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PRINCIPAL-AGENT PROBLEMS IN COMMERCIAL-BANK FAILURE DECISIONS

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I. Introduction

The 1980s proved to be a turbulent decade for the U.S. banking and financial system. More than 1,000 of the approximately 1,800 insolvent banks that have been closed, acquired, or received assistance to prevent closure since the Federal Deposit Insurance Corporation (FDIC) was established in 1933 were declared insolvent during the 1980s. In 1988-89 alone, 427 institutions were closed.

De facto failures, which are defined more broadly to include any regulator-induced cessation of autonomous operations, portray an even gloomier picture. This dramatic increase in the bank failure rate has intensified public criticism of deposit-institution regulators, since bank safety and soundness is a major regulatory responsibility.[1] The recent crisis in the savings and loan (S&L) industry helped the already existing problem to surface, and the public has become more eager to assess and assign blame.

This paper seeks to develop an empirical model of regulators' failure decision process. As Kane (1985) states, an accurate bank-failure model should begin by distinguishing between insolvency and failure, which are conceptually distinct events. This paper emphasizes that economic insolvency is a market-determined event and that failure, though conditioned on economic insolvency, is not an automatic consequence. Failure results from a conscious decision by regulatory authorities to acknowledge and to repair the weakened financial condition of the institution. Even when strong evidence of market-value insolvency exists, authorities may not declare the institution officially insolvent. Therefore, in a realistic analysis, bank failures need to be modeled within the framework of a regulatory decision-making process.

There is abundant literature on deposit institution failures. Among the empirical studies are Sinkey (1975), Altman (1977), Martin (1977), Avery and Hanweck (1984), Barth et al. (1985), Benston (1985), and Gajewski (1988).[2]

With the notable exception of Gajewski, most earlier bank-failure studies neglect the distinction between economic insolvency and failure. Failure is studied by statistically analyzing the power to predict individual failures from a large number of financial ratios obtained from balance sheets and income statements. Although Gajewski improves on these studies by stressing the distinction between insolvency and failure, he models each as a function of financial ratios only. Most studies have concentrated on relatively small institutions whose stock does not trade publicly. Therefore, the financial ratios used are based on book values rather than market values. In not using stock-market data, accounting-based studies implicitly assume that financial ratios provide an unbiased estimate of market-value insolvency.

To develop a framework for a regulatory decision-making process, it is important to consider principal-agent problems. The theory of public choice applies and extends economic theory to the realm of political or governmental decision-making (Buchanan [1960, 1967], Tulloch [1965], Niskanen [1971], Stigler [1977], and Buchanan and Tollison [1984]). Myers and Majluf (1984), Narayanan (1985), and Campbell and Marino (1988) apply public choice theory to explain the managerial decision-making of an enterprise. Again, based on public choice theory, Kane (1988, 1989) develops a model of regulatory decision-making.

This paper goes beyond previous empirical studies by modeling failure as an outcome of the regulatory decision-making process. Economic insolvency is treated as only one of the several conditioning factors that influence a failure decision. Unlike Gajewski's model, but following Kane's (1988), the empirical model of the regulator's failure decision developed here explicitly states the economic, political, and bureaucratic constraints and conflicts of interest as factors facing regulators. Concentrating on publicly traded institutions permits the use of stock-market data in determining economic insolvency.

The following section presents the necessary concepts. Section III develops the model, and section IV presents and interprets the empirical results. Finally, section V summarizes and concludes the analysis.

II. Insolvency vs. Failure: The Incentive Structure of Regulators

This section seeks to clarify the difference between economic insolvency and financial institution failures and to discuss the regulatory incentive structure that fosters this difference.

Official insolvency occurs when an institution's chartering authority judges its capital to be inadequate. However, the procedures by which this decision is made are not clear. To determine a depository institution's level of capital for regulatory purposes, it is helpful to divide its capital into two components: enterprise-contributed equity and federally contributed equity (Kane [1989]).

As Kane explains, enterprise-contributed equity is the capital of the institution net of the capitalized value of its deposit insurance guarantees. To the extent that federal guarantees are underpriced, the deposit insurer contributes de facto capital to the institutions. Federally contributed capital is determined by the amount of risk that insurance agencies are prepared to absorb. These valuable guarantees are actually equity instruments that make the U.S. government a de facto investor in deposit institutions. Unless an appropriate recapitalization rule is imposed on managers and stockholders, the capitalized value of the guarantees increases as the institution's enterprise-contributed equity decreases or as the riskiness of either its portfolio or its environment increases. Clearly, the value of the federally contributed capital should not be counted as a part of the institution's capital for regulatory purposes.

De facto or market-value insolvency exists when an institution can no longer meet its contractual obligations from its own resources. This occurs whenever the market value of the institution's nonownership liabilities exceeds the market value of its assets, or when the market value of its enterprise-contributed equity becomes negative.

Official (de jure) insolvency, or closure (de jure failure) occurs when the market-value insolvency is officially recognized and the firm is closed or involuntarily merged out of existence. De facto failure can be defined more broadly than closure as any regulator-induced cessation of autonomous operations.

Unlike economic insolvency, which is a market-determined event, de jure or de facto failure is an administrative option that the authorities may or may not choose to exercise even when strong evidence of market-value insolvency exists.

This distinction between economic insolvency and institutional failure need not exist. By forbearing from enforcing capital requirements, federal officials purposely allow economically insolvent institutions to operate, delaying a failure decision. Forbearance allows the accounting recognition of already existing losses to be deferred and generates the longer-run implicit cost of undermining market discipline against excessive risk-taking. As long as the guarantor allows market-value-insolvent institutions to operate, additional losses primarily accrue to the insurance agencies, increasing the value of insurance guarantees.[3]

Forbearance policies protect depositors at the cost of preventing or postponing individual bank failures and maintaining inefficient banks. These policies limit the community's ability to obtain an optimal allocation of resources, and they impose welfare losses on society as a whole (Meltzer [1967], Pyle [1984]).

Yet, as Kane (1989) notes, forbearance policies survive because they deliver benefits to politicians and top industry regulators. The economic, political, and bureaucratic constraints federal regulators face in making failure decisions lead them to adopt these policies.

Economic constraints of federal officials are embedded in the budget procedures that restrict the liquidity, staffing, and legal authority of the insurance agency. Budget procedures acknowledge the effects of explicit income and expenditures, but fail to account for the implicit long-run costs of forbearance policies and inefficient insolvency-resolution methods. These budget procedures are imposed on regulators by politicians who find forbearance attractive, rather than facing up to problems would force them to accept some of the blame for allowing the situation to deteriorate so badly.

Political and bureaucratic constraints of federal officials are embedded in career-oriented incentives, whereby officials aim to keep their constituencies and clientele happy. Their explicit salaries are lower than those found in the private sector. Economists conceive this gap to be bridged by implicit wages. Kane (1989) argues that these implicit wages are the nonpecuniary benefits of being in a high government office and the expected future wage increases that accrue in postgovernment employment (often within the regulated industry).

If regulators can successfully complete their term in government service, they can generally expect to see this experience rewarded with higher wages in postgovernment employment. The importance of the perceived quality of their performance makes federal officials very sensitive to the opinions of the institutions they regulate and to their trade associations. This leads regulators to be influenced by their constituencies, avoiding solutions unfavorable to them or promoting solutions that they find particularly desirable. Lobbying activities exaggerate and make the negative early effects of public policies more visible, further slowing the adoption of substantial changes in financial regulation. Regulators cannot make substantial changes without being perceived as causing or aggravating the problems. Adopting a coverup strategy helps top insurance officials to keep politicians at bay and at the same time allows them to avoid bad publicity.

