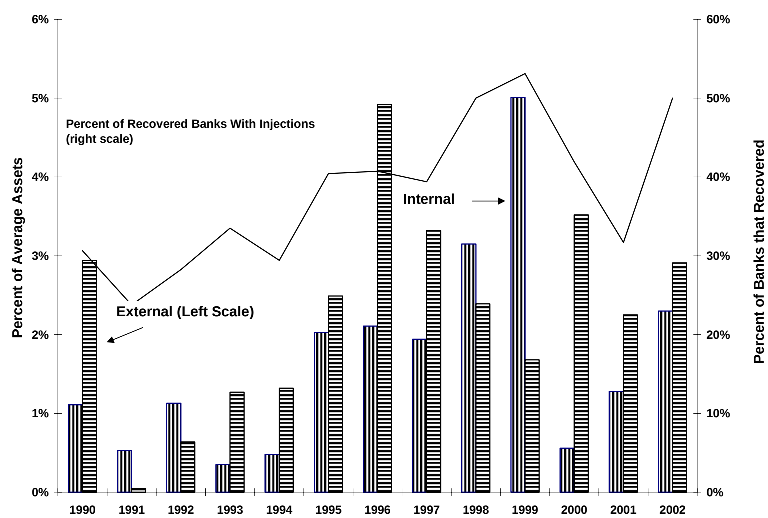


Figure 5
Net Income Increases
(12 months before downgrade versus 12 months before second event)

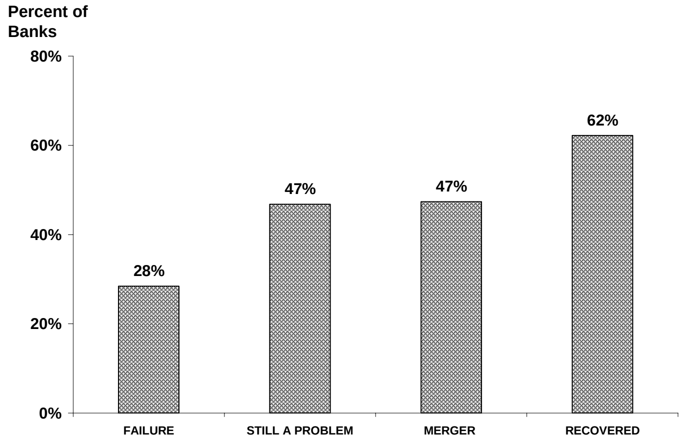


Figure 6
Loss Provision Increases
(12 months before downgrade versus 12 months before second event)

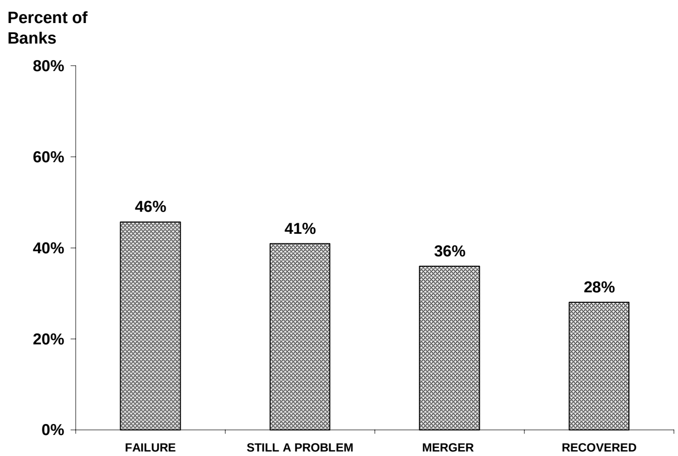


Figure 7
Net Non-Interest Income Increases
(12 months before downgrade versus 12 months before second event)

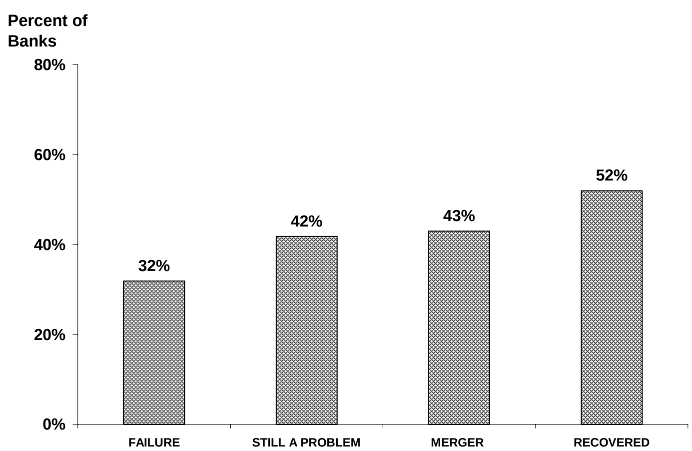


Figure 8
Loan Loss Reserve Increases
(12 months before downgrade versus 12 months before second event)

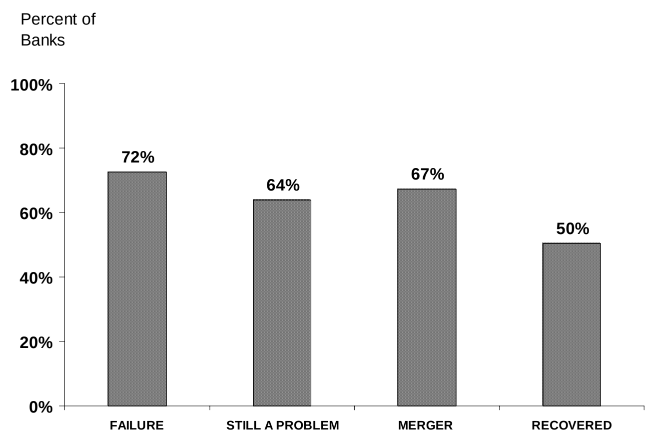


Figure 9
30-89 Days Past Due Loan Increases
(12 months before downgrade versus 12 months before second event)

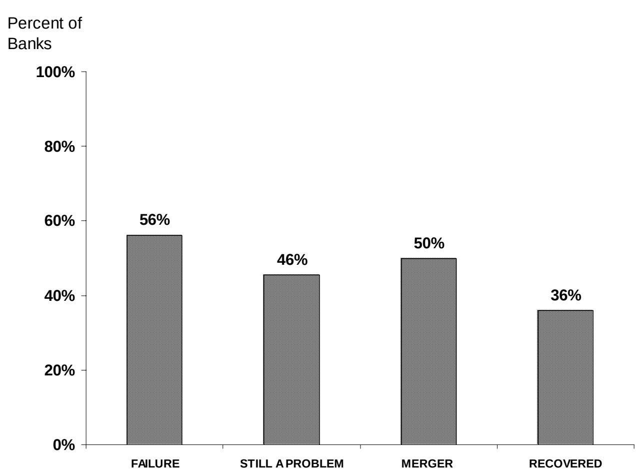


Figure 10
90 Days or More Past Due Loan Increases
(12 months before downgrade versus 12 months before second event)

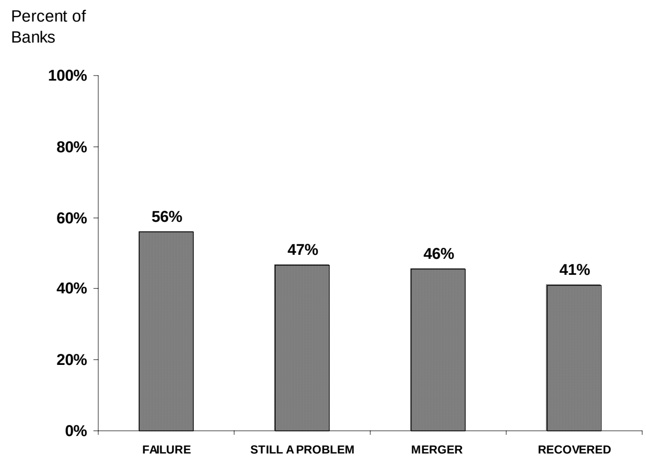


Figure 11
Non-accrual Loan Increases
(12 months before downgrade versus 12 months before second event)

