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Authors

Garbaccio, Richard F.
Hermalin, Benjamin E.
Wallace, Nancy E.

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UNIVERSITY OF CALIFORNIA AT BERKELEY

Department of Economics

Berkeley, California 94720

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Nonparametric Methods to Measure Efficiency: A Comparison of Methods

Richard F. Garbaccio, Benjamin E. Hermalin,
Nancy E. Wallace

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Abstract

Using data on 951 savings and loans, we compare two nonparametric methods for measuring efficiency: Data Envelopment Analysis (DEA) and algebraic methods based on Varian (1984). We show that both methods are vulnerable to measurement error, although both theoretically and empirically we find the Varian-style measures to be less vulnerable. We also suggest simple methods to identify problematic observations and to reduce their influence on the results. Because we have data on the future insolvency of our savings and loans, we can directly compare the two methods by seeing which does a better job of predicting insolvency (working under the hypothesis that efficiency and insolvency should be negatively correlated). We find that the Varian-style methods do better; moreover, we find that some of the DEA measures yield the implausible result that efficiency and insolvency are positively correlated.

Richard F. Garbaccio
Department of Agricultural and Resource Economics
University of California at Berkeley

Nancy E. Wallace
Haas School of Business
University of California at Berkeley

Benjamin E. Hermalin
Department of Economics and Haas School of Business
University of California at Berkeley
and
Yale Law School
Yale University

Nonparametric Methods to Measure Efficiency: A Comparison of Methods*

I. Introduction

Previous analyses of the efficiency of financial institutions have typically relied on parametric tests of efficiency (see, e.g., Verbrugge and Goldstein (1981), Verbrugge and Jahera (1981), Blair and Placone (1988), Akella and Greenbaum (1988), and Mester (1987, 1989, 1991, and 1992)). Although these papers offer important insights into the behavior of financial intermediaries, there are several, known limitations with parametric tests. Firstly, in order to test for efficiency, functional forms must be specified for the underlying cost or production functions. Thus, the standard parametric test for cost minimization is a test whether S&L managers minimize cost relative to some arbitrary approximation of the firm's true underlying production function. The strength of such a test relies on the maintained hypotheses that the cost function approximation is essentially accurate and that the specified distribution for the residuals from the fitted approximation is essentially accurate.

Nonparametric analyses of efficiency avoid some of the maintained assumptions required in parametric analysis; however, as we will discuss below they too rely on maintained assumptions for their implementation. The most common nonparametric approach is Data Envelopment Analysis (DEA), in which linear programming techniques are employed to construct a "best-practice frontier" from a sample of input/output data. Recent applications of DEA to financial institutions have found evidence of inefficiency (see Sherman and Gold

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(1985), Rangan *et al.* (1988), Berg *et al.* (1989), Ferrier and Lovell (1990), Aly *et al.* (1990), and Elysasiani and Mehdian (1990)).

A second nonparametric approach relies on algebraic tests of the consistency of observed input, output, and price data with the basic axioms of profit maximization and cost minimization. This approach was developed by Varian (1984; 1985; 1990) and builds on an earlier literature (Afriat (1972) and Hanoch and Rothschild (1972)). These nonparametric tests have been used to test for efficiency in Savings and Loan institutions by Hermalin and Wallace (1992a; 1992b). These studies, too, find evidence of inefficiencies in the operation of S&L institutions.

This study compares the performance of the Varian and the DEA approaches. We compare the two using data on 951 Savings and Loan (S&L) institutions in operation over the year beginning June 1987. Because our data set includes information on the solvency of observed firms, and because it is reasonable to assume that less efficient firms are more likely to become insolvent, we use solvency as a criterion against which to evaluate the performance of DEA and Varian-style measures of efficiency. Our minimum expectation is that these efficiency measures should distinguish solvent from insolvent firms. A secondary focus is to detect influential observations and determine their impact on these efficiency tests. In this way, we hope to demonstrate the possible bias that can be introduced in nonparametric analyses when the influence of apparent outliers (e.g., firms that report erroneous data or data with measurement error) is not carefully controlled for.[1] Moreover, we seek to identify simple methods that might be used to mitigate such problems.

[1] This is a point also made by Seaver and Triantis (1989).

II. The DEA Nonparametric Approach

Data Envelopment Analysis was first introduced by Farrell (1957) and later extended by Charnes *et al.* (1978), Fare *et al.* (1985), and others. DEA assumes that producers use an n-dimensional vector of inputs $\mathbf{x}$ available at an n-dimensional vector of fixed prices $\mathbf{p}$, and produce an m-dimensional vector of output $\mathbf{y}$ by minimizing costs. A linear programming problem is solved to construct a "best-practice" piecewise linear envelope (convex hull) over the observed input-output data. A firm's input efficiency is determined by minimizing the distance between its observed production decision and a best-practice input decision constructed as a weighted average of the decisions made by the nearest units on the best-practice convex hull. The minimization is carried out along a ray of the observed input proportions holding output fixed.