All of these constraints increase the career costs of serving the taxpayer well. To avoid jeopardizing their future careers, regulators adopt forbearance policies, imposing the resulting costs on the taxpayer. Because of conflicts of interest among politicians, regulators, and taxpayers, economically insolvent institutions do not necessarily "fail." For a failure decision to be made, regulators must decide that their normal attitude of forbearance is no longer in their bureaucratic interest.

III. The Model of Regulators' Decision-making

Economic theory can explain why deferring meaningful action can be the rational choice for federal officials. In economics, an agent's decision is modeled as the outcome of a constrained optimization problem, where the agent minimizes or maximizes an objective function subject to one or more constraints on his actions.

Kane adapts this optimization approach to develop a model of regulatory decision-making. The model incorporates incentive problems arising from distributional conflict, information asymmetry, externalities, and agency costs. As defined in Kane (1988), distributional conflict is inherent in any government action that benefits one segment of society at the expense of others. Externalities are uncompensated costs or benefits imposed on a private party as a result of an action by another. Agency costs are welfare or resource losses arising from conflicts between the interests of taxpayers as principals and the narrower interests of government officials appointed to serve as their agents. The model developed recognizes political pressures generated by distributional conflict and externalities, as well as the incentive problems arising from information asymmetries and principal-agent conflicts.

In his model, Kane (1988, 1989) envisions two extreme types of regulators. The first type, unconflicted or faithful agents, protect the interests of taxpayers, resisting politician-imposed restraints and career-oriented incentives. In contrast, conflicted or self-interested agents are tempted by these incentives and serve their narrower interests rather than, or in addition to, those of the taxpayer.

In making a failure decision for individual institutions, a value-maximizing or faithful agent compares the economic costs (implicit plus explicit) of allowing the institution to fail with those of allowing it to operate. At each period, the difference between these costs, which may be interpreted as the net cost of waiting, determines the failure decision. A failure decision for an individual institution maximizes the value of the insurance fund only if failure proves less costly than allowing the institution to operate (see Acharya and Dreyfus [1988] for a model of a faithful agent).

When an institution is closed, the value of its insurance guarantees may become an immediate claim against its insurance agency. The market value (MV) of a firm's capital is equal to the market value of its enterprise-contributed capital--its net value (NV)--plus the market value of its insurance guarantees (federally contributed capital). Federal guarantees provide credit enhancements that allow an institution to finance its operations at lower costs or with less enterprise-contributed equity.

The market value of deposit insurance guarantees can be defined as the incremental value these guarantees add to the market value of a financial institution's enterprise-contributed equity. The relationship is clarified in figure 1. For a well-capitalized institution, federal guarantees do not provide a significant level of credit enhancement. However, they are crucial for institutions with low or negative NV, especially after the institution becomes economically insolvent (NV=0). This hyperbolic relationship between MV and NV is approximated by the following function:

$$MV = 0.5NV + \sqrt{0.25NV^2 + c^2}. \tag{1}$$

This approximation is adopted because, in the limit, when NV takes on increasingly larger positive values, the incremental value of deposit insurance guarantees becomes increasingly less significant and MV approaches the 45-degree line (or NV). The function also satisfies the condition that for increasingly larger (in absolute terms) negative values of NV, the value of federal guarantees becomes increasingly crucial, offsetting the negative NV. Finally, in the limiting case, MV approaches the horizontal axis (zero).

Then the guarantee function is given by

$$G(NV) = MV - NV = -0.5NV + \sqrt{0.25NV^2 + c^2}. \tag{2}$$

As explained above, G(NV) is a claim against the insurance fund. If the institution is closed this period, with NV_o, in addition to possible payouts, the insurance agency also incurs paperwork costs (C_{pw}) of studying the institution's portfolio and negotiating a reprivatization. If the institution is allowed to operate one more period, its NV becomes

$$NV_1 = NV_o(1+r) + \epsilon, \tag{3}$$

where r is the rate of return and ϵ is a shock with standard error σ. Theoretically, the mean value of ϵ should depend on enterprise-contributed equity, portfolio riskiness, and regulatory closure rules. However, if we assume this mean to be zero and use Taylor's theorem, the expected value of the future guarantee is given by

$$EG(NV_1) \simeq G(NV_o) + rNV_oG'(NV_o) + 1/2(r^2NV_o^2 + \sigma^2)G''(NV_o) + \ldots. \tag{4}$$

Monitoring costs, C_m, are also incurred. In addition, depending on NV_o, there is a probability that the institution will be closed next period if the shock is negative. Thus, there is also an expected paperwork cost, which can be assumed to be a fraction of C_{pw} depending on the expected probability of closure next period. The net cost of waiting is given by

$$K(NV) = 1/1{+}r\ [EG(NV_1) + C_m + 1/2C_{pw}] - [G(NV_o) + C_{pw}] \tag{5}$$

$$\simeq 1/1{+}r\ [-rG(NV_o){+}rNV_oG'(NV_o){+}1/2(r^2NV_o^2{+}\sigma^2)G''(NV_o){+}C_m{-}1/2C_{pw}{-}rC_{pw}].$$

The faithful agent makes a failure decision if K is positive, and allows the institution to operate if K is negative.

On the right-hand side of equation (5), the first three terms collectively give the one-period expected change in the guarantee value. G(NV) is always positive, approaching zero or the absolute value of NV, as NV goes to positive or negative infinity, respectively. G'(NV) varies from 0 to -1 for the same range. G"(NV) is always positive and approaches zero as NV moves away from zero in either direction.

Because the third term is always positive, it drives the failure decision, particularly in the vicinity of NV=0, where the curvature is highest. The first term is always negative, and the second term is negative for positive NV, so that for high values of NV these terms plus

C_{pw} combine to offset the diminishing effect of the third term, and prevent failure. As NV becomes very large, the first term drops out, and the second and third terms go to negative and positive infinity, respectively, offsetting each other's effect. Thus, as the institution obtains more and more of its own capital, the cost of waiting becomes zero or negative (depending on the net monitoring minus paperwork costs), and the agent does not make a failure decision.

For negative NV, the second term is positive and encourages failure. However, the first term is always negative and greater in absolute value (since $G > NV$ and $0 > G' > -1$), so the combined effect of the first two terms is negative. As NV becomes more and more negative, however, the combined effect of the first two terms goes to zero. Thus, the overall effect of the three terms is dominated by the third term, which approaches positive infinity. Therefore, the more negative NV becomes, the costlier it is to wait.

In economic terms, the model indicates that if the guarantee value is expected to increase, the cost of waiting also increases. This is expected, since an increase in guarantee value leads to an increase in the claim against the insurance agency. Also, monitoring costs encourage a failure decision, whereas paperwork costs discourage it. A trade-off between the two costs clearly exists. However, if the faithful agent is able to resist economic constraints effectively, the relative contributior of monitoring and paperwork costs to the failure decision may be negligible. Theoretically, other variables do not affect the decision-making of faithful agents, but since the risk-taking incentives of low NV institutions are not modeled above, empirically NV may also enter directly.

