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MODELING LARGE COMMERCIAL-BANK FAILURES: A SIMULTANEOUS-EQUATION ANALYSIS

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I. INTRODUCTION

The decade of the 1980s has been a turbulent one for the United States banking and financial system. Since the establishment of the Federal Deposit Insurance Corporation (FDIC) in 1933, more than 1,500 banks have been closed. Over 800 of these failures occurred during the 1980s with 200 institutions failing in 1988 alone. The dramatic increase in the bank failure rate has intensified public criticism of deposit institution regulators, since bank soundness is a major regulatory responsibility.

This paper is concerned with modeling and predicting large commercial-bank failures. The adverse consequences of bank failures, such as loss of depositors' funds, failures of other banks, and financial distress caused by sharp contractions in the money supply are no longer considered serious concerns because of the Federal Reserve System's lender-of-last-resort responsibilities and federal deposit insurance (Benston, et al. [1986] and Kaufman [1985]). Nevertheless, deposit-insurance agencies are unintentionally destabilizing the financial system by subsidizing deposit-institution risk-taking through their insurance-pricing, coverage, monitoring, and insolvency-resolution policies (Kane [1985, 1986] and McCulloch, [1987]). Individual-institution insolvencies and failures remain a serious problem for the insurance system's implicit guarantors, namely the general taxpayer and conservatively managed institutions.

In cases where failure cannot be prevented, on average, the sooner the bank is declared insolvent and its management changed, the smaller the losses will be. Although not openly acknowledged by federal regulators, this fact underscores the importance of research in the area of failure prediction. Being able to model deposit institution failures can be helpful in controlling taxpayer loss exposure.

An accurate bank-failure model should begin by distinguishing between insolvency and failure. Insolvency and failure of financial institutions are separate processes. Legal insolvency occurs when an institution cannot cover its current liabilities. In economic terms, an institution becomes insolvent when the market value of its stockholder-contributed equity becomes negative. This happens when the market value of its nonequity liabilities exceeds the market value of its assets, net of deposit insurance guarantees. Failure is not an automatic consequence of legal or economic insolvency. It results from a conscious decision by regulatory authorities to acknowledge and act upon the weakened financial condition of the institution. Most earlier bank failure studies (Altman [1977], Avery and Hanweck [1984], Barth, et al. [1985]; Benston [1985]; Martin [1977]; and Sinkey [1975]) with the exception of Gajewski (1988), have neglected this difference between economic insolvency and failure. Failure is typically studied by analyzing a large number of financial ratios as if it were equivalent to insolvency. All the studies concentrate on small, untraded, institutions and assume that book values provide an unbiased estimate of market-value insolvency.

This paper goes beyond previous empirical studies in a significant way. It proposes to study insolvency and failure simultaneously, treating economic insolvency as only one of the various factors that influence the failure decision. The model of the regulator's failure decision developed here also recognizes as relevant factors general economic constraints as well as the economic, political, and bureaucratic constraints faced by the regulators.

Using a simultaneous-equations model makes it possible to study the determinants of economic insolvency and the regulators' reaction to this financial condition at the same time.

The paper is organized as follows: Section II develops the model and its theoretical foundation. The choice of variables and the functional form, as well as the expected signs, are discussed in section III. The estimation technique and data are explained in section IV. Section V presents and discusses the empirical results; section VI concludes the paper.

II. THE MODEL AND ITS THEORETICAL FOUNDATION

2.1 Federal Regulators and their Changing Incentives

Deposit insurance agencies serve multiple purposes (Kane, 1985). Their most important goal is to serve the president and the Congress by adapting to their economic policies and protecting them from public criticism whenever a crisis surfaces involving unsafe or unsound banking practices. Also, federal deposit insurance agencies cooperate with the office of the Comptroller of the Currency (which charters national banks), state banking departments (which supervise the entry and exit of state-chartered institutions), and the Federal Reserve to represent and enforce the beneficial interest of depositors. Through periodic examinations and continuous supervision, regulators try to prevent deposit institutions from abusing their informational advantage over their customers. These monitoring efforts make it hard for institutions to misrepresent their economic condition to depositors. By undertaking to guarantee deposits, insurance agencies also relieve the small account-holders (up to $100,000) of any need to worry about their deposits. Finally, deposit insurance has the macroeconomic goal of protecting the "safety and soundness" of the banking system. To promote public confidence in the system, insurance agencies try to prevent individual deposit institution failures.

Trying to achieve multiple goals, deposit insurance agencies often find themselves in conflict between the short-run benefits of avoiding deposit institution failures by bailing out clients and the long-run effects of such actions on market discipline. In addition to the conflicting goals of the insurance agencies, the deposit insurance bureaucrats also face changing incentives (Kane , 1988). Regulators, as opposed to the "faithful agent" image they prefer to portray, are in fact self-interested agents whose decisionmaking process is not necessarily determined by society's long-term goals. Kane (1988) points out, that when a problem becomes too difficult to resolve, it is to the regulator's interest to initially cover up and deny the problem instead of honorably confronting it. Regulators tend to bury their heads in the sand and hope the problem will disappear so that they can go on to lucrative post-government jobs, having adequately met the demands of their high post. Needless to say, the forbearance policies adopted in pursuit of self-interest are far from guarding the long-term interests of the public. The interests of the public and regulators once more coincide only when the size of the problem becomes so great that the probability of being able to further "cover up" and "get away" becomes very small.

2.2 Insolvency vs. Failure

The conflicting goals and corrupting incentives of the deposit insurers have led to forbearance policies, creating the distinction between the insolvency and the failure of an insured institution. Economic insolvency exists when the market value of an institution's stockholder-contributed equity becomes negative. However, "failure", the legal recognition of an institution's preexisting economic insolvency, is an option that the regulators may or may not choose to exercise.

There are five methods available to the regulators for resolving a potential failure:

1. deposit payoff, which kills the corporation by putting its offices out of operation;
2. direct assistance, usually in the form of a subsidized loan to (or taking an equity position in) the institution;'

3. bridge bank, which is interim FDIC operation of the failed institution;
4. reorganization, which means restructuring the institution's uninsured debt; and
5. financially assisted purchase-and-assumption transactions, where typically a healthier institution purchases at auction some or all of the failing institution's assets and assumes all of its deposits with compensation the from FDIC to balance the deal (Kane, 1985).

Legally, each time it resolves an insolvency, the FDIC must choose the resolution technique that minimizes the cost to the insurance fund. However, since the performance of insurance-agency bureaucrats is not judged by agency profits, in practice, the insurance agency's commitment to minimizing the risk of cumulative failures modifies its commitment to minimizing the economic costs of individual failures

In an effort to promote public confidence in the banking system and to serve their self-interest, deposit insurers often delay de jure failure of insolvent institutions, creating an artificial difference between insolvency and failure. The myopic handling of insolvencies tends to increase the expected future cost to the insurance agencies since the federal guarantees establish an asymmetric mechanism for sharing unanticipated gains and losses (Kane, 1986). This asymmetry exists since, due to stockholders' limited liability, the guarantor absorbs a larger share of unanticipated losses than of unanticipated gains. By allowing the insolvent institutions to operate, the insurance agencies increase the expected future cost to their fund since the asymmetry increases as the capital of the institution decreases. Also, uninsured creditors take advantage of this opportunity to improve their positions and it becomes in the interest of the stockholders of such institutions to take the largest risks possible. In addition, subsidies designed to stop the cumulative short-run spread of current losses to a few other institutions undermine longer-run market sanctions against risk-bearing for all institutions.

These long-run and system-wide implicit costs are often ignored. When a failure decision is eventually made, the resolution method chosen is seldom a deposit payoff due to the following pressures: (1) minimizing explicit short-run costs to the deposit insurance fund, (2) political consequences of adjustment costs imposed on individuals with broken banking connections, (3) possibility of bank closings being viewed as a blot on regulators' and politicians' records, and (4) increasing the chance of disrupting the public's confidence in other deposit institutions (Kane, 1985). In this study, insolvency-resolution methods other than shotgun stockholder recapitalization--such as nationalization, reorganization, interim FDIC operation, supervisory mergers, and financially assisted purchase and assumption transactions--are treated as instances of de facto failure.

2.3 The Model of the Regulators' Failure Decision

The model developed here assumes that the regulators' recognition of insolvency depends on their minimization of short-run explicit expected cost subject to various economic, political, and bureaucratic constraints. In each period, optimizing regulators are faced with two alternatives (failure/continue operation) in their decisionmaking process. Since one alternative must be chosen at each time, a binary-choice model is appropriate here. The binary decision by the regulators (about the ith institution) can be conveniently represented by a random variable that takes the value one if a failure decision is made and the value zero if the institution is allowed to operate. Since the FDIC's decision cannot be predicted with certainty, we model the choice probabilities. It is of interest to see how various explanatory variables affect the probability of a failure decision by the FDIC.