Relative to the best-practice hull, the pure *technical* efficiency of each observation is found by solving a linear programming problem for each of the K firms in the sample. The program is written as

$$\text{Min } T_k$$

subject to

$$\begin{aligned} \mathbf{y}_k &\leq \mathbf{zY} \\ T_k\mathbf{x}_k &\geq \mathbf{zX} \\ \sum_{i=1}^{K} z_i &= 1 \\ \mathbf{z} &\in \mathbf{R}_+^K \end{aligned} \tag{1}$$

where T_k is a scalar, $\mathbf{y}_k$ is the vector of outputs produced by the *kth* firm, $\mathbf{x}_k$ is its vector of inputs, Y is the $(K \times m)$ matrix of outputs, X is the $(K \times n)$ matrix of inputs, z is a vector of intensity weights reflecting each of the K firm's contribution to the bounding frontier. The solution, T_k^*, represents the smallest *fraction* of its input vector required by the *kth* firm to produce no less of any output. If it is not possible to produce the output vector with a smaller input vector, then $T_k^* = 1$ and the *kth* firm is considered to be technically efficient. If $T_k^* < 1$ the observation is inefficient. Note that technical efficiency in (1) is calculated relative to a production frontier that satisfies variable returns to scale, given the constraint $\Sigma_i^K z_i = 1$.[2]

Cost efficiency can be obtained for each firm by solving K linear programming problems of the form

$$\text{Min } \mathbf{p}_k \bullet \mathbf{x}_k$$

subject to

$$\begin{aligned} \mathbf{y}_k &\leq \mathbf{z}\mathbf{Y} \\ \mathbf{x}_k &\geq \mathbf{z}\mathbf{X} \\ \sum_{i=1}^{K} z_i &= 1 \\ \mathbf{z} &\in \mathbb{R}_+^K \end{aligned} \qquad (2)$$

where $\mathbf{p}_k$ is the input price vector. The solution $\mathbf{x}_k^*$ is the cost-minimizing input vector given input prices, $\mathbf{p}_k$, and outputs, $\mathbf{y}_k$. The *kth* firm's overall cost efficiency (OE_k) is measured as

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[2] The variable returns to scale constraint is imposed as the least restrictive constraint. Other studies (Aly, et al., 1990; Ferrier and Lovell, 1990) have also imposed constant returns to scale constraints under the assumption that nonconstant returns to scale represents a welfare cost which should be measured as an additional source of inefficiency in firm production.

the ratio $OE_k = \mathbf{p}_k\mathbf{x}_k^*/\mathbf{p}_k\mathbf{x}_k$. Slack in the solution to (1) above is assumed to reflect inappropriate input mix, so the *kth* firm's measure of allocative inefficiency (AE_k) can be written as $AE_k = \mathbf{p}_k\mathbf{x}_k^*/\mathbf{p}_k T_k^* \mathbf{x}_k$. Allocative inefficiency can be computed as

$$AE_k = \frac{OE_k}{T_k^*}. \tag{3}$$

A serious limitation of the DEA procedure is that increasing the number of firms in the sample leads to decreasing average levels of efficiency because there is an increasing probability that an efficient outlier will be included as K grows (Berg *et al.* (1990)). Also, when the reference technology is variable returns to scale, firms in the data set that are operating with inputs and outputs sufficiently different from other firms will always be identified as efficient only because there are no comparable units. This is particularly true of very large or very small firms. In addition, DEA assumes that the observed input, output, and price data for each firm are recorded without measurement error, as there are no standardized techniques to identify outliers and measure their relative effect on the construction of the fitted frontier. Finally, the advantages of statistical inference are not available to extrapolate trends in a sample to behavior in the larger population.

III. The Varian Nonparametric Approach

Varian (1984) offers an alternative nonparametric test based on the observation that if firm-level data are consistent with cost-minimizing behavior, then they must satisfy the Weak

Axiom of Cost Minimization (WACM):[3] Every firm i producing more output (y) than firm j must have greater costs than firm j evaluated at *firm j's factor prices*. Otherwise, firm j could have obtained more output with lower costs by using firm i's input vector; that is, firm j is not minimizing cost.[4] Let $CMEFF_j$ indicate whether firm j "passes" this test ($CMEFF_j = 1$ indicates pass, $CMEFF_j = 0$ indicates fail). Formally, the algebraic test is

$$CMEFF_j = \begin{cases} \mathbf{1}, \text{ if } \mathbf{p}_j \cdot \mathbf{x}_j < \mathbf{p}_j \cdot \mathbf{x}_i, \ \forall i \text{ such that } y_j \leq y_i \\ \mathbf{0}, \text{ otherwise} \end{cases}. \tag{4}$$

where, recall, $\mathbf{p}_j$ is the vector of factor prices faced by firm j and $\mathbf{x}_k$ is the vector of inputs used by firm k. Here we use an S&L's total assets as a measure of its output. This reflects the notion that S&Ls are engaged in "transformation production" (Humphrey (1985)): turning inputs into classes of revenue producing assets.