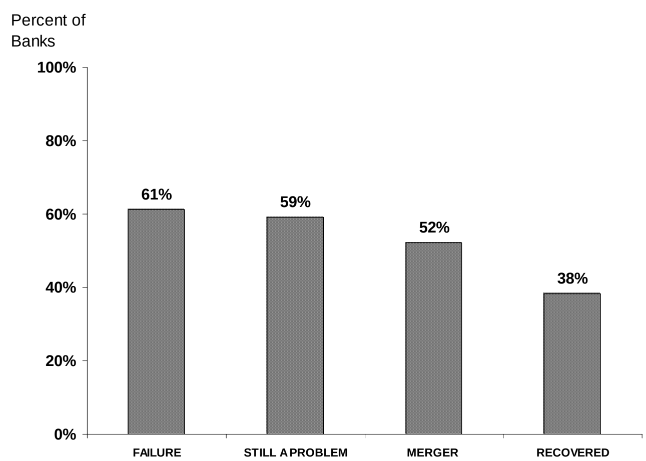


Figure 12
Other Real Estate Owned Increases
(12 months before downgrade versus 12 months before second event)

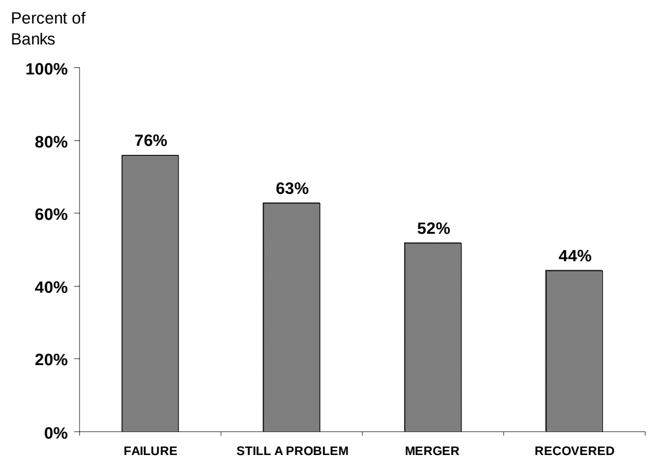


Figure 13
Risk-Based Capital Increases
(12 months before downgrade versus 12 months before second event)

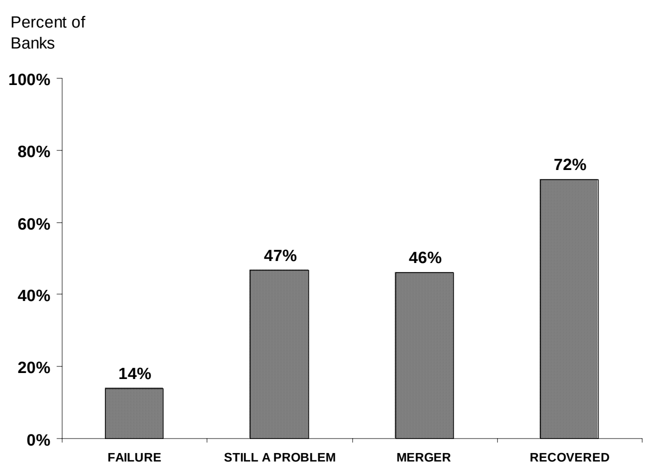


Figure 14
Tangible Capital Increases
(12 months before downgrade versus 12 months before second event)

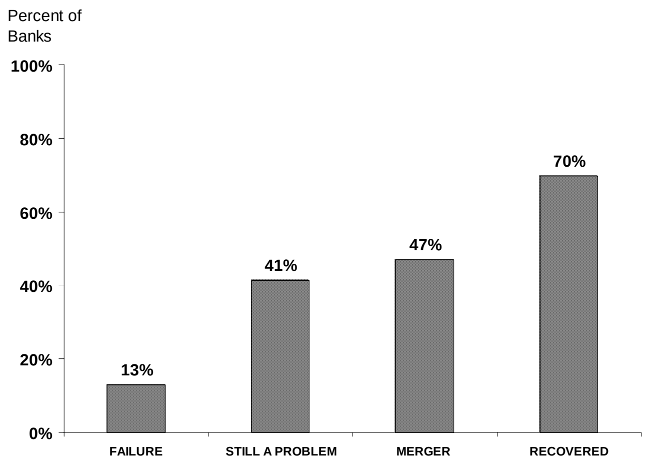


Figure 15
Percentage of Problem Banks with an Increase
In Volatile Liabilities, by State
(12 months before downgrade versus 12 months before second event)

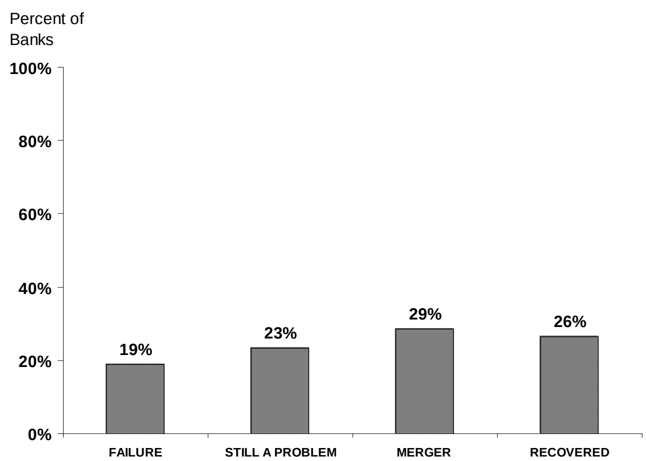


Figure 16
Percentage of Problem Banks with an
Increase in Loans and Securities with Maturities
Greater than or Equal to 5 years, by State
(12 months before downgrade versus 12 months before second event)

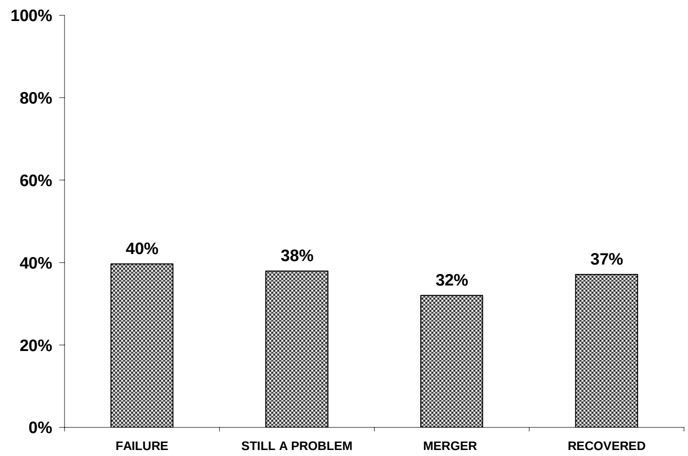


Figure 17
Percentage of Problem Banks with an
Improvement in the Efficiency Ratio, by State
(12 months before downgrade versus 12 months before second event)