Let F^* be a latent continuous variable that expresses the outcome of the FDIC's binary choice such that:

$F = 1$ when a failure decision is made,

$F = 0$ when the institution is allowed to continue operation.

Assume the following regulator cost function:

$$F[\alpha(X_1)] + (1-F)[c(X_2)],$$

where
$$\alpha(X_1) = X_1\beta_\alpha + e_\alpha,$$
$$c(X_2) = X_2\beta_c + e_c.$$

The functions $\alpha(X_1)$ and $c(X_2)$ are stochastic-constrained costs of failing the institution and allowing it to operate, respectively. The nonstochastic portions of these expressions can be modeled as linear functions of variable vectors, X_1 and X_2. Any unobservable random influences are captured by the stochastic error components e_α and e_c.

Hence, a failure decision is only made if the constrained cost of failing the institution is less than allowing the institution to operate and vice versa:

$F = 1$ if $\alpha(X_1) < c(X_2)$,

$F = 0$ $\alpha(X_1) > c(X_2)$.

Now we can define F^* as the net incentive to make a failure decision,

$F^* = c(X_2) - a(X_1)$.

A failure decision is made if the incentive is greater than zero, and the institution continues to operate autonomously if it is not:

$F = 1$ if $c > \alpha$ $F^* > 0$,

$F = 0$ $c < \alpha$ $F^* < 0$.

Placed in a regression framework this threshold argument may be expressed as:

$F^* = X\beta + v$ where $X_1, X_2 \subset X$ and $v = e_c - e_\alpha$

then,

$$\begin{aligned} E(F^*) = P(F=1) &= P(W > \Theta) \\ &= P(X\beta + v > \Theta) \\ &= P(X\beta + e_c - e_\alpha > \Theta) \\ &= P(e_\alpha - e_c < X\beta) \\ &= \mathcal{F}(X\beta) \end{aligned}$$

where $\mathcal{F}$ is the cumulative distribution function of the $e_\alpha - e_c$. The type of the probability model we get depends on the assumption about the distribution of errors.

Thus, the failure equation models a constrained-cost minimization by the regulators. The independent variables, X, include bank-specific variables, general economic condition variables as well as FDIC constraint proxies.

One of the variables that affect the regulators' failure decision, is the market value of stockholder-contributed equity. This net equity value summarizes the bank's financial condition. Using an option-pricing equation to estimate the value of the federal guarantees (Schwartz and Van Order [1988]; Markus and Shaked [1984]), it is possible to construct net equity by subtracting the estimated guarantee value from the market value of the institution. It is also important to note that the market value of the institution, from which the degree of insolvency (net value) is constructed, is an endogenous variable itself. Therefore, there is need for a separate equation to study the determinants of economic insolvency (Maddala, 1986).

The full model consists of three equations. The first equation models the determinants of economic insolvency or economic value of the institution. The second equation obtains the estimate of the market value of stockholder-contributed equity, or net economic value, by subtracting the estimated value of the guarantee from the estimated market value of the institution. Finally, the third equation estimates the probability of a failure decision by the regulators. In symbols:

$$MV_{i,t} = h\ (Y_{i,t}) + u_{1i,t} \quad (1)$$

$$NV_{i,t} = \hat{MV}_{i,t} - \hat{G}_{i,t} \text{ and } G_{i,t} = g(Z_{i,t}) + w_{i,t} \quad (2)$$

$$F_{i,t}^{*} = f(NV_{i,t},\ X_{i,t}) + u_{2i,t} \quad (3)$$

where,

$MV_{i,t}$ = market value of the ith institution's equity at time t. MV is the price per equity share multiplied by the number of shares outstanding.

$G_{i,t}$ = value of the ith institution's explicit and conjectural federal guarantees at time t.

$NV_{i,t}$ = net economic value of the ith institution at time t. It is constructed by subtracting the estimate of the federal guarantee value from the estimated market value of the institution.

$F_{i,t}^{*}$ = the incentive variable that determines how the FDIC and chartering authorities behave, as explained earlier.

$Y_{i,t}$, $Z_{i,t}$ and $X_{i,t}$ = vector of explanatory variables in insolvency, guarantee and failure equations; discussed in section III and listed in table 2.

Due to data limitations, the value of the guarantee will not be estimated using the guarantee equation. As will be explained in section III, it is possible to estimate this value within the first equation, making use of certain simplifying assumptions.

III. PREDETERMINED VARIABLES, FUNCTIONAL FORM, AND EXPECTED SIGNS

3.1 Statistical Market Value Accounting Model

In the existing literature, independent variables for studying the financial condition of the institutions (or their failure, since the distinction is not usually made), are primarily ratios computed from banks' regular financial statements. Akaike's information criterion, which is based on the log-likelihood function of the model, adjusted for the number of estimated coefficients, is commonly used in selecting the combination of variables that best fits a given set of data (Akaike, 1973). Usually, a large number of financial ratios are tried before the final model is obtained.

One alternative approach, recently introduced by Kane and Unal (1989), and applied by Thomson (1987) is the "Statistical Market Value Accounting Model (SMVAM)." This specification brings structure to the traditional "ad hoc" choice of regressors common to balance sheet and income statement analysis.

Assuming efficient markets, the model decomposes the market value of a firm's stock into three components. First, market value is decomposed into hidden and recorded capital reserves. Second, hidden capital reserves are decomposed into values that are "unbooked but bookable" and "unbookable" items. The model develops explicit estimates of both components of hidden capital,

SMVAM can have a flexible functional form. However, the following linear relationship is posited as a convenient specification:

$$MV_{i,t} = \beta_{oi,t} + \beta_{1i,t}BV_{i,t} + u_{1i,t} \text{ where,}$$

$\beta_{1i,t}BV_{i,t}$ is the market's estimate of the value of accounting or book net worth. $\beta_{1i,t}$ is the valuation ratio of the market to book value of the collected components of the ith institution's bookable equity (BV) at time t. Thus, an estimate of the "unbooked but bookable" capital is obtained.

poi,t captures the net value of unbookable assets and liabilities of firm i at time t. This value of off-balance-sheet items includes the value of a deposit institution's explicit and conjectural federal guarantees net of discounted future costs.

According to the model, the market participants estimate the market value of the elements of bookable equity by applying an appropriate mark-up or mark-down ratio, ($\beta_{1i,t}$), to the accounting net worth reported by the institution. If this ratio is (not) equal to one, the accounting value of an institution's equity represents an (biased) unbiased estimate of the components of stockholders' equity. A market premium (discount) exists when the ratio is greater (less) than one. In order to construct the market value of the institution's equity, market participants also estimate unbookable equity, the market value of off-balance-sheet items, which includes the FDIC guarantees ($\beta_{oi,t}$). A positive (negative) value implies that unbookable equity serves as a net source of (drain on) the institution's capital.

Hence in the above equation, $\beta_{oi,t}$ is the portion of market value accounted for by unbookable equity and $\beta_{1i,t}BV_{i,t}$ is the portion of market value accounted for by bookable equity. In the absence of measurement error, the theoretical values of the intercept and the slope coefficient are zero and one, respectively, if there are no off-balance-sheet items, and if the bookable assets and liabilities are marked to market.

Adopting SMVAM as the first equation of the model allows us to study the economic solvency (or insolvency) of an institution by studying the determinants of the market value of its equity. Assuming the unbookable equity of the institution mostly consists of the FDIC guarantees, $\beta_{oi,t}$ can be taken as an estimate of $G_{i,t}$, the value of federal guarantees. This assumption is a strong, yet appealing, one given that it simplifies the model considerably. Having obtained an estimate of $G_{i,t}$ within the first equation, the next value or stockholder-contributed equity (NV) is given by substracting $G_{i,t}$ from the predicted market value of the institution.

The equation can be estimated both in time-series, cross-sectional pooled data.

3.2 A Nonlinear Version

An alternative approach would be to consider a nonlinear version of the flexible relationship between market value and book value. Since stock price does not become negative, a nonlinear function is especially appealing at low or negative book values (see figure 1).