For a conflicted agent, additional factors affect the failure decision. The aforementioned political and bureaucratic constraints and career-oriented incentives make it more costly for the agent to make a failure decision. These effects are denoted by C_c, which represents the career costs. For a conflicted agent, the cost of waiting is given by

$$K(NV) = 1/1+r\ [EG(NV_1) + C_m + 1/2C_{pw}] - [G(NV_o) + C_{pw} + C_c]. \qquad (6)$$

The career cost of making a failure decision is greater, the greater the extent of conflicts between politicians and regulators and regulators and taxpayers. The net cost of waiting decreases as the conflicting incentive systems and constraints increase the career cost. The more conflicted the agent, the greater the C_c. It is not difficult to visualize an extreme case where the career cost becomes so high that it far outweighs the other factors and dominates the K(NV) function. This implies a zero or negative K(NV). In these circumstances, regardless of the institution's market-value insolvency, a failure decision will not be made.

An Empirical Model of the Failure Decision

It is possible to develop an empirical model of regulators' failure decision based on the theoretical failure model discussed above. In each period, optimizing regulators are faced with two alternatives in their decision-making process: failure vs. continuation of operations. Since one alternative must be chosen at each time, a binary choice model is appropriate here. The binary decision by the regulators (about the

i^{th} institution) can be conveniently represented by a random variable that takes the value one if a failure decision is made and takes the value zero if the institution is allowed to operate. Since the regulators' decision cannot be predicted with certainty, I model the choice probabilities. It is of interest to see how various explanatory variables affect the probability of a regulatory failure decision.

Let F* be a latent continuous variable that expresses the outcome of the regulators' binary choice such that

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

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

Assume the following stochastic regulator cost function:

$$F[\alpha(X_1)] + (1-F)[c(X_2)], \tag{7}$$

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 counterparts of the theoretical cost functions of failing the institution and allowing it to operate, respectively. The nonstochastic portions of these expressions can be modeled as 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.

Value maximization requires a failure decision to be made only if the cost of failing the institution is less than allowing the institution to operate, and vice versa:

$$\begin{aligned} F &= 1 \quad \text{if} \quad \alpha(X_1) < c(X_2), \\ F &= 0 \quad \phantom{\text{if}} \quad \alpha(X_1) > c(X_2). \end{aligned} \tag{8}$$

Now we can identify F* with our theoretical criterion variable, the net cost of waiting.

$$F^* = c(X_2) - \alpha(X_1). \tag{9}$$

A failure decision is made if this cost is greater than zero, and the institution is allowed to operate autonomously if it is not:

$$F = 1 \quad \text{if} \quad c > \alpha \quad F^* > 0, \tag{10}$$

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

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

$$F^* = X\beta + v, \text{ where } X_1, X_2 \subset X \text{ and } v = e_c - e_\alpha. \tag{11}$$

Then, $E(F^*) = P(F=1) = P(F^* > 0)$ (12)

$= P(X\beta+v > 0)$

$= P(X\beta+e_c-e_\alpha > 0)$

$= P(e_\alpha-e_c < X\beta)$

$= \mathcal{F}(X\beta)$,

where $\mathcal{F}$ is the cumulative distribution function of the e_α-e_c. The type of probability model obtained depends on the choice of this distribution function.

Thus, the failure equation models an optimization by the regulators. Constraints and incentives gain importance to the extent that the agent is conflicted. The exogenous variables, X, are specified in the theoretical model, (6). In practice, NV, G(NV), G'(NV), and G"(NV) can only be estimated (measured with error), and the costs C_m, C_{pw}, and C_c are unobserved. Therefore, potential regressors include estimated NV and expected change in the guarantee value (ΔGV) and regulatory constraint and incentive proxies.

One variable that ought to affect the regulators' failure decision is the market value of enterprise-contributed equity. This net equity value summarizes the bank's true financial condition. Naturally, a faithful agent's failure decision is highly influenced by this value. However, this may not be true for a conflicted agent. To investigate whether the agent's perception of the economic insolvency of an institution is based on market values or on an accounting distortion of the market-value solvency, the book value of the institution's equity is also considered.

The full model consists of three equations. The first models the determinants of the institution's capital. The second obtains the estimate of the market value of enterprise-contributed (net) equity, which in our case is stockholder-contributed equity, since the institutions considered in this study are stockholder-owned as opposed to mutually owned. Net economic value is constructed by subtracting the estimated value of the guarantee from the estimated market value of the institution's capital.[4] Finally, the third equation estimates the probability of a failure decision by the regulators. In symbols:

$$MV_{i,t} = h\ (BV_{i,t}) + u_{1i,t} \tag{13}$$

$$NV_{i,t} \equiv \hat{MV}_{i,t} - \hat{g}_{i,t} \quad \hat{g}_{i,t} = g[h(BV_{i,t}) + u_{1i,t}] \tag{14}$$

$$F_{i,t}^* = f(\Delta GV_{i,t},\ NV_{i,t},\ BV_{i,t},\ X_{i,t}) + u_{2i,t} \tag{15}$$

where

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

$BV_{i,t}$ = book value of the institution's equity at time t. BV is the book value of assets minus the book value of liabilities.

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

$NV_{i,t}$ = net economic value of the i^{th} institution at time t. It is constructed by subtracting the estimate of the federal guarantee value from the estimated market value of the institution's stock shares.

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

$\Delta GV_{i,t}$ = the one-period change in the guarantee value of the i^{th} institution as expected by the regulators at time t.

$X_{i,t}$ = vector of proxy variables for C_m, C_{pw}, and C_c, as explained below.

The first two equations of the model estimate the enterprise-contributed equity or net value (NV). I estimate the value of the guarantee within a regression-equation statistical market value accounting model (SMVAM) introduced by Kane and Unal (1990). The SMVAM studies the determinants of the market value of an institution's equity. A nonlinear version of the model is also developed. Once an estimate of the guarantee value is obtained, it is possible to construct net equity by subtracting the estimated guarantee value from the market value of the institution's equity.[5]

Because the emphasis of this paper is on modeling regulators' failure decisions, the reader is referred to Demirgüç-Kunt (1990a, 1990b) for a detailed derivation and estimation of the first two equations. The failure equation employs an estimate of NV given by the first two equations of the model, and ΔGV is obtained from equations (2), (3), and (4) above.

The failure equation is the empirical version of the theoretical failure-decision model developed above. The model predicts that an increase in ΔGV increases K, the cost of waiting, therefore making a failure decision more likely. Thus, in the empirical model, a positive coefficient is expected for ΔGV, indicating a greater probability of making a failure decision with an increase in ΔGV.

Choice of Proxy Variables

Equation (6) tells us that theoretically C_m increases and C_{pw} and C_c decrease the cost of waiting. Thus, empirically C_m is expected to have a positive coefficient, whereas C_{pw} and C_c are expected to have negative coefficients, making a failure decision more and less likely, respectively. One problem is that, since neither of these variables is observed, proxies must be used. Any residual effect that cannot be captured by the proxies reflects in the intercept. If the various costs are orthogonal to the proxies employed, the intercept may be interpreted as the monitoring cost net of paperwork and career costs. If the latter two costs outweigh the monitoring cost, the intercept will have a negative sign.