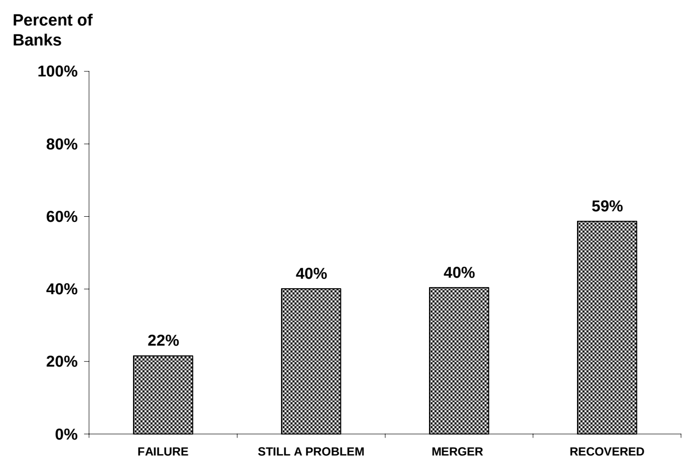
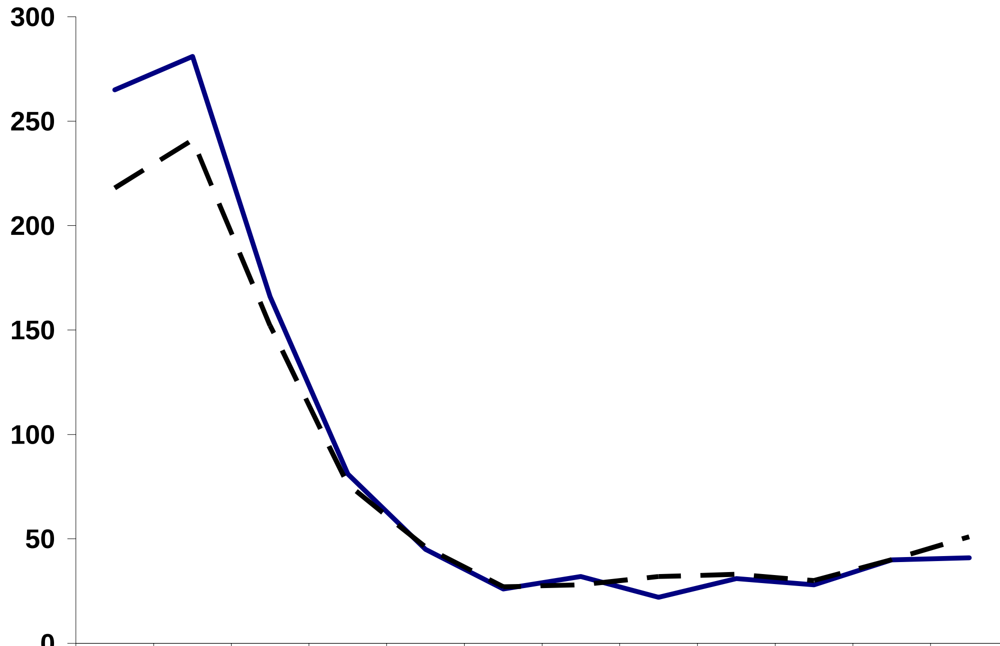
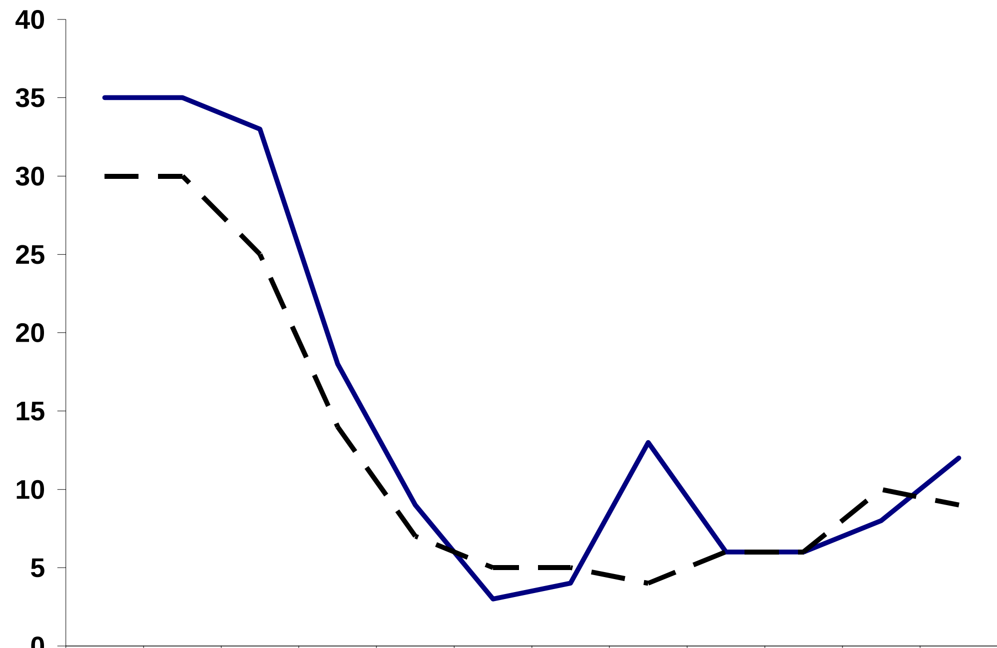


Figure 18
Recovery
(One-year Ahead Forecasts versus Actual)



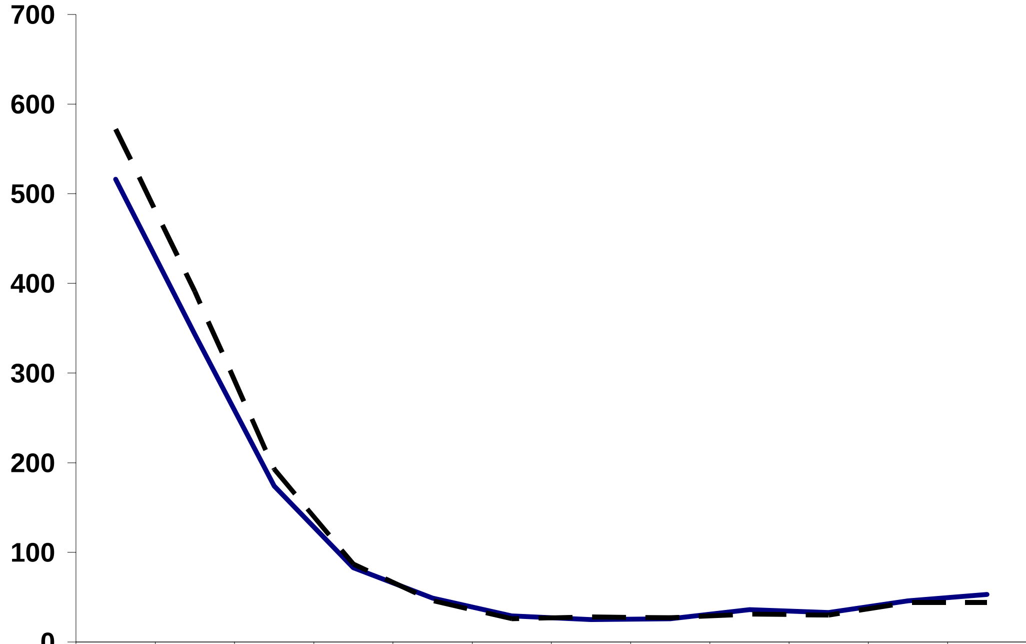
	91	92	93	94	95	96	97	98	99	00	01	02
Actual	265	281	166	81	45	26	32	22	31	28	40	41
Unordered	218	241	152	76	46	27	28	32	33	30	40	51

Figure 19
Acquired
(One-year Ahead Forecasts versus Actual)



