THE DETERMINANTS AND EARLY DETECTION OF INADEQUATE CAPITALIZATION OF U.S. COMMERCIAL BANKS

Julapa A. Jagtiani, James W. Kolari, Catharine M. Lemieux, and G. Hwan Shin*

*The authors are Senior Financial Economist, Federal Reserve Bank of Kansas City, Chase Professor of Finance, Finance Department, Texas A&M University, Director, Policy and Emerging Issues, Supervision and Regulation, Federal Reserve Bank of Chicago, and Visiting Professor, University of Texas at Pan American, respectively.

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Please address correspondence to: James W. Kolari, Finance Department, Texas A&M University, TAMU -- 4218, College Station, TX 77843-4218 Office phone: 979-845-4803 Fax: 979-845-3884 Email: j-kolari@tamu.edu

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Abstract

The Basle Agreement of 1988 is a twelve-nation banking accord that established international bank capital standards. A major implication of this agreement is that capital adequacy became central to regulatory oversight of banking systems around the world. From a policy perspective bank regulators seek to identify those institutions at risk of falling below capital standards in the near future. In this regard, this paper examines the efficacy of early warning systems (EWSs) with respect to the determinants and identification of capital inadequacy among U.S. commercial banks. Based on samples of banks in the late 1980s and early 1990s, EWS models are empirically tested using financial and economic data for individual banks. The empirical results reveal that banks pending capital deficiency are much different from other banks in terms of their financial health. Also, EWS models are able to detect the early onset of financial distress in commercial banks one year in advance with a reasonable degree of accuracy. We conclude that EWS models could be useful to bank regulators as both an off-site surveillance tool and a supplement to on-site examinations by supervisory personnel.

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I. Introduction

With the adoption of the Basle Agreement among 12 leading industrial countries in 1988, capital adequacy became central to the regulatory oversight of banking systems around the world. The Basle Committee meets under the auspices of the Bank for International Settlements (BIS) in Basle, Switzerland to periodically review international capital standards. Because it represents the cushion available to financial institutions to withstand unanticipated losses, capital is crucial to bank safety and soundness. By monitoring capital levels, supervisors seek to predict which financial institutions are most likely to fall below capital standards if subjected to an earnings or asset quality shock. In 1991 the passage of the Federal Deposit Insurance Improvement Act (FDICIA) emphasized capital levels as the appropriate benchmark to use in determining appropriate supervisory interventions to aid ailing financial institutions. By intervening when an institution is beginning to experience problems, it may be possible to avoid more serious problems. Research done by Curry, O'Keefe, Coburn and Montgomery (1999) found that between 1980 and 1996, 39 percent of problem banks that experienced supervisory actions were no longer considered problem banks two years later. Further analyses showed that supervisory actions were important determinants of changing bank behavior. Thus, being able to identify pending financial distress early is an important objective of bank supervision.

Most studies in the extant banking literature on financial distress have focused on the prediction of bank failure or closure by regulatory authorities.[1] These studies have examined the endpoint in the timeline of financial distress, which extends from the early stage of financial

[1] See Meyer and Pifer (1970); Sinkey (1975); Santomero and Vinso (1977); Bovenzi, Marino, and McFadden (1983); Korobrow and Stuhr (1985); West (1985); Maddala (1986); Lane, Looney, and Wansley (1986); Whalen

distress to the end stage of failure. As pointed out by Coats and Fant, "At this point, there is little practical use for a predictive algorithm since the distressed nature of the firm is obvious to virtually all of the firm's stakeholders…" (1993, p.147)[2]. In this regard, there have been two recent studies that have attempted to examine bank financial distress prior to the end stage event of failure.

Gilbert, Meyer, and Vaughan (1999) investigated banks with CAMEL downgrades from a safe level (rated 1 or 2) to a watchlist level (rated 3, 4, or 5).[3] Using logit analysis, Gilbert *et al*. found the ratio of total equity to total assets was one of the most important predictors of CAMEL downgrades. Also, closely related to the present study, Wheelock and Wilson (2000) applied competing-risks hazard models to examine the determinants of severe bank capital deficiency defined as total equity to total assets ratio below 2 percent. Banks with this level of capital are classified as critically undercapitalized by regulators and may be taken over by the FDIC under the FDIC Improvement Act of 1991. Their results indicated that measures of operating efficiency, asset quality, earnings, size, age, and organizational structure are significantly related to severe financial distress among banking institutions.

Extending the work cited above, this paper seeks to examine an early stage of financial distress so that supervisors can identify firms at risk and manage timely interventions to change bank behavior. We define adequately capitalized institutions as those banks with at least 5.5 percent primary capital to total assets ratio for the whole sample period.[4] This capital threshold

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and Thomson (1988); Espahbodi (1991); Thomson (1993); Kolari, Caputo, and Wagner (1996); and Kolari, Glennon, Shin, and Caputo (2002).

[2] In their study, auditor's reports were employed to define financially-troubled firms versus viable firms, and a neural network early warning system (EWS) was developed and tested on a sample of corporate firms.

[3] After an on-site examination, commercial banks receive CAMEL ratings on a scale of 1 (strongest) to 5 (weakest) from their chartering agency (i.e., the Federal Reserve for state member banks, state bank commissioner for state non-member banks, or the Comptroller of the Currency for national banks), where C = capital adequacy, A = asset quality, M = management, E = earnings, and L = liquidity.