Since total assets are positively — but not perfectly — correlated with production

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[3] Banker and Maindiratta (1990) contend that DEA analysis can be viewed as an extension of Varian's techniques to situations in which the data are not consistent with principles of profit maximization or cost minimization. DEA is a means to "subset-rationalize" (Bankar and Maindiratta (1990)) the firms that are consistent with cost minimization or profit maximization given the observed inputs, output, and prices of firms in the sample. Bankar and Maindiratta (1990), however, impose the assumptions of monotonicity, convexity, inclusion of observations, and minimum extrapolation to obtain the frontier, whereas Varian algebraically tests for principles of cost minimization or profit maximization in the data.

[4] Alternatively, firm j does not have access to firm i's technology. We do not, however, believe this is an important issue in this context: S&L "technology" is essentially common knowledge; moreover, there are no patents or other restrictions that keep S&Ls from adopting whatever technology they wish. Admittedly, it could be difficult for an S&L to expand its use of core deposits rapidly; but since Hermalin and Wallace (1992a) found that firms that made greater use of brokered deposits tend to be more efficient than those that do not, this objection does not seem particularly critical.

Note that because all comparisons are done at firm j's factor prices, firm j's factor prices are irrelevant to whether it is found to be efficient or inefficient; in particular, j *cannot* be found to be inefficient only because it faces greater factor prices than other S&Ls. Some people have suggested to us that this is a problem with the WACM test, as it allows firms that "overpay" for inputs to escape being tagged as inefficient. Since, however, only 2% of our firms are classified as efficient by WACM, it does not seem that being too liberal is one of the test's problems.

(and, thus, with costs), they are likely to be an imperfect proxy for transformation production. For this reason, we also carried out a complementary test for efficiency using a modification of Varian's (1984) test for the Weak Axiom of Profit Maximization, WAPM.[5] Firm j is WAPM-efficient if no firm generates greater revenues using an input mix, which, at firm j's factor prices, would cost firm j less than the input mix it chose. Formally, let R_j denote the jth firm's total revenue (the data appendix describes our measure of total revenue) and let $PMEFF_j$ indicate whether firm j is efficient according to our modified WAPM test ($PMEFF_j = 1$ indicates efficient, $PMEFF_j = 0$ indicates inefficient). Then, the WAPM algebraic test is:

$$PMEFF_j = \begin{cases} 1, \text{ if } p_j \cdot x_j < p_j \cdot x_i, \ \forall i \text{ such that } R_j \leq R_i \\ 0, \text{ otherwise} \end{cases} \quad (5)$$

Both WACM and WAPM are severe in the following sense. We say that firm i dominates firm j, if $i > j$ (where the ranking is by assets or revenue depending on the test) and $p_j \bullet x_i \leq p_j \bullet x_j$. Firm j fails WACM or WAPM if it is dominated by even just one firm. Given that data are never free from errors, such a severe test could lead to some truly efficient firms being accidently classified as inefficient. For this reason we also examined two other measures. Let $D_{CM}(j)$ denote the set of firms that dominate firm j using the WACM test; let $D_{PM}(j)$ denote the set of firms that dominate firm j using the WAPM test; and let $\#(\bullet)$

[5] The modification is that we treat all S&Ls as if they faced the same output prices, whereas Varian's WAPM test requires information — unavailable to us — on firm-level output prices. Although not ideal, we feel our treatment is reasonable in this context: To a large extent, S&Ls compete in a national capital market, so we would not expect much variation in output prices across firms. After all, even real estate lending has a national component: For instance, S&Ls in the midwest made loans to developers in Hawaii (Pizzo *et al.*, 1991).

be the function that counts the elements of a set (note $\#(\varnothing) = 0$). $CMEFF1_j$ indicates whether firm j is undominated in more than 99% of its potential comparisons. That is,

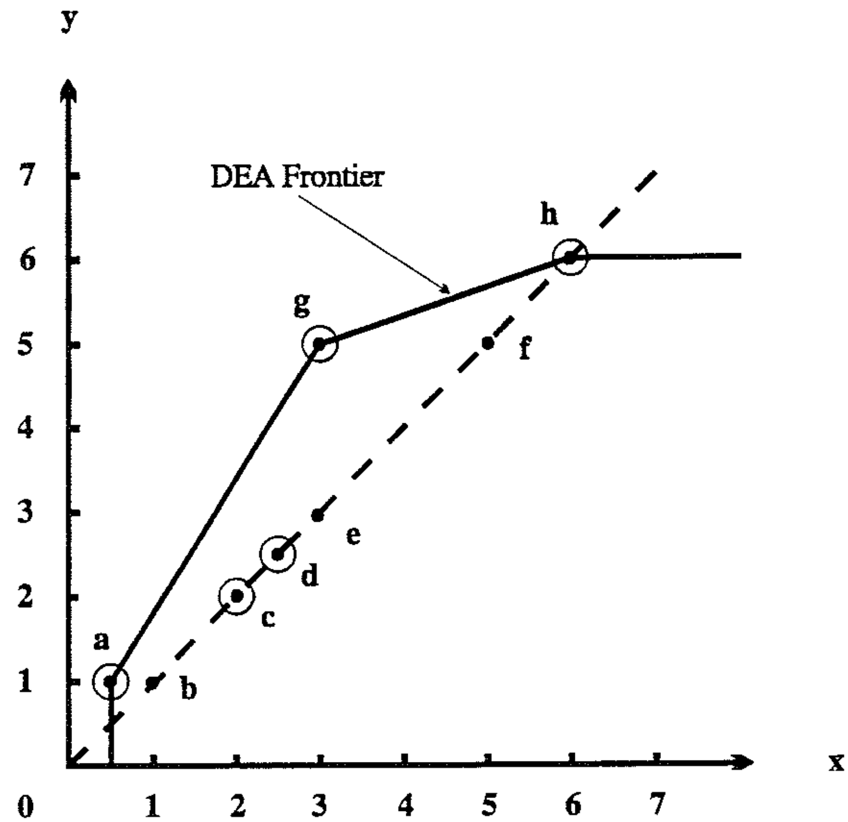
$$CMEFF1_j = \begin{cases} 1, \text{ if } \dfrac{\#(D_{CM}(j))}{\#(\{i \mid y_i \geq y_j\})} \leq .01 \\ 0, \text{ otherwise} \end{cases} \tag{6}$$