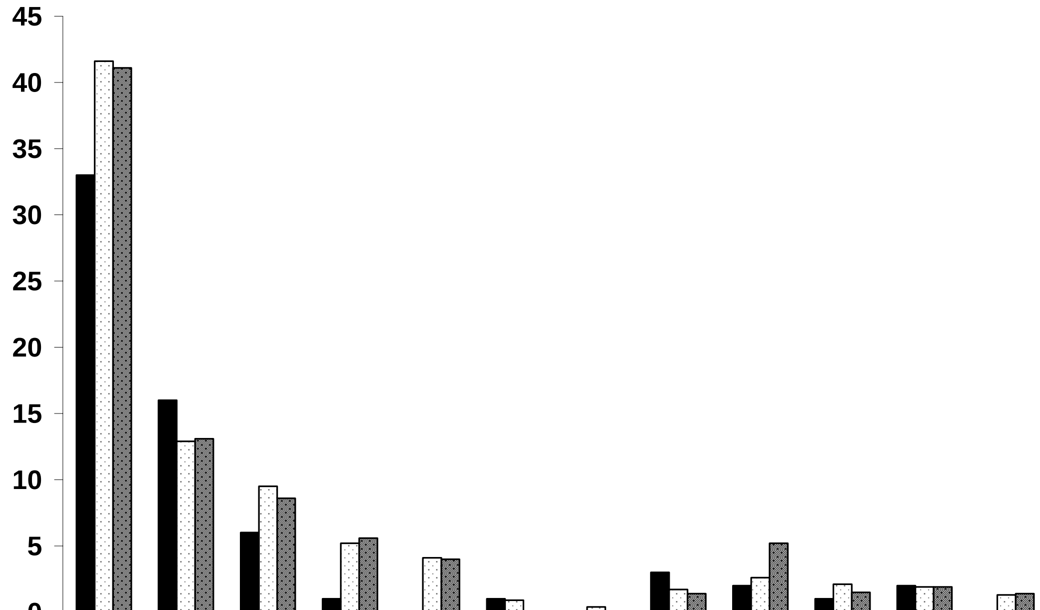
	91	92	93	94	95	96	97	98	99	00	01	02
Actual	35	35	33	18	9	3	4	13	6	6	8	12
Unordered	30	30	25	14	7	5	5	4	6	6	10	9

Figure 20
Still a Problem
(One-year Ahead Forecasts versus Actual)



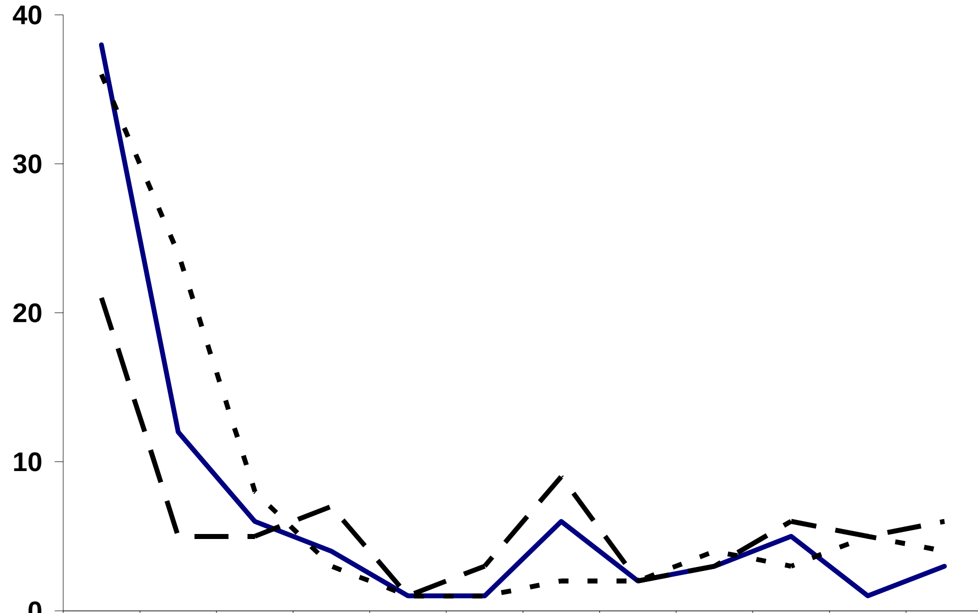
	91	92	93	94	95	96	97	98	99	00	01	02
Actual	516	343	174	83	49	29	25	26	36	33	46	53
Unordered	572	391	193	87	46	26	28	27	31	30	44	44

Figure 21
Comparative Forecasts vs. Actual
(One-year Ahead Forecasts versus Actual)



	91	92	93	94	95	96	97	98	99	00	01	02
Actual	33	16	6	1	0	1	0	3	2	1	2	0
Binary	41.6	12.9	9.5	5.2	4.1	0.9	0.4	1.7	2.6	2.1	1.9	1.3
Unordered	41.1	13.1	8.6	5.6	4.0	0.1	0.0	1.4	5.2	1.5	1.9	1.4

Figure 22
Failed Problem Banks: Total Problem-Bank List at Year End
Out-of Sample Forecasts



	92	93	94	95	96	97	98	99	00	01	02	03
Actual	38	12	6	4	1	1	6	2	3	5	1	3
Unordered	21	5	5	7	1	3	9	2	3	6	5	6
LDM Bivariate	36	24	8	3	1	1	2	2	4	3	5	4

Table 1
Explanatory Variables and Expected Signs for Predicting "Good" versus "Bad" States

Variable	Sign
Capital	
Tangible Equity Capital	+
Capital Injections:	
From BHC	+
Outside	+
Asset Quality	
Past Due Loans (30-89 days)	-
Past Due Loans (90+ days)	-
Non-accruing Loans	-
Other Real Estate Owned	-
Allowance for Loan Loss	+
Management	
Efficiency Ratio	-
Earnings	
Interest Income	+
Non-interest income	+
Interest Expense	-
Loss Provision	-
Loan Charge-offs	-
Salaries	-
Exp. Premises	-
Other non-int. exp.	-
Liquidity	
Volatile Liabilities	-
Loans plus Securities >= 5 years	+

Table 2
Mean and Standard Errors for Financial Variables, by State
(Standard Errors in parentheses)

	Recover	Merge	Still a Problem	Fail
Number of Banks	1,326	228	2,077	116
<u>Capital</u>				
Tangible Equity Capital	6.68 ***	6.57 ***	6.39 ***	3.90 ***
	(0.08)	(0.20)	(0.07)	(0.29)
Capital Injections:				
From BHC	0.19 ***	0.41 ***	0.20 ***	0.14 *
	(0.02)	(0.06)	(0.02)	(0.08)
Outside	0.36 ***	0.29 ***	0.29 ***	0.42 ***
	(0.04)	(0.09)	(0.03)	(0.13)
<u>Asset Quality</u>				
Past Due Loans (30 - 89 days)	1.88 ***	2.12 ***	2.43 ***	3.08 ***
	(0.04)	(0.10)	(0.03)	(0.14)
Past Due Loans (90+ days)	0.59 ***	0.65 ***	0.92 ***	1.17 ***
	(0.04)	(0.09)	(0.03)	(0.13)
Nonaccrual Loans and Leases	2.17 ***	2.56 ***	2.64 ***	3.82 ***
	(0.06)	(0.14)	(0.05)	(0.20)
Other Real Estate Owned	2.00 ***	1.88 ***	2.60 ***	3.19
	(0.07)	(0.17)	(0.06)	(0.23) ***
Allowance for Loan Loss	1.69 ***	1.97 ***	1.72 ***	2.11 ***
	(0.03)	(0.07)	(0.02)	(0.10)
<u>Management</u>				
Efficiency Ratio	88.32 ***	94.15 ***	94.43 ***	115.77 ***
	(0.67)	(1.62)	(0.54)	(2.28)