[4] Primary capital includes common and perpetual stock, surplus and undivided profits, contingency and other capital reserves, mandatory convertible debt instruments (up to 20% of primary capital exclusive of such instruments),

is consistent with regulatory standards for adequate capitalization during the sample period.[5] It is important to note that, while we utilize a well-recognized regulatory threshold for adequate capital, our main objective is to examine an early stage of financial distress, as opposed to regulatory compliance with capital standards. Estrella, Park, and Peristiani (2000) examined the relationship between different capital ratios and bank failure and found that the simple capital to assets ratio (leverage ratio) predicts bank failure as well as more complex risk-weighted capital ratios over one-year or two-year horizons. In addition, Estrella *et al*. recommended using the simple capital ratio as a tool to provide a timely signal of the need for supervisory action. Thus, our choice of a 5.5 percent primary capital to asset ratio is a plausible proxy for the early onset of financial distress.[6] While capital ratios do not directly translate into composite CAMEL ratings, falling below the adequate level of capital defined here is nearly equivalent to entering the watchlist area used by Gilbert, Myer and Vaughan (1999).

The sample period 1988-1990 was selected, rather than a more current time period, in order to have sufficient problem banks. The FDIC reported that there were over 1,000 problem banks during these two years. Throughout the latter part of the 1990s (1995-1999), the FDIC never classified more than 151 banks as problems. Since most troubled banks are small (with total assets of less than $1 billion), we focus on these banks in our study. Very small banks with less than $300 million in total assets are excluded from our sample due to the fact that these

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allowance for loan and lease losses, net worth certificates, and minority interests in consolidated subsidiaries. Intangible assets and goodwill were excluded.

[5] As of December 31, 1990, bank holding companies and state member banks could choose to conform to either the old 5.5 percent primary capital and 6 percent total capital standards or the new 7.25 percent minimum risk-based capital standard (see Federal Reserve Regulatory Services Manual Section 12 CFR 225 titled "Capital Adequacy Guidelines for Bank Holding Companies and State Member Banks: Leverage Measure").

[6] It should be noted that the primary capital ratio has the advantage of potentially providing an earlier warning system than institutional closure, assisted merger or acquisition, or liquidation by regulators. The latter discrete conditions typically occur after a prolonged period of financial distress and represent the endpoint in the distress continuum. Predicting banks that will become capital deficient in the near future is tantamount to identifying the early onset of financial distress, as opposed to the final stage of financial distress. In addition to primary capital, capital zones based on simple capital ratios were used by the Federal Reserve during our sample period to flag risky banks (see Spong, 1985 for more detail on the capital zones).

banks tend to be highly specialized institutions focusing on a market niche or serving a low population area.

Financial and economic data are collected for sample banks and employed to test two earning warning system (EWS) models: the parametric method of logit analysis and nonparametric method of trait recognition analysis (TRA). In-sample models are developed using 1988 data that seek to classify banks correctly in 1989. Employing these models, we pass 1989 data through them to generate out-of-sample results for 1990. Our out-of-sample tests measure the predictive accuracy of the EWS models. In brief, the empirical results reveal that there is a statistical difference between determinants of financial condition for banks that will become capital deficient and those that will remain adequately capitalized. Also, EWS model results, especially those for TRA, indicate that computer-based methods can successfully predict pending capital adequacy for over 90 percent of individual banks one year ahead of time. We conclude that EWS models could be useful to bank regulators as both an off-site surveillance tool and a supplement to on-site examinations by supervisory personnel.

Section II reviews relevant literature, section III describes our methodology, section IV discusses the empirical results, and section V gives concluding remarks.

II. Literature Review

Several studies have examined financial distress, which is a pre-condition to firm's failure.[7] In general, these studies have found that accounting information can detect incipient financial distress of nonfinancial firms, and that different firm states on the financial distress continuum appear to be independent of one another. In other words, it has been documented that different sets of variables are important in predicting financial distress at the various states on the financial distress continuum. Therefore, EWS models previously developed to predict the late

state of regulatory closure or bankruptcy of commercial banks will likely differ from those seeking to predict an early stage of financial distress, such as deterioration in capital ratios.

Gilbert, Meyer, and Vaughan (1999) defined four possible states of U.S. commercial banks: bank failure, survival, safe (CAMELS ratings 1 or 2 by supervisors), and watchlist (CAMELs ratings 3, 4, or 5 by supervisors). Samples of banks from the 1980s and 1990s were used to compare the performance of econometric models (such as logit analyses) versus supervisory screens in predicting failures of banks 12 to 24 months before failure. Relevant to the present study, they also estimated EWS models of the likelihood that a bank will be downgraded from safe to watchlist 12 to 24 months prior to the fall in supervisory rating. In general, they found that EWS models outperformed supervisory screens in prediction accuracy. The equity capital ratio was found to be one of the most significant variables in their tests. The authors concluded that supervisors can use off-site surveillance via econometric methods to flag banks with increased financial distress and thereby supplement information obtained from on-site supervisory screens.