The asset size (A) variable proxies both C_{pw} and C_c. Clearly, the larger the institution, both financially and administratively, the more difficult it becomes to resolve its insolvency (Conover [1984], Seidman [1986]). The size of the institution is directly related to the amount of paperwork costs incurred in the event of its failure. Also, institution size is expected to capture the economic, political, and bureaucratic constraints that increase regulators' career costs. Economic considerations are more likely to be binding constraints in larger institutions. In addition, political and bureaucratic constraints tend to increase the career costs of failure decisions, especially where giant institutions are concerned. In an effort to protect their performance image, conflicted regulators try not to get involved with large-bank failures, which often prove to be much more visible and troublesome than failures of smaller institutions. Therefore, ceteris paribus, regulators are expected to be less likely to make failure decisions for larger institutions. In accordance with the theoretical model, proxies for C_{pw} and C_c are expected to have negative signs.

The number of problem banks (PB), the bank failure rate (BFI), the general failure rate (FI), and the variance of interest rates (VAR) are also included as political and bureaucratic constraint proxies that increase the career costs of making a failure decision. Theoretically, if these proxies could capture only the effects of political and bureaucratic constraints, we would expect them to have negative signs, since higher C_c lowers the cost of waiting and leads to a lower probability of failure. Unfortunately, this may not be the case, since these variables may capture several counteracting effects.

An increase in bank failures, potential bank failures, general business failures, or financial volatility may indicate a worsening of the financial environment for institutions and may affect an individual bank's NV adversely. In this case, these variables naturally make a failure decision more likely, having positive signs. However, the assumption made here is that the financial condition of the institution is being controlled. Since the variables NV and ΔGV are estimated, it is questionable that this assumption is fully justified. At best, we may claim that the institution's financial condition is partially controlled.

An additional effect is captured by the PB and BFI variables, which may indicate possible trends in regulatory decision-making. In other words, an increased number of bank failures or potential bank failures may actually signal that a regulator is getting tougher, a trend that may continue into the future. A general increase in the probability of making a failure decision in the last period may indicate a similar increase this period. Ceteris paribus, a tougher regulator last period may mean a greater likelihood of failure for an individual bank this period. This effect is not expected to be dominant for FI and VAR, since they are relatively unrelated to regulators' past failure decisions.

If the extent of institutional solvency (or insolvency) could have been perfectly controlled for, and no trends existed in regulatory decision-making, then all of the above variables would capture only the political and bureaucratic constraints that increase the career costs of making a failure decision. As already discussed, political and bureaucratic constraints affect decisions, since conflicted regulators are more concerned with preserving their perceived performance images than with serving the taxpayer. This requires them to be very sensitive to public opinion. Regulators also tend to be especially careful in financially difficult times, protecting their clientele in order not to damage their own performance image.

In summary, PB, BFI, FI, and VAR are included to capture the extent of insolvency tolerated by the regulators. To the extent that the financial condition of institutions is controlled for, PB, BFI, FI and VAR are candidate proxies for C_c. Finally, if more than one effect is present, the signs of the coefficients depend on the relative magnitude of these effects.

During the period sampled in this study, the FDIC's fund size (R) and number of examiners (EX) capture the economic constraints that politicians at least partly impose on regulators. Explicit costs of insolvency resolution and monitoring effort are restricted by the budget procedures to which the regulators are subject. Naturally, without effective monitoring, insolvencies remain hidden, and even those that are discovered cannot be resolved without adequate funds. If funding is insufficient and examiner force is inadequate, a self-interested regulator (in order to avoid conflict with politicians) may allow short-run cost considerations to determine failure decisions, instead of maximizing the value of the insurance fund. Career costs that are especially high would not allow many insolvencies to be resolved, because conflict with politicians in an effort to relax these constraints would make it appear that the regulator was causing the problems. Clearly, an increase in available funds or in the number of examiners would lower the career costs (C_c) of making a failure decision by lessening the possibility of conflict between politicians and regulators. Therefore, the coefficients of these proxies are expected to have positive signs.

Finally, to investigate possible differences in decision-making among federal and state regulators, a charter (C) variable is included. The failure decision is made by the Office of the Comptroller of Currency if the bank has a national charter and by the State Banking Commission if it has a state charter. In both cases, the failure decision is usually made following the recommendation of the insurance agency.

The empirical model of large-bank failures developed in this paper is based on a theoretical regulatory failure decision-making model. Hypothetically, a faithful agent's decision-making is unaffected by C_c. However, although most of the proxy variables are included to proxy for C_c, it is difficult to distinguish empirically between the effect of C_c and that of other costs, C_m and C_{pw}, on the failure decision. This study does not claim to measure the extent of "faithfulness" of the agents. However, to the extent that faithful agents can resist economic constraints, we can assume empirically that their decision is mostly determined by NV and ΔGV--the economic insolvency of the institution. In contrast, a completely self-interested agent's failure decision is dominated by C_c--the regulatory constraint and incentive proxies. Conflicted agents, who are at neither extreme, make their decision based on both the extent of the institution's insolvency (either an economic or distorted accounting measure of insolvency) and regulatory constraints and incentives. Given these assumptions, the significance of the proxy variables included may signal the extent of conflict that exists between regulators and taxpayers.

IV. The Data and the Empirical Results

Panel data are used in estimating the model. A list of failed banks with assets greater than $90 million (since smaller banks seldom prove to have actively traded stocks) is obtained from the FDIC's Annual Reports and the American Banker for the period 1973-1989. In this study, failure decisions are defined to include various insolvency resolution methods such as liquidation, purchase and assumption transactions, reorganization, nationalization, and direct assistance.[6]

Annual data on the number of shares, book value per share, total assets, and price range are 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 majority of the failed banks (75 percent) are from southern states (Texas, New Mexico, Oklahoma, Louisiana, Mississippi, Tennessee, and California), and the rest are from New York, Pennsylvania, Wisconsin, Illinois, and Alaska.

The universe of nonfailed banks is identified from Moody's Bank Manual in three steps. First, each listed bank is screened to choose the banks that come from the above 12 states. Second, all of these banks that fall within the failed-bank asset range are kept. Finally, all FDIC-member banks with actively traded stock (as reported in the Bank Manual) are chosen to constitute the universe of nonfailed banks. The banks in this universe are FDIC members and have traded stock throughout the sample period (1963, or the date of charter, to 1987).

The candidate banks are then separated into two groups based on their home state. A random sample of 50 nonfailed banks is chosen from the two groups of candidate banks so that the nonfailed sample has the same geographic dispersion: 75 percent from the southern states, and 25 percent from the rest. The resulting control sample also has a roughly similar asset-size dispersion as the failed sample. The same annual data are collected for the nonfailed banks.

Interest-rate data are obtained from Standard & Poor's Basic Statistics. The business failure rate is from Dun & Bradstreet's Business Failure Record, and the charter data are obtained from the Board of Governors of the Federal Reserve System's reports of condition data tapes. The data for the rest of the variables are collected from the FDIC's Annual Reports. Variable definitions are given in table 2.

Empirical Results

As exogenous variables, the failure equation includes estimates of enterprise-contributed equity value (NV) for individual institutions and the one-period expected change in their guarantee value. In addition, career-cost proxy variables are included to capture the regulators' economic, political, and bureaucratic constraints and career-oriented incentives.

The failure equation is estimated by the logit maximum likelihood method using cross-sectional and time-series pooled data. Generally, in estimation of binary qualitative response models, the choice between a logit or a probit model is not important (Amemiya [1981]). When separate samples are drawn from different groups with unequal sampling rates, the estimated coefficients of the probit model are biased, although this problem does not arise with the logit model (Maddala [1983]). This is also true in our case, since all failed banks with traded stock are included in the failed category, but only a sample of the nonfailed banks is included in the nonfailed category.