Table 2 (Continued)
Mean and Standard Errors for Financial Variables, by State
(Standard Errors in parentheses)

	Recover		Merge		Still a Problem		Fail	
Number of Banks	1,326		228		2,077		116	
Earnings								
Total Interest Income	8.80	***	8.99	***	9.59	***	10.58	***
	(0.09)		(0.21)		(0.07)		(0.29)	
Total Non-interest income	1.41	***	1.44	***	1.45	***	1.98	***
	(0.06)		(0.15)		(0.05)		(0.21)	
Total Interest Expense	4.47	***	4.51	***	5.27	***	6.51	***
	(0.06)		(0.14)		(0.05)		(0.20)	
Loan-Loss Provision	1.35	***	2.23	***	1.81	***	3.21	***
	(0.07)		(0.16)		(0.05)		(0.22)	
Loan Charge-offs	1.46	***	1.78	***	1.80	***	2.86	***
	(0.05)		(0.12)		(0.04)		(0.17)	
Expenses on Premises	0.68	***	0.75	***	0.77	***	0.96	***
	(0.01)		(0.03)		(0.01)		(0.04)	
Salaries	2.06	***	2.08	***	2.18	***	2.56	***
	(0.03)		(0.08)		(0.03)		(0.11)	
Other non-int. exp	2.23	***	2.54	***	2.43	***	3.29	***
	(0.05)		(0.11)		(0.04)		(0.16)	
Liquidity								
Volatile Liabilities	13.26	***	13.62	***	14.96	***	15.04	***
	(0.27)		(0.65)		(0.22)		(0.91)	
Loans + Sec., > 5 years	66.13	***	68.11	***	68.71	***	68.04	***
	(0.31)		(0.76)		(0.25)		(1.06)	

* Indicates significantly different from 0 at 10% level
** Indicates significantly different from 0 at 5% level
*** Indicates significantly different from 0 at 1% level

Table 3
Differences in Means and Standard Errors of Financial Variables for Selected Pairs (Standard Errors in parentheses)

	Recover - Merger	Recover - Still a Problem	Recover - Failure	Merger - Still a Problem	Still a Problem - Failure	Merger - Failure
Capital						
Tangible Equity Capital	0.10	0.29 **	2.78 ***	0.19	2.49 ***	2.68 ***
	(0.22)	(0.11)	(0.30)	(0.22)	(0.29)	(0.35)
Capital Injections:						
From BHC	(0.22) ***	(0.01)	0.04	0.21 ***	0.05	0.26 **
	(0.06)	(0.03)	(0.08)	(0.06)	(0.08)	(0.10)
Outside	0.07	0.08	(0.06)	0.00	(0.14)	(0.13)
	(0.10)	(0.05)	(0.13)	(0.10)	(0.13)	(0.16)
Asset Quality						
Past Due Loans (30 - 89 days)	(0.24) **	(0.55) ***	(1.20) ***	(0.31) **	(0.65) ***	(0.96) ***
	(0.11)	(0.05)	(0.15)	(0.11)	(0.15)	(0.18)
Past Due Loans (90+ days)	(0.06)	(0.33) ***	(0.58) ***	(0.27) **	(0.25) *	(0.52) ***
	(0.10)	(0.05)	(0.13)	(0.10)	(0.13)	(0.16)
Nonaccrual Loans and Leases	(0.39) **	(0.47) ***	(1.65) ***	(0.09)	(1.18) ***	(1.27) ***
	(0.15)	(0.07)	(0.20)	(0.15)	(0.20)	(0.24)
Other Real Estate Owned	0.12	(0.59) ***	(1.19) ***	(0.72) ***	(0.59) **	(1.31) ***
	(0.18)	(0.09)	(0.24)	(0.18)	(0.24)	(0.29)
Allowance for Loan Loss	(0.29) ***	(0.04)	(0.42) ***	0.25 **	(0.38) ***	(0.13)
	(0.08)	(0.04)	(0.11)	(0.08)	(0.11)	(0.13)
Management						
Efficiency Ratio	(5.83) ***	(6.10) ***	(27.44) ***	(0.28)	(21.34) ***	(21.62) ***
	(1.76)	(0.86)	(2.37)	(1.71)	(2.34)	(2.79)

Table 3 (Continued)
Differences in Means and Standard Errors of Financial Variables for Selected Pairs
(Standard Errors in parentheses)

	Recover - Merger	Recover - Still a Problem	Recover - Failure	Still a Problem - Merger	Still a Problem - Failure	Merger - Failure
Earnings						
Total Interest Income	(0.19)	(0.79) ***	(1.78) ***	(0.60) **	(0.99) ***	(1.59) ***
	(0.22)	(0.11)	(0.30)	(0.22)	(0.30)	(0.36)
Total Non-interest income	(0.03)	(0.04)	(0.57) **	(0.01)	(0.53) **	(0.54) **
	(0.17)	(0.08)	(0.22)	(0.16)	(0.22)	(0.26)
Total Interest Expense	(0.03)	(0.79) ***	(2.03) ***	(0.76) ***	(1.24) ***	(2.00) ***
	(0.15)	(0.07)	(0.21)	(0.15)	(0.20)	(0.24)
Loan-Loss Provision	(0.88) ***	(0.46) ***	(1.85) ***	0.42 **	(1.40) ***	(0.97) ***
	(0.17)	(0.08)	(0.23)	(0.17)	(0.23)	(0.27)
Loan Charge-offs	(0.32) **	(0.33) ***	(1.39) ***	(0.02)	(1.06) ***	(1.08) ***
	(0.13)	(0.07)	(0.18)	(0.13)	(0.18)	(0.21)
Expenses on Premises	(0.07) **	(0.09) ***	(0.28) ***	(0.02)	(0.19) ***	(0.21) ***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Salaries	(0.03)	(0.12) **	(0.50) ***	(0.09)	(0.38) ***	(0.48) ***
	(0.08)	(0.04)	(0.11)	(0.08)	(0.11)	(0.13)
Other non-int. exp	(0.30) **	(0.20) ***	(1.06) ***	0.11	(0.86) ***	(0.76) ***
	(0.12)	(0.06)	(0.16)	(0.12)	(0.16)	(0.19)
Liquidity						
Volatile Liabilities	(0.36)	(1.70) ***	(1.78) *	(1.34) *	(0.09)	(1.43)
	(0.70)	(0.35)	(0.95)	(0.69)	(0.94)	(1.12)
Loans + Sec., > 5 years	(1.98) **	(2.57) ***	(1.91) *	(0.60)	0.66	0.07
	(0.82)	(0.40)	(1.11)	(0.80)	(1.09)	(1.31)

* Indicates mean differences are significantly different at 10% level
** Indicates mean differences are significantly different at 5% level
*** Indicates mean differences are significantly different at 1% level

Table 4
Selected Descriptive Statistics for Data in Logits
Mean, Standard Deviation, Minimum and Maximum Values of Financial Ratios for each State