In addition, Catanach and Perry (1996) found that, among numerous studies attempting to predict S&L failure, only one variable was significant in all such studies – the equity capital ratio. Relevant to our purpose, they observed that: "Barth *et al.* (1989) indicate that the importance of the net worth ratio is not surprising since it is the variable that regulators use in closing institutions. Consequently, capital ratios may better represent dependent variables than independent variables in distress studies for financial institutions." (1996, p. 12).

Following this line of reasoning, Wheelock and Wilson (2000) conducted a study of the determinants of bank failure with the dependent variable defined as total equity to total assets ratios less than 2 percent. They identified 51 banks that were critically undercapitalized (i.e.,

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[7] See Altman (1964); Altman and McGough (1974); Altman, Haldeman, and Narayanan (1977); Ohlson (1980); Zmijewski (1984); Fydman, Altman, and Kao (1985); Zavgren (1985); Lau (1987); DeAngelo and DeAngelo

under the regulatory definition imposed by the Federal Deposit Insurance Corporation Act of 1991) with at least $50 million in total assets in the sample period 1984-1993. Because regulators have discretion in closing critically undercapitalized institutions, the 2 percent capital ratio can be considered to be a maximum threshold for financial distress. A competing-risks hazard model was constructed using 18 independent variables representing capital adequacy, asset quality, management, earnings, liquidity, size, age, and organizational structure. Interestingly, the variables significant in identifying critically undercapitalized banks were also significant in further tests based on a sample of banks closed by the FDIC as failed. Thus, the determinants of bank failure and extreme financial distress are quite similar to one another.[8]

Our study attempts to contribute further empirical evidence on financial distress in banking by using the equity capital ratio as the dependent variable to reflect an early stage of distress. Our objective is to develop a model that predicts one of two states -- capital adequate versus inadequate -- where the latter state represents capital levels that fall below a minimum threshold employed by bank supervisors. As mentioned earlier, we utilize a 5.5 percent capital ratio threshold to define the onset of financial distress. An advantage of our study with respect to previous studies of legal or regulatory failure is that our financial distress event is not biased by regulatory actions that typically take place as equity capital falls close to or below critical levels. Also, unlike Wheelock and Wilson, who focused on the determinants of critically undercapitalized institutions, we examine the efficacy of EWS models with respect to undercapitalized banks in general. Like Wheelock and Wilson, we provide information on the determinants of financial distress; however, we also report evidence on the ability of EWS models to predict such distress one year ahead of time.

(1990); Platt and Platt (1990); Coats and Fant (1993); Ward (1994); and Johnsen and Melicher (1994).

[8] Additional tests in the paper examined whether the same variables could be used to explain the time to acquisition of banks. The results were somewhat different from the failure tests, which could be to the fact that most acquired firms were not under financial distress.

III. Empirical Methodology

Two different EWS approaches are utilized in this paper: logit analysis and trait recognition analysis (TRA).

A. Logit Analysis

Logit is one of the most commonly employed parametric EWS methodologies in business academic studies as well as bank regulatory practice, especially in detecting potential failure risk – see Amemiya (1973, 1981) for a detailed discussion of this technique. The logit model has the statistical property of not assuming multivariate normality among the independent variables (see Espahbodi (1991, p. 56)). It formulates a multiple regression model of the following form:

$$\text{Log}(P_i/1\text{-}P_i) = \beta_{1i}(X_{1i}) + \beta_{2i}(X_{2i}) + \ldots + \beta_{ni}(X_{ni}), \qquad (1)$$

where P_i is the probability that bank i is a member of the capital inadequate group of banks as opposed to the capital adequate group of banks. The dependent variable is the log of banks' odds of capital inadequacy versus capital adequacy. A major advantage of logit models is that the statistical software is relatively simple to implement. After selecting the logit program and options and inputting data for the variables, the program can be run, and results are produced with no further researcher effort.

As discussed in the next section, our stepwise logit analysis employs 41 explanatory variables that are most important in terms of discriminatory power.[9] In view of work by Aldrich and Nelson (1984) and Stone and Rasp (1991) on miscalibration problems related to degrees of freedom and disparate sample sizes of the response groups, we infer that our sample sizes (to be discussed shortly) are sufficient to obtain efficient estimates of the logit parameters (i.e., the cumulative distribution of the error terms in the regression relationship approximates a logistic function).

Despite the widespread popularity of logit analysis as an effective EWS approach, it does have some drawbacks. For example, it is based on statistical assumptions that may not hold in the data (see section *B* below). Also, the model is not well suited to exploring interactions between large numbers of variables due to losses in degrees of freedom (e.g., in our case of 41 variables only a select group of interaction variables could be examined). Relatedly, interaction variables are typically computed by multiplying two variables, which tends to lose information. Consider two banks wherein one bank has a high return on assets and low capital ratio and the other bank has a low return on assets and high capital ratio. The product of the return on assets and capital ratio would be moderate in level in both cases; as such, their interaction would lose information about each of the component ratios. Finally, it is not possible to determine from the parameter estimates generated by logit models which variables are most useful in predicting capital inadequate banks versus those useful in predicting capital adequate banks. The results only indicate the effectiveness of each variable in discriminating between capital adequate and capital inadequate banks. While logit methods seek to minimize overall prediction errors, they do not provide any information about how each variable affects Type I and Type II errors (i.e., misclassifying a capital inadequate banks as capital adequate or a capital adequate banks as having inadequate capital, respectively).

