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AN ANALYSIS OF BANK FAILURES: 1984 TO 1989

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Abstract

This paper models the regulatory decision to close a bank as a call option. A two-equation model of bank failure, which treats bank closings as regulatorily timed events, is constructed from the call option closure model and estimated for bank failures occurring from 1984 through 1989. The two-equation model is also compared with two single-equation models in terms of both in-sample and out-of-sample predictive accuracy.

I. Introduction

Banking was relatively free of failures from the late 1930s to the mid-1960s. In the 1970s, bank failure rates increased but still remained at relatively low levels. The most notable development in the 1970s was that large banks started to populate the ranks of failed banks. During the 1980s, bank failures increased dramatically and as in the 1970s the failures were not limited to small banks. Multi-billiondollar institutions such as Continental Illinois Bank and Trust Company of Chicago, First Republic Bancorp of Dallas, and MCorp of Houston, joined the ranks of the banks that either failed or needed assistance from the Federal Deposit Insurance Corporation(FDIC) to remain open.

When compared to the failure rates for general business, bank failure rates during the 1980s are relatively low. For example, the 145 bank failures in 1986 translates into an annual failure rate of one percent, much lower than the 8.7 percent annual failure rate for general businesses in 1986. Even though bank failure rates are still low relative to general business failure rates, the ability to statistically model and predict bank failures is important from a public policy standpoint. For one, the ability to detect a deterioration in'bank condition from accounting data reduces the costs of monitoring banks by reducing the need for on-site examinations(see Benston et. a1 [1986, ch. 10] and Whalen and Thomson [1988]). furthermore,the ability to predict failures reduces the cost of bank failures to the FDIC.

Extensive literature on bank failures exists.' Statistical techniques used to predict and/or classify failed banks include multivariate discriminate analysis(see Sinkey [1975]), factor analysis and logit regression (see West [1985]), event history analysis (see Lane et al. [1986, 1987]), and a two-step logit regression procedure suggested by Maddala (1986) (see Gajewski (1988]) to classify banks as failed and nonfailed. Recently, this work has been extended by Demirguc-Kunt (1989a, 1990) to include market data and a model of the failure decision. Unfortunately, market data are available for only the largest banking institutions and the majority of banks that fail are small, with no market data available.

This study uses book data from the June and December Federal Financial Institutions Examination Council Reports of Condition and Income (call reports) from 1983 through 1988 in statistical models of bank failure. Maddala's (1986) two-step logit regression procedure is compared with single-equation models for classifying banks as failed or nonfailed. The analysis implicitly recognizes that insolvency and failure are separate events and the failure equations contain proxy variables to control for this. Furthermore, measures of local economic conditions are incorporated into the analysis.

The historically high number of failures for each year in the sample period allows each year to be investigated separately. Previous studies he: to pool the failures across years to get a sufficiently large failed bank sample, making it difficult to construct holdout samples and to do out-of-sample forecasting. This was especially true for tests across years The sample in this study is not limited in this way. Once failures for one year are classified by the model, failures in subsequent years can be used t- determine the out-of-sample predictive ability of the model. For example, the failure prediction model used to classify failures in 1984 can be applied to the 1983 data for banks that fail in 1985 and 1986.

II. Modeling Bank Failure

The failure of a depository institution occurs when a regulator declares that it has failed. Bank chartering agencies at the state and federal level have the authority to close banks.[2] However, for simplicity, our discussion of the failure process will assume that the FDIC has the ability to fail banks. Furthermore, we assume that all bank liabilities are insured deposits.[3] The decision to allow a bank to fail can be studied in an option-pricing framework. Merton (1977, 1978) shows that deposit insurance can be modeled as the European put option, $p(A,T-t;D)$, to sell the assets of the bank, A, to the FDIC for the value of the deposits, D, at time t-T. Following Buser et al. (1981), the FDIC is assumed to levy a fixed-rate explicit deposit insurance premium, ρ and a variable-rate implicit deposit insurance premium. The implicit premium consists of a regulatory tax and an American call option expiring at t-T,'

(1) $C(\chi,T-t;A-D+\lambda)$,

where χ = the charter value of the bank, and $A-D+\lambda$ = exercise price.

The first term in the call option in equation (1), χ, consists of the value of the deposit insurance subsidy, π, plus firm-specific options for future business activities, 6. Some of these firm-specific options may be lost when a bank fails. The exercise price is the market value of equity, A-D, which includes χ (see Kane and Unal [1990] and Thomson (1987]) and the nonactuarial costs to the FDIC associated with the failure of a bank, λ (see Kane [1986; 1989, ch. 4)).[5] If we set $\lambda = 0$, then the call option becomes $C(\chi, T-t; A-D)$ and the FDIC will exercise the option at t-T whenever the value of enterprise-contributed capital, $A - D - \pi < \delta$.[6]

When $\lambda \neq 0$, the FDIC will exercise its call option at some point after the value of enterprise-contributed capital becomes negative. λ represents constraints on the FDIC's ability to close banks. Kane (1986) divides λ into four components, which include: information constraints, c_i, legal and political constraints, c_p, implicit and explicit funding constraints, c_f, and administrative and staff constraints, c_s. c_i represent the monitoring costs the FDIC must incur to detect the insolvency of a financial institution. The FDIC faces a trade-off between these costs and expected loss when an institution is found to be insolvent. Therefore, higher c_i costs imply reduced value of the FDIC call.

c_p arise out of principal-agent problems that exist in bureaucratic regulatory agencies. Kane (1989, ch. 4) models bank and thrift regulatory agencies as self-maximizing bureaucracies whose primary task may be conceived as acting as the agent for taxpayers (the government's principal) to ensure a safe and sound banking system and to minimize the exposure of the taxpayer to loss. These regulators also must cater to a political clientele who are intermediate or competing principals. As illustrated by the cases of Lincoln Savings and Loan in California and Vernon Savings and Loan in Texas, the political costs to the regulator of closing insolvent institutions can be quite large. Principal-agent problems also arise from the post-government career opportunity set facing a regulator. As Kane (1989) points out, individual regulators have incentives to not take actions in the public's interest if they are seen to damage their post-government career prospects, especially if the developing crisis can be pushed off into future and into someone else's tenure as regulator. Therefore, c_p increases the exercise price of the FDIC call option and results in the exercise of the call after enterprise-contributed capital becomes negative.

The ability of the FDIC to close an institution is constrained by the value of the deposit-insurance put option held by the depositors of the bank relative to the explicit and implicit balance in the insurance fund. The explicit insurance reserve is the value of the FDIC's fund net of outstanding commitments and guarantees related to past, current, and future failures. The implicit funding source incorporates the FDIC's line of credit with the Treasury and the implicit backing of the fund by the Treasury. However, tapping the Treasury line of credit or drawing on the implicit Treasury guarantees (for example, the issuance of notes by the FSLIC) has political costs associated with it. The forbearance policies adopted by the now-defunct FSLIC after it became insolvent in the early 1980s graphically illustrate the importance of this constraint on the ability of the FDIC to close institutions as they are found to be insolvent. As funding constraint costs, c_f, increase (the real value of the insurance reserve decreases), the exercise price of the FDIC's call option rises and the value of the call falls.[7]

When there are a large number of troubled institutions, or even a few large troubled institutions, the ability of the FDIC to close these institutions is affected by the size and ability of its staff. Staff constraints arise for two reasons. First, since the FDIC's budget is part of the federal budget, there are incentives to minimize staff; second, the ability of the FDIC to attract and retain good people is limited by its ability to provide compensation packages that are competitive with the private sector. Both of these have been problems for the FDIC in recent years.

Naturally, the greater the staff constraints (the greater the size of c_r), the greater the exercise price of the FDIC call option.

From the call-option formula, the probability a bank will be closed after its enterprise-contributed capital is exhausted is

$$(2) \quad P(FAIL \mid A - \chi \le D) = f(\underset{(+)}{\chi},\ \underset{(-)}{A - D},\ \underset{(-)}{c_i},\ \underset{(-)}{c_r},\ \underset{(-)}{c_f},\ \underset{(-)}{c_a}).$$

Modeling the closure decision as a call option suggests that the empirical model for failure should be a two-step two-equation model that includes a solvency equation and a failure equation (see Demirguc-Kunt [1989a, 1990] and Gajewski [1988]).

$$(3) \quad y_j = \beta_0 + \sum_{i=1}^{n} \beta_i x_{i,j} + e_j,$$

$$(4) \quad DFAIL_j = \phi_0 + \phi_1 \hat{y}_j + \sum_{i=1}^{n} \phi_{i+1} z_{i,j} + \epsilon_j,$$

where: y_j = market-value solvency of bank j,

$x_{i,j}$ = i'th predetermined variable related to y_j,

e_j = random error term,

$DFAIL_j$ = dummy variable equal to 1 if bank j is failed, zero otherwise,

$\hat{y}_j$ = predicted value of y_j from equation (3); theoretically it is enterprise-contributed capital,

$z_{i,j}$ = constraints on FDIC's ability to close insolvent banks,

ϵ_j = random error term, assumed to be correlated with e_j.[8]

The solvency equation explicitly recognizes that insolvency is a necessary but not sufficient condition for the FDIC to exercise its closure call option. In Demirguc-Kunt's (1989a, 1990) studies, which use market data, the purpose of this equation is to separate enterprise-contributed capital from government-contributed capital (primarily in the form of deposit-insurance subsidies and forbearances). Unfortunately, it is difficult in practice to do this using book measures of solvency like those employed here and in Gajewski (1988). Therefore, equation (3) may not be able to control for government-contributed capital in book solvency measures. An alternative motivation for equation (3) is to recognize the simultaneous nature of book solvency measures (see Maddala [1986]). In practice, this is the primary justification for the two-equation system used here and in Gajewski (1988).