The equation is estimated using NV obtained from linear and nonlinear versions of the insolvency equation (Demirgüç-Kunt [1990a, 1990b]). This is done to investigate the sensitivity of results to possible nonlinearity in estimation of NV. For each version of the equation, a preferred specification is obtained based on three criteria recommended by Amemiya (1981): 1) model chi-square, 2) Akaike's information criterion, and 3) in-sample classification accuracy.

Model chi-square is the outcome of a likelihood-ratio test of the joint significance of all variables in the model. It is measured as twice the difference in log likelihood of the current model from the likelihood based only on the intercept. The null hypothesis that all of the explanatory variables in the model are zero is rejected if the calculated chi-square statistic is greater than a critical value.

Akaike's (1973) information criterion (AIC) is desirable in comparing models with different degrees of freedom, since it makes an adjustment to penalize for the number of parameters estimated. It is given by

$$AIC = -l + K,$$

where l is the log likelihood of the model and K is the number of parameters to be estimated. We seek the model for which AIC is the smallest.

To determine the classification accuracy of the model, three criteria are considered: error 1, error 2, and total correct. Error 1 is a misclassification of a failed bank as nonfailed, and error 2 is a misclassification of a nonfailed bank as failed. It is often argued that the costs of these misclassification errors are unequal, with error 1 being relatively more costly. This reasoning would require a greater emphasis on minimizing error 1. However, to develop an overall indicator of the model's predictive accuracy, it is assumed that these costs are the same.

Total correct provides an equally weighted measure of both errors. This measure is preferred to the total percentage of correctly classified observations, which is weighted by the number of observations in each group. When there is a disproportionate number of observations in one group (in our case, nonfailures), then the total percentage correctly classified is heavily biased toward the accurate classification of nonfailures. In our case, if a model classifies all institutions as nonfailed, 98 percent of the observations are correctly classified, although total correct is only 50 percent. Thus, since using the percentage of correctly classified observations can be misleading (unless the sample is equally divided between the two categories), equally weighted total correct is used to determine the prediction accuracy.

The reported specifications are tested using the Davidson and Mackinnon (1984) test for limited dependent variable models. For either version, the null hypothesis of no misspecification cannot be rejected at 5 percent significance level.

The failure equation employs an estimated NV, the measure of insolvency obtained from the first two equations. Because of this two-stage estimation, the variance-covariance matrix obtained from logit underestimates the correct standard errors. The second-stage variance-covariance matrix is calculated using Amemiya's (1979) method. Even with the corrected asymptotic standard errors, conventional tests may err in the direction of nonsignificance in the case of qualitative response models (Maddala [1986]). Therefore, as Maddala recommends, the significance of variables is determined using likelihood-ratio tests.

The results of the failure equation are presented in table 3. The preferred specifications of the linear and nonlinear versions retain nine and five exogenous variables, respectively.

The constant term is negative and significant for both versions. If career-cost proxies are orthogonal to monitoring and paperwork costs, this intercept may be interpreted following equation (6) as the monitoring costs net of paperwork costs. The negative sign indicates that the paperwork costs outweigh monitoring costs.

The expected change in guarantee value has a positive coefficient in both cases, although it proves significant only in the nonlinear version. This result is consistent with the prediction of the failure-decision model developed in section III. An increase in the expected guarantee value increases the cost of waiting, therefore making a failure decision more likely. This occurs since the guarantee value is a potential claim against the insurance agency, and an expected increase in this claim increases the probability that regulators will make a failure decision.

The coefficient of NV is negative and significant in both versions. Clearly, an increase in the net economic value of an institution reduces the regulatory pressure 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 significance. This indicates that NV carries superior information about the institution's enterprise-contributed equity and that no relevant additional information is contained in BV. Specifications including only BV are also inferior based on the above criteria.

These results indicate that bank-specific variables have the intuitively expected effects on regulatory decision-making. Thus, controlling for the institutions' solvency or insolvency, the variables A, BFI, FI, PB, VAR, EX, and R are career-cost proxies included to capture regulators' economic, political, and bureaucratic constraints and incentives.

The coefficient of asset size, A, is negative and significant in both cases. As a proxy for economic constraints, these results are expected. Clearly, the larger the institution, the more binding the economic constraints and the more difficulty in dealing with its insolvency, both financially and administratively (Conover [1984], Seidman [1986]). It is also possible to interpret this result as evidence of binding political and bureaucratic constraints. The significantly negative coefficient of the size variable confirms the widely held hypothesis that failure decisions are less likely for larger institutions (Kaufman [1985]).

BFI is negative in both versions but proves significant only in nonlinear specification. FI has a negative (yet insignificant) coefficient in the linear version and does not enter the nonlinear specification. These negative coefficients are consistent with the decision-making process of a conflicted regulator.

PB and VAR are also expected to capture the insolvency-toleration effect. However, these variables do not enter the nonlinear specification. In the linear specification, the significance of their contribution cannot be rejected (using likelihood-ratio tests). Both have positive but individually insignificant coefficients, indicating that the expected insolvency-toleration effect is outweighed by other factors.

The size of the FDIC's problem-bank list summarizes the extent to which banks are recognized as lacking in capital adequacy, asset quality, management skills, earnings, or liquidity (the CAMEL rating). Many problem banks may be de facto insolvent. To the extent that authorities try to delay failure, potential failures (many of which may be virtually beyond saving) tend to appear on this list for some time before being acted upon. Therefore, an increase in potential failures may indicate an increase in the probability of a failure decision for economically insolvent banks.

VAR is included to proxy for the volatility of the financial environment. An increase in this variance indicates increased uncertainty for financial institutions. A conflicted agent is expected to protect his clientele during such unfavorable times. However, if the financial condition of the institution is not perfectly controlled for, a counteracting effect is also present, since a deteriorating financial environment leads to lower NV for institutions. Although insignificant, the positive sign of the coefficient suggests the dominance of this effect.

EX and R are included to capture, at least partially, the economic constraints faced by regulators. An increase in these variables lessens the possibility of conflict between politicians and regulators, thus lowering the career costs of making failure decisions.

EX has a significant and positive coefficient in both specifications. An increase in the number of examiners raises the probability of a failure decision by relaxing the economic constraints on finding hidden insolvencies and therefore lowers the career costs of making a failure decision. For given levels of skill and client population, the greater the number of examiners employed at time t-1, the more frequent and thorough the examinations should be. This increases the probability that the FDIC will discover insolvent institutions, making a failure decision more likely at time t.

R enters only the linear specification and has a positive (yet individually insignificant) coefficient. As expected, the availability of funds to absorb losses constrains the regulators' failure decision. If reserves increase, the resource constraint becomes less binding, so that a failure decision becomes more likely.

Finally, the federal chartering authority (Office of the Comptroller of the Currency) and state chartering authorities (as a group) do not differ significantly in their decision-making. The charter dummy variable does not enter the preferred specification of either version.

In summary, although it is difficult to proxy regulators' career costs, the empirical results provide evidence of conflict between regulators and taxpayers. The significance of economic insolvency coefficients is consistent with both self-interested and faithful regulators. A faithful agent's decision function is determined by the institutions' economic insolvency. A self-interested agent's decision is instead dominated by career cost considerations--hence the constraint and incentive proxies. However, in cases where the agent's perceived performance image is positively affected by reacting to the economic insolvency of institutions, the self-interested agent may also consider the financial condition of institutions.