$PMEFF1_j$ indicates whether firm j is undominated in more than 99% of its potential comparisons. Notationally, its definition is analogous to $CMEFF1_j$ except the ratio is $\#(D_{PM}(j))/\#(\{i \mid R_i \geq R_j\})$. These measures are more robust with respect to Type-I errors than $CMEFF_j$ and $PMEFF_j$; but, on the other hand, they do increase the potential for Type-II errors.

The limitations with the Varian techniques are, in many ways, parallel to DEA's. Because the data are sorted from largest to smallest, the largest firms will, by definition, be treated as efficient only because there are no comparable units. Tests for WACM and WAPM analysis require an aggregate measure for output or total profits, whereas DEA can compare firms relative to a long vector of outputs and, therefore, allows for a richer representation of the firm's actual production decisions. Similar to DEA, one must assume that the input, output, and price data are observed without error. Here, too, there are no standardized techniques to identify outliers.

On the other hand, WACM and WAPM, because they rely on fewer assumptions, are more conservative tests. In particular, as shown in the following example, DEA's convexity

Figure 1



assumption can lead to serious bias if there are a few firms with erroneous data that appear very efficient. The potential marginal effects of such firms in defining the best-practice frontier is large. Assume that the true production function generating the data plotted in Figure 1 is $y = x$, where y is a single output and x is a single input. We observe input/output data for firms b, c, d, e, f, and h correctly. Two firms, a and g, however, either report misleading information or there is other measurement error. DEA forms the best-practice convex hull in terms of firms a, g, and h. The pure technical efficiency of firms b, c, d, e, and f is measured relative to this best-practice frontier and an intensity weighted average (using the z_k's from equation 1) of firms a and g. As a result they are all found to be technically inefficient (i.e. $T_k^* < 1$), so that they are producing their output, y, with too much input, x. Assuming that all prices are unity, WACM identifies the circled firms a, c, d, g, and h as efficient. Under the WACM analysis firm a CMEFF dominates firm b and firm g CMEFF dominates firms e and f. Thus, algebraic WACM correctly identifies two additional firms as efficient because firm a no longer plays a role in determining the relative efficiency of firms c, d, and e.

When data are obtained with measurement error, which is likely to be the case in most real world situations, WACM is more likely than DEA to avoid the biases evident in this example because the marginal effect of a single institution is smaller. This, in turn, is because, unlike DEA, there is no convexity assumption to give excessive weight to outliers.

IV. Empirical Comparison of DEA and WACM/WAPM Analysis

We compared DEA and WACM/WAPM using data on 951 Savings and Loan institutions that operated over year starting June 1987. Following Hermalin and Wallace (1992a; 1992b), we assume that S&Ls produce assets using three inputs: labor, physical capital, and deposits. As discussed further in the data appendix, the price of labor is the average wage rate per employee over four quarters. The unit price of physical capital is rent, depreciation, utilities, equipment, and furniture expenses divided by the total number of branch offices operated by the institution. The deposit price is the interest paid on deposits in

Federal Home Loan Bank Advances, fixed maturity deposits, NOW accounts, passbook accounts, and money market accounts divided by total deposits in these accounts over the four quarters. Since dollars are dollars, we use total assets as a measure of output, y, for the WACM test. Eight classes of output define the output vector, $\mathbf{y}$, used in the DEA approach: Assets held as mortgages, mortgage backed securities, other lending (consumer lending and commercial lending), real estate owned as the result of foreclosure, service corporations (primarily vehicles for holding commercial real estate and junk bonds), cash and noninterest earning deposits, mortgage sales, and mortgage servicing. The factor inputs, $\mathbf{x}$, used in the DEA analysis are the same as those used for the WACM/WAPM analysis.