III. The Data

Bank failures from July 1984 through June 1989 comprise the failed bank sample. A bank is considered failed if it is closed, merged with FDIC assistance, or requires FDIC assistance to remain open. Our list of bank failures is taken from the FDIC's Annual Report from 1984 through 1987 and from FDIC press releases. It includes only FDIC-insured commercial banks in the United States (excluding territories and possessions).

The non-failed sample includes banks in the United States operating from June 1982 through June 1989 that filed complete call reports. This sample is drawn randomly from the call reports and attention is paid to ensure that the non-failed sample is representative of the population of nonfailed banks. For instance, the majority of banks in the population are small banks; therefore, the non-failed sample is drawn in a manner that ensures that small banks are adequately represented. Data for the failed banks are drawn from the June and December call reports for 1982 through 1988. Data for each failed bank are collected for up to nine semi-annual reports prior to the bank's failure date. A total of 1,736 banks are included in the nonfailed sample. The number of failed banks in the sample in each year appears in table 1.[9]

Data on economic condition used in the study are drawn from several sources. State-level gross domestic output data are obtained from the Bureau of Economic Analysis for the years 1980 through 1986. County level employment data are taken from the Bureau of Labor Statistics County Statistics Files for the years 1980 through 1986. State-level personal income data are taken from the Bureau of Economic Analysis annual personal income files for the years 1981 through 1988, and business failure data are taken from Dun and Bradstreet for the years 1982 through 1988. All of the economic condition data are annual data. Therefore, the business-failure and personal income data were matched with the December call report data of the same year and the following June call-report data. The gross domestic output and employment data were matched with the December and June call-report data in a similar manner, but with a two-year lag.

IV. The Empirical Model

The purpose of this study is to model bank failures of all sizes. This precludes the use of market data in equations (3) and (4). because stock market data are only available for a limited number of large banking organizations.[10] Therefore, the proxy variables used in this study are based on balance sheet and income data from the call reports. Equations (3) and (4) used in the study are specified as follows:

$$(3a)\quad NCAPTA_{j,t} = \beta_0 + \beta_1 NCAPTA_{j,t-1} + \beta_2 NCLNG_{j,t} + \beta_3 LOANHER_{j,t} + \beta_4 LOANTA_{j,t} + \beta_5 LIQ_{j,t} + \beta_6 OVRHDTA_{j,t} + \beta_7 ROA_{j,t} + \beta_8 AVGDEP_{j,t} + \beta_9 INSIDELN_{j,t} + \beta_{10} BOUTDVH_{j,t} + \beta_{11} UMPRTC_{j,t} + \beta_{12} CPINC_{j,t} + \beta_{13} BFAILR_{j,t} + e_{j,t},$$

$$(4a)\quad DFAIL_{j,t} = \phi_0 + \phi_1 \widehat{NCAPTA}_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}.$$

Equation (3a) disentangles solvency effects from other effects in the proxy variables. The dependent variable in the solvency equation, NCAPTA, is defined as the ratio of primary capital (book equity capital plus the reserve for loan losses) net of nonperforming loans to total assets.[11] This variable is similar to Sinkey's (1977) net capital ratio variable, which is the ratio of primary capital net of classified assets to total assets.[12] NCAPTA should be a better proxy for enterprise-contributed capital than a primary capital-to-assets ratio because it adjusts equity capital for the impact of bad loans. In addition, Sinkey (1977) and Whalen and Thomson (1988) show that similar proxy variables are highly related to the true condition of the bank.

The lagged value of the dependent variable, $NCAPTA_{t-1}$, is included in equation (3a) to increase the predictive power of the equation. This is important because the predicted value of NCAPTA, $\widehat{NCAPTA}$, is a regressor in equation (4a). Because we are primarily interested in equation (3a) as a predictor of solvency, we do not correct the standard errors of the regression for hereroscedasticity, nor do we attempt to interpret its coefficients.

The next set of variables in equation (3a). NCLNG, LOANHER, LOANTA, LIQ, OVRHDTA, AVGDEP, and INSIDELN, are all variables included in equation (4a) that are also related to solvency, and are described below. Finally, four measures of economic conditions in the bank's markets are included to incorporate the effects of local economic conditions on the solvency of the bank. These economic conditions variables include: BOUTDVH, which is a Herfindahl index constructed from state-level gross domestic output by the one-digit standard industrial classification code in the state where the bank is headquartered; UMPRTC, which is county level unemployment in the county where the bank's main office is located; CPINC, which equals the percent change in personal income in the state where the bank is headquartered; and BFAILR, which is the small-business failure rate in the state where the bank is headquartered.

Equation (4a) is the failure equation, and DFAIL is the *dummy* variable for failure. The first variable in equation (4a) is $\widehat{NCAPTA}$, the predicted value of the solvency proxy from equation (3a). The remaining regressors in (4a) are included to proxy for the effects of χ, c_i, c_p, c_f, and c_a on the failure decision. Note that many of the regressors may proxy for one or more of these constraints.

The natural logarithm of average deposits per banking office, AVGDEP, is used as the proxy for the enterprise-contributed portion of the charter value, 6. The level of deposits per banking office should be positively correlated to the value of the banking franchise and therefore positively related to failure.

Six variables (NCLNG, LOANTA. LOANHER, OVERHDTA, ROA. and LIQ) are included as regressors in equation (4a) to proxy for the FDIC's information system, or c_i in the call option. These variables are related to the FDIC's ability to decipher the true condition of a bank and, therefore, the FDIC's ability to close a bank when it becomes insolvent. The better these variables are able to predict insolvency, the lower the information costs faced by the FDIC. In essence, by including these proxy variables in equation (4a), we are incorporating a statistical monitoring or early warning system in the spirit of those used by the FDIC to complement on-site examination.[13]

The first three early warning system variables are proxies for asset quality, NCLNG, and portfolio risk, LOANTA and LOANHER. NCLNG is the ratio of net charge-offs to total loans. This variable should be positively related to failure. LOANTA is the ratio of total loans net of the loan loss reserve to total assets. It is the weight of risky assets in the total asset portfolio and, therefore, a proxy for portfolio risk. LOANTA should be positively related to failure. Finally, LOANHER is a loan portfolio Herfindahl constructed from the main loan classifications on the call reports.'' This is a measure of overall loan portfolio concentration and, therefore, diversifiable portfolio risk. LOANHER should be positively related to failure.

The next three early warning system variables are proxies for operating efficiency, OVRHDTA, profitability, ROA, and liquidity, LIQ. OVRHDTA is overhead as a percent of assets, which should be positively related to failure. ROA is the return on assets and should be negatively related to failure. In addition, ROA may also proxy for legal and political constraints. As we have seen with the forbearance policies adopted for thrift institutions, insolvent institutions that are profitable are less likely to be closed down than insolvent institutions that are losing money. As a proxy for c_p, ROA should also be negatively related to failure. Finally, LIQ is defined as the ratio of nondeposit liabilities to cash and investment securities and should be positively related to failure. Note that a liquidity crisis that may arise out of insolvency might force the FDIC to close an insolvent institution by increasing the political costs of not acting. Therefore, the less liquid the institution, the greater the probability it will be closed.

BRANCHU is included in the regression to control for differences in state branching laws. BRANCHU is a dummy variable that equals one if the bank is in a unit banking state and zero otherwise. The presence of branching restrictions reduces the failure-resolution options for the FDIC and therefore represents a legal constraint on the FDIC's ability to close a bank.[15] Therefore, BRANCHU should be negatively related to failure.

DBHC is a *dummy* variable equal to one if the bank is part of a bank holding company and zero otherwise. Banks in bank holding companies are less likely to be closed by the FDIC if there are other solvent holding company subsidiaries. This variable is based on the "source of strength doctrine" espoused by the Federal Reserve. Source of strength represents a regulatory philosophy that the parent holding company should first exhaust its resources in an attempt to make its banking subsidiaries solvent before the FDIC intercedes. Prior to the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA), the source of strength doctrine had no teeth because regulators could not force bank holding companies to bail out insolvent bank subsidiaries and the FDIC had to resort to complicated administrative and legal procedures to seize holding company assets that were outside the insolvent banking subsidiaries. Therefore, DBHC, which proxies for legal and administrative costs faced by the FDIC, should be negatively related to failure.