Thus, in deciding whether the agent is faithful or self-interested, the crucial coefficients are not those of the insolvency variables but those of the career cost proxies. Significant proxy coefficients indicate the existence of conflict. However, since the decision function is not completely dominated by career costs, it is less likely that the regulators are purely self-interested.

It is possible to conclude that the regulator-agents are neither completely self-interested nor completely faithful. As hypothesized throughout, regulators are conflicted agents, and their failure decisions are determined both by the extent of the institutions' insolvency and by regulatory constraints and incentives.

The Predictive Power of the Model

The predictive power and the statistical fit of the model are also reported at the end of table 3. The summary statistics are model chi-square, AIC, and in-sample classification accuracy.

For both versions, the null hypothesis that all explanatory variables in the model are insignificant is rejected at the 1 percent significance level (degrees of freedom are nine and five for the linear and nonlinear versions, respectively). According to all three criteria, the failure equation constructed using the nonlinear NV estimate performs better. The nonlinear specification results in a higher chi-square and lower AIC values and has superior classification accuracy.

For the nonlinear specification, error 1 is 3 percent (only one bank misclassified), and error 2 is 8 percent. The linear specification misclassifies 9 percent of failed institutions and 19 percent of nonfailed institutions. Total correct is 86 and 95 percent for linear and nonlinear versions, respectively.

To study further the contribution of regulatory constraints and incentives to failure decision-making, the failure equation is also estimated for three alternative specifications: 1) using only career-cost proxies, 2) using only economic-insolvency variables from the linear model, and 3) using only economic-insolvency variables from the nonlinear model. Results are reported in table 4. Interestingly, the model with career-cost proxies has a prediction accuracy of only 77 percent. The NV obtained from the linear specification does better in classifying the failed banks: The incidence of error 1 falls to 23 percent. Finally, the NV obtained from the nonlinear specification does much better: Error 1 stays at 23 percent and error 2 falls to 14 percent. Its prediction accuracy is also the highest among the three specifications, at 82 percent. The results indicate that NV produced by the nonlinear model has greater discriminatory power.

A Holdout Test

The prediction accuracy discussed above is the in-sample prediction accuracy of the models, where the estimated model is used to reclassify the observations in the sample. This classification accuracy is useful in choosing among competing models because it is a determinant of statistical fit (Maddala [1986]). However, in-sample classification accuracy may be overstated, since the very same observations used to construct the model are classified. The use of a holdout sample is therefore important in order to validate a model. The rest of this section aims to test the sensitivity of the model's prediction accuracy in classifying a holdout sample.

As a holdout sample, the 1988-1989 failures (eight failed banks) and eight nonfailed banks (randomly selected from the nonfailed sample) are identified. The test proceeds as follows: First, delete all the observations belonging to failed (including the nonfailed observations of the failed banks) and nonfailed banks. Second, estimate the linear and nonlinear versions of SMVAM for the remaining failed and nonfailed banks. Third, estimate the two specifications of the failure equation using the NV constructed from the nonlinear and linear versions of SMVAM, respectively. Finally, classify the holdout sample using the estimated models.

The coefficients of the estimated equations are not reported, since they are not significantly different from the results presented in table 3. Here, the emphasis is on the accuracy of the model for classifying the holdout sample.

Both the linear and nonlinear versions of the failure equation correctly classify all eight failed banks as failed. Error 2, the error of misclassifying the holdout nonfailed institutions as failed, is 6 percent for the nonlinear version and 11 percent for the linear version. These results indicate that the model performs well out of sample.

This is not surprising, since the choice of variables in the model (for both equations) is independent of the institutions included, unlike the usual approach in bank-failure literature.[7]

V. Summary and Conclusions

The model developed in this paper seeks to express the regulator's failure decision process. Developing a theoretical model of failure decision-making makes it possible to incorporate explicitly into the empirical model the regulatory constraint and incentive effects. The results obtained from the empirical failure model shed light on various issues. First, regulatory constraints and incentives significantly influence the failure decision. The economic insolvency of an institution is also an important determinant of the failure decision, indicating that regulators are conflicted, rather than completely self-interested, agents of the taxpayer. Second, NV is a better indicator of economic insolvency than BV.

In conclusion, the best failure model supports the hypothesis that it is useful to allow both for the financial condition of the institutions and for regulatory constraints and incentives in modeling the regulatory decision-making process. Although NV is a good indicator of the likelihood of a failure decision, the classification accuracy increases to more than 90 percent only when regulatory constraints are taken into consideration. Results indicate the existence of binding economic, political, and bureaucratic constraints. The significance of constraint proxies confirms the existence of substantial conflicts between regulatory and taxpayer interests. The results underline the importance of the difficult but necessary task of improving the incentive system for deposit institution regulators.

The model of bank failure developed in this paper is more complete than earlier ones in that it acknowledges and incorporates the regulatory aspect of failure process. The explanatory and discriminatory power of the model supports the approach taken in this study.

The conclusions reached also apply to the S&L industry. S&Ls and commercial banks show symptoms of the same disease, but for S&Ls, the problem is at a more advanced stage. This model could be used to analyze S&L failure decisions and to compare and contrast findings that apply for banks and S&Ls.

In all research, important caveats usually exist. Here, the analysis is restricted by the available data. With a richer data set, many useful extensions could be performed.

Failure decisions include various insolvency resolution methods such as liquidation, purchase and assumption transactions, reorganization, nationalization, and direct assistance. In the data set, however, 85 percent of the failures are purchase and assumption transactions. All of the above insolvency resolution methods are therefore combined into one category of failure. However, the cost to the insurance agency is believed to vary across the different methods. With an extended data set, it would be useful to identify and analyze factors pertaining to the choice of different types of insolvency resolution methods. Another important extension would be to study changes in regulatory decision-making over the years.

Footnotes

1. For a thorough discussion of safe and sound banking, see Benston et al. (1986).

2. See Demirgüç-Kunt (1989) for a review of empirical literature on deposit institution failures.

3. Risk-taking incentives of market-value-insolvent institutions are discussed in the literature. See Meltzer (1967), Scott and Mayer (1971), Kareken and Wallace (1978), McCulloch (1981, 1987), Kane (1981a, 1981b, 1985, 1986, 1989), Pyle (1983, 1984), and Benston et al. (1986).

4. Due to correlation between u_1 and u_2, the estimated guarantee value is subtracted from estimated MV (instead of MV) to obtain NV. In this way, the consistency of the failure equation estimator is retained. See Demirgüç-Kunt (1990a) for further discussion.

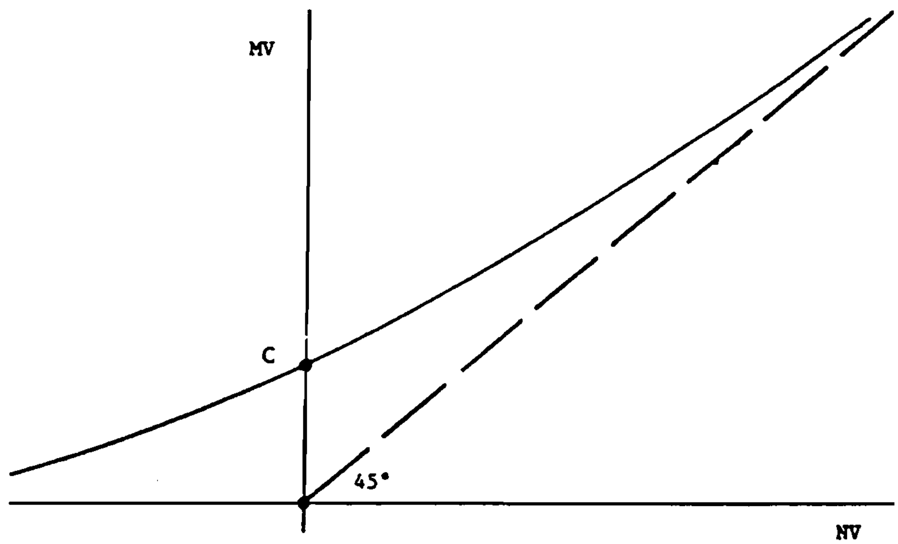
5. Different methods of estimating deposit insurance guarantee value are discussed in Demirgüç-Kunt (1990a).