B. Trait Recognition Analysis

Trait recognition analysis (TRA) is a nonparametric technique that identifies systematic patterns in the data. TRA was originally developed in the hard sciences and used to predict the risk of earthquakes and the location of oil and uranium fields.[10] In recent years it has been applied to predicting bank failure -- see Kolari, Caputo, and Wagner (1996) and Kolari, Glennon,

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[9] To enhance the predictive power of the stepwise logit models, we set the threshold for adding variables to the model at a significance level of 30 percent.

[10] See Bongard *et al*. (1966); Gelfand *et al*. (1976); Briggs and Press (1977); Briggs, Press, and Guberman (1977); Caputo *et al*. (1980); and Benavidez and Caputo (1988).

Shin, and Caputo (2002) for detailed discussions of this technique. TRA is most closely associated with neural network models in that it seeks to exploit information contained in complex interactions of the independent variable set. However, in neural network models variable interactions are contained in a hidden or latent layer that cannot be observed, whereas TRA identifies and documents all variable interactions.

TRA also avoids some of the pitfalls of traditional econometric models, such as assumptions about the underlying distribution or independence of the variables. Econometric models assume that the dependent variable is drawn from a specific distribution. Deviations from this assumption could be caused by such things as sample selection bias or truncated variables. Other assumptions common to econometric models include: the error terms in the regression equation have a common variance and are independent, the independent variables are uncorrelated, all important variables are observable, and the equations are correctly specified. Statisticians have devised numerous diagnostic statistics to identify the degree of the problem and correction factors that may be applied. However, as Judge, *et al*. (1982) have cautioned,

> " . . . there is great potential for making an erroneous decision. The models presented above [econometric models that relax the assumption of fixed parameters] are only as good as the structural information imposed on the parameter variation. At present there is usually little but intuition and ad hoc rules of thumb to guide us in our selection of an appropriately general parameterization of the statistical model." (1982, p. 510)

A unique aspect of TRA is that variable interactions are formed to be consistent with the logic of a financial analyst, rather than simple cross products of variables as in logit or other discriminatory methods (including neural network models). For example, an interaction variable could be defined as a high return on assets and low capital ratio, or vice versa. As such, information about the components of interaction variables is not lost. In general, there are five steps to building a TRA model: (1) selecting cutpoints for each variable, (2) binary coding of the variables, (3) constructing a trait matrix for each observation, (4) identifying good and bad traits (or features), and (5) implementing voting matrix classification rules.

STEP 1. Variables believed to be important factors in explaining capital deterioration are collected. The number of variables does not impact the efficiency of the analysis as it does in traditional econometric analysis so more potentially relevant variables can be included in the analysis. Cutpoints are used to divide the distribution of each independent variable into three regions: upper, middle, and lower. The regions should be constructed so banks that are capital adequate and capital inadequate are predominantly in the upper or lower regions, respectively, and the middle region contains a mix of these two groups of banks. For example, for ROA capital inadequate banks would be clustered in the lower ROA range, capital adequate banks would be clustered in the high ROA range, and the middle range would contain a mixture of capital adequate and inadequate banks. The cutpoints that divide the variables into the three regions can be determined in several ways; plots of the distribution of the variable for capital adequate and inadequate banks and manual selection of cutpoints, a general rule such as one standard deviation around a sample mean, or expert knowledge based on theory or practice. We used a mathematical approach that mimics manual selection. We compute the difference between the following two measures: (1) the absolute value of the proportion of capital adequate banks to the left of an arbitrarily selected cutpoint (i.e., lower region) minus the proportion of capital inadequate banks to the left of this cutpoint; (2) the absolute value of the proportion of capital adequate banks to the right of an arbitrarily selected cutpoint (i.e., upper region) minus the proportion of capital inadequate banks to the right of this cutpoint. This number varies from 0 to 2. Assuming a 0 value, 50 percent of each group of banks would be in both lower and upper regions. Assuming the value is 2, 100 percent of one group would be in the lower region and 100 percent of the other group would be in the upper region (i.e., optimal separation). We selected cutpoints for which this value was at a maximum. Cutpoints are expressed as standard

deviations from the mean for ease of understanding their location in the distribution of each variable.

STEP 2. The lower, middle, and upper regions of the distribution for each variable (as defined by the two cutpoints) are coded, 00, 01, 11, respectively. Given j = 1, …, n banks and i = 1, …., p variables, the jth bank's vector of variables $X_{ij} = [X_1, \ldots, X_p]$ is recoded into binary form $X_{ij} = [B_1, B_2, \ldots. B_L]$, where L is the length of the string and two digits describe each variable. For example, variable vector [X1, X2, X3] = [010011] implies that bank j is in the middle (01), lower (00), and upper (11) regions of the distributions of X1, X2, and X3, respectively.

One disadvantage of classifying the variables in this manner is that continuous variables are converted to discrete categories. While it is true that some information may be lost, it does permit testing of complex interactions between the regions for each of the variables. Another beneficial side effect is that the analysis is less sensitive to outliers that can distort the results of traditional econometric analysis.

STEP 3. Once the variables are divided into the relevant regions and combinations of the regions are developed, a matrix of traits is constructed for each bank in the sample. The matrix allows for all possible interactions of the segmented variables' distributions. For example, one trait could be a high return on assets and low capital ratio, and vice versa for a second trait. In this way interactions between variables can incorporate information on the level of each of the variables. Of course, single variables are included in the trait matrix. And, in contrast to other discriminatory methods, three variable interactions can be explored (e.g., high return on assets, low capital, and moderate to high levels of loan losses).