Two of the FDIC constraints, c_f and c_a, are difficult to proxy for directly in this study because of the cross-sectional nature of some of our tests. However, there is a variable, SIZE, which is indirectly related to both c_f and c_a. SIZE is the natural logarithm of total assets held by the bank. The larger the bank, the more complicated its portfolio and transactions are likely to be and, therefore, administrative costs of resolving bank failures should be higher for large banks than for small ones. Holding the loss per dollar of assets constant, larger banks impose greater losses on the FDIC fund than smaller ones. Therefore, the funding constraint is more likely to be binding as the total assets of the insolvent bank increase. Finally, the political fallout from a large-bank failure is much greater than for small ones, so SIZE also proxies for political constraints. All three constraints imply that SIZE should be negatively related to failure.

The last regressor included in equation (4a), INSIDELN, is a measure of fraud. INSIDELN is the ratio of loans to insiders to total assets. Loans to insiders and their friends are a major source of fraud in failed bank cases. Although insolvency due to fraud, or fraud-related losses in insolvent institutions are difficult to detect, the presence of fraud increases the exposure of the FDIC fund to loss if the bank is not closed promptly and also reduces political opposition to the bank's closure. Therefore, the presence of fraud increases the probability that the FDIC will close the bank and INSIDELN should be positively related to failure.

The Alternative Model

To judge the classification and predictive accuracy of the two-equation model, the following one-equation model is specified.

$$(5)\quad DFAIL_{j,t} = \phi_0 + \phi_1 NCAPTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}.$$

Equation (5) is simply equation *(4a)* with the actual value of NCAPTA used to proxy for solvency instead of $\widehat{NCAPTA}$, the predicted value of NCAPTA from equation (3a). Since we are also interested in the effects of local or regional economic conditions on the probability of bank failure, equation (5) is also estimated with economic condition variables as regressors.

$$(5a)\quad DFAIL_{j,t} = \phi_0 + \phi_1 NCAPTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \phi_{13} BOUTDVH_{j,t} + \phi_{14} UMPRTC_{j,t} + \phi_{15} CPINC_{j,t} + \phi_{16} BFAILR_{j,t} + \epsilon_{j,t}.$$

V. The Empirical Results

The panel nature of the data allows two types of tests to be done. First, the data are pooled in over time (using the June 1983 through the December 1988 call reports), and the predictive accuracy of the models is assessed for up to

48 months before failure. Second, using the June 1983, June 1984, June 1985, and June 1986 call reports, we assess the in-sample and out-of-sample accuracy of the models.

Results from the Two-Equation Model in the Pooled Sample

A two-step procedure is used in estimating equations (3a) and (4a). First, (3a) is estimated using ordinary least squares (OLS) and the predicted value of NCAPTA is saved for use as a regressor in equation (4a). Equation *(4a)* is then estimated using logit.[16] Both equations (3a) and (4a) are estimated using data at each call date for the nonfailed sample and for banks in the failed sample whose failure date is between six and 12 months, 12 and 18 months, 18 and 24 months, 24 and 30 months, 30 and 36 months, 36 and 42 months, and 42 and 48 months from the call date. The results appear in tables 2 and 3 respectively. In table 2 we see that the adjusted R^2 ranges from a low of 0.8266 for regressions using banks that fail 36 to 42 months from the call report date to a high of 0.8645 for banks that fail six to 12 months from the call report date.[17] Since the main purpose of estimating equation (3a) is to construct the solvency regressor for equation (4a), it is important that the equation has a good fit.

Table 2 shows that ϕ_1, the coefficient on $\widehat{NCAPTA}$, is negative and significant for banks failing within 30 months of the call date and positive for banks failing from 30 to 48 months from the call date. However, it is only positive and significant for the 36- to 42-month subsample. The positive sign on ϕ_1 for banks failing after 30 months is paradoxical because it indicates book solvency is positively related to failure. This, however, is not a new result. One possible explanation of this result is that banks beginning to experience difficulties readjust their balance sheets by selling assets on which they have unrealized capital gains for the purpose of cosmetically improving their capital positions.

The coefficient on **NCLNG**, ϕ_2, is negative for all banks and insignificant for all the regressions except the 30- to 36-month and 42- to 48-month subsamples. The expected sign for ϕ_2 is positive. ϕ_3, the coefficient on LOANHER, is positive (expected sign is negative) and insignificant for all subsamples.

ϕ_4 is positive and significant at the one percent level for all subsamples. In other words, banks whose loan portfolios make up a higher percentage of their assets have a higher probability of failure. The sign on ϕ_4 is consistent with LOANTA being a proxy for portfolio risk. ϕ_5, the coefficient on LIQ, is positive and significant for all subsamples except 30 to 36 months and 42 to 48 months, where it is positive and insignificant. As predicted by our model, the less liquid a bank, the greater the probability the FDIC will close it when the bank becomes insolvent.

As predicted by our model, the coefficient on **OVRHDTA**, ϕ_6, is positive and significant at the one percent level for all subsamples. In other words, banks that are more efficient are less likely to be closed by the FDIC when they become insolvent than are inefficient banks. ϕ_7 is negative and significant for all subsamples. As predicted by the model, insolvent banks that are profitable are less likely to be closed than unprofitable ones. This result is consistent with the forbearance policies of the federal bank and thrift regulators during the 1980s. Thrifts had to be both insolvent **and** losing money to be targeted for closure prior to the passing of **FIRREA** in 1989.

ϕ_8 is positive and significant at the one percent level for all subsamples. This is consistent with INSIDELN proxying for fraud, which, according to our model, should be positively related to closure. On the other hand, the coefficient on the branching dummy, ϕ_9, is positive and significant in all subsamples. The sign on ϕ_9 is opposite that predicted by the theory and indicates that BRANCHU may be proxying for geographical diversification of assets and liabilities or, since most unit banking states are in the Great Plains area and the Southwest, **BRANCHU** may be proxying for regional economic activity. As we shall see when we look at the regression on equation (5a), it appears that BRANCHU is proxying for the latter.

ϕ_{10} is negative and significant in all subsamples. As predicted by our theory, bank holding company affiliation reduces the probability a bank will be closed when it is found to be insolvent.[18] The coefficient on SIZE, ϕ_{11}, is also negative and significant in all subsamples. This is consistent with SIZE proxying for the higher administrative, funding, and political costs associated with closing larger banks. Finally, the coefficient on AVGDEP (the proxy for charter value), ϕ_{12}, is positive and significant in all subsamples. A positive sign on ϕ_{12} is consistent with our modeling of the closure decision (as in Buser et al. [1981]) as a call option on the bank's charter.

Single-Equation Models

An alternative to the two-equation model is the estimation of a single-equation model, such as equation (5). This model does not attempt to correct for the endogeneity of NCAPTA. If the error terms in equations (3) and (4) are independent, then there is no difference econometrically between estimating equations (3a) and (4a) or simply estimating equation *(5).* In addition, since one criteria by which bank failure models are judged is their predictive accuracy, a poor fit of the data to the solvency equation may reduce the predictive accuracy of the failure equation enough to cause us to prefer a single-equation model like equation (5) to the two-equation model.

As seen in table 4, the results from estimating equation (5) are similar to the two-equation model results in table 3. However, there are a few noteworthy differences in the results. First, as in table 3, ϕ_1 is positive for banks failing over 30 months from the call date and positive and significant in the 36- to 42-month subsample. However, ϕ_1 is also positive and significant in the 42- to 48-month subsample for equation (5). Second, ϕ_2 in both models turns up with the urong sign (negative), but ϕ_2 is negative and significant in six of the seven subsamples in table 4, compared with two in table 3. In all, the results of both models are consistent with the call option closure model; however, based on this criteria, the empirical results of the two-equation model are slightly superior to those of equation (5).

The two-equation model estimated in this paper attempts to control for the impact of regional economic conditions on the solvency of a bank by including proxy variables for economic conditions in the solvency equation. Therefore, its slightly better empirical performance based on theoretical criteria may simply be due to the extra information associated with the inclusion of the economic condition variables. To investigate this possibility, we estimate equation (5a) as our second alternative model. The results of this model appear in table 5.

Table 5 shows that for the first eight regressors the results for equation (5a) are virtually identical to those for equation (5). However, except for the 42- to 48-month subperiod, ϕ_9 is no longer significant once the economic condition proxies are included as regressors. Furthemore, ϕ_9 is negative in two of the subperiods. The coefficients on BHC (ϕ_{10}), SIZE (ϕ_{11}) and AVGDEP (ϕ_{12}) are also essentially the same for both (5) and (5a), except that ϕ_{11} is insignificant for the 42- to 48-month subperiod for equation (5a).

