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"PREDICTING CREDIT UNION FAILURES: A DATA ENVELOPMENT ANALYSIS OF RHODE ISLAND INSTITUTIONS"

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I. Introduction

The deregulation of financial institutions in the early 1980s has lead to two related, but distinct, research avenues. The common thread shared by both research areas is the study of production and cost efficiencies. One research prospective concerned the issues surrounding acquisitions and mergers of banking institutions. Analysts examined the competitive structure and efficiency of unit banking, branch banking, and interstate banking. Economies of scale and scope were measured as an aid to merger policy. Econometric estimates of production or cost functions such as Cobb-Douglas or constant elasticity of substitution forms were utilized. More recently, the use of the translog model imposed fewer restrictions on the functional form of the input-output relationship, on the dual relationship between production and cost, and on the cost complementarities usually evident in the estimation process[1]. These stochastic approaches continue and are useful when input substitution or complementarity are a central focus of the analysis. More recently, non-parametric approaches have been utilized where input relatedness is not a feature of the analysis and can be assumed to have minimal effects.

The second research avenue emerged from ailing and failing financial institutions. The crises of depository institutions propelled government financial analysts, private consultants, and academic researchers to develop models and procedures to predict those institutions likely to fail, and subsequently, to prevent them from their eventual bankruptcy. The methodologies involved include the use of accounting data, often organized as financial ratios[2], to construct

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[1]For Example, several often cited sources include Bentson (1965), Lawrence and Shay (1986), Gilligan and Smirlock (1984), Berger et al. (1987), and Gropper (1991).

[2]Examples of extensive listings of financial ratios used to predict thrift failures can be found in Elmer and Borowski (1988). These ratios were incorporated in an expert system described in footnote 3. Salchenberger, Cinar, and Lash (1992) summarized financial ratios used in stochastic models. Similarly, Pantalone and Platt (1987) selected the important variables from an extensive list using multiple discriminant analysis.

indices to rate the viability of the firms[3]; stochastic regression, correlation, and discriminant analysis to predict failures[4]; non-parametric frontier analyses to rank the degree of managerial inefficiencies of existing firms.

Non-parametric techniques have been less frequently employed in the efficiency analysis of financial institutions[5]. These techniques specifically measure management efficiency. Management efficiency models evaluate the operating aspects of the bank, often in terms of the ability to control costs and expenditures. These studies have been exclusively devoted to commercial banks and thrifts. In the current study a non-parametric technique, data envelopment analysis (DEA), addresses the managerial inefficiency of credit unions. The measurement of managerial inefficiency is expected to accelerate into the future as the financial viability of these institutions is altered by rapidly changing regulatory and communication technology environments.

Several approaches have been utilized to analyze operating efficiencies of depository institutions. DEA uses free-form functional representation of organizations and does not depend upon a specific functional form. Stochastic models rely on deviations from average performance to measure the degree of inefficiency, while DEA utilizes deviations from a "best practice" frontier. The frontier approach conforms most closely to the "extremal" notions of maximum production per dollar input or

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[3]Ratings agencies like Standard and Poors Credit Overview prefer the opinion of expert analysts to evaluate the financial health of an institution. The expert system often combines publicly available financial data into a single index. These results may be augmented by rules which segment heterogeneous S&Ls in order to account for special circumstances. Such systems can be viewed as subjective. See Elmer and Borowski (1988).

[4]Stochastic techniques, often designed to classify viable from weak and failing institutions, utilize financial ratios as independent variables. These multivariate techniques invariably encounter severe multicollinearity among the predictor variables. See Salchenberger, Cinar, and Lash (1992), and Booth, Alam, Ahkam, and Osyk (1989) for a summary of the logit, probit, multiple discriminant, and regression-outlier models.

[5]Sherwin and Gold (1985), Rangan et al. (1988), Ferrier and Lovell (1990), Aly et al. (1990), Charnes et al. (1990), Elyasiani and Mehdian (1990), and Yue (1992).

minimum cost per unit output. Although stochastic frontier models have recently been introduced, these techniques suffer from the problems of specifying the functional form and the error distribution.

Non-stochastic methods of efficiency measurement like an expert system which is based on various financial ratios used to construct an index, have an implicit weighting problem. Variables are either equally weighted or subjectively weighted. In stochastic models, optimization is based upon uniform weights for each variable. Unique to the DEA approach is that the weights used to determine credit union efficiency are not allowed to vary for each credit union. Each credit union thus selects a variable's importance-weight so as to achieve the highest degree of efficiency, thus allowing a different input transformation function for each credit union.