	All	Recover	Merge	Still a Problem	Fail
Number of Banks	3747	1326	228	2077	116
Capital					
Tangible Equity Capital					
Mean	6.42	6.68	6.57	6.39	3.90
Standard Deviation	3.12	2.54	3.42	3.37	2.76
Minimum	-4.77	-0.10	-4.77	-1.26	-1.37
Maximum	63.10	38.34	34.52	63.10	15.79
Capital Injections:					
From BHC					
Mean	0.20	0.19	0.41	0.20	0.14
Standard Deviation	0.87	0.82	1.41	0.84	0.65
Minimum	-1.07	-1.07	0.00	-0.93	-0.02
Maximum	12.87	9.98	12.87	8.97	4.74
Outside					
Mean	0.36	0.36	0.29	0.29	0.42
Standard Deviation	1.38	1.46	1.52	1.25	2.24
Minimum	-2.03	-1.89	-0.07	-2.03	-0.62
Maximum	25.16	15.98	15.98	25.16	18.38
Asset Quality					
Past Due Loans (30 - 89 days)					
Mean	2.24	1.88	2.12	2.43	3.08
Standard Deviation	1.58	1.38	1.84	1.60	1.95
Minimum	0.00	0.00	0.00	0.00	0.25
Maximum	18.66	12.41	18.66	13.96	9.59
Past Due Loans (90+ days)					
Mean	0.79	0.59	0.65	0.92	1.17
Standard Deviation	1.39	0.81	0.81	1.66	1.82
Minimum	0.00	0.00	0.00	0.00	0.00
Maximum	44.66	10.25	6.22	44.66	14.42
Nonaccrual Loans and Leases					
Mean	2.51	2.17	2.56	2.64	3.82
Standard Deviation	2.13	1.83	2.62	2.19	2.36
Minimum	0.00	0.00	0.00	0.00	0.05
Maximum	24.71	15.60	24.71	17.67	11.18
Other Real Estate Owned					
Mean	2.36	2.00	1.88	2.60	3.19
Standard Deviation	2.55	2.13	1.97	2.79	2.63
Minimum	-10.05	0.00	0.00	-10.05	-0.24
Maximum	20.20	18.61	10.99	20.20	12.48
Allowance for Loan Loss					
Mean	1.74	1.69	1.97	1.72	2.11
Standard Deviation	1.13	1.08	2.01	1.03	0.95
Minimum	0.11	0.11	0.36	0.14	0.28
Maximum	26.45	19.82	26.45	14.13	5.63
Management					
Efficiency Ratio					
Mean	92.91	88.32	94.15	94.43	115.77
Standard Deviation	25.00	22.85	25.34	25.09	29.99
Minimum	-30.64	-30.64	35.09	29.38	26.72
Maximum	198.71	193.89	195.03	198.71	194.40

Table 4 (Continued)
Selected Descriptive Statistics for Data in Logits
Mean, Standard Deviation, Minimum and
Maximum Values of Financial Ratios for each State

	All	Recover	Merge	Still a Problem	Fail
Earnings					
Total Interest Income					
Mean	9.30	8.80	8.99	9.59	10.58
Standard Deviation	3.14	2.60	4.63	3.14	4.11
Minimum	-0.01	-0.01	5.24	0.97	4.47
Maximum	64.32	33.69	64.32	32.78	26.25
Total Non-interest income					
Mean	1.45	1.41	1.44	1.45	1.98
Standard Deviation	2.31	2.18	1.84	2.38	3.20
Minimum	-0.09	-0.09	0.00	-0.05	0.18
Maximum	46.35	37.82	16.34	46.35	30.51
Total Interest Expense					
Mean	4.98	4.47	4.51	5.27	6.51
Standard Deviation	2.18	1.76	2.25	2.28	2.95
Minimum	-0.68	-0.68	1.25	0.25	0.95
Maximum	17.01	14.74	15.42	17.01	16.57
Loan-Loss Provision					
Mean	1.72	1.35	2.23	1.81	3.21
Standard Deviation	2.43	1.72	6.07	2.02	2.69
Minimum	-13.56	-2.17	-1.54	-13.56	-0.42
Maximum	87.33	23.14	87.33	24.55	13.82
Loan Charge-offs					
Mean	1.71	1.46	1.78	1.80	2.86
Standard Deviation	1.89	1.41	3.52	1.86	2.06
Minimum	-6.32	-0.49	-6.32	0.00	0.25
Maximum	47.20	19.12	47.20	24.12	11.50
Expenses on Premises					
Mean	0.75	0.68	0.75	0.77	0.96
Standard Deviation	0.46	0.40	0.44	0.47	0.67
Minimum	-0.48	-0.48	0.00	-0.04	0.15
Maximum	4.46	3.38	2.79	4.35	4.46
Salaries					
Mean	2.14	2.06	2.08	2.18	2.56
Standard Deviation	1.18	0.95	0.99	1.23	2.32
Minimum	0.00	0.06	0.00	0.04	0.43
Maximum	22.99	16.14	9.17	22.36	22.99
Other non-int. exp					
Mean	2.39	2.23	2.54	2.43	3.29
Standard Deviation	1.68	1.55	2.43	1.61	2.12
Minimum	-3.03	-3.03	0.45	-0.41	0.71
Maximum	32.70	22.46	32.70	25.38	14.86
Liquidity					
Volatile Liabilities					
Mean	14.28	13.26	13.62	14.96	15.04
Standard Deviation	9.85	9.51	11.08	9.90	9.26
Minimum	0.00	0.00	0.00	0.00	0.00
Maximum	90.19	86.08	90.19	89.43	51.54
Loans + Sec., > 5 years					
Mean	67.74	66.13	68.11	68.71	68.04
Standard Deviation	11.51	11.39	12.15	11.43	11.21
Minimum	19.40	24.31	19.40	22.14	37.34
Maximum	102.02	102.02	96.38	101.05	90.33

Table 5
Multinomial Logit Regressions of Determinants of Bank State: Recovery versus Failure