What is interesting about the results in table 5 is that ϕ_{13}, ϕ_{14}, and ϕ_{15} are negative and significant for all subperiods. In other words, failure is negatively related to state-level economic concentration (BOUTDVH), to county level unemployment (UMPRTC), and to changes in state-level personal income (CPINC). If BOUTDVH and UMPRTC are controlling for differences in the relationship between book and market solvency across regions, then we would expect ϕ_{13} and ϕ_{14} to be positive. The negative sign on CPINC is, however, consistent with its use as a proxy for differences between market and book solvency across regions. On the other hand, BOUTDVH and UMPRTC could be picking up increased political constraints associated with closing banks in depressed regions like the Southwest. These political constraints increase as the number of insolvencies in a region increases. Finally, the coefficient on BFAILR, ϕ_{16}, is negative and insignificant for all subsamples.

Tables 6, 7, and 8 contain the results for the three models estimated using cross-sectional data from the June call reports in 1984, 1985, and 1986, and from failures occurring in the subsequent calendar year. Cross-sectional estimation was done for two reasons: first, we wanted to indirectly test the pooling restriction imposed in the earlier tests, and second, we wanted to investigate the ability of the model to predict failures outside the sample. To facilitate out-of-sample forecasting, we also split the nonfailed sample into two random samples of 868 banks. One sample is to be used in in-sample forecasting and the second is to be used for out-of-sample forecasting. As seen in tables 6, 7, and 8, with the exception of ϕ_7 and ϕ_{10}, there does not appear to be a significant difference between the coefficients of each model across years. Therefore, the results of the tests in tables 3, 4, and 5 do no appear to be sensitive to the pooling restriction.[19]

In-Sample Classification Accuracy

The second criteria for judging bank failure models is the classification accuracy of the model. First, how well does the model do in discriminating between failed and nonfailed banks within the sample? Second, how well does the model discriminate between failed and nonfailed banks outside the sample?

For the pooled data, only in-sample forecasting is done. Tables 3, 4, and 5 contain the overall classification accuracy of the three models along with each model's type-I and type-I1 error. Type-I error occurs when a failed bank is incorrectly classified as a nonfailed bank. Type-I1 error occurs when a nonfailed bank is classified as a failed bank. The overall classification error is the weighted sum of the type-I and type-I1 errors. Typically, there is a trade-off between type-I error and overall classification accuracy. Since type-I error is seen to be more costly than type-I1 error for failure prediction models, the "best" model in terms of prediction is one that jointly minimizes type-I error and overall classification error.

Overall, the in-sample classification accuracy of all three models is very good. Using the ratio of failed to nonfailed observations in the sample as the probability cutoff point, we find that type-I error is as low as 7.438 percent for equation (5) in the 6- to 12-month subsample and as high as 29.801 percent for equation (4) in the 42- to 48-month subsample. Overall classification error ranges from 6.856 percent in the 6- to 12-month sample for (5a) to 21.381 percent in the 42- to 48-month sample for equation (4). As expected, both type-I errors and overall classification errors increase with time to failure. Equation (5) has the lowest type-I error for the 6- to 12-month and 12- to 18-month subperiods while equation (Sa) has the lowest type-I error for the remaining subperiods. Furthermore, (Sa) has the lowest classification error of all of the models. Therefore, based on in-sample forecasting accuracy from the pooled data, equation (5a) appears to be the "best? model.[20]

Out-of-Sample Forecasting

One reason for studying bank failures is to construct statistical models of failure that can be used to identify failures in the future. Such models are referred to as off-site monitoring or early warning systems in the literature and are used by regulators as a complement to on-site examinations of banks. Out-of-sample forecasting yields information on the usefulness of the bank failure model as an examination tool. Out-of-sample forecasting also gives us information on the stability of the failure equation over time.

The out-of-sample forecast is done using the estimated coefficients from the cross-section logit regressions on equations (4a), (S), and (5a), using data from the June 1984, June 1985, and June 1986 call reports and half of the nonfailed sample. The failed sample consists of all banks failing in the year following the year the call-report data is drawn from. The coefficients for equations (4a), (5), and (5a) estimated over this sample appear in tables 6, 7, and 8 respectively. The second half of the nonfailed sample, NF_2, is used as the nonfailed holdout sample for forecasting. Three failed holdout samples were also constructed for equations (5) and (5a) (except for June 1986, for which only two could be constructed) and two failed holdout samples were constructed for equation (4a). The first failed holdout sample consists of banks failing in the second calendar year following the call report. The second failed holdout sample consists of banks failing in the third calendar year following the call report. The third holdout sample [not available for equation (4) in any year or for equations (5) and (5a) in 1986] is made up of banks failing in the fourth calendar year following the call report.[21]

The results for this out-of-sample forecasting experiment appear in table 9. Table 9, panel A shows the results using the June 1984 call report data to predict failures in 1986, 1987, and 1988. The cutoff point (PPROB) for classifying banks as failed or nonfailed is the ratio of failed to nonfailed banks from the in-sample regressions. Other cutoff points yield similar results. With PRROB = 0.132, table 9-A shows that the three models misclassify between 10 and 11 percent of the banks in the holdout sample using NF_2 and 1986 failures. The type-I error rate indicates that all three models misclassify over two-thirds of the failures, while roughly two percent of the nonfailed sample (type-I1 error rate) is misclassified. Looking at the results for the 1987 failure and 1988 failure holdout samples (using NF_2 as the nonfailed sample in both cases), table 9-A shows that both type-I errors and overall classification errors for all three models increase as we attempt to forecast further and further into the future. Panels B and C show that the results for June 1985 and June 1986 call reports are similar to those using June 1984 data. As was the case in the in-sample forecasting, equation (5a) appears to dominate the other two models in terms of both its overall classification accuracy and type-I error rate for all of the holdout samples.

Given the high type-I error rates, one might question the usefulness of the models as early warning models of failure. However, the type-I error rate could be lowered by lowering PPROB enough so that the type-I error rates are acceptable. What is interesting from the standpoint of an early warning application is the low classification error and the low type-I1 error. If one wanted to use this model to determine which banks should be examined next, low type-I1 error is extremely important because the FDIC has limited examination resources.[22]

In practice, the first out-of-sample experiment is of little use for designing early warning models because it requires that we be able to identify failures in subsequent years in order to apply it. Therefore, a second out-of-sample experiment, which is able to mimic an early warning model in practice, is performed. Using the June 1984 call-report data, we estimate our three models using the entire nonfailed sample and the failures occurring in the next calendar year. The coefficients are then used to do out-of-sample forecasting using June call data for 1985, 1986, 1987, and 1988 on the nonfailed sample and failures in the calendar year following the call report as the holdout samples. Again the PPROB is set equal to the ratio of failed banks to nonfailed banks used in the in-sample logit regressions.

The results of the out-of-sample forecasting in table 10 show that using the 1984 version of the failure model, our out-of-sample classification error ranges from a high of 5.965 percent for equation (5) in June of 1986 to a low of 2.537 percent for equation (5a) in June of 1988. Type-I error ranges from a high of 51.880 for equation (4a) in June of 1985 to a low of 22.078 percent in June of 1989. It is somewhat curious that the out-of-sample classification accuracy of all three models increases as we get further and further from the call date of the in-sample experiment. Also, for the June 1985 and June 1986 experiments equation (5) does the best job of out-of-sample prediction while equation (5a) dominates on this criteria for June 1987 and June 1988. Again, note that the type-I error for the out-of-sample regressions could be lowered at the expense of the type-I1 error (and overall classification error) by lowering PPROB.

The performance of all three models in the second out-of-sample forecasting experiment suggests that they could be used as part of an early warning system of failure. Note, however, that our failure equation is designed to model the failure decision and not insolvency itself. A true early warning system would be designed to detect insolvency, which is a necessary but not sufficient condition for the bank to be closed.

IV. Conclusion

Bank failures are regulatorily timed events. The decision to fail a bank can be modeled as a call option whose value is a function of the bank's charter, its solvency, and costs to the FDIC of closing the bank. A two-equation model that explicitly recognizes that insolvency and failure are separate events is set up and estimated. Two single-equation models were also estimated to provide a benchmark against which to judge the two-equation model. Overall, the two-equation model performs quite well in testing. It has good classification accuracy in both the in-sample and out-of-sample test. Furthermore, for the two-equation model, the majority of the regression coefficients are significant with the correct sign in all of the subsamples used in the study.

Comparing the two-equation model with the alternative single-equation models, we find that the single-equation models perform slightly better in terms of in-sample and out-of-sample classification accuracy (both in terms of type-I and type-II errors). This, however, does not indicate a rejection of the two-equation model in favor of the single-equation models; rather, it is an indication that we need to improve the predictive accuracy of the solvency equation in the two-equation model. Finally, the addition of economic condition variables to the single-equation model's failure equation generally improves the predictive accuracy of the single-equation model.