The shortcomings of DEA are well known. The non-stochastic properties of the model yield point estimates of production efficiency and no tests of statistical significance can be made. Moreover, the existence of noisy data makes it difficult to distinguish measurement error from deviant performance on the part of an inefficient credit union. Thus, DEA should be viewed as an alternative method of assessing the financial viability of an institution.

The Rhode Island Credit Union Crises

The current study focuses on the 1991 well-publicized state-wide banking crisis in Rhode Island. In 1990, the mismanagement of the Heritage Loan and Investment Company resulted in its bankruptcy, which in turn triggered the insolvency of its insurer, the Rhode Island Share and Deposit Indemnity Corporation (RISDIC). In January 1991, Governor Bruce Sudlum closed 45 RISDIC-insured institutions, of which 35 were credit unions. This action immediately directly or indirectly affected 70 percent of the residents of Rhode Island. Twenty five of the closed credit unions were in excellent financial health and they resumed regular operations after obtaining federal share insurance. This protection was provided by the National Credit Union Share Insurance (NCUSIF), an agency under the jurisdiction of the National Credit Union Administration (NCUA). Another four institutions were permanently closed and their assets were acquired by the Depositor Economic Protection Corporation (DEPCO), a government agency established specifically for handling the assets and obligations of bankrupted institutions. Another six institutions were acquired by other financial institutions. The remaining 25 RISDIC-insured credit unions qualified for NCUA insurance.

Call Report financial data have been compiled by the Banking Division, Rhode Island Department of Business Regulation. DEA and corresponding sensitivity analysis measurements are used to rank the relative technical efficiencies of the Rhode Island credit unions, using this 1991 data. This ranking method provides an alternative to the use of financial ratios which are used to determine the quality of a financial institution's soundness and management as part of the CAMEL system. The CAMEL system, like other expert systems, utilizes other criterion including subjective factors as part of the analysis. These factors can lead to some difficulties and criticisms of the CAMEL system.

In Tables 1 and 2, the technical efficiency rankings of all Rhode Island credit unions are computed and used to establish an efficiency frontier. From the Rhode Island frontier, the RISDIC insured credit unions' efficiency are compared to actions undertaken as a result of RISDIC insolvency. Specifically, insolvent institutions which either were subsequently closed (assets acquired by DEPCO) or were acquired by other existing institutions. Using two different DEA model specifications, it is observed that nine of the ten credit unions acquired by other existing institutions or by DEPCO appear in the bottom one-third (model #1) and bottom 37th percentile (model #2) of the technical efficiency rankings. The correspondence between the lowest technical efficiency rankings and the disappearance of these firms is surprisingly close. Based on these preliminary results, DEA is offered as an important methodology for future evaluations of the financial viability of credit unions. After a discussion of DEA methodology (Section II) and of the credit union efficiency models (Section III), a detailed evaluation of the efficiency of the RISDIC insured institutions is made (Section

IV). Finally, the validity of the DEA approach to forecast future financial institution failures is discussed (Section V).

II. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is an analytical tool for evaluating the relative technical efficiency of a set of organizations that exhibit the same multiple inputs and multiple outputs. As a linear programming implementation of Farrell's (1957) notion of technical efficiency, DEA is an "extremal" approach to efficiency evaluation, constructing an efficient frontier composed of those organizations that consume as little input as possible while producing as much output as possible from the given level of input consumption. Those organizations that comprise the efficient frontier are technically efficient, while those organizations not on the efficient frontier are technically inefficient (enveloped by the efficient organizations).

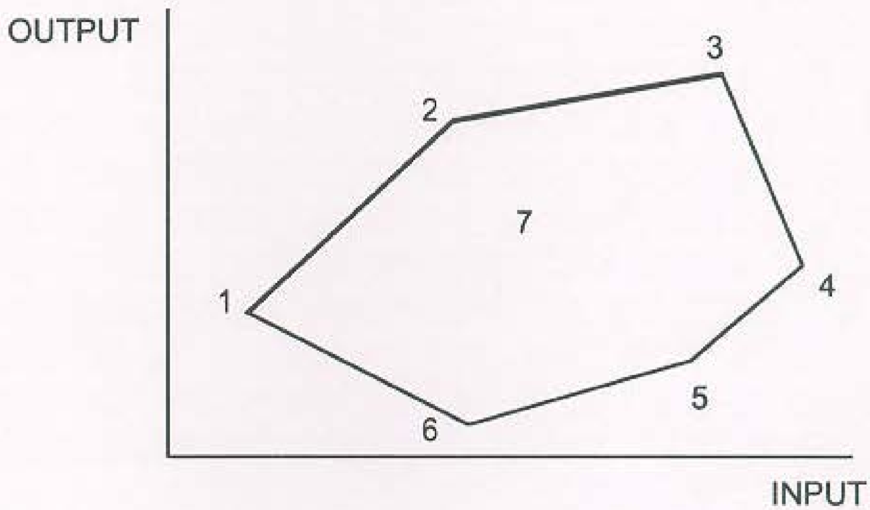
The original model of DEA, known as the ratio or CCR model (Charnes et al., 1978), has been joined by other DEA models (Charnes et al., 1982 and Banker et al., 1984), including the additive model (Charnes et al., 1984), the model of interest in this paper. In the additive model of DEA, the observed input consumption and output production for a number of organizations (Decision Making Units or DMUs) are measured. The measures of input consumption and output production for a given DMU are referred to as the DMU's component vector. The component vectors for all of the DMUs are combined to form the empirical production possibility set, *PE*