We report the results of our WACM and WAPM tests in Tables 2a and 2b. Table 2a reveals 53 of the S&Ls to be CMEFF efficient and 50 to be PMEFF efficient (36 of these are the same institution). Using the less stringent 1% cutoff, 218 institutions are CMEFF1 efficient and 179 are PMEFF1 efficient (133 of these are the same institution). Chi-squared tests reject the null hypothesis that CMEFF and PMEFF or CMEFF1 and PMEFF1 are independent at better than the .0001 level. We conclude that WACM and WAPM are positively correlated and can be viewed as measuring the same phenomenon.

In Tables 3a and 3b, we compare S&Ls' WACM and WAPM efficiency classifications with their insolvency status. As discussed in the data appendix, an institution is insolvent if it was unable to meet its FIRREA capital requirement by 7 December 1989 or had been taken over by the Resolution Trust Corporation by 7 December 1989. Twenty six percent (250 institutions) we insolvent by these criteria. Twenty percent of the WAPM *efficient* institutions are insolvent. Similarly, 26% of the WACM *efficient* institutions are insolvent.

The null hypothesis that the probability of insolvency differs between efficient and inefficient institutions cannot be rejected for either of these stringent efficiency measures. In Table 3b we consider the same test for the WACM and WAPM efficiency measures using the 1% cutoff (i.e., *CMEFF1* and *PMEFF1*). Now, between 13% and 17% of the efficient institutions are insolvent. Moreover, using these more robust efficiency measures, we can reject the null hypothesis that efficiency and insolvency are unrelated. That is, by accounting for possible measurement error, we are better able to capture the relation between efficiency and solvency.

In Table 4, we compare the results for the DEA measures of allocative, pure technical, and overall efficiency. As discussed in Banker and Maindiratta (1990), institutions might be classified as WACM or WAPM inefficient because they are technically or allocatively inefficient. There is a statistically significant difference in the mean values of the DEA efficiency measures between CMEFF or PMEFF efficient and inefficient institutions. On average, if a firm is CMEFF or PMEFF efficient it is also more efficient using the DEA measures. The mean values for pure technical and overall efficiency measures are also higher for CMEFF1 and PMEFF1 efficient institutions and the differences are statistically significant. Institutions that are CMEFF1 and PMEFF1 efficient are, however, *less* likely to be allocatively efficient; moreover, this difference in means test is also significant. Therefore, whereas pure technical and overall efficiency measures seem to be reflecting the same phenomena as the Varian-style measures, it appears that the allocative efficiency measure is reflecting something different.

In Tables 5a and 5b, we report the difference of means tests for the solvent and insolvent institutions classified by their Varian efficiency measures. With two exceptions, the difference in means tests are statistically insignificant for the pure technical and overall efficiency measures; which suggests that these measures have no more explanatory power than the Varian-style measures. More troubling is that the two exceptions (pure technical efficiency and overall efficiency for PMEFF1-efficient firms) have the wrong sign.[6] Turning to the allocative efficiency measure, we find more statistically significant difference in means tests, but they all have the wrong sign! This is in keeping with our earlier finding that the allocative efficiency measure and the Varian-style measures seem to be measuring different phenomena. Moreover, whatever it is that the allocative efficiency measure is measuring, it is *positively* correlated with insolvency. Overall, DEA appears to have difficulty distinguishing solvent institutions from insolvent institutions correctly. Table 6 offers further evidence for this view: Again, DEA allocative efficiency is found to be significantly *greater* for *in*solvent institutions, while the other two measures cannot distinguish between solvent and insolvent institutions. Moreover, the results in Tables 4-6 suggest that DEA is less able to distinguish insolvent from solvent institutions than are the Varian-style measures of efficiency.

In an effort to control for the known size-related biases in DEA and Varian-style measures, we estimate Probits to explore the relationship between S&L insolvency, asset size, and efficiency. The Log-Likelihood is

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[6] Indeed, the nearly significant tests for overall efficiency in Table 5b (*CMEFF1* = 0) and (*PMEFF1* = 0) also have the wrong sign.

$$\mathcal{L} = \sum_{n=1}^{N} \left(INSOLVENT_n \log\Phi\left(\beta' x_n\right) + (1 - INSOLVENT_n) \log[1 - \Phi\left(\beta' x_n\right)] \right)$$

where $INSOLVENT_n = 1$ indicates the S&L is insolvent and $INSOLVENT_n = 0$ indicates solvent, β is a coefficient vector, and $\mathbf{x}_n$ is asset size and efficiency.

The results of the Probit analyses are reported in Table 7. The nonlinear relationship between asset size and insolvency is apparent in all cases, where the probability of insolvency increases up to a maximum institution size of about $7 billion dollars and then decreases. Consistent with our earlier findings, the DEA measures of overall and pure technical efficiency are *not* statistically significant predictors of insolvency. Also consistent with our earlier findings, the allocative efficiency is a statistically significant and *positive* predictor of insolvency. The Varian-style efficiency measures all have the expected negative coefficients; and all, but the severe form of WACM efficiency (CMEFF), are statistically significant at the 10% level or better. The Varian-style measures, thus, yield the reasonable result that the more efficient an S&L is, the less likely it will become insolvent. The DEA results suggest, less plausibly, that either efficiency is unrelated to insolvency or that efficiency is positively correlated with insolvency.