Footnotes

1) Bank failure studies include Avery and Hanweck (1984), Barth et. a1 (1985), Bovenzi et al. (1983), Demirguc-Kunt (1989a, 1990), Gajewski (1988, 1989), Hanweck (1977), Lane et al. (1986, 1987), Meyer and Pifer (1970), Pantalone and Platt (1987), Rose and Scott (1978), Santomero and Vinso (1977), Short et al. (1985), Sinkey et al. (1987), and West (1985). For a review of this literature see Demirgiic-Kunt (1989b).

2) The decision to close a bank is usually based on some measure of solvency. Prior to 1933, the solvency test applied in national bank closing cases was <u>either</u> incapacity to pay obligations as they matured **or** balance-sheet insolvency. Since then, the Office of the Comptroller of the Currency has tended to use <u>only</u> the former, "maturing obligations" test, although the statutory basis for the latter, "balance-sheet" test remains in the statue books. Compare 12 U.S.C. Section 191 (balance-sheet or maturing obligations) with **id.**, Section 91 (usually interpreted as "maturing obligations" only).

3) For most banks, all of their deposit liabilities are implicitly or explicitly insured **and** the majority of bank liabilities are deposit liabilities. Therefore, this assumption should not qualitatively affect the results.

4) This option is similar to Brumbaugh and Hemmel's (1984) deposit-insurance call option. When the FDIC chooses to exercise its call option on the bank's charter it must purchase the deposit insurance put option back from the depositors. The net loss to the FDIC equals $\alpha\chi - p(A-\chi, T-t; D)$, where a is the percent of charter value remaining after the bank is closed and $p(A-\chi, T-t; D)$ is the value of the deposit insurance put.

5) A complete model for valuing federal deposit insurance would have to account for this charter-related call option. Such analysis would require the use of complex options (see Geske [1979] and Stulz [1982]). However, since this paper is primarily aimed at modeling bank failure we will concentrate on the call option held by the FDIC.

6) Enterprise-contributed capital is the market value of the bank's equity net of government-contributed capital, mostly consisting of the subsidized value of deposit insurance forbearances and guarantees (see Kane and Unal [1990] and Thomson [1987]).

7) Funding constraints are not always separate from the political constraints. As the value of the insurance fund decreases, politicians and self-maximizing bureaucrats have incentives to cover up the emerging weakness of the fund by adopting forbearance policies aimed at delaying the closing of insolvent institutions. For evidence of this type of behavior by regulators see Kane (1989, ch. 5).

8) If ϵ_j and e_j are uncorrelated, then one can simply estimate equation *(4)* directly, using y_j instead of $\hat{y}_j$.

9) The call report data were screened for errors. Banks in the failed and nonfailed samples for whom screening revealed errors in their data were deleted from the sample. In addition, banks in the nonfailed sample who were missing a June or December call report between 1982 and 1988 were also deleted.

10) In addition, stock market data is usually only available for bank holding companies and not for individual banks.

11) Nonperforming loans is the sum of loans 90 days past due but still accruing, and nonaccruing loans.

12) Classified assets is an item found only on a bank's confidential examination report and it is measured infrequently and often unavailable to researchers.

13) The purpose of early warning systems is to detect the deterioration of a bank's condition between scheduled examinations so that the FDIC can move that institution up in the on-site examination queue (see Whalen and Thomson (1988]). Papers that look at early warning systems include Korobow and Stuhr (1983), Korobow et al. (1977), Pettway and Sinkey

(1980), Rose and Kolari (1985), Sinkey (1975, 1977, 1978), Sinkey and Walker (1975), Stuhr and Van Wicklen (1974), Wang et al. (1987), and Whalen and Thomson (1988).

14) The loan portfolio classifications used to construct the loan portfolio Herfindahl include: real estate loans, loans to depository institutions, loans to individuals, commercial and industrial loans, foreign loans, and agricultural loans.

15) For a discussion of the different failure-resolution techniques available to the FDIC see Caliguire and Thomson (1987).

16) The OLS (logit) regressions are estimated using the proc reg (logist) regression procedure in SAS.

17) Banks failing within six months of the call report date were not included in the sample because a call report is not available until three to six months after the date of the call report.

18) In the cases where all or the majority of bank subsidiaries of a bank holding company were closed at once (for example, Bank Texas Group, First Republic Bancorp of Dallas and MCorp of Houston), the failed bank subsidiaries were aggregated into a single observation and treated as a single failure in our tests.

19) We also did cross-sectional regressions using all of the data (both failed and nonfailed) for the June 1984, June 1985 and June 1986 call reports and the entire failed sample and failures in the next calendar year for these call reports. The results were not materially different from those reported in tables 6, 7, and 8.

20) The in-sample forecasting properties of the cross-sectional equations yield similar results at each call report period. Equation (5a) appears to dominate equations (4) and (5) in terms both **type-I** error and overall classification accuracy (see tables 6, 7, and 8).

21) When the data were collected, we collected information on failures up to four years before the failure. Since the lagged value of **NCAPTA** is used in the two-equation model, we can only construct holdout samples up to three years from the call date instead of four for equation (4a).

22) One other thing to note is that with the exception of failures after June 1989, our nonfailed sample is free of failures in the future. Therefore, the type-I1 error rates of other studies and overall classification rates are high-biased because, as our results show, failure models are capable of classifying at least 25 percent of future failures within four years of the call report data.

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Table 1

Number of Failed Banks in the Sample[a]

Year	Number of Failed Banks
1984	78
1985	115
1986	133
1987	193
1988	174
1989[b]	77

a. Number of banks in nonfailed sample in each year is 1,736.
b. 1989 failure numbers are for the first six months of the year.

Source: Federal Deposit Insurance Annual Reports and press releases.

Table 2

OLS Regression Results For Equation (3a) From the Pooled Sample

X < Failures Occurring ≤ Y Months of the Call Report Date

	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
β_0	0.02443'	0.02934	0.02692	0.03517	0.03762	0.04199	0.03766
	(.0020)*	(.0020)*	(.0021)*	(.0023)*	(.0026)*	(.0029)*	(.0031)*
β_1	0.08606	0.82980	0.83117	0.79306	0.77208	0.75778	0.79238
	(.0036)*	(.0036)*	(.003a)*	(.0040)*	(.0043)*	(.0046)*	(.0054)*
β_2	-0.05580	0,00100	-0.01594	0.07035	0.09196	0.08956	0.12619
	(0111)*	(.0116)	(.0126)	(.0138)*	(.0162)*	(.0183)*	(.0240)*
β_3	0.00146	0.00187	0.00254	0.00357	0.00350	0.00535	0.00245
	(.0012)	(.0012)	(.0012)†	(.0013)*	(.0015)†	(.0016)*	(.0017)
β_4	-0.01708	-0.01879	-0.01812	-0.02013	-0.02148	-0.02235	-0.01952
	(.0009)*	(.0009)*	(.0010)*	(.0011)*	(.0012)*	(.0013)*	(.0014)*
β_5	-0.00198	-0.00176	-0.00190	-0.00106	-0.00117	-0.00220	-0.00264
	(.0006)*	(.0006)*	(.0006)*	(.0006)‡	(.0006)‡	(.0010)†	(.0012)†
β_6	-0.43744	-0.31200	-0.16893	-0.25816	-0.26197	-0.32495	-0.33131
	(.0775)*	(.0778)*	(.0822)†	(.0880)*	(.0962)*	(.1048)*	(.1143)*
β_7	0.80390	0.81634	0.76620	0.85522	0.98905	0.97475	1.00194
	(.0169)*	(.0172)*	(.0213)*	(.0234)*	(.0275)*	(.0312)*	(.0365)*
β_8	-0.00111	-0.04953	-0.00917	-0.05112	-0.03496	-0.00690	-0.01639
	(.0118)†	(.0118)*	(.0123)	(.0129)*	(.0137)†	(.0156)	(.0181)
β_9	-0.02520	-0.00123	-0.00118	-0.00160	-0.00173	-0.00202	-0.00188
	(.0002)*	(.0002)*	(.0002)*	(.0002)*	(.0002)*	(.0002)*	(.0002)*
β_{10}	0.03040	0.02191	0.02683	0.01391	0.01324	0.01065	0.00924
	(.0065)*	(.0065)*	(.0068)*	(.0074)‡	(.0092)	(.0098)	(.0083)
β_{11}	-0.00005	0.00000	-0.00000	0.00007	0.00005	0.00008	0.00005
	(.0000)‡	(.0000)	(.0000)	(.0000)†	(.0000)	(.0000)†	(.0001)
β_{12}	0.00640	-0.00241	-0.00467	-0.00236	0.00333	0.00014	-0.00131
	(.0064)	(.0051)	(.0050)	(.0054)	(.0058)	(.0061)	(.0062)

Table 2 (cont.)