6. Detailed explanations and definitions of these insolvency resolution methods can be found in Benston et al. (1986), Kane (1985), Caliguire and Thomson (1987), and Demirgüç-Kunt (1990a).

7. See Demirgüç-Kunt (1989).

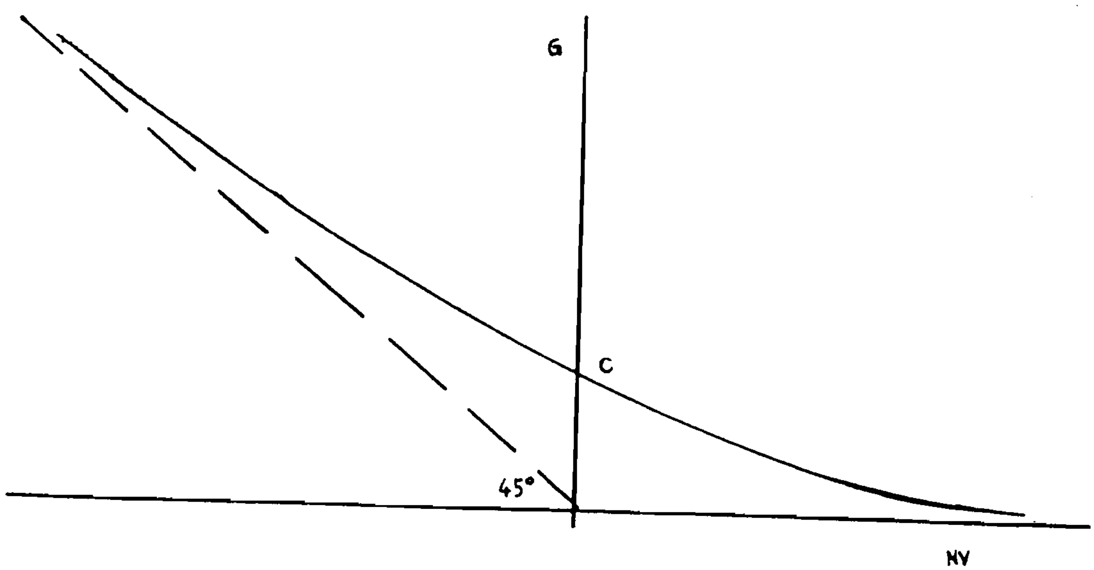
Figure 1 The Relationship Between MV and NV

$$MV = 0.5NV + \sqrt{0.25NV^2 + c^2}$$



The Relationship Between G(NV) and NV

$$G(NV) = -0.5NV + \sqrt{0.25NV^2 + c^2}$$



Source: Author.

Table 1 Failed Banks With Assets More Than $90 Million, 1973-1989

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

Table 1 (continued)

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

Table 1 (continued)

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

Table 1 (continued)

Failure Date	Bank	Assets	Failure Type
1989	Texas American Bancshares Inc., Texas (TAB)	$5.9 billion	P&A
1989	National Bancshares Corp. of Texas, Texas (NBC)	2.7 billion	P&A

Notes: P&A = Purchase & assumption transaction (27)

DA = Open bank assistance (4)

P = Deposit payoff (1)

Sources: Federal Deposit Insurance Corporation Annual Reports and American Banker.

Table 2 Variable Definitions and Sources

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 capital stock, surplus, undivided profits, and reserves. Data are obtained from Moody's Bank Manuals.
EX_t	=	the number of examiners the FDIC employs at time t, obtained from 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 rate at time t. This variable is calculated from the FDIC's Annual Reports, table 122. The calculation is based on total deposits of failed institutions (1970 is taken as the base year). It is adjusted for inflation using the Producer Price Index (PPI), obtained from Standard & Poor's Basic Statistics.
PB_t	=	number of FDIC problem banks at time t. It is obtained from various issues of the FDIC's Annual Reports.
R_t	=	the FDIC insurance fund (adjusted for inflation using the PPI) 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. It is adjusted for inflation using total bank assets.
VAR_t	=	annual variance of the six-month Treasury bill and long-term government security rates. Interest-rate data are obtained from Standard & Poor's Basic Statistics.
C_t	=	a dummy variable that takes 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.

Source: Author.

Table 3 Logit Analysis of Regulators' Failure Decision

Dependent Variable: Failure		
Independent Variables	Linear	Nonlinear
Const.	-88.78**	-79.53**
	(26.43)	(21.66)
$ECGV_t$	0.10	0.50**
	(0.08)	(0.13)
NV_t/A_t	-1.68**	-5.78**
	(0.65)	(0.88)
EX_{t-1}	8.36**	8.20**
	(3.21)	(2.88)
BFI_{t-1}	-0.05	-1.88**
	(0.39)	(0.63)
FI_{t-1}	-1.28	
	(1.01)	
PB_{t-1}	1.44	
	(1.10)	
R_{t-1}	3.18	
	(5.22)	
A_t	-0.43*	-2.14**
	(0.21)	(0.50)
VAR_t	0.11	
	(0.09)	
Summary Statistics		
Model Chi-Square	101.04**	194.98**
AIC	111.73	60.76
Classification		
Error 1	3/32 = 9%	1/32 = 3%
Error 2	19%	8%
Total Correct	86%	95%

Notes: Dependent variable takes the value one for failed institutions and zero for operating institutions.
*Significantly differs from zero at 5 percent.
**Significantly differs from zero at 1 percent.
Standard errors are given in parentheses.
Variable definitions and sources are given in table 2.
Source: Author.

Table 4 Logit Analysis of Regulators' Failure Decision--Regulator Constraints vs. Economic Insolvency

Dependent Variable: Failure

Independent Variables	Constraints	Linear	Nonlinear
Const.	-105.64** (26.98)	-7.47** (1.09)	-15.32** (1.73)
$ECGV_t$		0.05 (0.06)	0.48** (0.10)
NV_t/A_t		-1.32** (0.29)	-3.08** (0.40)
EX_{t-1}	10.95** (3.14)		
BFI_{t-1}	0.63* (0.29)		
FI_{t-1}	-2.01* (0.93)		
PB_{t-1}	2.24* (1.03)		
R_{t-1}	2.91 (5.20)		
A_t	0.00 (0.11)		
VAR_t	0.18* (0.09)		
Summary Statistics			
Model Chi-Square	93.01**	33.92**	112.53**
AIC	99.74	134.29	94.98
Classification			
Error 1	9/32=28%	6/32=23%	6/32=23%
Error 2	19%	27%	14%
Total Correct	77%	75%	82%

Notes: Dependent variable takes the value one for failed institutions and zero for operating institutions.
*Significantly differs from zero at 5 percent.
**Significantly differs from zero at 1 percent.
Standard errors are given in parentheses.
Variable definitions and sources are given in table 2.
Source: Author.