$$PE = \{(Y^T, X^T) = \sum_{i=1}^{n} \mu_i (Y_i^T, X_i^T); \sum_{i=1}^{n} \mu_i = 1, \mu_i \geq 0\} \tag{1}$$

where Y_i and X_i represent the output production and input consumption, respectively, for the *ith* DMU.

The technical efficiency status (efficient or inefficient) for each DMU is determined by comparing its component vector to *PE*. If no component vector in *PE*, observed or hypothetical, can be found that strictly dominates the tested DMU, then the DMU is said to be technically efficient. Those DMUs, for which a component vector can be found in PE that strictly dominates, are said to be technically inefficient. Figure 1 provides a graphical depiction of a set of DMUs for a single-input single-output example. From Figure 1, DMUs #1, #2, and #3 would be technically efficient while DMUs #4, #5, #6, and #7 would be technically inefficient. Segments $\overline{12}$ and $\overline{23}$ comprise the efficient frontier.

FIGURE 1



Mathematically, the test for the technical efficiency status of DMUi is achieved by solving the following linear program:

$$\begin{aligned} \min \quad & (-e^T s^+ - e^T s^-) \\ s.t. \quad & Y\lambda - s^+ = Y_i \\ & X\lambda + s^- = X_i \\ & e^T\lambda = 1 \\ & \lambda,\ s^+,\ s^- \geq 0 \end{aligned} \qquad LP$$

where Y and X represent the matrices of output production and input consumption, respectively, scaled by component averages to assure a units invariant model[6]; the right hand side values, Y_i and X_i represent the component vector for DMU*i*; s^+ and s^- represent the shortfall in production and excess in consumption, respectively; e^T vector is the sum vector, guaranteeing a convex combination of the observed DMUs.

The execution of *LP* serves to categorize the observed DMUs as technically efficient or technically inefficient. In the proposed analysis of the credit unions (specifically the credit unions acquired by DEPCO or other financial institutions), however, the execution of *LP* does not yield a rank ordering of the DMUs from most robustly efficient to most robustly inefficient. To develop this rank ordering, one additional linear program must be executed for each DMU, with the result yielding an ∞-norm measure of the minimum distance to a Pareto optimum point (efficient frontier).

Charnes et al. (1992) developed a sensitivity analysis technique based on the ∞-norm measure of a vector that defines the necessary simultaneous perturbations to the component vector of a given DMU to cause it to move to a state of "virtual" efficiency. Virtual efficiency is defined as a point of the efficient frontier where any minuscule detrimental perturbation (increases in inputs and/or decreases in outputs) will cause an efficient DMU to become inefficient or any minuscule favorable perturbation (decrease in inputs and/or increase in outputs) will cause an inefficient DMU to become efficient.

For an efficient DMU, the ∞-norm measure (herein termed stability index) defines the largest "cell" in which all simultaneous perturbations to the input and output components will not cause a change of the efficiency status from technically efficient to technically inefficient. As such, the larger the stability index the more robustly efficient the DMU is said to be. That is, those efficient DMUs with small stability indices will become technically inefficient with smaller detrimental perturbations than