X < Failures Occurring ≤ Y Months of the Call Report Date

	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
β_{13}	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(.0000)	(.0000)‡	(.0000)	(.0000)†	(.0000)	(.0000)†	(.0000)
$\bar{R}^2$	0.8645[b]	0.8584	0.8521	0.8401	0.8314	0.8266	0.8405
ϴ[c]	18086	16316	14522	12716	10905	9084	7095

Model: $NCAPTA_{j,t} = \beta_0 + \beta_1 NCAPTA_{j,t-1} + \beta_2 NCLNG_{j,t} + \beta_3 LOANHER_{j,t} + \beta_4 LOANTA_{j,t} + \beta_5 LIQ_{j,t} + \beta_6 OVRHDTA_{j,t} + \beta_7 ROA_{j,t} + \beta_8 AVGDEP_{j,t} + \beta_9 INSIDELN_{j,t} + \beta_{10} BOUTDVH_{j,t} + \beta_{11} UMPRTC_{j,t} + \beta_{12} CPINC_{j,t} + \beta_{13} BFAILR_{j,t} + e_{j,t}$.

a. Standard errors in parentheses.

b. Adjusted R^2.

c. Total number of observations, both failed and nonfailed.

Notes: * = Significant at 1 percent.

† = Significant at 5 percent.

‡ = Significant at 10 percent.

Source: Author.

Table 3

Logit Regression Results for Equation (4a) From the Pooled Sample

X < Failures Occurring ≤ Y Months of the Call Report Date

	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
ϕ_0	-1.69555*	-4.68530	-7.28915	-9.07995	-10.5591	-10.8012	-9.19922
	(.8217)†	(.7766)*	(.7918)*	(.8164)*	(.8790)*	(.9600)*	(1.438)*
ϕ_1	-35.6714	-21.9425	-11.0920	-4.32690	2.58890	7.12558	3.37884
	(1.715)*	(1.709)*	(1.795)*	(1.760)†	(1.948)	(1.951)*	(3.237)
ϕ_2	-2.10586	-4.97404	-3.55677	-9.43894	-12.9909	-5.84463	-14.4746
	(3.528)	(4.006)	(4.410)	(4.952)‡	(5.870)†	(6.407)	(10.01)
ϕ_3	0.85438	0.59689	0.55673	0.17085	0.14597	0.00245	0.58832
	(.5664)	(.5193)	(.5252)	(.5530)	(.5961)	(.6373)	(.9634)
ϕ_4	7.28951	8.90826	9.67700	9.70557	10.4889	9.88290	7.35884
	(.5595)*	(.5304)*	(.5280)*	(.5422)*	(.5951)*	(.6282)*	(.9329)*
ϕ_5	0.45180	0.43141	0.34133	0.30811	0.04951	0.13070	0.32575
	(.1340)*	(.1209)*	(.1173)*	(.1265)†	(.2015)	(.2350)‡	(.4608)
ϕ_6	194.422	198.096	251.602	275.293	259.773	273.441	251.789
	(25.85)*	(24.87)*	(25.29)*	(25.93)*	(27.84)*	(29.82)*	(41.13)*
ϕ_7	-47.4507	-62.9322	-60.8266	-66.8934	-70.3194	-55.8672	-76.1634
	(5.622)*	(6.083)*	(6.802)*	(7.158)*	(8.400)*	(9.183)*	(13.91)*
ϕ_8	25.6953	30.2655	30.3379	32.2883	30.3384	30.1479	23.8651
	(3.909)*	(3.459)*	(3.401)*	(3.459)*	(3.612)*	(3.868)*	(5.902)*
ϕ_9	0.24243	0.39097	0.39224	0.30184	0.42500	0.37900	0.82053
	(.1214)†	(.1117)*	(.1086)*	(.1130)*	(.1204)*	(.1294)*	(.2035)*
ϕ_{10}	-0.52709	-0.46922	-0.47321	-0.39165	-0.38172	-0.41076	-0.33641
	(.1182)*	(.1087)*	(.1054)*	(.1087)*	(.1158)*	(.1229)*	(.1925)‡
ϕ_{11}	-0.90008	-0.83729	-0.80938	-0.70417	-0.65194	-0.64426	-0.38900
	(.0991)*	(.0922)*	(.0896)*	(.0898)*	(.0978)*	(.1075)*	(.1602)†
ϕ_{12}	0.43783	0.54516	0.68215	0.72893	0.74708	0.75648	0.40778
	(.1219)*	(.1122)*	(.1100)*	(.1113)*	(.1191)*	(.1302)*	(.1954)†

Table 3 (cont.)

X < Failures Occuring ≤ Y Months of the Call Report Date

	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
χ^{2}[b]	3459.32*	2607.19*	1917.22*	1246.65*	1523.09*	910.94*	317.29*
TypeI[c]	9.054	14.162	17.192	20.885	22.699	26.733	29.801
TypeII[d]	8.819	12.846	16.359	17.561	17.838	19.124	21.198
Class[e]	8.847	12.901	16.395	17.709	18.056	19.462	21.381
PPROB[f]	0.042	0.044	0.046	0.047	0.049	0.049	0.022

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 NC\hat{A}PTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}$.

a. Standard errors in parentheses.
b. Model chi-square with 12 degrees of freedom.
c. Type I error: percent of failed banks classified as nonfailed.
d. Type II error: percent of nonfailed banks classified as failed.
e. Class: percent of all banks misclassified.
f. PPROB: probability cutoff value, approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at 1 percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 4

Logit Regression Results for Equation (5) From the Pooled Sample

	X < Failures Occuring ≤ Y Months of the Call Report Date						
	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
ϕ_0	-0.96671*	-3.74423	-5.88586	-7.95867	-9.33218	-9.28732	-10.4187
	(.8745)	(.7946)*	(.7760)*	(.7948)*	(.8479)*	(.9195)*	(1.503)*
ϕ_1	-42.3731	-30.5644	-18.5722	-11.0295	1.77564	5.66029	7.70472
	(1.707)*	(1.620)*	(1.525)*	(1.567)'	(1.724)	(1.667)*	(1.932)*
ϕ_2	-5.74819	-7.98422	-11.2572	-13.2754	-19.6326	-14.3427	-14.3208
	(3.726)	(4.081)‡	(4.463)†	(4.914)†	(5.872)-	(6.265)†	(8.209)‡
ϕ_3	1.01056	0.49413	0.88768	0.37164	0.79117	0.89250	0.94932
	(.6121)‡	(.5420)	(.5255)‡	(.5503)	(.5584)	(.5920)	(.6900)
ϕ_4	6.90372	8.42196	9.11404	9.43382	9.62790	8.69855	8.34784
	(.5933)*	(.5470)*	(.5243)*	(.5393)*	(.5683)*	(.5911)*	(.6765)*
ϕ_5	0.48045	0.47223	0.38353	0.32872	0.11556	0.37975	0.37919
	(.1284)*	(.1229)*	(.1141)*	(.1209)*	(.1887)	(.2360)	(.3761)
ϕ_6	201.736	207.206	257.080	275.101	244.812	257.004	284.084
	(27.61)*	(26.02)'	(25.27)-	(25.72)'	(27.42)'	(29.03)*	(33.53).
ϕ_7	-45.0675	-55.2277	-60.8254	-63.1525	-77.5459	-65.2046	-70.2942
	(5.690)'	(5.889).	(6.438)'	(6.801)*	(7.999)*	(8.574)*	(10.45)*
ϕ_8	28.8434	32.2487	32.2761	32.4707	30.0495	31.2010	30.8855
	(4.104)*	(3.601)*	(3.433)*	(3.457).	(3.561)*	(3,749)'	(4.192)*
ϕ_9	0.25096	0.45066	0.47279	0.34310	0.49027	0.45098	0.80699
	(.1308)‡	(.161)	(.1097)*	(.1131)*	(.1182)*	(.1270)*	(.1492)*
ϕ_{10}	-0.53971	-0.54570	-0.54763	-0.45105	-0.37342	-0.42407	-0.41455
	(.1279)*	(.1128)*	(.1059)*	(.1086)*	(.1140)	(.1210)*	(.1408)*
ϕ_{11}	-0.92820	-0.85646	-0.84981	-0.74691	-0.65532	-0.66411	-0.45685
	(.1087)*	(.0963)*	(.0918)*	(.0909)*	(.0970)*	(.1073)*	(.1209)*
ϕ_{12}	0.42278	0.54163	0.64972	0.71536	0.66293	0.68673	0.55454
	(336)	(176)	(1120)	(.1123	(.1181)*	(.1295)*	(.1459)*

Table 4 (cont.)