The FDIC receives a compound option in exchange for its guarantee. However, as emphasized throughout the paper, the FDIC's ability to exercise this option is limited by its economic, political, and bureaucratic 'constraints. The received option is a call option, written not directly on the firm's assets, but on the right to close out the firm's stockholders and put a given percentage of the insolvent firm's unallocated losses to the uninsured depositors by liquidating the firm (Kane, 1986). In order to minimize its losses, the FDIC should exercise its takeover option and close the institution as soon as it becomes economically insolvent. Thus, theoretically, the insurer can take over the equity of the firm at, or past, the point of market-value insolvency. If the FDIC could exercise its option at market-value insolvency, the put half of the compound option need not be exercised since net worth is approximately zero and any losses would be minimal. Delays in exercising the takeover option due to the aforementioned constraints may allow an already insolvent institution to become more and more insolvent, causing the put half of the compound option to gain importance once the call half is eventually exercised. The implicit and explicit cost to the FDIC increases to the extent that regulator's constraints prevent this put half of the option from being exercised.

The nonlinear function shown in figure 1 represents the relationship between market and book values. The broken line is the value of the option at expiration when the option is in the money (the institution is economically solvent). If the institution is market-value solvent, MV approaches a constant proportion of BV. The horizontal axis to the left of point a, where the bank just becomes economically insolvent, is the value of the option at expiration when it is out of money. As the takeover of the bank is delayed due to regulator constraints, and BV decreases to the left of a, MV approaches zero. The FDIC has the option to take over the firm at, or to the left of, point a.

Optimally, this option should be exercised at point a, when the institution becomes economically insolvent. At this point, MV of the institution differs from zero by the value of the charter and federal guarantees. The value of the charter is composed of the value of business relationships built over time, firm-specific options for profitable future business opportunities, and monopoly rents that may accrue to the institution from restrictive branching laws and other regulations that restrict competition. However, we will assume that, at the point of economic insolvency, the contribution of charter value to MV is negligible. To the extent this assumption is valid, at point a, MV differs from zero by the value of the FDIC guarantees. The parameters of the model have the following interpretations:

CASE A - figure 1 (ii): In the absence of measurement error, if bookable assets and liabilities are marked to market and there are no off-balance-sheet items:

a = the optimal exercise point. At a, BV=0 and the bank is economically insolvent.

b = the slope of the asymptote that reflects the relationship between MV and BV as they approach each other at large positive values. In this case, since the accounting value of the institution's equity represents an unbiased estimate of stockholder equity, b is equal to one.

c = at the exercise point, the MV of the institution differs from zero by the charter value and the value of the FDIC guarantees. It is where the curve intercepts the MV axis.

CASE B - figure 1 (i) and (iii): if bookable equity is not marked to market and off-balance-sheet items exist:

a = the bank becomes economically insolvent where BV is greater (less) than zero if BV over (under) estimates the stockholder equity and off-balance-sheet items are a drain on (the source of) the institution's capital.

b = in this case, accounting value is a biased estimate of stockholder equity. If a is greater (less) than zero, a market discount (premium) is expected; thus, the coefficient is less (greater) than one. There is a discount and a premium in figure 1 (i) and 1 (iii) respectively.

c = the interpretation of the coefficient is the same but it is no longer given by the MV intercept since c is the value of the firm at a. The MV intercept either under (figure 1,i) or over (figure 1,iii) estimates c in this case.

This nonlinear version can also be adopted as the first equation of the model. Assuming away the value of the charter at the point of economic insolvency allows us to get an estimate of the guarantee value within the first equation ($c = G_{i,t}$). With this specification, it is also possible to allow c to vary for each bank at any point in time by parameterizing it to be a function of ris iness of the bank and size of the liabilities ($c_{i,t}=G_{i,t}$). Here, a linear function is chosen to avoid further complication of the model. However, it is also possible to use a nonlinear specification for c.

The construction of the NV is similar to that of the linear case but c is used as an estimate of the guarantee value instead of β_o

Again, the equation can be estimated both as a time-series for each bank and cross-sectionally in each period or with time-series, cross-sectional pooled data. k

3.3 Choice of Variables in the Failure Equation

The point of this paper is that the failure of a financial institution, unlike others, is determined by the regulators and not just by market forces. Therefore, it is only appropriate to study failure within the framework of a regulator decision-making model. The financial condition of the institution, as summarized by the net value (NV), is important but is not the only factor that influences the regulator's failure decision. Regulator constraints, such as political and legal constraints, information and staff constraints, and funding constraints reflected in the implicit and explicit reserves of the insurance fund, are also important determinants in the decision-making process. General economic conditions may also influence the failure decision through their effect on regulator constraints.

The following variables are included to account for different regulator constraints. Exact variable definitions are in table 4.

The number of examiners, EX, is a proxy for staff constraint. Ceteris paribus, inadequate manpower to deal with insolvencies is expected to act as a deterrent in making a failure decision. A good-sized, highly-skilled staff is necessary not only to spot insolvencies but also to go ahead and resolve these cases.

The FDIC's fund size, R, is another important constraint. Naturally without adequate funds, insolvencies cannot be resolved, even if the regulators are aware they exist. Thus, the failure decision should also be dependent on the adequacy of the insurance fund.

The asset size, A, for individual institutions is not included only as an economic constraint. Clearly, the larger the institution, the more difficult it is to financially resolve its insolvency. Also, the size variable is expected to capture the political and bureaucratic constraints of the regulators that become binding, especially when large institutions are concerned. In an effort to protect their self-interest, regulators apparently try not to get involved with large-bank failures, since they tend to be much more visible.

Number of problem banks, PB, and a bank failure index, BFI, are also included to explain regulator behavior. These variables capture more than one effect. Controlling for the financial condition of the institution, an increased number of bank failures or potential bank failures may protect institutions from failing due to regulators' political and bureaucratic constraints. To promote safety and soundness of the banking system, regulators try to spread failures evenly through time. Thus, a large number of failure decisions made recently may delay present failure decisions. However, it is also possible to view these variables as lagged taste variables, or as a measure of inertia in regulator behavior. An increased number of failures or potential failures may actually signal that a regulator is getting tougher, a trend that may continue into the future.

A general business failure rate, FI, is also included to capture the political and bureaucratic constraints of the regulators. Since this variable is not related to regulators' past behavior, it should be able to capture the protection effect explained above.

Interest rates and percentage changes in interest rates are also included to determine if they have any particular effect on the regulators' decision-making process.

Finally a charter variable, C, is included to see if the decision-making process differs among different regulatory bodies. The decision to fail an institution is made by the Office of the Comptroller of the Currency if the bank has a national charter and by the state banking commission if it has a state charter.

IV. ESTIMATION TECHNIQUE AND DATA SET

4.1 The Model

The model consists of three equations. The first equation models economic insolvency, the second constructs the net economic value, and the third estimates the probability of the regulator's failure decision. Since determinants of insolvency and failure are based on similar factors, the error terms of these equations, which capture the unobservable influences, will be correlated (Maddala, 1986). This dependence of u_1 and u_2 causes the otherwise recursive system to become simultaneous. A recursive system is one in which the matrix of coefficients of the endogenous variables is triangular and the contemporaneous covariance matrix is diagonal. The absence of F^* from the first equation satisfies the first condition; however, the dependence of the error terms violates the second. This dependence of u_1 and u_2 causes NV to be correlated with u_2 and a direct estimation of the failure equation results in inconsistent estimates. To obtain consistent estimates, a simultaneous technique has to be used. A two-stage method recommended by Maddala (1986) is used in this study.

In estimation of simultaneous equations, the problem of identification arises. It is concerned with the question of whether any specific equation in a model can in fact be estimated. In other words, it is not a matter of estimation method, but whether meaningful estimates of structural coefficients can be obtained. For identification, (1) restrictions on structural parameters, (2) restrictions on the covariance matrix, and/or (3) respecification of the model to incorporate additional variables may be necessary. The identification of this model requires that u_1 and u_2 be independent (upon which the system becomes recursive) or, in our case, at least one regressor from the first equation not to be included among the regressors of the failure equation.

4.2 The First Equation

The specification of the first equation was tested by including the proxy variables from the failure equation. The proxy variables and their various combinations were rejected by F-tests in favor of the simplest model. The stability of the coefficients was tested using a Chow test. This is a test of equality between two sets of coefficients that are estimated from subsamples (usually of equal size) of the original sample. The statistic has an F distribution. The hypothesis of no structural shift could not be rejected for the pooled sample of failed and nonfailed banks at a 5 percent significance level. Due to autocorrelated disturbances, a Cochrane-Orcutt method was used in estimation. This is an iterative method that gives estimators that converge to maximum likelihood estimators. Presence of heteroskedasticity was detected using Breusch-Pagan-Godfrey and Goldfeld-Quandt tests. The Breusch-Pagan-Godfrey test has a chi-square statistic based on the regression of squared residuals on the explanatory variables. The Goldfeld-Quandt test splits the sample in two and calculates a ratio of residual sums of squares from the two regressions. The resulting statistic has an F distribution. In both tests, the null hypothesis is a homoskedastic error structure.