In summary, insolvency comparisons suggest that DEA does not accurately identify problem institutions. In fact, on average, it identifies poor performers as more efficient. The Varian-style measures, particularly the more robust ones that use the 1% cutoff, are more likely to classify properly poor performers as inefficient. In an attempt to further understand why DEA is misleading, we next seek to identify problem outliers in DEA.

V. The Effect of Outliers and Output Measurement on DEA

One important advantage of parametric analysis of production frontiers in financial institutions is that the results from these methods are remarkably robust to the specification of outputs (Mester (1989), Berger and Hanweck (1990), and Benston *et al.* (1983)). Several recent studies (Berg *et al.* (1989) and Ferrier and Lovell (1990)) have found that DEA is very sensitive to the specification of outputs. In DEA, more output classes means more output specialization; and this means more ostensibly efficient institutions because the number of comparable institutions is reduced for each institution. Thus, although DEA can accommodate a richer specification of output (in contrast to Varian-style measures) the results are sensitive to the number of elements in the output vector.

To explore this issue further, we solved the linear programs (equations (1) and (2) above) with the single output measure (total assets) used by the Varian efficiency measures. As shown in Table 8, the mean values of the DEA efficiency measures decreased when total assets alone was used to measure output.[7] Moreover, although it is not reflected in the table, the *relative* efficiency of the firms in the sample also changed with the alternative specification of output.

We, then, considered the effects of outliers on the results of the DEA and the Varian-style analyses. For each firm that defined the best-practice frontier, we computed the mean of the intensity weights (the z's) generated by the solutions to the pure technical efficiency program (equation (1)). We also calculated the number of times each such observation

[7] We also reconstructed Tables 4 - 7 using the new results and found very similar results. The DEA measures poorly distinguished solvent from insolvent institutions. Only the results for pure technical efficiency for the overall sample (the equivalent to Table 6) led to statistically significant differences between insolvent and solvent firms.

received a positive intensity weight (i.e., "defined" the best-practice frontier for other observations).[8] We then reviewed the observed data for each dominant institution. We report the results of this analysis for the ten most dominant firms in Table 9. It is clear from the table that the observation in row one is a very important determinant of the DEA results: It "defines" the best-practice frontier for 66% of the S&Ls in our sample. Moreover, its high mean intensity suggests that "inefficient" institutions would do better to adopt a strategy that heavily mimics this institution's strategy. The wisdom of this suggestion is, however, questionable, as this institution became insolvent. Moreover, further examination of this institution reveals that its apparent "super" efficiency is due to its having the smallest deposit base of any institution in the sample (not too surprising given its future insolvency).[9] For the same reason, this institution was also CMEFF and PMEFF efficient; and it was solely responsible for 28% of the WACM violations and 29% of the WAPM violations. Its effect on the CMEFF1 and PMEFF1 results were, however, negligible.[10]

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[8] For example, using the fictitious data in Table 1, we would obtain the following table:

Observation	Mean Intensity Weight	Percentage of Observations for which this observation receives a positive intensity weight.
a	.453	62.5
b or *c* or *d* or *e* or *f*	0	0
g	.423	62.5
h	.125	12.5

[9] We carried out the same analysis for overall efficiency and, again, found numerous dominant firms that were insolvent.

[10] The analogue to Table 9, in which output is measured as total assets, yields similar results. Four of the ten dominant observations are the same. The mean intensity weights, however, are greater, as are the percentage of firms for which a dominant firm has a positive intensity weight (e.g., for the institution in row one, the mean intensity is .445

In Table 10, we recompute the pure technical efficiency measures after dropping the most dominant insolvent institution (row one in Table 9). Although the overall dominance of any single institution has been reduced, there are now more insolvent institutions included in the dominant group. The dominant insolvent institutions define part of the best-practice frontier in about 20% of the programs and they are also CMEFF and PMEFF efficient. These findings suggest that the results from DEA should be presented along with an analysis of the intensity weights and the dominance of firms defining the "best-practice" frontier. Without sufficient information concerning the dominance of single firms and the possible bias caused by measurement error. DEA results should be viewed with caution.

V. Conclusions

We compared two nonparametric methods to measure efficiency in the operation of financial institutions, data envelope analysis (DEA) and Varian-style algebraic tests. Both methods assume that the data are measured without error or other serious biases. We have found, in the context of an empirical application, that DEA's convexity assumption makes it very vulnerable to measurement error because the resulting outliers will define the best-practice frontier and, thus, "identify" efficient firms as inefficient. We have suggested straightforward methods to evaluate the possible severity of such biases. These include evaluating the intensity weights and carefully evaluating the firms that define the best-practice frontier. Those few firms that play a dominant role in defining the best-practice frontier should, in particular, be viewed with suspicion.

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and it defines the best-practice frontier in 86% of the pure technical efficiency programs).

Our findings also suggest that the Varian-style measures, in their more severe form (CMEFF and PMEFF), may also suffer from Type-I errors; although this bias appears to be less severe than with DEA — a result suggested by the underlying theory (see Section III). Moreover, alternative Varian-style measures, such as CMEFF1 and PMEFF1, were found to reduce the effects of outliers and to produce more reasonable empirical results. Admittedly, these results may, to some degree, be a function of our particular application, but the logic underlying them makes them suggestive even if they are not conclusive.