STEP 4. A search routine is used to identify traits that are frequently found in one group but infrequently found in the other group. These discriminatory traits are known as features.

Both good features common in capital adequate banks and bad features common in capital inadequate banks are produced. Traits that are not useful in discriminating between the two groups of banks are dropped from the analyses. The researcher must select minimum and maximum frequencies (in terms of proportions) of capital adequate and inadequate banks. For example, a minimum of 80 percent of capital adequate banks and maximum 30 percent of capital inadequate banks in the upper region of the variables' distributions could be used to define a good feature. The researcher manually changes these parameters in the program to define so-called *good* and *bad* features and yield different classification and prediction results.

STEP 5. Banks are classified as safe or unsafe depending on the number of good or bad features that they have. This can be likened to the decision that the researcher must make when using logit where a cut-off must be defined to classify the dependent variable as a "0" or a "1". If only good or bad features are present, the classification is easy. However, when both good and bad features are present, the decision rule is based on the dominance of one type of feature over another. In effect, a voting matrix is created to display the observations in cells defined by the number of good and bad features. If the number of good features is greater than the number of bad features for a bank, it is classified as capital adequate, and vice versa for capital inadequate banks.

Like logit, TRA is not without drawbacks. The most serious difficulty is the considerable hands-on manipulation required by the researcher. In contrast to logit models, TRA software demands that users perform a number of intermediate steps, such as creating and inputting cutpoints as well as selecting the minimum and maximum percentage definitions of features. These steps are time consuming and *ad hoc* in nature. Consequently, some amount of researcher expertise with the independent variables is beneficial in conducting TRA analyses. Another drawback of TRA is that no measures of variables importance are available at this time. This

shortfall is not an issue if the researcher's goal is to successfully predict capital adequacy; however, if the focus of the analyses is on the determinants of capital adequacy, the logit model is more appropriate due to statistical measures of variables' significance.

C. Data

Financial data for U.S. commercial banks with total assets between $300 million and $1 billion were collected from the Call Reports of Income and Condition for year-end 1988, 1989, and 1990. Our explanatory variables for predicting banks that will become capital inadequate include a wide variety of on- and off-balance sheet measures used by regulators to gauge bank risks, including profitability, loan risk, operational risk, liquidity risk, interest rate gap, bank size, derivatives exposure, loan commitments, years in the banking business, and changes in loan compositions. We also incorporate a number of control variables that reflect economic conditions, including information on business bankruptcy filings in the state in the past year, rural versus urban location of the bank, and income per capita and permits per capita in the state where the banks are located.

Our research methodology is implemented in two steps. First, for the original sample using year-end 1989 data, each sample bank was assigned a dummy value of 1 (adequate capital) if the ratio of primary capital to total assets is equal to or greater than 5.5 percent, and 0 (inadequate capital) otherwise. Financial and economic data are assembled for the original sample one-year prior to the capital inadequacy event or year-end 1988, and the logit and TRA models are developed. Second, the data for 1990 holdout sample was then coded as 0 or 1 based on the 5.5 percent primary capital ratio as of year-end 1990. One-year prior (year-end 1989) data for the independent variables were passed through the logit and TRA models for holdout sample banks. As such, the holdout sample allows us to observe the predictive ability of the EWS models with data that was not employed in their development.

After dropping institutions with missing data, the following sample sizes were obtained for the original and holdout samples:

	Capital adequate	Capital inadequate	Total
Original samples (1989):	451	71	522
Holdout sample (1990):	461	77	538

IV. Empirical Results

Table 1 lists the independent variables and provides basic statistics for the original and holdout samples. The independent variables are the various characteristics of the banks (such as profitability, liquidity risk, market risk, off-balance sheet risk, foreign exchange risk, suspect loans, operating efficiencies, size, age, volatility, and growth) and economic variables (such as per capita income, bankruptcy filings, and number of permits per capita). The t-statistics in Table 1 test the null hypothesis of no significant difference in the levels of a particular variable for capital adequate versus inadequate banks. Asterisks indicate a failure to accept the null hypothesis and acceptance of the alternate hypothesis that there was a significant difference in the levels of the respective variable between the two response groups. In the original one-year prior sample, 21 out of 41 independent variables are significantly different in the two response groups, while 19 out of 41 independent variables are significantly different in the holdout one-year prior sample. In most cases, significant variables in the original sample are also significant in the holdout sample.

Generally speaking, capital deficient banks tended to have lower profitability, higher risk, and higher levels of expenses than other banks. These results suggest that banks pending capital deficiency have financial profiles that substantially differ from well-capitalized banks. Also, banks that were capital inadequate tended to be located in states with higher business bankruptcy filings and in urban regions as opposed to rural regions. The numerous significant differences

between capital adequate versus inadequate banks suggest that it would be appropriate for our variables to be used as predictors of capital deficiency in EWS models.