To correct for heteroskedasticity, the first equation (including the constant-term) was deflated by (i) total assets, and (ii) book value. However, because heteroskedasticity tests after these corrections still indicated the presence of heteroskedasticity, White's (1980) consistent estimator of the variance-covariance matrix was calculated. When the process generating the heteroskedasticity is unknown, White suggests using the undeflated least-squares coefficient estimates, since they remain unbiased and consistent.

Yet for hypothesis testing, his alternative estimator of the variance-covariance matrix needs to be used instead of the least squares covariance matrix estimator, which is inconsistent. White's estimator does not require a formal modeling of the structure of the heteroskedasticity since it requires only the regressors and the estimated least squares residuals for its computation and, in cases when heteroskedasticity cannot be estimated, it allows correct inferences and confidence intervals to be obtained.

In estimating the first equation for failed institutions owned by bank holding companies (approximately 1/5th of the failed sample), an additional problem arises.

The data used are the individual bank's book value. However, the holding company's market value is used instead of the bank's market value, since the stock of the bank seldom trades separately. As Kane and Unal (1989) discuss at length, to the extent that holding companies have other bank and nonbank subsidiaries, and to the extent that the book value of these subsidiaries are correlated with the book value of the bank, the regression estimates will be biased. In order to see the extent of this bias, the first equation was also estimated omitting the holding-company-owned failed banks. Fortunately, the bias does not seem to be important since the regression estimates of the test run were not statistically different from the ones obtained from the full sample. For the nonfailed banks, this problem does not arise because the holding companies included in the sample are one or multibank holding companies without nonbank subsidiaries, and holding company market value and consolidated book value are used in estimating the regressions.

The linear version of the first equation was estimated using ordinary lease squares (OLS) for individual banks' time-series and also for all banks using time-series, cross-section pooled data. The nonlinear version of the equation was estimated using nonlinear least squares (NLS) with panel data. The coefficient that captures the FDIC quarantees, $C_{i,1t}$, was parameterized to be a linear function of the institution's rick and size of the liabilities. The average annual stock price range was used to proxy risk; liabilities were given by the total assets, minus the book value. This specification allows the FDIC guarantee value to vary both across time and among institutions with respect to their size and riskiness.

4.3 The Failure Equation

The limited variation permitted in the dependent variable of the second equation makes it equivalent to a qualitative response or choice model (Amemiya [1981] and Maddala [1983]). In these statistical models, the endogenous random variables take only discrete values. When the dependent variable is dichotomous, which is the case in our failure equation, then the model becomes a binary-choice model.

As Amemiya states, in such models it does not matter whether a probit or a logit model is used. However, since in our case the sampling rates of failures and nonfailures are unequal, the estimated coefficients of the probit model are biased. This problem does not arise with the logit model, which makes it preferable to the probit model (Maddala, [1983 and 19861). Thus, the Logit Maximum Likelihood Method is used in estimating the failure equation. The method is actually a two-stage one, since in the first stage NV is constructed by subtracting the federal guarantee estimate from the predicted MV. The reason predicted MV is used instead of the actual MV is that MV is correlated with u_2 and an NV constructed in that way would bias the failure equation coefficients. In the second stage, this constructed NV is used as one of the explanatory variables and the failure equation is estimated by logit technique using pooled data.

One problem with the two-stage method should be noted. The asymptotic variance-covariance matrix from the second stage underestimates the correct standard errors because it ignores the fact that the explanatory variable NV is estimated. The correct asymptotic variance-covariance matrix is calculated using Amemiya's (1978, 1979) method. The corrected variance-covariance matrix has an extra positive semidefinite term that the two-stage method omits.

When evaluating binary choice models, care must be taken (Judge et al. [1985]). Estimated coefficients do not indicate the increase in the probability of the failure decision given a one-unit increase in the corresponding independent variable. Instead, the amount of increase in probability depends upon the original probability and thus upon the initial values of all the independent variables and their coefficients. This is true since $P(F=1) = F(X\beta)$ and $\delta P(F=1)/\delta x_i = f(X\beta)\beta_i$, where $f(.)$ is the probability density function associated with $F(.)$. Therefore, while the size of the coefficient indicates the direction of the change, the magnitude depends upon $f(.)$, which reflects the steepness of the cumulative distribution function at $X\beta$. In other words, a change in the explanatory variable has different effects on the probability of failure decision, depending on the bank's initial probability of failure. This is intuitively plausible, since one would expect that if a bank has an extremely high (or low) probability of failure, a marginal change in the independent variables will have little effect on its prospects. The same marginal change might have a great effect if the bank's probability of failure were somewhere around 0.5.

4.4 Data Set

Panel data are used in estimating this model. A list of failed banks with assets over $90 million (since smaller banks seldom have actively traded stocks) was obtained from Federal Deposit Insurance Corporation Annual Reports for the period 1973-1988. Annual data on number of shares, book value per share, total assets, and price range were collected from Moody's Bank Manual for each bank, where possible, from 1963 up to the date of failure.

The names of the 32 failed banks, for which complete data could be collected, are given in table 1. Banks have an asset size range of $92 million to $47 billion. A random sample of 42 nonfailed banks within this asset range having roughly similar asset size dispersion was chosen. Nonfailed banks are from the same geographic locations as the failed banks, have actively traded stock, and are FDIC members. The same annual data were collected for the nonfailed banks.

Interest-rate data are obtained from Standard and Poor's Basic Statistics. The business-failure rate is from Dun & Bradstreet's Business Failure Record. The charter data are obtained from the Federal Reserve Board of Governors reports of condition data tapes. The data for the rest of the variables are collected from Federal Deposit Insurance Corporation Annual Reports. For variable definitions see table 2.

V. RESULTS

5.1 First Equation Results

The linear version of the first equation is estimated with time-series data for each bank individually and with pooled data for all institutions. The results for individual banks are given in table 3. The coefficient estimates can be summarized as follows:

β_o, the intercept, is significant 34 percent of the time. Its sign is positive in almost all the cases, implying that the off-balance-sheet items serve as a net source of the institutions' capital. One positive component of the intercept is the value of the federal deposit insurance guarantee and this positive value is consistent with the hypothesis that underpriced deposit insurance would contribute significantly to the market values of undercapitalized institutions.

β_1, the BV coefficient, is highly significant and positive 95 percent of the time. It is significantly different from unity in 60 percent of the cases and is less than unity in 45 percent of the cases. The combined $\beta=0$ and $\beta_1=1$ condition necessary for recorded equity to be an unbiased estimate of market value holds only for 28 perecent of the banks. These figures are consistent with Kane's (1985) claim that accounting representations of the economic performance of major banks are somewhat deceptive.

The results of the first equation, estimated using time-series cross-section pooled data for failed, nonfailed, and all pooled samples, are given in table 4. Pooled OLS results are consistent with the results for individual banks.

The intercepts for all three samples are positive. However, they are only significant for failed and all pooled samples. Also, the intercept of the failed banks is significantly greater than those of the nonfailed and all pooled samples, indicating the higher value of the deposit insurance guarantee for undercapitalized institutions.

The slope coefficients of all samples are significantly (at 10 percent for nonfailed banks) less than unity and the slope coefficient of the failed banks is significantly less than those of the nonfailed and all banks. These results indicate not only that the market discounts financial institutions' bookable equity, but also that the bookable equity of the failed institutions is discounted to a greater extent.

The nonlinear version of the first equation is estimated with pooled data and the results are also given in table 4. The coefficient c, which is expected to capture the value of the federal guarantees, is parameterized to be a linear (as a convenient simplification) function of the institution's riskiness and size of its liabilities. NLS results are similar to those obtained using OLS:

a, the exercise price, where the institutions are economically insolvent, is positive and significant for all three samples. This indicates that the BV of financial institutions significantly overstates MV. The extent of overvaluation as a percentage of total assets is about 4 percent for nonfailed and 6 percent for failed banks. The BV of failed institutions typically overstates their MV to a significantly greater extent than that of healthy institutions.

b, the slope of the asymptote, corresponds to β_1 in SMVAM. The results obtained are the same; the market discounts the bookable equity of institutions in general, and the BV of failed banks is discounted significantly more.

d, the coefficient of the risk variable, is positive and significant in all cases. As expected, the value of the FDIC guarantees increases with an increase in the riskiness of the institutions. It is also important to note that an equal amount of additional risk increases the value of the guarantee for the unhealthy institutions to a significantly greater extent (about 10 times greater) than the healthy ones.

e, the coefficient of the size of liabilities, is also positive and significant for all samples. Naturally, the value of the guarantee increases as the liabilities increase. However again, an equal amount of increase in liabilities increases the value of the guarantee significantly more for unhealthy institutions than for healthy ones.