Explanatory Variables	1990	1991	1992	1993	93-94	93-95	93-96	93-97	94-98	95-99	96-00	97-01	98-02
Intercept													
Constant	-0.2388	10.6388 ***	-2.0548	-2.8325	8.4024 *	7.0800 *	6.2905	6.0942	14.2305	-2.8352	3.9788	1.0819	-0.6638
Capital													
Tangible Equity for PCA	0.7743 ***	1.0350 ***	0.7071 ***	-0.1248	-0.1827	-0.0345	-0.0198	-0.0262	1.4338	0.2043	-0.0802	-0.0156	-0.0120
BHC Capital Injections	2.0621	-0.3816	0.6065	0.5490	0.4402	0.3137	0.3806	0.3978	-3.1364	-0.6126	-0.3481	-0.6839 *	-0.6238
External Capital Injections	0.0021	0.1636	5.1764 **	0.8219	1.1397	1.5649	1.5940	1.6146	-0.9101	-0.3444 *	-0.2561	-0.2861 **	-0.2477
Asset Quality													
Loans Past Due 30 to 89 Days	-0.4142 ***	-0.4417 ***	-0.2429	-0.8305 **	-0.4773 **	-0.2567	-0.1913	-0.1730	0.5548	0.3001	0.5276	0.1184	0.0400
Loans Past Due 90 Days or More	-0.4630 ***	-0.1805	-0.5600	-0.3232	-0.1968	-0.3677 **	-0.4260 ***	-0.4530 ***	-1.0422 **	-0.5484 ***	-0.3320	-0.1901	0.0021
Nonaccrual Loans and Leases	-0.2163 **	-0.3689 ***	-0.4007 **	-0.7762 *	-0.6210 ***	-0.5803 ***	-0.6002 ***	-0.6283 ***	-2.9354 **	-0.6012 **	-0.3506	-0.2224	-0.1628
Other Real Estate Owned	-0.3847 ***	-0.2984 ***	0.1820	0.3759	0.3007	0.2900	0.3299	0.3245	7.6096 **	0.6112	0.0660	-0.0690	-0.1354
Allowance for Loan Losses	0.3333	0.7585 ***	0.1987	2.5538 **	0.9456 *	0.7284	0.7687 *	0.7911 *	4.1672	0.8971	1.0031	1.0392	0.9083
Management													
Efficiency Ratio	-0.0010	-0.0218	-0.0233	0.0277	-0.0398	-0.0406	-0.0328	-0.0341	-0.0417	0.0685	0.0308	0.0411	0.0498
Earnings													
Total Interest Income	1.0295	-0.9335	0.6710	2.3293	-0.3460	-0.3550	-0.1461	-0.1235	-3.0691	0.4429	0.4718	0.6600	1.0897
Total Non-interest Income	0.6360	-0.6387	0.3575	2.2171 *	0.4048	0.1514	0.2814	0.2917	-2.3035	0.7560	0.4635	0.5670	0.7607
Total Interest Expense	-1.2585 *	-0.0224	-0.6493	-1.2851	0.7541	0.3780	0.0680	0.0577	-0.7468	-0.9387	-1.0633	-1.3890 *	-1.6172
Loan-loss Provision	-0.7479 ***	-0.6765 ***	-0.1868	-1.2186 *	-0.9301 **	-0.8185 **	-0.9011 **	-0.9159 **	0.1979	-0.5587	-0.8741	-0.6199	-0.3175
Loan Chargeoffs	0.7248 ***	0.6950 ***	-0.4833	0.8751	0.6614	0.7422	0.7013 *	0.6955 **	1.5349	0.6323	0.6174	0.4337	0.2000
Expenses on Premises	-0.3109	-0.3120	-2.5638	-1.7553	-0.6163	-0.9336	-1.0243	-0.9938	-2.3193	-2.3415	-2.7488 *	-3.4456 **	-3.7522 **
Salaries	-1.4292 **	0.5001	0.9138	-1.6762	-0.0150	0.1143	-0.0836	-0.1369	7.9328	-0.6335	-0.3216	-0.3277	-0.2640
Other Non-interest Expense	-0.3044	0.0733	-0.4493	-3.4496 **	-0.7108	-0.3225	-0.4617	-0.4250	-0.0248	-1.1180	-0.7435 *	-0.7250	-1.2015
Liquidity													
Volatile Liabilities	-0.0130	0.0180	0.0191	-0.0726	-0.0456	-0.0072	0.0087	0.0117	-0.3340 *	-0.0723 *	-0.0434	-0.0387	-0.0349
Loans Plus Securities >=5yrs	0.0225	0.0033	0.0730	0.0743	0.0807	0.0792	0.0798	0.0856	0.0863	0.0708	0.0208	0.0473	0.0345
Log Likelihood	-584.9	-662.5	-561.8	-328.8	-505.8	-597.7	-660.9	-708.4	-416.7	-339.3	-315.9	-348.5	-410.6
Number of Observations	866	897	713	413	607	717	781	843	495	377	341	375	428
Akaike Information Criteria	1289.8	1445.0	1243.6	777.6	1131.6	1315.4	1441.8	1536.8	953.4	798.5	751.7	816.9	941.3
Pseudo R squared	0.090	0.222	0.170	0.195	0.162	0.159	0.144	0.145	0.172	0.121	0.102	0.103	0.078

Significance at 1%, 5% and 10% levels are indicated by ***, ** and * asterisks, repectively.

Table 6
Multinomial Logit Regressions of Determinants of Bank State: Merger versus Failure
Estimation Period (Years)

Explanatory Variables	1990	1991	1992	1993	93-94	93-95	93-96	93-97	94-98	95-99	96-00	97-01	98-02
Intercept													
Constant	-4.4684	9.6836 **	-7.5929	-5.191	4.203	4.6942	4.5547	4.7692	11.3291	-5.1144	0.9346	-0.6199	-1.9189
Capital													
Tangible Equity for PCA	0.5301 ***	0.8500 ***	0.7454 ***	-0.0461	-0.1382	-0.0093	-0.0002	-0.0191	1.4089	0.2249	-0.0238	-0.0080	-0.0014
BHC Capital Injections	2.1647	-0.1048	0.3075	1.0384	0.7004	0.5830	0.5993	0.5579	-3.1430	-0.8561	-0.5000	-0.7831 *	-0.5443
External Capital Injections	-0.9151	-0.0810	5.0893 **	0.8027	0.9729	1.3522	1.3519	1.3907	-1.6622 **	-1.2036 **	-0.5297 *	-0.4764 *	-0.4560 *
Asset Quality													
Loans Past Due 30 to 89 Days	-0.6823 ***	-0.4077 **	-0.2239	-0.8464 **	-0.4781 **	-0.1863	-0.2035	-0.1915	0.6182	0.3477	0.5696	0.2731	0.2128
Loans Past Due 90 Days or More	-0.3236	-0.0706	-0.5440	-0.1931	-0.2134	-0.5354 **	-0.5049 **	-0.5198 **	-0.9865 **	-0.3893 *	-0.2086	-0.1001	0.0566
Nonaccrual Loans and Leases	-0.2397	-0.4158 ***	-0.3294 **	-0.7045	-0.6407 ***	-0.5988 ***	-0.6019 ***	-0.6018 ***	-2.9516 **	-0.4764 *	-0.1760	-0.0955	-0.1115
Other Real Estate Owned	-0.1902 *	-0.4054 ***	0.2594	0.3367	0.3322	0.2715	0.3054	0.3055	7.6746 **	0.5882	0.0078	-0.0945	-0.1525
Allowance for Loan Losses	0.3356	0.8715 ***	0.3666	2.6342 **	1.2752 **	0.9467 **	0.9844 **	0.9958 *	4.3713	0.5819	0.7722	0.8808	0.8598
Management													
Efficiency Ratio	0.0094	-0.0345	-0.0171	0.0437	-0.0179	-0.0297	-0.0320	-0.0379	-0.0522	0.0580	0.0218	0.0396	0.0435
Earnings													
Total Interest Income	1.1992	-1.5633 **	0.5040	2.2421	-0.1898	-0.5105	-0.3677	-0.3640	-3.3443	0.2597	0.5499	0.6946	0.9715
Total Non-interest Income	0.7799	-1.4107 **	0.2819	2.5038 **	0.5521	0.1408	0.1259	0.0759	-2.6277	0.6042	0.4134	0.6291	0.6470
Total Interest Expense	-0.9474	0.7870	-0.4657	-0.8863	0.7604	0.6581	0.4352	0.4075	-0.3228	-0.5881	-0.7982	-1.1075	-1.3550
Loan-loss Provision	0.1164	-0.1086	0.0177 ***	-1.0359	-0.6691	-0.5882	-0.6731 **	-0.7569 **	0.2790	-0.6447	-0.7495	-0.5020	-0.2115
Loan Chargeoffs	-0.0145	0.0398	-0.7365 **	0.8755	0.3109	0.3865	0.3321	0.3975	1.0550	0.7349	0.5245	0.3932	0.1833
Expenses on Premises	-0.8320	1.1644	-1.5325	-1.7446	-0.2103	-0.4991	-0.4863	-0.3517	-1.2111	-1.3686	-1.4539	-2.0358	-2.7002
Salaries	-1.7712 *	1.4012 *	0.8435	-1.5131	-0.0220	0.2606	0.1441	0.1638	8.1622	-0.6658	-0.5979	-0.7600	-0.4629
Other Non-interest Expense	-0.2371 *	0.6104 **	-0.0030 **	-4.1409	-1.3090	-0.4806	-0.4177	-0.3441	0.2520	-0.8389	-0.6434	-0.8411	-1.0175
Liquidity													
Volatile Liabilities	-0.0085	-0.0177	0.0025	-0.1507 *	-0.1159	-0.0679	-0.0431	-0.0379	-0.3553 **	-0.0813 *	-0.0253	-0.0431	-0.0287
Loans Plus Securities >=5yrs	0.0159	0.0091	0.0927 **	0.0593	0.0729	0.0791	0.0805	0.0855 *	0.1157	0.0861	0.0125	0.0277	0.0228
Log Likelihood	-584.9	-662.5	-561.8	-328.8	-505.8	-597.7	-660.9	-708.4	-416.7	-339.3	-315.9	-348.5	-410.6
Number of Observations	866	897	713	413	607	717	781	843	495	377	341	375	428
Akaike Information Criteria	1289.8	1445.0	1243.6	777.6	1131.6	1315.4	1441.8	1536.8	953.4	798.5	751.7	816.9	941.3
Pseudo R squared	0.090	0.222	0.170	0.195	0.162	0.159	0.144	0.145	0.172	0.121	0.102	0.103	0.078

Significance at 1%, 5% and 10% levels are indicated by ***, ** and * asterisks, repectively.