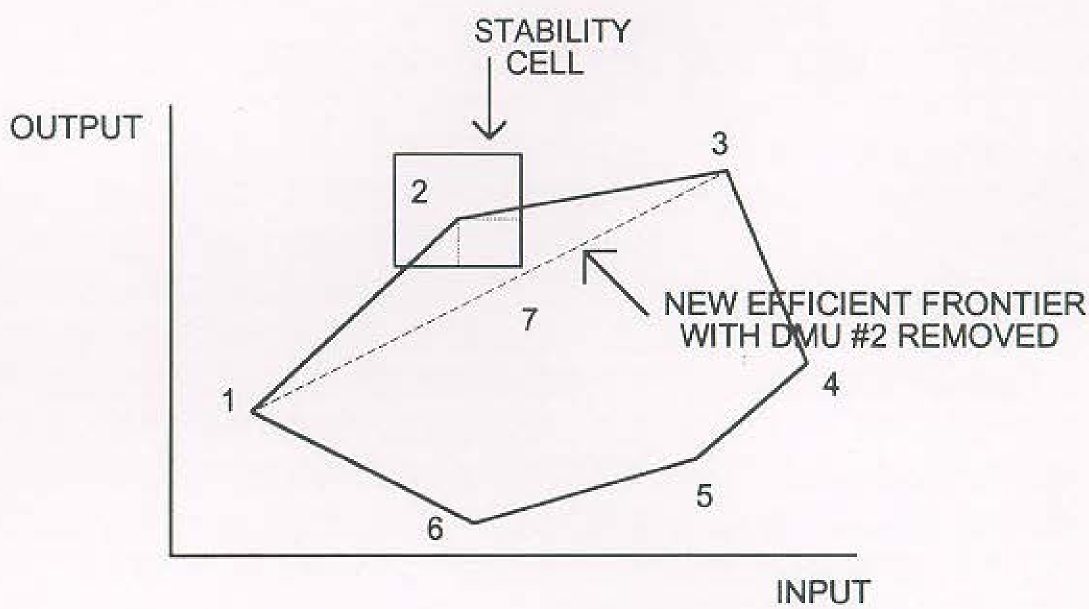
[6]The efficiency scores assigned to (inefficient) DMUs will vary according to the unit of measure chosen for each production and consumption level. See Haag and Jaska (1994) for a complete numerical analysis and explanation. This problem is corrected by pre-scaling the data by component averages (Haag, Jaska, and Semple, 1992).

those efficient DMUs with larger stability indices. Mathematically, the stability index for efficient DMUi is determined by solving the following linear program:

$$\begin{array}{lllll} \min & \theta & & & \\ s.t. & Y^{(E)}\lambda - s^{+} & & + \theta d_O & = Y_i \\ & X^{(E)}\lambda & + s^{-} & - \theta d_I & = X_i \\ & e^T\lambda & & & = 1 \\ & \lambda,\ s^{+},\ s^{-},\ \theta & & & \geq 0 \end{array} \tag{3}$$

where θ represents the stability index; $Y^{(E)}$ and $X^{(E)}$ represent the matrix of outputs and inputs, respectively, with the component vector for efficient DMUi omitted; d_O^T and d_I^T are vectors given by (1, 1, ..., 1). Observe that θ simultaneously increases inputs and decreases outputs to arrive at an optimal solution. Figure 2 provides a graphical depiction of the ∞-norm measure (stability cell) for efficient DMU #2.

FIGURE 2

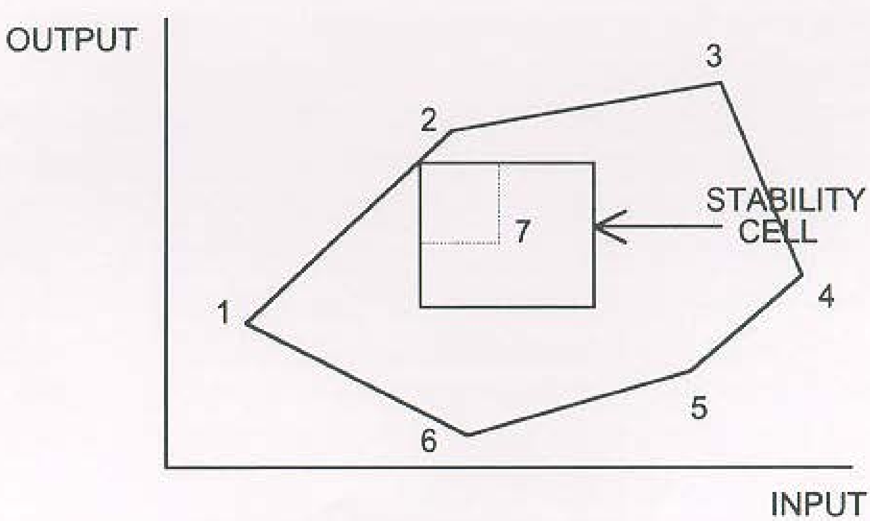


For an inefficient DMU, the stability index defines the necessary minimum favorable perturbations (decreases in inputs and increases in outputs) that must be undertaken to cause the DMU to become virtually efficient. Therefore, the larger the stability index for an inefficient DMU the more robustly inefficient the DMU would be. That is, an inefficient DMU with a large stability index rests a greater distance from the efficient frontier that an inefficient DMU with a smaller stability index. Mathematically, the stability index for inefficient DMUi is determined by solving the following linear program:

$$\begin{array}{lllll} \max & \theta & & & \\ s.t. & Y\lambda - s^{+} & & -\theta d_{O} & = Y_i \\ & X\lambda & + s^{-} & + \theta d_{i} & = X_i \\ & e^{T}\lambda & & & = 1 \\ & \lambda,\ s^{+},\ s^{-},\ \theta & & & \geq 0 \end{array} \tag{4}$$

where all notations are defined in prior formulations. Observe that θ simultaneously decreases inputs and increases outputs to arrive at an optimal solution. Figure 3 provides a graphical depiction of the ∞-norm measure (stability cell) for inefficient DMU #7.