Tables 2 and 3 provide details of the logit and TRA models, respectively, developed from the original sample using 1988 data. As shown in Table 2, 15 out of 41 variables are retained in the one-year prior logit model. Out of these 15 variables, 12 were significant in the univariate t-tests shown in Table 1. Thus, both the univariate and multivariate statistical analyses are consistent with one another for the most part in terms of identifying significant predictors. In a multivariate context each of the variables in the stepwise logit model contributes unique discriminatory information not available in the other variables. Notably, the following independent variables are significant at the 10 percent level: X1 (profitability), X6 (urban versus rural location of bank), X9 and X11 (growth rates of commercial and industrial loan and consumer loans, respectively), X13, X29, X32, and X33 (credit risk measures), X18 (number of full-time employees), X37 (other real estate loans), and X40 (investment securities)

Banks that expanded their consumer lending rapidly tended to significantly add risk to their portfolio, which subsequently resulted in losses and deterioration in the capital ratio. It is possible that these banks attracted marginally creditworthy customers. In contrast, rapid expansion of commercial and industrial loans (rather than consumer loans) tended to increase profitability and reduced the likelihood that the capital ratio would fall below the threshold limit. We interpret this finding to mean that business customers pay higher loan fees and often pay fees on other investment and payment services which boost profitability more than consumer loans.[11]

[11] Another possible explanation may be related to policies for dealing with problem loans in these two types of portfolios. For consumer loans, it is customary to charge-off problem loans rapidly due to their short-term nature. For commercial and industrial loans, however, banks are more likely to work with borrowers for a longer period of time; in turn, it takes longer for problem business loans to be placed on nonaccrual status than consumer loans. As long as interest is accruing, business loan growth would contribute to reported income, reducing declines in capital ratios. This difference between business and consumer loans is, however, likely to decrease if the time horizon is longer than one year.

Other results indicate that banks with higher proportions of assets invested in investment securities had a greater cushion against bad lending decisions and, consequently, were less likely to encounter financial distress. Likewise, more profitable banks with greater net income to total assets tended to have a lower probability of financial distress in the near future. Finally, the likelihood of financial distress was reduced by lower credit risk, in addition to larger numbers of bank employees.

Table 3 lists the cutpoints selected for independent variables in our TRA models. These standard deviations from the mean are used to define lower, middle, and upper regions for binary coding purposes. With the exception of X4 (business bankruptcy filings), the cutpoints were less than one standard deviation above or below the mean level for the variables. These results suggest that low and high regions were not extreme levels and, as such, capital adequate and inadequate banks tended to be found well within normal levels of typical financial measures of bank condition. By inference, we interpret this to mean that it is relatively difficult to discern capital adequate versus inadequate banks from any particular financial ratio; instead, a multivariate analysis is needed.

Unlike the logit model, most of the 41 independent variables were included in the TRA model; indeed, 31 out of 41 variables are employed in the TRA features.[12] This evidence implies that capital adequacy is a broad concept that requires review of a wide array of different kinds of financial and economic variables. Also, since more than 90 percent of the features were interaction variables, we infer that capital adequacy is a complex concept involving multiple measures of bank financial condition.

[12] To conserve space we do not list the good and bad features of our TRA models, which are available upon request from the authors. The 10 variables not entering the features list in the TRA model are X2, X3, X4, X15, X20, X23, X26, X31, X36, and X41. Only one of these variables, or X23, entered the logit model. Thus, variables unimportant in TRA analyses tended to also be insignificant in the logit analyses.

Table 4 contains the classification results for the original 1989 sample and the prediction results for the holdout 1990 sample. Because logit models can be run with a variety of prior probabilities of capital adequacy, we report mean results in panel A for two ranges of prior probabilities: 0.80 – 0.90 and 0.10 – 0.20 (i.e., prior probabilities are incremented by 0.02 to run six models for each range). It should be noted that the actual probability of being in the capital adequate group in the original sample is 86 percent, such that the former range is most consistent with our sample data. Nonetheless, we report results for the latter range to give a more complete description of the logit results. Similarly, we report mean results for the TRA models run within ranges of minimum and maximum percentages used to define the good and bad features (i.e., a total of 20 models are tested).

The overall classification and prediction results for TRA tend to dominate the logit models. On average the classification and prediction results are fairly good at 88 percent and 85 percent, respectively, using the sample-based prior probability range of 0.80-0.90. However, Type I errors (i.e., misclassifying a capital inadequate bank as adequate) are quite high, with 83 percent misclassification in the original sample and 90 percent prediction error in the holdout sample. Type I errors are most serious, as they mean that the model failed to warn regulators that the bank was going to fall below capital standards in the near future. Using a much lower prior probability range of capital adequacy of 0.10 – 0.20, Type I errors for the logit models dropped substantially to 30 percent in the original sample and 43 percent in the holdout sample.

TRA not only performed better in terms of overall accuracy but with respect to reducing Type I errors also. Overall classification and prediction accuracy was strong at 99 percent and 91 percent, respectively. Importantly, this accuracy did not sacrifice Type I errors, with only 2 percent misclassification in the original sample and 9 percent prediction error in the holdout sample occur.

Overall, these results bode well for computer-based methods of evaluating potential capital inadequacy of commercial banks. Our findings demonstrate that logit models can provide information on the determinants of capital inadequacy that bank supervisors should monitor, while TRA models can serve as effective early warning systems (EWSs) of pending capital adequacy for individual banks that enables more efficient allocation of supervisory resources. Thus, EWS models could be useful in the supervisory process as an off-site surveillance tool and as a supplement to on-site examinations by supervisory personnel.