References

Acharya, S., and J. Dreyfus, "Optimal Bank Reorganization Policies and the Pricing of Federal Deposit Insurance," unpublished manuscript, New York University, Department of Finance, 1988.

Akaike, H., "Information Theory and an Extension of the Maximum Likelihood Principle," in B.N. Petrov and F. Csaski, eds., Second International Symposium on Information Theory. Budapest: Akademiai Kiado, 1973.

Altman, E.I., "Predicting Performance in the Savings and Loan Association Industry," Journal of Monetary Economics, 1977, 3, 443-66.

Amemiya, T., "The Estimation of a Simultaneous Equation Tobit Model," International Economic Review, 1979, 169-81.

_________, "Qualitative Response Models: A Survey," Journal of Economic Literature, 1981, 1483-1536.

Avery, R.B., and G.A. Hanweck, "A Dynamic Analysis of Bank Failures," Bank Structure and Competition, Conference Proceedings, Federal Reserve Bank of Chicago, 1984, 380-95.

Barth, J.R., R.D. Brumbaugh, Jr., D. Sauerhaft, and G.H.K. Wang, "Thrift Institution Failures: Causes and Policy Issues," Bank Structure and Competition, Conference Proceedings, Federal Reserve Bank of Chicago, 1985.

Benston, G.J., An Analysis of the Causes of Savings and Loan Association Failures, Monograph Series in Finance and Economics, New York University, 1985.

_________, R.A. Eisenbeis, P.H. Horvitz, E.J. Kane, and G.J. Kaufman, Perspectives on Safe and Sound Banking. Cambridge, Mass.: MIT Press, 1986.

Buchanan, J.M., Fiscal Theory and Political Economy. Chapel Hill, N.C.: University of North Carolina Press, 1960.

_________, Public Finance in Democratic Process. Chapel Hill, N.C.: University of North Carolina Press, 1967.

_________, and R.D. Tollison, The Theory of Public Choice. Ann Arbor, Mich.: University of Michigan Press, 1984.

Caliguire, D.B., and J.B. Thomson, "FDIC Policies for Dealing with Failed and Troubled Institutions," Economic Commentary, Federal Reserve Bank of Cleveland, October 1, 1987.

Campbell, T.S., and A.M. Marino, "On the Incentives for Managers to Make Myopic Investment Decisions," Los Angeles: University of Southern California, Working Paper, 1988.

Conover, C.T., Testimony in U.S. Congress, Subcommittee on Financial Institutions Suspension, Regulation, and Insurance of the Committee on Banking, Finance, and Urban Affairs, Inquiry into Continental Illinois Corp. and Continental Illinois National Bank: Hearings, Sept. 18 and 19 and Oct. 4, 1984, 91-111, 98th Congress, 2nd Session: 287-88.

Davidson, R. and J.G. Mackinnon, "Convenient Specification Tests for Logit and Probit Models," Journal of Econometrics, 1984, 241-62.

Demirgüç-Kunt, A., "Deposit Institution Failures: A Review of Empirical Literature," Economic Review, Federal Reserve Bank of Cleveland, 1989 Quarter 4, 2-18.

________, "Modeling Large Commercial-Bank Failures: A Simultaneous-Equations Analysis," Ph.D. dissertation, The Ohio State University, 1990a.

________, "On the Valuation of Deposit Institutions," World Bank, mimeo, 1990b.

Gajewski, G.R., "Bank Risk, Regulator Behavior, and Bank Closure in the Mid-1980s: A Two-Step Logit Model," Ph.D. dissertation, The George Washington University, 1988.

Kane, E.J., "Deregulation, Savings and Loan Diversification, and the Flow of Housing Finance," in Savings and Loan Asset Management Under Deregulation. San Francisco: Federal Home Loan Bank of San Francisco, 1981a, 81-109.

________, "Impact of Regulation on Economic Behavior: Accelerating Inflation, Technological Innovation, and the Decreasing Effectiveness of Banking Regulation," Journal of Finance, 1981b, 355-67.

________, The Gathering Crisis in Federal Deposit Insurance. Cambridge, Mass.: MIT Press, 1985.

________, "Appearance and Reality in Deposit Insurance," Journal of Banking and Finance, 1986, 175-88.

________, "Changing Incentives Facing Financial-Services Regulators," paper presented at the Federal Reserve Bank of Cleveland Conference on Bank Structure, 1988.

________, The S&L Insurance Mess: How Did It Happen? Cambridge, Mass.: MIT Press, 1989.

________, and H. Unal, "Modeling Structural and Temporal Variation in the Market's Valuation of Banking Firms," Journal of Finance, 1990.

Karaken, J.H., and N. Wallace, "Deposit Insurance and Bank Regulation: A Partial Equilibrium Exposition," Journal of Business, 1978, 413-38.

Kaufman, G.J., "Implications of Large Bank Problems and Insolvencies for the Banking System and Economic Policy," Occasional Papers, SM-85-3, Federal Reserve Bank of Chicago, 1985.

Maddala, G.S., Limited Dependent and Qualitative Variables in Econometrics. New York: Cambridge University Press, 1983.

________, "Econometric Issues in Empirical Analysis of Thrift Institutions' Insolvency and Failure," Invited Research Working Paper No. 56, Federal Home Loan Bank Board, 1986.

Martin, D., "Early Warning of Bank Failure," Journal of Banking and Finance, 1977, 249-76.

McCulloch, J.H., "Interest Rate Risk and Capital Adequacy for Traditional Banks and Financial Intermediaries," in S. Maisel, ed., Risk and Capital Adequacy in Commercial Banks. Chicago: University of Chicago Press for the National Bureau of Economic Research, 1981, 223-48.

________, "The Ohio S&L Crisis in Retrospect: Implications for the Current Federal Deposit Insurance Crisis," Paper presented at the Federal Reserve Bank of Chicago Conference on Bank Structure and Competition, 1987.

Meltzer, A.H., "Major Issues in the Regulation of Financial Institutions," Journal of Political Economy, Supplement 75, 1967, 482-501.

Myers, S.C., and N. Majluf, "Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have," Journal of Financial Economics, 1984, 187-221.

Narayanan, M.P., "Managerial Incentives for Short-Term Results," Journal of Finance, 1985, 1469-84.

Niskanen, W.A., Bureaucracy and Representative Government. Chicago: Aldine Publishers, 1971.

Pyle, D.H., "Pricing Deposit Insurance: The Effects of Mismeasurement," Federal Reserve Bank of San Francisco and University of California, Berkeley, 1983.

________, "Deregulation and Deposit Insurance Reform," Economic Review, Federal Reserve Bank of San Francisco, 1984.

Scott, K.W., and T. Mayer, "Risk and Regulation in Banking: Some Proposals for Deposit Insurance," Stanford Law Review, 1971, 857-902.

Seidman, W., Presentation by FDIC Chairman to the National Press Club, Washington, D.C., October 1986.

Sinkey, J., "A Multivariate Statistical Analysis of the Characteristics of Problem Banks," Journal of Finance, 1975, 21-36.

Stigler, G.J., The Citizen and the State: Essays on Regulation. Chicago: University of Chicago Press, 1977.

Tulloch, G., The Politics of Bureaucracy. Washington, D.C.: Public Affairs Press, 1965.