FIGURE 3



III. Credit Union Model

To evaluate the technical efficiency of credit union operations, a determination must be made of those components that will be minimized (inputs) and those components that will be maximized (outputs). Call Report data for this analysis of the 57 credit unions in Rhode Island were reported as of January 1991. Incomplete data were given for three institutions (one NCUA insured and two RISDIC insured institutions). This resulted in a usable population of 54 institutions. The obtained financial data are given as follows:

Total payroll and employee benefits expense
Total general and administrative expenses
Net interest income
Total loans
Total shares and deposits
Interest costs
Liabilities (borrowed funds to support loans).

Absent from this list is some measure of the ratio of delinquent or non-performing loans. As data could not be obtained concerning this information, credit union efficiency was modeled in two different forms, given as follows:

MODEL #1:
- Inputs:
  - Interest costs
  - Payroll and benefits expense
  - General and administrative expense
  - Ratio of loans to shares, deposits, and liabilities
- Outputs:
  - Net interest income

MODEL #2:
- Inputs:
  - Interest costs
  - Payroll and benefits expense
  - General and administrative expense
- Outputs:
  - Net interest income.

Both models use three of the same inputs and the same output. Because interest cost, payroll and benefits expense, and general and administrative expense represent the cost of operation, they are minimized as inputs. Net interest income, representing the income sheet production of operation, is maximized as the output. Because data were not forthcoming on the measure of bad loans, models #1 and #2 differ by adding the ratio of loans to shares, deposits, and liabilities (basic financial measure of liquidity). Using this formulation in model #1, credit unions with smaller ratios of money loaned to reserves (shares, deposits, and liabilities) will have a better chance to be technically more efficient than those credit unions with a higher lending ratio. Tables 1 and 2 show the analysis of models #1 and #2, respectively, for the 54 credit unions. A complete list of the numerical inputs and outputs can be found in Appendix A.

IV. Evaluation of Credit Union Technical Efficiency

In this section, the efficiency rankings of the 33 RISDIC insured credit unions are evaluated in Tables 3 and 4. The 21 NCUA-insured credit unions are not included because their insurer, the NCUSIF program of NCUA, continued to provide share protection. Moreover, since the CAMEL rankings for these institutions are not available, and the insurer was not insolvent, no independent valuation of the DEA efficiency rankings are possible. However, several important efficiency comparisons with the RISDIC-insured credit unions are possible.

Tables 3 and 4, column 1, illustrate the efficiency rankings of the 33 RISDIC-insured credit unions out of the 54 Rhode Island credit unions. The efficiency rankings are validated by the subsequent actions taken by federal NCUA reinsurance on one hand, or the acquisitions of weaker credit unions by other financial institutions or by DEPCO on the other hand. The 23 credit unions deemed financially viable were NCUA reinsured (REOPEN) and had the top 24 efficiency scores on both Table 3 (Model 1) and Table 4 (Model 2). On the other hand, or the ten weaker credit unions without NCUA reinsurance, six were acquired by other financial institutions and four were acquired by DEPCO or dissolved. Significantly, nine of ten of these credit unions had the nine lowest DEA efficiency rankings in both Tables 3 and 4. One credit union (#32), having "ACQUIRED" status, appeared in the midrange of the DEA efficiency scores in both Tables 3 and 4.

The RISDIC CAMEL ratings apparently did not differentiate the ten weaker institutions very well since numerous "best" rankings of 1s and 2s appeared. From Table 3 the mean CAMEL score of the upper two-thirds of the efficiency ranks was 1.7 and for the lower one third of the efficiency ranks was 2.2. Similarly, from Table 4 the mean CAMEL score of the upper two-thirds of the efficiency scores was 1.6 and for the lower one-third of the efficiency ranks was 2.3. For institutions facing insolvency, a CAMEL score between 4 and 5 might be more appropriate.