$\bar{c}$, the mean value of the FDIC guarantees implied by d and e coefficients and the mean value of risk and liabilities, is significantly positive for each group. The value of the guarantee is significantly greater for the failed banks as expected.

The results for both the linear and nonlinear versions of the first equation indicate significant differences among failed and nonfailed banks. To sum up, the value of unbookable equity is much higher for unhealthy institutions. Also, the valuation ratio of the market to book value of these institutions' bookable equity is significantly lower than that of healthy ones. The BV of unhealthy institutions overstates their MV to a greater extent and these institutions enjoy a greater FDIC guarantee value that increases more with a marginal increase in risk or liability size. The book value accounting is misleading in general and it seems to misrepresent the economic performance of the unhealthy institutions to a greater extent.

5.2 Failure Equation Results

The failure equation is estimated using (i) a linear version and (ii) a nonlinear version of the first equation. The key difference is in the way the NV variable is constructed. As explained in section III, the linear version constructs NV by subtracting the estimate of unbookable equity (β_o) from the predicted MV of the institutions. The NV obtained from the nonlinear version subtracts the c value again from the predicted MV of the institutions. For failed and nonfailed banks, their respective pooled sample coefficient estimates are used. For comparison purposes, the failure equation is estimated using BV instead of NV, as well as using both BV and NV for each case. Also, the relative importance of the regulator constraint variables, BV and NV is examined.

The results of the failure equation, using the linear version of the first equation, are presented in table 5:

The constant term is negative and significant, implying that the higher the overall average charter value of the institutions, that is, the higher the value of institutions' ongoing customer relationships and profitable future business opportunities, the less likely the regulators are to fail an institution.

As expected, the coefficient of net value is also negative and significant. Clearly, an increase in the net economic value of an institution reduces the pressure the regulators feel to fail it. BV, when included without the NV, also has a negative and significant coefficient. However, when it is included with NV, its coefficient loses its significance.

Regulator constraint variables, such as the number of examiners and the insurance fund, both have positive and significant coefficients. Ceteris paribus, an increase in the number of examiners or the size of the fund, by relaxing the economic constraints against failure, makes a failure decision for an institution more likely. For given skill levels and population of clients, the greater the number of examiners employed at time t-1, the more thorough the examinations will be. This increases the probability that the FDIC will discover insolvent institutions, making a failure decision for an institution more likely at time t. Similarly an increase in the available funds to the FDIC would increase the probability of an insolvent institution's failure and supervisory merger.

The coefficients of the bank-failure index and the number of problem banks are also positive and significant. These two variables capture three separate and possibly counteracting effects. First, the number of problem banks and the failure index are lagged taste variables. A higher failure index or number of problem banks at time t-1 indicates that regulators are getting tougher in dealing with institutions, which makes it more likely that an individual institution will fail at time t. Second, a higher bank-failure index signals a deterioration of the economic environment for banks in general and it is expected to increase the probability of a failure decision for individual banks. Similarly, the FDIC's problem bank list includes those banks recognized as possessing low capital adequacy, asset quality, management skills, earnings, and/or liquidity. Many of these banks may be de facto insolvent. To the extent authorities try to delay failure, potential failures (many of which are beyond saving) tend to appear on this list for some time before being acted upon. Therefore, an increase in potential failures at time t-1 may also be indicative of the deteriorating economic environment for banks and of an increase in the probability of a failure decision for individual banks at time t. Third, given that the financial condition of an institution is controlled for, an increase in bank failures or number of problem banks may actually protect individual institutions, taking into account the regulators' political and bureaucratic constraints and self-serving incentives. In the face of accumulating trouble, regulators may become more lenient in their failure policies in an effort to cover-up and get-away. This final factor counteracts the first two. The positive coefficients obtained for these variables indicate that the first two factors are larger in magnitude than the last one.

A general business failure rate is perhaps a better indicator of the overall economy and should be able to capture this "protection" effect more clearly, since its coefficient is not blurred by the first two effects. When included, the coefficient is indeed consistently negative. However, it fails to be significant.

The coefficients of asset size and relative asset size with respect to the insurance fund are negative and significant. These variables not only capture economic constraints but also capture the political and bureaucratic constraints associated with so-called "too large to fail" banks. The coefficients reflect the well-known tendency of the regulators to treat the larger banks differently.

The interest and percentage change in interest variables have positive but insignificant coefficients. They do not add significant information to the decision-making process.

Finally, the coefficient of the charter variable is negative but insignificant. This indicates that although the federal regulators tend to be more lenient, the decision-making processes of the federal and state regulators are not statistically different.

The coefficient estimates all have expected signs and most of the key variables turn out to significantly affect the regulators' failure decision, although as Maddala (1986) notes, conventional tests based on asymptotic standard errors may err in the direction of nonsignificance in the case of logit models.

The predictive power of the model is also given in table 5. The two types of errors are error 1, the error of misclassifying a failed bank as nonfailed, and error 2, the error of misclassifying a nonfailed bank as failed. Error 1 has a range of 3 percent (only one bank misclassified) to 9 percent (3 banks were misclassified). The specification using BV instead of NV misclassifies 16 percent of the failed banks. Error 2 has a range of 10 percent to 16 percent for different specifications and, using BV instead of NV, the model misclassifies 14 percent of the nonfailures. It is often argued that the costs of these misclassification errors are not the same and that error 1 is relatively more costly. However, if we assume these costs are the same and also weigh the two errors equally, this equally weighted total correct prediction determines the discriminatory power of the model. Alternative specifications of the model have 88 percent to 93.5 percent prediction accuracy. The lowest prediction accuracy is 85 percent, which belongs to the single equation specification with BV instead of NV.

The results of the failure equation, using the nonlinear version of the first equation, are presented in table 6. Obtained results are not substantially different. The explanatory variables have the same signs. One difference is that the interest varible gains significance, but the size variable is no longer significant with this specification. Summary statistics are improved, indicating a better fit, and predictive power is slightly higher. The range of error 1 is lower at 3 percent to 6 percent and error 2 is unchanged. Thus equally-weighted prediction accuracy is also slightly improved at 89.5 percent to 93.5 percent.

To further study the differences between various specifications, the failure equation is estimated using (1) only regulator constraints, (2) only BV, (3) only NV from linear specification, and (4) only NV from nonlinear specification. The results are given in table 7. It is interesting to see that the model with only regulator constraint variables has a prediction accuracy of 76 percent. This is almost as high as the discriminatory power of the model with only BV, which is 77.5 percent. The NV, obtained from the linear specification, does significantly better in classifying the failed banks. The error 1 falls to 16 percent and prediction accuracy increases to 80 percent. Finally, the NV obtained from the nonlinear specification does even better. Almost all the failed banks (except one) are correctly classified with error 1 at 3 percent. Its prediction accuracy is also the highest among the four specifications, at 85 percent.

Although the nonlinear version of the first equation does seem to produce an estimate of NV that has a greater discriminatory power by itself, the results of the full model indicate that the linear version of the first equation does equally well. The linear version may be preferred in practice since it simplifies the estimation of the model considerably.

The results obtained from the failure equation shed light on various issues. First, regulator constraints are important in determination of the failure decision. Second, NV is a much better indicator of financial condition than BV. Third, nonlinear estimation of the first equation seems to enhance the NV's own discriminatory power, probably better capturing the true net economic value of the unhealthy institutions.

In conclusion, the best failure model, as hypothesized throughout, is the one that allows both the financial condition of the institutions and the regulator constraints to determine the decision-making process. Although NV is a good indicator of the likelihood of a failure decision, the classification accuracy increases to over 90 percent only when the regulator constraints are taken into consideration. This is expected since failure is a regulator-determined event and regulator constraints do have a significant additional contribution in explaining the decision-making process.