Table 7
Multinomial Logit Regressions of Determinants of Bank State: Still a Problem versus Failure
Estimation Period (Years)

Explanatory Variables	1990	1991	1992	1993	93-94	93-95	93-96	93-97	94-98	95-99	96-00	97-01	98-02
Intercept													
Constant	-1.7037	9.8229 ***	-5.7298	-8.1433	3.4994	1.9090	2.3718	2.9545	11.8183	-4.7010	2.4569	-0.1438	-1.3300
Capital													
Tangible Equity for PCA	0.6653	0.9255	0.6366	-0.0180	-0.1213	0.0157	0.0210	0.0161	1.4656	0.2476	0.0092	0.0247	0.0209
BHC Capital Injections	1.8868	-0.2906	0.5581	0.8628	0.4019	0.2479	0.2982	0.3084	-3.3388	-0.8366	-0.3956	-0.6834	-0.6538 *
External Capital Injections	-0.2729	0.1045	5.0410 **	0.4656	0.9132	1.4138	1.4588	1.4872	-0.9185	-0.3014	-0.1564	-0.1621	-0.1645
Asset Quality													
Loans Past Due 30 to 89 Days	-0.1508 *	-0.1852 *	-0.0386	-0.6301	-0.2901	-0.0618	-0.0480	-0.0389	0.6652 *	0.3108	0.5140	0.1504	0.1100
Loans Past Due 90 Days or More	-0.1451	-0.0449	-0.2691	-0.1211	0.0590	-0.0202	-0.0798	-0.0852	-0.6682	-0.2518	-0.1519	-0.0492	0.0091
Nonaccrual Loans and Leases	-0.0503	-0.0609	-0.2043	-0.5441	-0.4911 ***	-0.4661 ***	-0.5049 ***	-0.5101 ***	-2.9075 ***	-0.5721	-0.3620	-0.2440	-0.2381
Other Real Estate Owned	-0.1520 *	-0.0992	0.3269	0.5932	0.5444 **	0.5269 **	0.5422 **	**	7.8727	0.7603	0.1889	0.0840	-0.0439
Allowance for Loan Losses	0.2190	0.4678 **	-0.1398	2.0740	0.6592	0.3662	0.4775	0.4219	3.8584	0.5901	0.8449	0.7692	0.8030
Management													
Efficiency Ratio	-0.0094	-0.0479 **	-0.0088	0.0608	-0.0183	-0.0160	-0.0218	-0.0298	-0.0504	0.0616	0.0153	0.0351	0.0417
Earnings													
Total Interest Income	0.5102	-1.4084 **	0.8538	2.3853	-0.2317	-0.2204	-0.1554	-0.2602	-3.2794	0.3022	0.3374	0.6819	0.9719
Total Non-interest Income	0.0929	-1.6561 ***	0.4092	2.3166 *	0.4836	0.2710	0.2199	0.1216	-2.5602	0.6202	0.2145	0.5437	0.6399
Total Interest Expense	-0.4149	0.7310	-0.8402	-1.6448	0.4186	0.0461	-0.0415	0.0889	-0.4817	-0.5840	-0.6594	-1.1102	-1.3588
Loan-loss Provision	-0.5443 *	-0.2876	0.0509	-0.8631	-0.5969	-0.4833	-0.5775 *	-0.5975 *	0.4569	-0.4709	-0.8459	-0.6286	-0.3183
Loan Chargeoffs	0.5898 *	0.2622	-0.6566 *	0.8309 *	0.5432	0.6234	0.5602	0.5720	1.3316	0.6531	0.6585	0.5533	0.3056
Expenses on Premises	-0.0152	1.0657	-1.8408	-1.8289	-0.4222	-0.9661	-0.7504	-0.6864	-1.6630	-1.7840	-2.0767	-3.3064 *	-3.3969 **
Salaries	-0.4521	1.5279 ***	0.6316	-1.4041	0.2488	0.3225	0.2618	0.3786	8.4899	-0.3599	0.0343	-0.2674	-0.2008
Other Non-interest Expense	0.1244	0.8622 **	-0.4144	-3.9178 **	-1.0867 *	-0.6549	-0.5648	-0.4626	0.1029	-1.0150	-0.5520	-0.6832 *	-0.9796
Liquidity													
Volatile Liabilities	-0.0006	0.0166	0.0404	-0.0821	-0.0456	-0.0061	0.0126	0.0192	-0.3160 *	-0.0456	-0.0169	-0.0090	-0.0073
Loans Plus Securities >=5yrs	0.0273	0.0089	0.0877 **	0.0966	0.1024 *	0.1027 **	0.0997 **	0.1050 **	0.1040	0.0777	0.0213	0.0394	0.0348
Log Likelihood	-584.9	-662.5	-561.8	-328.8	-505.8	-597.7	-660.9	-708.4	-416.7	-339.3	-315.9	-348.5	-410.6
Number of Observations	866	897	713	413	607	717	781	843	495	377	341	375	428
Akaike Information Criteria	1289.8	1445.0	1243.6	777.6	1131.6	1315.4	1441.8	1536.8	953.4	798.5	751.7	816.9	941.3
Pseudo R squared	0.090	0.222	0.170	0.195	0.162	0.159	0.144	0.145	0.172	0.121	0.102	0.103	0.078

Significance at 1%, 5% and 10% levels are indicated by ***, ** and * asterisks, repectively.

Table 8
Means Ratio - 1990
(Percent of assets)

Variable	Sign
Capital	
Tangible Equity Capital	5.3409
Capital Injections:	
From BHC	0.1399
Outside	0.1888
Asset Quality	
Past Due Loans (30-89 days)	2.2262
Past Due Loans (90+ days)	0.7964
Non-accruing Loans	2.6136
Other Real Estate Owned	2.6808
Loan Charge-offs	1.6613
Allowance for Loan Loss	1.7465
Management	
Efficiency Ratio	93.5429
Earnings	
Interest Income	9.6398
Net Interest Margin	
Non-interest income	1.2205
Interest Expense	5.8164
Loss Provision	1.6035
Salaries	1.9194
Exp. Premises	0.6952
Other non-int. exp.	2.0764
Liquidity	
Volatile Liabilities	14.4676
Loans and Sec. > 5 years	65.1021

Table 9
Effects of One-Percentage Point Change
In Selected Variables

	At Mean	Increase in Other Real Estate Owned to 3.6808%	Increase in Capital to 6.3409%
Recovery	= **16.41%**	**13.45%**	**18.08%**
Merger	= 1.82	1.81	1.57
Remain a problem bank	= 80.82	83.60	79.87
Failure	= 0.95	1.14	0.48