No analysis of credit union failures would be complete without examining the relationship between efficiency and scale of operation. In Figure 4, 33 RISDIC efficiency scores are plotted against asset size on a non-linear scale. An obvious relationship exists between asset size and robust inefficiency. Three out of the four largest credit unions were dissolved by DEPCO. In addition, nine out of the thirteen largest credit unions with assets in excess of 10.4 million dollars were dissolved by DEPCO of acquired by other financial institutions. Apparently, the largest credit unions faced the greatest risks, however one of the five largest credit unions was the most efficient in the group. Thus, the greatest managerial inefficiencies (largest negative efficiency score) were encountered by the largest firms, and the least and most inefficiencies were felt by these five largest firms. Therefore, asset size would have to be considered a major factor contributing to credit union failure.

V. Summary

The 1991 Rhode Island banking crisis provides both pre and post bankruptcy information. This environment offers an excellent opportunity for exploring the use of alternative techniques for evaluating the (technical) efficiency of credit unions. In the present analysis, Data Envelopment Analysis (DEA) has been used to evaluate the technical efficiency of 54 such institutions. These institutions were the subject of CAMEL analysis by regulators. Since the CAMEL reports and acquisition analysis are not made available to the public for NCUA insured credit unions, we can only compare the DEA results with the observable survival records of these institutions. By rating these institutions according to their robustness of efficient and inefficient classifications, a virtually identical fit exists between technical efficiency and actions taken by the NCUA reinsurance and DEPCO activities. It is noted that nine out of ten of the credit unions not being reinsured had the very lowest efficiency rankings using the two model specifications.

Based on these results, DEA offers an objective, plausible alternative technique for evaluating technical efficiency of savings and loans and predicting failure (bankruptcy). As with all techniques, DEA should be used in conjunction with other information to improve the forecasting experience of past efforts.

TABLE 1.

MODEL 1 WITH LOANS TO RESERVES RATIO INCLUDED

EFFICIENCY RANK	CREDIT UNION	STATUS	EFFICIENCY RANK	CREDIT UNION	STATUS
1	40	INSURED	28	13	REOPEN
2	20	REOPEN	29	45	INSURED
3	27	REOPEN	30	26	REOPEN
4	22	REOPEN	31	34	INSURED
5	21	REOPEN	32	51	INSURED
6	31	REOPEN	33	53	INSURED
7	15	REOPEN	34	37	INSURED
8	39	INSURED	35	46	INSURED
9	16	REOPEN	36	3	ACQUIRED
10	28	REOPEN	37	52	INSURED
11	30	REOPEN	38	47	INSURED
12	18	REOPEN	39	42	INSURED
13	29	REOPEN	40	50	INSURED
14	35	INSURED	41	23	ACQUIRED
15	19	REOPEN	42	43	INSURED
16	49	INSURED	43	41	INSURED
17	8	REOPEN	44	12	ACQUIRED
18	11	REOPEN	45	54	INSURED
19	32	ACQUIRED	46	4	DEPCO
20	33	REOPEN	47	5	ACQUIRED
21	1	REOPEN	48	25	DEPCO
22	48	INSURED	49	36	INSURED
23	9	REOPEN	50	17	DEPCO
24	24	REOPEN	51	6	ACQUIRED
25	2	REOPEN	52	10	DEPCO
26	7	REOPEN	53	44	INSURED
27	14	REOPEN	54	38	INSURED

TABLE 3. MODEL #1
33 RISDIC INSURED CREDIT UNIONS

DEA EFFICIENCY RANK	CREDIT UNION	STATUS	RISDIC CAMEL RATING BEST(1) - WORST(5)
(1)	(2)	(3)	(4)
2	20	REOPEN	1
3	27	REOPEN	1
4	22	REOPEN	2
5	21	REOPEN	1
6	31	REOPEN	1
7	15	REOPEN	1
9	16	REOPEN	1
10	28	REOPEN	2
11	30	REOPEN	3
12	18	REOPEN	1
13	29	REOPEN	1
15	19	REOPEN	4
17	8	REOPEN	1
18	11	REOPEN	2
19	32	ACQUIRED	2
20	33	REOPEN	1
21	1	REOPEN	2
23	9	REOPEN	1
24	24	REOPEN	3
25	2	REOPEN	2
26	7	REOPEN	3
27	14	REOPEN	1
28	13	REOPEN	1
30	26	REOPEN	2
36	3	ACQUIRED	2
41	23	ACQUIRED	1
44	12	ACQUIRED	2
46	4	DEPCO	3
47	5	ACQUIRED	2
48	25	DEPCO	2
50	17	DEPCO	2
51	6	ACQUIRED	3
52	10	DEPCO	4