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Table 1
DEA Frontier for Pure Technical Efficiency

	Intensity Weights								Pure Technical Efficiency
Observation	z_a	z_b	z_c	z_d	z_e	z_f	z_g	z_h	T_k^*
a	1.00	0	0	0	0	0	.00	0	1.000
b	1.00	0	0	0	0	0	.00	0	.500
c	.75	0	0	0	0	0	.25	0	.563
d	.625	0	0	0	0	0	.375	0	.575
e	.25	0	0	0	0	0	.75	0	.792
f	.00	0	0	0	0	0	1.00	0	.600
g	.00	0	0	0	0	0	1.00	0	1.000
h	.00	0	0	0	0	0	.00	1.00	1.000

TABLE 2a
Comparison of the Weak Axiom of Cost Minimization (WACM) and the Weak Axiom of Profit Maximization (WAPM) Sample (N=951)

(Null Hypothesis: CMEFF and PMEFF are independent)

CMEFF	PMEFF		Totals
	0	1	
0	884	14	898
1	17	36	53
Totals	901	50	951

$\chi^2 = 442.51$, Prob. = .000

TABLE 2b
Comparison of the Weak Axiom of Cost Minimization (WACM) and the Weak Axiom of Profit Maximization (WAPM) When Violations Occur in 1% or Fewer of Comparisons Sample (N=951)

(Null Hypothesis: CMEFF1 and PMEFF1 are independent)

CMEFF1	PMEFF1		Totals
	0	1	
0	687	46	733
1	85	133	218
Totals	772	179	951

$\chi^2 = 329.42$, Prob. = .000

TABLE 3a

Comparison of Insolvency with the Weak Axiom of Cost Minimization (WACM) and the Weak Axiom of Profit Maximization (WAPM) Sample (N=951)

(Null Hypothesis: CMEFF (PMEFF) is independent from Insolvency)

Efficiency Measures	Insolvency		Totals
	0	1	
CMEFF = 0	677	221	898
CMEFF = 1	39	14	53
Totals	716	235	951
χ^2 (1) = .088, Prob. = .767			
PMEFF = 0	676	225	901
PMEFF = 1	40	10	50
TOTALS	716	235	951
χ^2 (1) = .630, Prob. = .428			

TABLE 3b

Comparison of Insolvency with the Weak Axiom of Cost Minimization (WACM) and the Weak Axiom of Profit Maximization (WAPM) When Violations Occur in 1% or Fewer of Comparisons Sample (N=951)

(Null Hypotheses: CMEFF1 (PMEFF1) is independent from Insolvency)

Efficiency Measures	INSOLVENCY		Totals
	0	1	
CMEFF1 = 0	536	197	733
CMEFF1 = 1	180	38	218
Totals	716	235	951
χ^2 (1) = 8.056, Prob. = .005			
PMEFF1 = 0	560	212	772
PMEFF1 = 1	156	23	179
Totals	716	235	951
χ^2 (1) = 16.676, Prob. = .000			

Table 4a
DEA Nonparametric Analysis: Mean Values for Allocative, Pure Technical and Overall Efficiency By Varian Efficiency Measures (CMEFF and PMEFF)

Mean of the Efficiency Measure	CMEFF			PMEFF		
	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*
Allocative Efficiency (AE)	.926	.956	*-3.663******	.926	.957	*-3.514******
Pure Technical Efficiency (T)	.753	.948	*-14.498******	.753	.956	*-12.639******
Overall Efficiency (OE)	.697	.908	*-12.958******	.697	.911	*-10.575******
Number of Observations	898	53		901	50	

Table 4b
DEA Nonparametric Analysis: Mean Values for Allocative, Technical and Overall Efficiency By Varian 1% Efficiency Measures (CMEFF1 and PMEFF1)

Mean of the Efficiency Measure	CMEFF1			PMEFF1		
	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*
Allocative Efficiency (AE)	.935	.903	*5.240******	.929	.918	*1.369**
Pure Technical Efficiency (T)	.734	.864	*-12.097******	.739	.870	*-11.247******
Overall Efficiency (OE)	.687	.781	*-8.344******	.688	.799	*-8.692******
Number of Observations	733	218		772	179	

*** Significant at better than the 1% level. * Significant at better than the 10% level.

Table 5a
DEA Nonparametric Analysis: Mean Values for Allocative, Technical and Overall Efficiency By Insolvency and Varian Efficiency Measures (CMEFF and PMEFF)

Mean Efficiency Measure	CMEFF=1			CMEFF=0			PMEFF=1			PMEFF=0		
	Insolvency			Insolvency			Insolvency			Insolvency		
	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*
Allocative Efficiency (AE)	.959	.949	*.522*	.921	.939	*-3.961******	.957	.960	*-.119*	.921	.939	*-3.914******
Pure Technical Efficiency (T)	.952	.937	*.504*	.754	.750	*.314*	.953	.969	*-.569*	.753	.752	*.108*
Overall Efficiency (OE)	.914	.890	*.668*	.694	.706	*-1.018*	.913	.932	*-.473*	.694	.707	*-1.130*
Number of Observations	39	14		677	221		40	10		676	225	