	X < Failures Occurring ≤ Y Months of the Call Report Date						
	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
χ^{2}[b]	3829.50*	2846.98*	2058.67*	1589.65*	1257.39*	925.57*	732.52*
TypeI[c]	7.438	13.439	15.732	20.175	23.123	26.603	26.498
TypeII[d]	6.918	11.130	15.257	17.256	18.481	19.689	19.196
Class*	6.939	11.228	15.279	17.387	18.696	20.009	19.515
PPROB[f]	0.042	0.044	0.046	0.047	0.049	0.049	0.046

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 NCAPTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}$.

a. Standard errors in parentheses.
b. Model chi-square with 12 degrees of freedom.
c. Type I error: percent of failed banks classified as nonfailed.
d. Type 11 error: percent of nonfailed banks classified as failed.
e. Class: percent of all banks misclassified.
f. PPROB: probability cutoff value approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at 1 percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 5

Logit Regression Results for Equation (5a) From the Pooled Sample

	X < Failures Occuring ≤ Y Months of the Call Report Date						
	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
ϕ_0	2.38697*	-0.16296	-1.41553	-3.27400	-4.70151	-4.52455	-5.86895
	(1.051)†	(.9453)	(.9333)	(.9547)*	(1.033)*	(1.124)*	(1.271)*
ϕ_1	-41.9440	-30.7100	-18.2812	-11.0825	1.06135	4.71928	7.20813
	(1.732)*	(1.653)*	(1.561)*	(1.605)*	(1.726)	(1.677)*	(1.958)*
ϕ_2	-5.08410	-8.60812	-14.6276	-17.2478	-23.9171	-19.1503	-19.1044
	(3.720)	(4.133)†	(4.572)*	(5.066)*	(6.016)*	(6.517)*	(8.595)†
ϕ_3	0.88626	0.31785	0.75250	0.21899	0.57943	0.62892	0.57109
	(.6129)	(.5415)	(.5248)	(.5487)	(.5560)	(.5905)	(.6900)
ϕ_4	6.83831	8.24747	8.96009	9.36032	9.47497	8.60227	8.34408
	(.5952)*	(.5531)*	(.5324)*	(.5482)*	(.5777)*	(.6059)*	(.6970)*
ϕ_5	0.48751	0.48380	0.41567	0.35344	0.18775	0.40038	0.23246
	(.1310)*	(.1281)*	(.1160)*	(.1181)*	(.1838)	(.2161)‡	(.3595)
ϕ_6	193.371	192.712	234.768	261.389	229.734	242.423	282.598
	(28.04)*	(26.40)*	(25.55)*	(26.11)*	(27.79)*	(29.43)*	(34.27)*
ϕ_7	-43.8748	-52.7425	-62.8707	-65.9745	-82.6363	-72.6391	-78.5720
	(5.689)*	(5.944)*	(6.550)*	(6.949)*	(8.105)*	(8.808)*	(10.81)*
ϕ_8	28.4403	30.0781	30.8587	31.3988	29.4992	30.4453	30.6184
	(4.202)*	(3.671)*	(3.482)*	(3.523)*	(3.652)*	(3.849)*	(4.317)*
ϕ_9	0.05340	0.13683	0.09577	-0.04100	0.05713	-0.02900	0.29639
	(.1375)	(.1254)	(.1192)	(.1237)	(.1309)	(.1396)	(.1492)†
ϕ_{10}	-0.66409	-0.65224	-0.65862	-0.57259	-0.50422	-0.58750	-0.58766
	(.1307)*	(.1154)*	(.1086)*	(.1114)*	(.1168)*	(.1247)*	(.1453)*
ϕ_{11}	-0.78703	-0.71757	-0.67593	-0.56533	-0.45271	-0.42109	-0.18141
	(.1109)*	(.0979)*	(.0932)*	(.0921)*	(.0976)*	(.1082)*	(.1208)
ϕ_{12}	0.22823	0.36891	0.43476	0.48875	0.44530	0.44791	0.28947
	(.1370)‡	(.1201)*	(.1148)*	(.1155)*	(.1205)*	(.1320)*	(.1459)†

Table 5 (cont.)

X < Failures Occuring ≤ Y Months of the Call Report Date

	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
ϕ_{13}	-11.1229	-12.8840	-20.6188	-20.7040	-21.4024	-22.0803	-18.6833
	(3.696)*	(3.272)*	(3.427)*	(3.532)*	(4.041)*	(4.380)*	(4.766)*
ϕ_{14}	-0.06069	-0.04453	-0.02805	-0.03726	-0.05399	-0.06944	-0.08682
	(.0200)*	(.0178)†	(.0168)‡	(.0909)†	(.0189)*	(.0221)*	(.0297)*
ϕ_{15}	-12.1944	-15.1171	-13.9465	-15.0079	-14.1911	-16.1181	-19.3252
	(2.583)*	(2.242)*	(2.072)*	(2.116)*	(2.226)*	(2.288)*	(2.662)*
ϕ_{16}	-0.00080	-0.00058	-0.00036	-0.00079	-0.00004	0.00012	-0.00114
	(.0009)	(.0008)	(.0007)	(.0008)	(.0008)	(.0010)	(.1459)
χ^2 [b]	3884.46*	2937.13*	2174.88*	1709.46*	1374.68*	1063.92*	854.93
TypeI [c]	7.989	11.994	16.044	17.895	20.356	19.952	20.189
TypeII [d]	6.809	11.041	14.574	16.285	17.723	18.491	17.627
Class [e]	6.856	11.081	14.639	16.357	17.845	18.558	17.739
PPROB [f]	0.042	0.044	0.046	0.047	0.049	0.049	0.046

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 NCAPTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \phi_{13} BOUTDVH_{j,t} + \phi_{14} UMPRTC_{j,t} + \phi_{15} CPINC_{j,t} + \phi_{16} BFAILR_{j,t} + \epsilon_{j,t}.$

a. Standard errors in parentheses.
b. Model chi-square with 16 degrees of freedom.
c. Type I error: percent of failed banks classified as nonfailed.
d. Type II error: percent of nonfailed banks classified as failed.
e. Class: percent of all banks misclassified.
f. PPROB: probability cutoff value approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at 1 percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 6
Cross-Sectional Logit Regressions on Equation (4a)
Using Data From the June 1984, June 1985 and June 1986 Call Reports.

Call Date	8406 1985 Failures	8506 1986 Failures	8606 1987 Failures
ϕ_0	-4.12778[b]	-6.38731	-0.36220
	(2.406)†	(2.389)*	(1.905)
ϕ_1	-17.2502	-25.1703	-36.9618
	(5.588)*	(5.570)*	(4.743)*
ϕ_2	33.5509	1.87540	5.58827
	(19.17)‡	(12.66)	(8.380)
ϕ_3	2.81493	0.18769	-0.56754
	(1.309)	(1.529)	(1.524)
ϕ_4	11.1755	9.69989	7.47663
	(1.717)*	(1.693)*	(1.363)*
ϕ_5	1.92067	1.65323	1.15570
	(1.070)‡	(0.797)†	(.3791)*
ϕ_6	277.520	266.802	487.186
	(84.75)*	(87.24)*	(79.11)*
ϕ_7	-63.3471	-74.0080	-18.2734
	(27.11)†	(21.10)*	(16.56)
ϕ_8	43.3303	35.2427	51.6627
	(11.45)*	(10.23)*	(12.07)*
ϕ_9	-0.02822	0.25178	0.11707
	(.3178)	(.3015)	(.2953)
ϕ_{10}	-0.31745	-0.03424	-0.84152
	(.3062)	(.3209)	(.2961)*
ϕ_{11}	-1.42992	-0.67168	-0.90646
	(.2968)*	(.2180)*	(.2280)*
ϕ_{12}	0.91558	0.57524	0.43068
	(.3441)*	(.2756)†	(.2865)
χ^2[c]	361.44*	410.17*	612.86*
TypeI[d]	14.782	15.038	13.542
TypeII[e]	11.866	10.829	8.064
Class[f]	12.208	11.389	9.057
PPROB[g]	0.132	0.153	0.221

Table 6 (cont.)

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 \widehat{NCAPTA}_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}$.

a. Using the predicted value of NCAPTA from equation (3a) and half of the nonfailed sample.
b. Standard errors in parentheses.
c. Model chi-square with 12 degrees of freedom.
d. Type I error: percent of failed banks classified as nonfailed.
e. Type II error: percent of nonfailed banks classified as failed.
f. Class: percent of all banks misclassified.
g. PPROB: probability cutoff value approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at 1 percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 7
Cross-Sectional Logit Regressions on Equation (5)
Using Data From the June 1984, June 1985 and June 1986 Call Reports.