TABLE 4. MODEL #2
33 RISDIC INSURED CREDIT UNIONS

DEA EFFICIENCY RANK	CREDIT UNION	STATUS	RISDIC CAMEL RATING BEST(1) - WORST(5)
(1)	(2)	(3)	(4)
2	20	REOPEN	1
3	21	REOPEN	1
4	15	REOPEN	1
5	31	REOPEN	1
7	27	REOPEN	1
8	28	REOPEN	2
9	30	REOPEN	3
10	18	REOPEN	1
11	29	REOPEN	1
13	19	REOPEN	4
15	8	REOPEN	1
16	11	REOPEN	2
17	32	ACQUIRED	2
18	33	REOPEN	1
19	1	REOPEN	2
21	9	REOPEN	1
22	24	REOPEN	3
23	2	REOPEN	2
24	7	REOPEN	3
25	16	REOPEN	1
26	14	REOPEN	1
27	15	REOPEN	1
29	26	REOPEN	2
30	22	REOPEN	2
33	3	ACQUIRED	2
39	23	ACQUIRED	1
42	4	DEPCO	3
44	5	ACQUIRED	2
46	12	ACQUIRED	2
47	6	ACQUIRED	3
51	25	DEPCO	2
53	10	DEPCO	4
54	17	DEPCO	2

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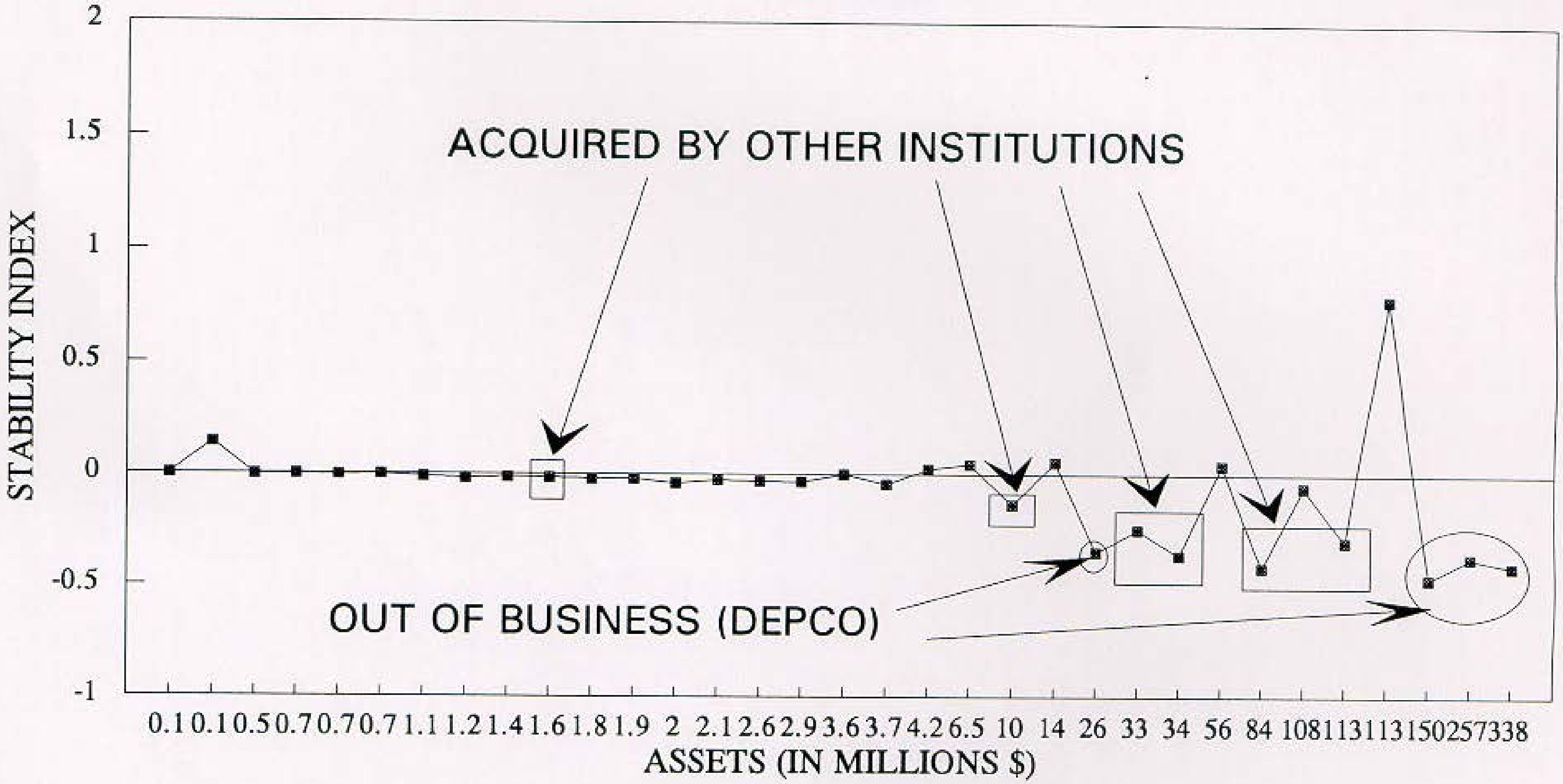
FIGURE 4