V. Conclusions

The Basle Agreement of 1988 was a landmark international banking accord among 12 major industrial countries that proposed uniform capital standards. Pursuant to this agreement, capital standards have become central to bank regulatory oversight of financial institutions. From a regulatory standpoint, an important goal is to identify banks prior to the onset of financial distress as reflected in below-standard capital levels. In this regard, this paper has sought to empirically test the efficacy of early warning system (EWS) models with respect to the identification of capital inadequacy among U.S. commercial banks in the near future. We defined an early stage of financial distress to occur when the ratio of total equity to total assets falls below 5.5 percent, which was an initial regulatory threshold for capital adequacy purposes during our sample period. Our sample included all insured U.S. banks with total assets in the range of $300 million to $1 billion from year-end 1988 to year-end 1990. Financial and economic variables typically employed by bank regulators to evaluate safety and soundness are gathered for the sample banks and employed to develop logit and the trait recognition analysis (TRA) models as computer-based EWSs. A holdout sample is used to test the prediction accuracy of the models.

Our results demonstrate that banks pending capital deficiency in the near future are much different from other banks in terms of their financial health. We find that capital adequacy is a broad concept that is determined by a wide array of different kinds of financial and economic variables. In this respect the TRA results highlight the importance of complex interaction variables in identifying banks that will become capital deficient. Further EWS model results, especially those for TRA, indicate that computer-based methods can successfully predict pending capital adequacy for over 90 percent of individual banks one year ahead of time. We conclude that EWS models could be useful to bank regulators as both an off-site surveillance tool and a supplement to on-site examinations by supervisory personnel.

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Table 1. Descriptive Statistics for the Independent Variables: Means and t-Tests[a]

		Original Sample 1988 Data:		*Hold-Out Sample 1989 Data:*	
X_j	*Variable Description*	*Capital Inadequate*	*Capital Adequate*	*Capital Inadequate*	*Capital Adequate*
X1	Net income after taxes to total assets	-0.0001	0.010***	0.001	0.010***
X2	Non-interest expenses to total assets	0.035	0.031***	0.034	0.031*
X3	Number of bankruptcy filings	23,286	24,111	24,044	27,623
X4	Business bankruptcy filings information	3,032	2,159**	2,692	2,167*
X5	Dummy 0,1 variable for de novo bank (as measured by age less than 10 years)	0.072	0.067	0.078	0.076
X6	Dummy 0, 1variable for MSA (metropolitan statistical area) versus rural location of the main office	0.971	0.905***	0.974	0.891***
X7	Total assets (in $1,000)	530,755	496,46	535,403	498,962
X8	Average quarterly loan growth over the year for agricultural loans to total loans (%)	17.105	5.319	6.056	32.121
X9	Average quarterly loan growth over the year for commercial and industrial loans (C&I) to total loans (%)	2.422	4.405	3.048	2.082
X10	Average quarterly loan growth over the year for commercial real estate to total loans (%)	12.073	8.578	4.129	6.874
X11	Average quarterly loan growth over the year for consumer loans to total loans (%)	9.008	4.555**	24.947	9.263
X12	Average quarterly loan growth over the year for mortgage loans to total loans (%)	5.680	302.44	11.041	5.958
X13	Provisions for loan and lease losses to total assets	0.015	0.009***	0.013	0.009***
X14	Other borrowed funds to total assets	0.017	0.017	0.016	0.016
X15	Core deposits to total deposits	0.455	0.479	0.482	0.505
X16	Total cash dividends to total assets	0.003	0.005**	0.003	0.005***
X17	Net interest income plus non-interest income to non-interest expenses	1.396	1.643***	1.486	1.670***
X18	Number of full-time employees to total assets	0.0006	0.0005**	0.0006	0.0005***
X19	Short-term interest rate gap (as measured by short-term assets minus short-term liabilities) to total assets	0.138	0.117	0.164	0.100***
X20	Income per capita, as measured by personal income to labor force at the state level	34.294	33.030	38.557	36.482***
X21	Loans made to insiders to total assets	0.002	0.003	0.003	0.002
X22	Insured deposits to total liabilities	0.655	0.720***	0.730	0.734
X23	Jumbo CDs to total assets	0.158	0.123***	0.154	0.123***
X24	Short-term assets to short-term liabilities	2.212	5.773	1.599	3.441
X25	Total loans to core deposits	2.380	16.212	1.596	9.168
X26	Total loans to total deposits	0.798	3.672	0.758	7.707
X27	Average maturity of assets (years)	3.809	4.461**	3.562	4.501***
X28	Non-performing loans past due more than 90 days and still accruing to total assets	0.004	0.003*	0.005	0.003***