VI. CONCLUSIONS

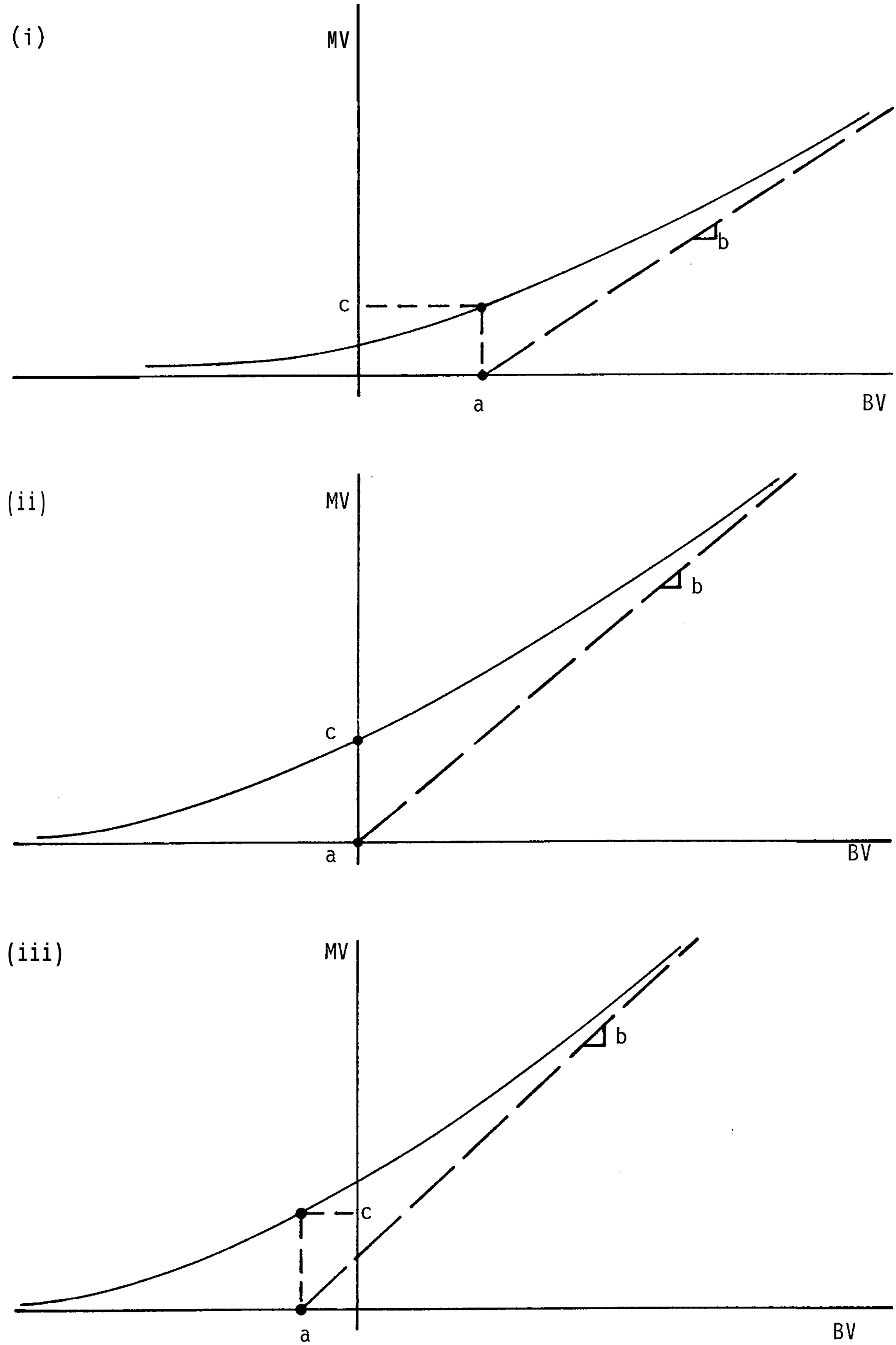
The purpose of this paper is to develop an accurate model of large bank failures. In order to achieve this end, insolvency and failure of institutions are studied simultaneously and economic, political, and bureaucratic regulator constraints are taken into account. The maintained hypothesis throughout the study is that the contribution of regulator constraints to the failure determination is significant since failure is a regulator-determined event, and any model of bank failure that does not distinguish between failure and insolvency cannot be complete.

In studying the insolvency of institutions, the importance of obtaining a stockholder-contributed equity value is stressed. Through the use of Kane and Unal's (forthcoming 1989) SMVAM, the market value of the institutions' equity is decomposed into its components. The results of the insolvency equation indicate major differences between failed and nonfailed banks. The unbookable equity of failed institutions is much greater than that of the nonfailed institutions. Further, the bookable equity, which is discounted in general for all institutions, is discounted to a greater extent for failed institutions. The value of the federal deposit-insurance guarantee, which is a positive component of the institution's unbookable equity, is greater for failed institutions and increases with an increase in the riskiness of the institution or the size of its liabilities. Also, an equal increase in riskiness or liability size induces a greater increase in guarantee value for the unhealthy banks.

The failure equation studies the regulator's failure decision process. The net value of the institution constructed from the insolvency equation is an important variable in the failure equation, since it summarizes the financial condition of the institution. However, as expected, the regulator constraint variables also play a significant role in failure determination. Net economic value has a discriminatory power that consistently outperforms that of the book value. This is not surprising since the first equation results indicate that book value greatly misrepresents the financial condition of the institutions and especially that of the failed ones.

The model of bank failure developed in this study is more complete since it takes into consideration a previously ignored determinant of the decision-making process. The results obtained support the approach taken in this paper.

FIGURE I: $MV = 0.5b(BV-a) + \sqrt{0.25b^2(BV-a)^2 + c^2} + u$



Source: Author

Table 1: List of Failed Banks

Date	Bank	Assets	How
Oct. 1973	United States National Bank San Diego, California (USN)	1.3B	P&A
Oct. 1974	Franklin National Bank New York, N.Y. (FNB)	3.6B	P&A
Oct. 1975	American City Bank & Trust Co., N.A., Milwaukee, Wisconsin (ACB)	148M	P&A
Jan. 1975	Security National Bank Long Island, New York (SNB)	198M	R
Feb. 1976	The Hamilton National Bank of Chattanooga, Tennessee (HNB)	412M	P&A
Dec. 1976	International City Bank & Trust Co., New Orleans, Louisiana (ICB)	176M	P&A
Jan. 1978	The Drovers' National Bank of Chicago, Illinois (DNB)	227M	P&A
Apr. 1980	First Pennsylvania Bank, N.A. Philadelphia, Pennsylvania (FPC)	5.5B	OBA
Oct. 1982	Oklahoma National Bank & Trust Co., Oklahoma City, Oklahoma (ONB)	150M	P&A
Feb. 1983	United American Bank in Knoxville, Knoxville, Tennessee (UAB)	778M	P&A

Table 1: List of Failed Banks (continued)

Date	Bank	Assets	How
Feb. 1983	American City Bank Los Angeles, California (ACB)	272M	P&A
Oct. 1983	The First National Bank of Midland, Midland, Texas (FNM)	1.4B	P&A
May 1984	The Mississippi Bank Jackson, Mississippi (MBJ)	227M	P&A
July 1984 .	Continental Illinois National Bank & Trust Co., Chicago, Illinois (CIB)	47B	OBA
Aug. 1986	Citizens National Bank & Trust Co., Oklahoma City, Oklahoma (CNO)	166M	P&A
May 1986	First State Bank & Trust Co. Edinburg, Texas (FSB)	134M	P&A
June 1986	Bossier Bank & Trust Co. Bossier City, Louisiana (BBT)	204M	P&A
July 1986	The First National Bank & Trust Co., Oklahoma City, Oklahoma (FNB)	1.6B	P&A
Sept. 1986	American Bank & Trust Co. Lafayette, Louisiana (ABL)	189M	P&A
Dec. 1986	Panhandle Bank & Trust Co. Borger, Texas (PBT)	107M	P&A

Table 1: List of Failed Banks (continued)

Date	Bank	Assets	How
Aug. 1986	First Citizens Bank Dallas, Texas (FCB)	93.8M	P&A
Nov. 1986	First National Bank & Trust Co. of Enid, Oklahoma (FBT)	92.4M	P
Jan. 1987	Security National Bank & Trust Co., Norman, Oklahoma (SBT)	174.4M	P&A
Oct. 1987	Alaska National Bank of the North, Alaska (ANB)	189M	P&A
Feb. 1988	Bank of Dallas Dallas, Texas (BOD)	170M	P&A
March 1988	Union Bank & Trust Co., Oklahoma City, Oklahoma (UBT)	167.5M	P&A
Apr. 1988	First City Bancorp of Texas, Houston, Texas (CBT)	11B	OBA
Apr. 1988	Bank of Santa Fe Santa Fe, New Mexico (BSF)	151M	OBA
July 1988	First Republicbank Dallas, N.A., Dallas, Texas (FRC)	19.4B	P&A
March 1989	Mcorp, Dallas, Texas (MCP)	20B	B

Table 1: List of Failed Banks (continued)

Date	Bank	Assets	How
1989*	Texas American Bancshares Inc. Texas (TAB)	5.9B	?
1989*	National Bancshares Corp of Texas, Texas (NBC)	2.7B	?