ACQUIRED BY OTHER INSTITUTIONS
OUT OF BUSINESS (DEPCO)
STABILITY INDEX
2
1.5
1
0.5
0
-0.5
-1
0.1 0.1 0.5 0.7 0.7 0.7 1.1 1.2 1.4 1.6 1.8 1.9 2 2.1 2.6 2.9 3.6 3.7 4.2 6.5 10 14 26 33 34 56 84 108 113 113 150 257 338
ASSETS (IN MILLIONS $)

CREDIT UNION	INTEREST COSTS *	PAYROLL EXPENSE *	G&A EXPENSE *	LIQUIDITY MEASURE **	NET INTEREST INCOME *
	INPUT #1	INPUT #2	INPUT #3	INPUT #4***	OUTPUT #1
1	107.3	45.7	60.6	0.8315	225.0
2	144.3	114.9	65.2	0.9061	322.1
3	601.3	160.9	323.2	0.8815	483.7
4	2129.8	449.9	343.7	0.9584	828.3
5	2551.3	445.1	404.5	0.8805	911.9
6	6544.4	1443.3	1125.2	0.8919	3929.1
7	149.3	78.0	83.8	0.8483	284.6
8	71.0	34.4	38.3	0.7559	169.0
9	121.5	54.7	33.1	0.8736	207.8
10	10995.7	1840.6	1657.1	0.9422	5184.8
.11	68.0	59.7	67.5	0.7699	172.1
12	6919.5	2634.7	1426.3	0.8361	5295.7
13	189.7	157.8	69.7	0.9964	290.6
14	155.4	62.0	55.9	0.8596	166.8
15	46.5	119.2	101.0	0.0765	601.1
16	148.0	112.6	210.6	0.5503	345.9
17	25889.8	3392.5	2925.2	0.8955	4833.2
18	47.5	9.0	16.2	0.9758	89.5
19	42.6	9.9	18.9	0.7717	72.2
20	8014.6	934.1	2412.2	0.7399	10021.5
21	129.1	40.2	42.7	0.6812	618.4
22	593.9	110.2	321.6	0.4691	803.7
23	2307.0	576.1	483.3	0.9960	1710.9
24	144.4	56.8	57.4	0.8921	314.2
25	20121.6	2407.4	2121.2	0.9202	7969.4
26	6164.0	2981.8	2318.4	0.7668	7496.9
27	5.9	1.5	2.8	0.5011	9.5
28	3.9	5.0	4.5	1.1014	13.8
29	36.5	8.4	15.8	1.0460	66.2
30	40.7	6.3	27.7	0.8583	57.2
31	3267.8	1070.9	860.2	0.6182	4220.2
32	96.3	79.0	26.2	1.0088	165.1
33	81.8	28.7	50.3	0.8315	83.1
34	402.5	145.3	162.3	0.7401	496.5
35	267.7	69.2	33.2	1.1091	426.5
36	4995.3	1645.5	1528.7	0.8481	3073.5
37	754.6	271.7	334.2	0.7026	602.6
38	6551.6	1418.9	961.3	0.9620	3017.2
39	750.8	114.3	88.9	0.7165	1136.5
40	12074.0	1006.7	611.5	0.6306	9243.0
41	4210.1	552.4	423.3	0.8593	2522.3
42	1517.3	377.2	187.2	0.7693	664.1
43	6359.5	1466.4	1605.9	0.7392	2564.8
44	7364.0	1821.1	1006.3	0.9504	5485.2
45	213.4	75.3	73.4	0.6157	214.0
46	6517.5	1542.9	1147.6	0.6508	4828.8
47	2449.9	520.0	417.9	0.7115	1683.7
48	91.9	27.6	31.4	0.7193	83.7
49	56.2	100.7	18.3	0.6950	162.5
50	2739.6	400.1	402.8	0.7124	1427.2

51	646.1	132.1	144.2	0.6916	610.0
52	1104.4	473.4	233.7	0.8941	922.3
53	2404.3	440.5	457.2	0.5880	1868.0
54	2643.9	459.5	420.3	0.8543	1170.4

* Given in 000's

** Ratio of loans to shares, deposits, and liabilities

*** Used as Input #4 in Model #1 only