Call Date	8406 1985 Failures	8506 1986 Failures	8606 1987 Failures
ϕ_0	-2.90000[b]	-6.00878	-0.42736
	(2.499)	(2.370)†	(1.962)
ϕ_1	-29.2032	-30.9763	-44.9557
	(5.542)*	(4.655)*	(5.243)*
ϕ_2	30.7407	-5.43586	6.62939
	(19.15)	(13.71)	(8.583)
ϕ_3	2.87023	0.36111	-0.84956
	(1.357)†	(1.584)	(1.614)
ϕ_4	10.4566	9.11993	7.52807
	(1.694)*	(1.726)*	(1.484)*
ϕ_5	2.18184	1.77137	1.12728
	(1.199)‡	(.8420)†	(.3913)*
ϕ_6	293.006	305.681	498.460
	(85.92)*	(94.35)*	(83.83)*
ϕ_7	-44.8089	-73.7367	1.90407
	(26.83)*	(20.44)*	(17.48)
ϕ_8	41.5933	35.5167	49.2025
	(11.35)*	(10.29)*	(12.47)*
ϕ_9	0.09472	0.17676	0.18351
	(.3240)	(.3132)	(.3188)
ϕ_{10}	-0.41478	0.01218	-0.82034
	(.3170)	(.3478)	(.3124)†
ϕ_{11}	-0.88631	-0.75022	-0.99663
	(.3153)*	(.2386)*	(.2492)*
ϕ_{12}	0.99108	0.66451	0.56195
	(.3607)*	(.2980)†	(.3124)†
χ^2[c]	383.54*	443.92*	659.85*
TypeI[d]	14.783	14.286	11.458
TypeII[e]	10.484	9.908	6.567
Class[f]	10.987	10.490	7.453
PROB[g]	0.132	0.153	0.221

Table 7 (cont.)

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 NCAPTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \epsilon_{j,t}$.

a. Using half of the nonfailed sample.
b. Standard errors in parentheses.
c. Model chi-square with 12 degrees of freedom.
d. Type I error: percent of failed banks classified as nonfailed.
e. Type II error: percent of nonfailed banks classified as failed.
f. Class: percent of all banks misclassified.
g. PPROB: probability cutoff value approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at one percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 8
Cross-Sectional Logit Regressions on Equation (5a)
Using Data From the June 1984, June 1985 and June 1986 Call Reports[a]

Call Date	8406 1985 Failures	8506 1986 Failures	8606 1987 Failures
ϕ_0	0.41054[b] (2.851)	0.54427 (2.874)	1.38233 (2.340)
ϕ_1	-31.5300 (5.824)*	-29.8974 (4.751)*	-43.5108 (5.215)*
ϕ_2	21.9335 (20.01)	-1.21438 (13.72)	7.19583 (8.774)
ϕ_3	2.56701 (1.387)‡	0.41171 (1.633)	-0.92490 (1.614)
ϕ_4	10.1274 (1.743)*	9.48711 (1.799)*	7.37133 (1.523)*
ϕ_5	2.71040 (1.215)†	1.52626 (.8142)	0.94988 (.3984)†
ϕ_6	301.452 (86.83)*	242.802 (96.12)†	489.163 (86.14)*
ϕ_7	-49.9100 (27.18)‡	-69.7858 (20.67)*	-0.41036 (17.66)
ϕ_8	39.5835 (12.15)*	30.8386 (10.75)*	50.0041 (13.20)*
ϕ_9	0.11320 (.3428)	-0.17378 (.3510)	0.03302 (.3617)
ϕ_{10}	-0.79283 (.3414)*8i	-0.15807 (.3650)	-0.98695 (.3332)*
ϕ_{11}	-1.13224 (.3189)*	-0.67094 (.2526)*	-0.91419 (.2619)*
ϕ_{12}	0.58398 (.3750)	0.42180 (.3168)	0.49576 (.3233)
ϕ_{13}	-10.2246 (9.416)	-16.3569 (9.322)‡	1.87244 (8.242)
ϕ_{14}	-0.07424 (.0708)	-0.02965 (.0505)	-0.09033 (.0459)†

Table 8 (cont.)

Call Date	8406 1985 Failures	8506 1986 Failures	8606 1987 Failures
15	-22.9118	-30.1852	-28.0164
	(7.740)'	(8.808)*	(14.32)‡
ϕ_{16}	-0.00130	-0.00092	0.00161
	(.0026)	(.0030)	(.0026)
χ^{2c}	402.59*	462.30*	667.31*
TypeI[d]	11.304	11.278	9.375
TypeII[e]	10.484	9.562	7.028
Class[f]	10.580	9.790	7.453
PPROB[g]	0.132	0.153	0.221

Model: $DFAIL_{j,t} = \phi_0 + \phi_1 NC\hat{A}PTA_{j,t} + \phi_2 NCLNG_{j,t} + \phi_3 LOANHER_{j,t} + \phi_4 LOANTA_{j,t} + \phi_5 LIQ_{j,t} + \phi_6 OVRHDTA_{j,t} + \phi_7 ROA_{j,t} + \phi_8 INSIDELN_{j,t} + \phi_9 BRANCHU_{j,t} + \phi_{10} BHC_{j,t} + \phi_{11} SIZE_{j,t} + \phi_{12} AVGDEP_{j,t} + \phi_{13} BOUTDVH_{j,t} + \phi_{14} UMPRTC_{j,t} + \phi_{15} CPINC_{j,t} + \phi_{16} BFAILR_{j,t} + \epsilon_{j,t}.$

a. Using half of the nonfailed sample.
b. Standard errors in parentheses.
c. Model chi-square with 12 degrees of freedom.
d. Type I error: percent of failed banks classified as nonfailed.
e. Type II error: percent of nonfailed banks classified as failed.
f. Class: percent of all banks misclassified.
g. PPROB: probability cutoff value approximately equal to the ratio of failed and nonfailed observations.

Notes: * = Significant at 1 percent.
† = Significant at 5 percent.
‡ = Significant at 10 percent.

Source: Author.

Table 9

Out-of-Sample Forcasts for Equations (4a), (5),and (5a)

A. June 1984 Call Data: 86, 87 and 88 Failures and NF_2, with PPROB=0.132.[a]

Equation	Failures in 1986 (4a)	(5)	(5a)	Failures in 1987 (4a)	(5)	(5a)
TYPEI[b]	68.421	66.165	64.662	79.781	78.689	67.213
TYPEII[c]	2.189	2,074	1.843	1.958	2.074	1.843
CLASS[d]	10.989	10.589	10.190	15.509	15.414	13.225

Equation	Failures in 1988 (4a)	(5)	(5a)
TYPE1	N/A	83.660	74.834
TYPEII	N/A	2.074	1.843
CLASS	N/A	14.328	12.659

B. June 1985 Call Data: 87, 88, and 89 Failures and NF_2, with PPROB=0.153.

Equation	Failures in 1987 (4a)	(5)	(5a)	Failures in 1988 (4a)	(5)	(5a)
TYPEI	70.466	66.321	63.731	68.421	71.930	71.930
TYPEII	2.074	2.189	1.728	2.304	2.189	1.728
CLASS	14.515	14.138	13.007	13.186	13.956	13.282

Equation	Failures in 1989[e] (4a)	(5)	(5a)
TYPEI	N/A	83.652	75.342
TYPEII	N/A	2.189	1.728
CLASS	N/A	8.820	7.439

C. June 86 Call Data: 88 and 89 Failures and NF_2, with PPROB=0.221.

Equation	Failures in 1988 (4a)	(5)	(5a)	Failures in 1989 (4a)	(5)	(5a)
TYPEI	55.172	54.598	52.874	65.333	64.000	62.667
TYPEII	3.571	2.880	3.226	3.226	2.880	3.226
CLASS	12.188	11.516	11.516	8.165	8.059	7.953

a. NF_2 is nonfailed holdout sample.
b. Type I error: percent of failed banks classified as nonfailed.
c. Type II error: percent of nonfailed banks classified as failed.
d. Class: percent of all banks misclassified.
e. Failures for the first half of 1989.
Source: Author.

Table 10

Out-of-Sample Forcasting for Equations (4a), (5), and (5a) Using Coefficients Estimated from Logit Regressions on 1985 Failures and the Entire Nonfailed Sample Using June 1984 Call Report Data[a]

	June 1985 Call Data Failures in 1986			June 1986 Call Data Failures in 1987		
Equation	(4a)	(5)	(5a)	(4a)	(5)	(5a)
TYPEI[b]	51.880	45.113	52.632	41.146	32.292	39.583
TYPEII[c]	1.786	1.901	0.864	2.074	2.074	1.728
CLASS[d]	5.350	4.976	4.548	5.965	5.083	5.498

	June 1987 Call Data Failures in 1988			June 1988 Call Data Failures in 1989[e]		
Equation	(4a)	(5)	(5a)	(4a)	(5)	(5a)
TYPEI	33.908	29.885	27.586	33.766	25.974	22.078
TYPEII	1.786	1.184	2.074	2.016	2.074	1.671
CLASS	4.712	4.398	4.398	3.365	3.223	2.537

	In-Sample Forcast		
Equation	(4a)	(5)	(5a)
TYPEI	15.652	15.652	12.745
TYPEII	12.730	11.636	10.211
CLASS	12.912	11.885	10.913

a. Out-of-sample forecasting done with PPROB (probability cutoff) equal to 0.066 (ratio of failed to nonfailed banks for the in-sample logit regressions).
b. Type I error: percent of failed banks classified as nonfailed.
c. Type II error: percent of nonfailed banks classified as failed.
d. Class: percent of all banks misclassified.
e. Failures for the first half of 1989.
Source: Author.