Notes: * indicates that a failure decision is pending.

P&A - Purchase & Assumption transaction (23)

OBA - Open Bank Assistance (4)

P - Deposit Payoff (1)

R - Reorganization (1)

B - Bridge Bank (1)

Source: Federal Deposit Insurance Corporation Annual Reports.

Table 2: Variable Definitions and Sources

First Equation

MV_t - market value of the institution's equity at time t. MV is the price per share multiplied by the number of shares outstanding. All data are obtained from Moody's Bank Manuals.

BV_t - book value of the institution's equity at time t. BV is the book value of assets, minus the book value of liabilities and is given by the sum of common stock capital, surplus, undivided profits, and reserves. Data are obtained from Moody's Bank Manuals.

Failure Equation

F_t - the binary failure variable as explained in section II.

NV_t - the stockholder-contributed net equity value of the institution at time t. It is constructed by equation 2 in section II.

EX_t - the number of examiners the FDIC employs at time t. It is obtained from the FDIC's Annual Reports.

BFI_t - business failure rate at time t. This variable is obtained from Dun & Bradstreet's Business Failure Record.

FI_t - bank failure index at time t. This variable is calculated from the Federal Deposit Insurance Corporation's Annual Report, table 122. The calculation is based on total deposits of failed institutions and 1970 is taken as the base year.

PB_t - number of problem banks at time t. It is obtained from various issues of the FDIC's Annual Reports.

R_t - the FDIC insurance fund at time t. It is obtained from the FDIC's Annual Reports.

A_t - total asset size of the institution at time t, as given in Moody's Bank Manuals.

Table 2: Variable Definitions and Sources (continued)

INT_t - yearly average of the 6-month T-bill rate calculated from monthly data. It is obtained from Standard and Poor's Basic Statistics.

TIN_t - percentage change in the INT variable.

C_t - a dummy variable that takes on the value one if the bank has a national charter and the value zero if it has a state charter. Data are obtained from the Federal Reserve Board of Governors reports of condition data tapes.

Guarantee Equation

G_t - the FDIC guarantee value at time t.

B_t - the face value of the institution's debt at time t.

V_t - current value of the assets of the institution at time t.

r_t - market rate of interest on riskless securities at time t.

T - length of time until the next audit of the bank's assets.

σ^2_t - the instantaneous variance of the value of assets for the institution at time t.

Table 3 : First Equation Results for Each Bank with Time-Series Data
Linear Version

Banks	β_o	β_1	R^2
Failed Banks:			
USN	14.130**	0.892**	0.89
1963-72	(4.186)	(0.141)	
FNB	151.0438**	0.026**	0.23
1963-73	(36.890)	(0.340)	
ACB	-0.401	1.299**	0.61
1963-74	(2.853)	(0.342)	
SNB	32.649	9.786*	0.56
1963-74	(24.199)	(0.342)	
HNB	4.816	1.151*	0.34
1963-75	(10.280)	(0.507)	
ICB	6.501	0.437	0.12
1966-75	(4.055)	(0.509)	
DNB	-3.847	1.570*	0.71
1963-77	(10.157)	(0.787)	
FPC	130.081	0.509	0.64
1968-79	(167.694)	(0.637)	
ONB	1.546**	0.856**	0.82
1963-81	(0.439)	(0.097)	
UAB	1.910	0.945**	0.48
1963-82	(5.177)	(0.238)	
ACB	-2.168	2.016** **	0.86
1964-82	(20.00)	(0.262)	
FNM	6.387	1.469** **	0.93
MBJ	3.620	0.460** **	0.49
1963-83	(1.925)	(0.215)	
CIB	446.246**	0.393** **	0.68
1963-83	(98.323)	(0.097)	

Table 3 : First Equation Results for Each Bank with Time-Series Data
Linear Version (continued)

Banks	β_o	β_1	R^2
Failed Banks:			
CNO 1966-85	10.046** (1.440)	0.529** ** (0.133)	0.45
BBT 1967-85	4.908** (0.683)	0.413** ** (0.062)	0.72
FNB 1963-85	20.432 (14.932)	0.872** (0.160)	0.79
ABL 1963-85	2.180 (1.625)	0.893** (0.194)	0.50
PBT 1963-85	0.743 (0.608)	1.028** (0.196)	0.61
FCB 1970-85	2.249** (0.453)	0.243** ** (0.085)	0.76
FBT 1970-85	4.529* (2.242)	0.424 (0.308)	0.36
SBT 1978-86	10.392 (5.168)	0.447 (0.294)	0.64
ANB 1964-86	2.237 (2.073)	0.745** (0.199)	0.68
BOD 1963-87	0.881 (1.446)	1.652** ** (0.271)	0.87
UBT 1972-87	2.520* (1.192)	1.212** (0.151)	0.82
CBT 1963-87	166.582* (72.814)	0.519** ** (0.149)	0.79
BSF 1963-87	1.04* (0.42)	0.756** ** (0.058)	0.92
FRC 1963-87	190.189** (38.487)	0.510** ** (0.065)	0.87

Table 3 : First Equation Results for Each Bank with Time-Series Data
Linear Version (continued)

Banks	β_o	β_1	R^2
Failed Banks:			
MCP 1963-87	79.001 (53.299)	0.619**** (0.094)	0.91
TAB 1963-87	10.347 (14.774)	0.915** (0.084)	0.90
NBC 1963-87	-0.247 (3.461)	1.159**** (0.041)	0.97
Operating Banks:			
CFB 1963-87	1.039 (7.627)	0.794**** (0.061)	0.93
CNB 1963-87	1.861 (1.001)	0.649**** (0.114)	0.87
CWB 1963-87	0.474 (1.123)	0.678**** (0.079)	0.88
ONB 1964-87	2.119 (1.370)	0.637** (0.250)	0.78
CCT 1963-87	4.513** (1.279)	0.334**** (0.106)	0.50
FNB 1963-87	0.111 (1.190)	1.194** (0.191)	0.85
FNM 1963-87	0.455 (1.202)	0.812** (0.136)	0.91
FNS 1963-87	2.037 (3.569)	0.960** (0.257)	0.76
MBT 1963-87	0.255 (0.308)	1.103**** (0.054)	0.95
NBT 1963-87	2.221 (1.426)	0.668**** (0.067)	0.91

Table 3 : First Equation Results for Each Bank with Time-Series Data Linear Version (continued)

Banks	β_o	β_1	R^2
Operating Banks:			
WHC 1963-87	-21.847 (23.686)	1.525** ** (0.174)	0.93
VNB 1963-87	0.717 (0.616)	0.761** ** (0.082)	0.90
FCC 1968-87	18.634 (14.557)	0.624** * (0.179)	0.51
PBT 1970-87	1.891 (1.896)	0.604* * (0.214)	0.36
CNH 1970-87	5.548** (1.391)	0.877** (0.177)	0.63
NBC 1972-87	0.781** (0.132)	0.296** ** (0.024)	0.97
OSB 1975-87	1.717** (0.206)	0.298** ** (0.036)	0.88
NCB 1976-87	-7.177 (3.098)	1.692** ** (0.157)	0.89
SLB 1977-87	1.685** (0.70)	0.011* ** (0.005)	0.77
FAB 1978-87	3.730** (0.913)	0.302* ** (0.153)	0.39
PSB 1978-87	1.680 (1.934)	0.338 ** (0.259)	0.40
FMB 1975-87	9.743* (4.067)	0.209* ** (0.067)	0.67
VBC 1964-87	-6.730 (5.031)	1.176** * (0.084)	0.96
FAC 1968-87	12.622 (25.653)	0.847** (0.196)	0.76

Table 3 : First Equation Results for Each Bank with Time-Series Data Linear Version (continued)

Banks	β_o	β_1	R^2
Operating Banks:			
BTN 1966-87	215.527 (134.011)	0.661** * (0.145)	0.80
WFC 1968-87	258.105** (43.213)	0.438** ** (0.059)	0.78
FCT 1974-87	515.514* (252.178)	0.257 ** (0.183)	0.47
CUC 1975-87	-23.006 (50.474)	0.882* (0.452)	0.65
CNC 1972-87	19.581 (23.485)	1.705** ** (0.277)	0.75
ABI 1973-87	15.175 (61.864)	1.702** ** (0.178)* **	0.89
BOC 1973-87	-9.971 (9.007)	0.894** (0.104))	0.92
CFI 1968-87	13.803 (16.391)	0.892** (0.150)	0.90
FES 1970-87	-44.105 (34.789)	1.156** (0.332)	0.93
RNC 1970-87	-35.923 (31.348)	1.123** (0.082)	0.93
CMN 1968-87	22.056** (3.958)	0.360** (0.080)	0.76
CPC 1973-87	7.744* (3.004)	0.663** ** (0.120))	0.75
GAC 1971-87	9.027 (11.310)	0.573 (0.296)	0.50
SMB 1968-87	-4.935* (2.026)	1.671** * (0.116)	0.97

Table 3 : First Equation Results for Each Bank with Time-Series Data Linear Version (continued)

Banks	β_o	β_1	R^2
Operating Banks:			
HBM 1972-85	1.402 (4.141)	0.689$^{**}_{*}$ (0.152)	0.69
BAL 1968-87	1.899 (1.821)	0.961** (0.069)	0.92

Notes: Standard errors are given in parentheses.
Superscripts: * significantly differs from zero at 5%
** significantly differs from zero at 1%
Subscripts: * significantly differs from one at 5%
** significantly differs from one at 1%
The annual data on number of shares, book value per share, and price range were collected from Moody's Bank Manual for each bank.