X29	Non-performing loans past due more than 90 days and not accruing to total assets	0.018	0.006***	0.016	0.006***
X30	Agricultural non-performing loans to total agricultural loans	0.014	0.014	0.014	0.014
X31	Commercial and industrial (C&I) non-performing loans to total commercial and industrial loans	0.034	0.019***	0.032	0.021**
X32	Consumer non-performing loans to total consumer loans	0.010	0.006*	0.008	0.007
X33	Real estate non-performing loans to total loans secured by real estate	0.048	0.014***	0.039	0.014***
X34	Foreign exchange transactions to total assets	0.001	0.015	0.001	0.011
X35	Off-balance sheet interest rate risk (as measured by all foreign exchange derivatives and futures, forward, and options contracts) to total assets	0.017	0.010	0.013	0.013
X36	Off-balance sheet loan commitments (as measured by standby letters of credit) to total assets	0.128	0.117	0.126	0.110
X37	Other real estate loans to total assets	0.010	0.003***	0.007	0.038**
X38	Number of permits per capita, as measured by housing permits issued to labor force in the state	0.011	0.011	0.010	0.010
X39	Provision for loan and lease losses to total assets	0.011	0.004***	0.009	0.004***
X40	Investment securities (as measured by the book value of investment securities) to total assets	0.138	0.217***	0.129	0.217***
X41	Volatility of consumer loan volume	0.273	0.206**	0.210	0.215

[a]T-tests for mean differences in the capital inadequate versus adequate banks at the following levels of significance: *** -- 0.01, ** -- 0.05, and * -- 0.10.

Table 2. Stepwise Logit Model[a]

Variables	*Parameter Estimate*	*Standard Error*	*P-Value*
Intercept	0.70	1.42	0.2444
X1 – Net income after taxes/total assets	-117.0***	34.49	0.0007
X6 – Dummy variable for urban versus rural location	1.61*	0.92	0.0800
X8 – Agricultural loan growth rate	0.003	0.002	0.2031
X9 – Commercial and industrial loan growth rate	-0.04**	0.02	0.0232
X11 – Consumer loan growth rate	0.02**	0.01	0.0296
X13 – Provisions for loan and lease losses/total assets	95.74***	30.66	0.0018
X15 – Other borrowed funds/total assets	-6.71	2.42	0.0056
X17 – Net interest income plus non-interest income/ non-interest expenses	-0.64	0.54	0.2330
X18 – Number of full-time employees/total assets	-2,373.2**	998.5	0.0175
X23 – Jumbo CDs/total assets	-2.00	1.62	0.2171
X29 – Non-performing loans past due more than 90 days/ total assets	-57.00**	24.40	0.0195
X32 – Non-performing consumer loans/consumer loans	16.82*	9.04	0.0629
X33 – Non-performing real estate loans/real estate loans	9.63	7.07	0.1732
X37 – Other real estate loans/total assets	41.95**	17.62	0.0172
X40 – Investment securities/total assets	-9.80***	2.01	0.0001

[a]The p-value threshold for entering variables was increased from the default value of 0.10 to 0.30 in order to improve prediction performance on the holdout sample. Asterisks indicate variable significance at the following levels: *** -- 0.01, ** -- 0.05, and * -- 0.10.

Table 3. Cutpoints for the Independent Variables in the Trait Recognition Model

Variable	*Left Cutpoint*	*Right Cutpoint*	*Variable*	*Left Cutpoint*	*Right Cutpoint*
X1	-0.24	0.07	X23	-0.03	0.36
X2	-0.27	0.49	X24	-0.05	0.61
X3	-0.68	0.30	X25	-0.06	0.19
X4	-0.30	2.26	X26	-0.03	0.01
X5	0.00	0.01	X27	-0.06	0.73
X6	0.00	0.01	X28	-0.01	0.28
X7	-0.27	0.01	X29	0.00	0.21
X8	-0.11	0.34	X30	-0.10	0.54
X9	-0.45	0.32	X31	0.00	0.65
X10	-0.19	0.36	X32	0.00	0.23
X11	-0.05	0.36	X33	-0.23	0.17
X12	-0.03	0.01	X34	-0.03	0.03
X13	-0.06	0.16	X35	-0.18	1.93
X14	-0.17	0.34	X36	-0.06	0.04
X15	0.00	0.02	X37	-0.06	0.62
X16	-0.41	0.03	X38	-0.75	1.32
X17	-0.26	0.02	X39	-0.18	0.01
X18	-0.69	0.51	X40	-0.75	0.11
X19	0.00	0.22	X41	-0.02	0.53
X20	-0.21	0.18			
X21	-0.27	0.01			
X22	-0.04	0.42			

Table 4. Classification and Prediction Results for Logit and TRA Models

A. Mean Results for Logit Model

Range of prior probability of capital adequacy tested (6 models): 0.80 – 0.90

Original Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	17%	83%
Adequate	1%	99%

Percentage Correct: 88%

Holdout Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	10%	90%
Adequate	3%	97%

Percentage Correct: 85%

Range of prior probability of capital adequacy tested (6 models): 0.10 – 0.20

Original Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	70%	30%
Adequate	18%	82%

Percentage Correct: 80%

Holdout Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	57%	43%
Adequate	8%	92%

Percentage Correct: 75%

B. Mean Results for TRA Model

Ranges of model features tested (20 models):
Good features: 66% - 76% minimum capital adequate banks and
30% - 36% maximum capital inadequate banks
Bad features: 70% - 78% minimum capital inadequate banks and
30% - 40% maximum capital adequate banks

Original Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	98%	2%
Adequate	1%	99%

Percentage Correct: 99%

Holdout Sample

Actual:	Predicted: Inadequate	Adequate
Inadequate	91%	9%
Adequate	10%	90%

Percentage Correct: 91%