Source: Author.

Table 4: First Equation Results with Pooled Samples
Linear and Nonlinear Versions

1. Nonfailed Banks Pooled - 1963-87:

OLS:	β : 14.019 (10.313)	β_1: 0.804*** (0.129)			
NLS:	a: 81.315*** (9.618)	b: 0.832*** (0.030)	d: 6.766*** (2.644)	e: 0.005*** (0.001)	$\bar{c}$: 11.040*** (3.027)

2. Failed Banks Pooled - 1963-87:

OLS:	β : 52.155*** (13.739)	β_1: 0.516*** (0.073)			
NLS:	a: 122.910*** (6.911)	b: 0.524*** (0.125)	d: 69.344*** (9.276)	e: 0.017*** (0.003)	$\bar{c}$: 54.870*** (6.301)

3. Failed/Nonfailed Banks Pooled - 1963-87:

OLS:	β : 25.159*** (7.122)	β_1: 0.721*** (0.083)			
NLS:	a: 95.815*** (8.586)	b: 0.716*** (0.022)	d: 14.838*** (3.954)	e: 0.0124*** (0.001)	E: 27.073*** (1.834)

$\bar{c}$ = RISK*d + $\bar{L}$*e

See notes to table 7.

Source: Author.

Table 5: Logit Analysis of Bank Failures - First Equation Linear

Dependent Variable : Failure

Independent Variables	Alternative Specifications (1)	(2)	(3)	(4)	(5)
Const.	-87.455***	-60.715***	-103.693***	-66.905***	-106.651***
	(24.070)	(14.683)	(28.406)	(15.117)	(26.062)
NV_t/A_t	-2.467***	-2.489***	-2.442***		-6.679***
	(0.498)	(0.488)	(0.501)		(1.505)
BV_t/A_t				-3.056***	1.804
				(0.475)	(1.159)
X_{t-1}	9.162***	5.730***	9.284***	6.182***	10.556***
	(3.243)	(2.078)	(3.075)	(2.105)	(3.424)
BFI_{t-1}	0.459**	0.458**	0.121	0.552**	0.528**
	(0.231)	(0.218)	(0.258)	(0.227)	(0.255)
FI_{t-1}	-1.188	-0.685	-1.800	-0.996	1.399
	(1.048)	(0.974)	(1.183)	(0.942)	(1.187)
PB_{t-1}	1.398**	1.023*	0.245	1.518***	1.154
	(0.667)	(0.567)	(0.649)	(0.564)	(0.733)
A_t/R_{t-1}	-0.378***	-0.387***		-0.130	-1.051***
	(0.170)	(0.146)		(0.121)	(0.265)
INT_t	0.238				0.253
	(0.162)				(0.168)
$TINT_t$	0.005				0.004
	(0.003)				(0.015)
R_{t-1}			3.554**		
			(1.531)		
A_t			-0.375***		
			(0.146)		
C_t	-0.105				
	(0.539)				

Table 5: Logit Analysis of Bank Failures - First Equation Linear (continued)

	Alternative Specifications				
	(1)	(2)	(3)	(4)	(5)
Summary Statistics					
Model Chi-square	121.87***	118.75***	122.79***	130.35***	165.69***
-2 Log L	184.63	187.75	183.71	168.48	133.14
Classification					
Error 1	3%	9%	3%	16%	3%
Error 2	16%	15%	15%	14%	10%
Total Correct	90.5%	88%	91%	85%	93.5%

See notes to table 7

Source: Author

Table 6: Logit Analysis of Bank Failures - First Equation Nonlinear

Dependent **Variable : Failure**

Independent Variables	Alternative Specifications (1)	(2)	(3)	(4)	(5)
Const.	-87.300*** (24.375)	-57.663*** (14.650)	-105.562*** (28.609)	-66.905*** (15.117)	-103.081*** (26.317)
NV_t/A_t	-1.757*** (0.361)	-1.728*** (0.348)	-1.748*** (0.364)		-3.139*** (0.829)
BV_t/A_t				-3.056*** (0.475)	-0.171 (1.822)
EX_{t-1}	9.045*** (3.273)	5.280*** (2.075)	9.166*** (3.103)	6.182*** (2.105)	10.078*** (3.437)
BFI_{t-1}	0.509** (0.231)	0.519** (0.217)	0.129 (0.259)	0.552** (0.227)	0.604** (0.258)
FI_{t-1}	-1.096 (1.057)	-0.523 (0.982)	-1.756 (1.198)	-0.996 (0.942)	-1.184 (1.163)
PB_{t-1}	1.608** (0.665)	1.178** (0.566)	0.268 (0.653)	1.518** (0.564)	1.698** (0.727)
A_t/R_{t-1}	-0.024 (0.163)	-0.032 (0.133)		-0.130 (0.121)	0.000 (0.169)
INT_t	0.277* (0.163)				0.346** (0.173)
$TINT_t$	0.004 (0.013)				0.002 (0.015)
R_{t-1}			3.630*** (1.534)		
A_t			-0.022 (0.138)		
C_t	-0.077 (0.560)				

Table 6: Logit Analysis of Bank Failures - First Equation Nonlinear (continued)

	Alternative Specifications				
	(1)	(2)	(3)	(4)	(5)
Summary Statistics					
Model Chi-square	135.94***	131.97***	137.14***	130.35***	165.67***
-2 Log L	170.56	174.54	169.36	168.48	133.16
Classification					
Error 1	3%	6%	3%	16%	3%
Error 2	16%	15%	15%	14%	10%
Total Correct	90.5%	89.5%	91%	85%	93.5%

See notes to table 7.

Source: Author.

Table 7: Failure Decision - Regulator Constraints vs. Financial Condition

Dependent Variable : Failure

Independent Variables	Alternative Specifications (1)	(2)	(3)	(4)
Const.	-108.140*** (26.596)	-13.138*** (1.369)	-11.194*** (1.209)	-11.852*** (1.454)
NV_t/A_t			-2.329*** (0.348)	-1.957*** (0.313)
BV_t/A_t		-3.127*** (0.428)		
EX_{t-1}	12.714*** (3.523)			
BFI_{t-1}	0.670*** (0.226)			
FI_{t-1}	-2.105** (0.999)			
PB_{t-1}	2.360*** (0.645)			
INT_t	0.301 (0.185)			
$TINT_t$	0.005 (0.014)			
A_t/R_{t-1}	0.029 (0.823)			
	-0.377 (0.479)			

Table 7 : Failure Decision - Regulator Constraints vs. Financial Condition (continued)

	Alternative Specifications (1)	(2)	(3)	(4)
Summary Statistics				
Model Chi-square	94.14***	69.94***	59.89***	73.01***
-2 Log L	212.37	228.89	246.61	233.50
Classification				
Error 1	28%	26%	16%	3%
Error 2	20%	19%	24%	27%
Total Correct	76%	77.5%	80%	85%

Notes: Standard errors are given in parentheses. Single, double, triple asterisks indicate significance at 10, 5, 1 percents respectively. Interest data are obtained from Standard and Poor's Basic Statistics. Bank-failure index is calculated from the FDIC's 1987 Annual Report, table 122, base year taken as 1970. Business-failure rate is obtained from Dun & Bradstreet's Business Failure Record. Year-end book value, price range, number of shares outstanding, and asset size variables are collected from Moody's Bank Manual. The data for the rest of the variables are obtained from FDIC Annual Reports.

Source: Author.

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