Table 5b
DEA Nonparametric Analysis: Mean Values for Allocative, Technical and Overall Efficiency By Insolvency and Varian 1% Efficiency Measures (CMEFF1 and PMEFF1)

Mean Efficiency Measure	CMEFF1=1			CMEFF1=0			PMEFF1=1			PMEFF1=0		
	Insolvency			Insolvency			Insolvency			Insolvency		
	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*	0	1	*Diff. in Means Test (T Stats.)*
Allocative Efficiency (AE)	.901	.911	*-.661*	.931	.945	*-3.621******	.918	.916	*.072*	.925	.942	*-4.117******
Pure Technical Efficiency (T)	.860	.883	*-.934*	.733	.738	*-.453*	.859	.945	*-3.739******	.738	.741	*-.291*
Overall Efficiency (OE)	.776	.805	*-1.080*	.682	.700	*-1.415*	.789	.867	*-2.213****	.683	.700	*-1.451*
Number of Observations	180	38		536	197		156	23		560	212	

*** Significant at better than the 1% level. ** Significant at better than the 5% level.

Table 6
DEA Nonparametric Analysis
Mean Values for Allocative, Pure Technical and Overall Efficiency
By Insolvency
(N = 951)

Mean Efficiency Measure	INSOLVENCY		
	0	1	*Diff. in Means Test (T Stats.)*
Allocative Efficiency (AE)	.923	.940	*-3.720******
Pure Technical Efficiency (T)	.765	.761	*.277*
Overall Efficiency (OE)	.706	.717	*-.920*
Number of Observations	716	235	

*** Significant at better than the 1% level.

Table 7
Probit Analysis of Insolvency on
DEA Efficiency Measures and Varian Efficiency Measures
(Dependent Variable Insolvency)
(n=951)

Independent Variables	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency
Constant	-2.628*** (-3.558)	-.501** (-2.102)	-.718*** (-3.225)	-.870*** (14.981)	-.867*** (-14.930)	-.808*** (-12.786)	-.789*** (-12.925)
Asset	.308*** (4.412)	.358*** (5.130)	.351*** (4.966)	.342*** (4.943)	.357*** (5.059)	.321*** (4.762)	.333*** (4.762)
Asset Squared	-.023*** (-3.276)	-.026** (-3.574)	-.025*** (-3.539)	-.025*** (-3.469)	-.025*** (-3.427)	-.023*** (-3.180)	-.023*** (-3.149)
Allocative Efficiency (AE)	1.908** (2.388)						
Pure Technical Efficiency (T)		-.506 (-1.601)					
Overall Efficiency (OE)			-.229 (-.718)				
CMEFF				-.091 (-.449)			
PMEFF					-.389* (-1.742)		
CMEFF1						-.275** (-2.418)	
PMEFF1							-.537*** (-4.081)
χ^2 (3)	37.728	34.433	32.274	32.059	35.016	37.853	49.809

*** Significant at better than the 1% level. ** Significant at better than the 5% level. * Significant at better than the 10%

Table 8
DEA Nonparametric Analysis:
Mean Values for Allocative, Pure Technical and Overall Efficiency
When Output Measured as Total Assets and by Eight Element Output Vector
(n=951)

Mean of the Efficiency Measure	Output Measured As	
	Total Assets	Portfolio of Eight Activities
Allocative Efficiency (AE)	.859	.927
Pure Technical Efficiency (T)	.637	.764
Overall Efficiency (OE)	.542	.709

Table 9
Dominant Institutions in the DEA "Best-Practice" Frontier for Pure Technical Efficiency with Output Measured as Portfolio of Activities
(n=951)

Ranking Number	Mean Intensity Weight $\overline{z_k} = \frac{\sum_{l=1}^{951} z_{kl}}{951}$	Percentage of Institutions for which this Observation Receives a Positive Intensity Weight	Insolvent	Asset Size ($000)
1	.266	65.9	Yes	176,083.25
2	.075	24.7	No	109,944.19
3	.067	28.5	Yes	105,051.73
4	.038	27.7	Yes	151,896.44
5	.031	13.8	No	106,265.57
6	.029	15.1	No	247,614.05
7	.025	22.7	No	938,474.15
8	.022	11.1	No	112,060.41
9	.021	42.4	No	1,611,278.84
10	.017	29.4	No	3,161,787.63

Table 10
Dominant Institutions in the DEA "Best-Practice" Frontier for Pure Technical Efficiency with Output Measured as Portfolio of Activities When the Most Dominant Institution (Observation 1 above) is Deleted
(n=950)

Ranking Number (Ranking in Analysis used to Generate Table 9)	Mean Intensity Weight $\overline{z_k} = \frac{\sum_{i=1}^{950} z_{ki}}{950}$	Percentage of Institutions for which this Observation Receives a Positive Intensity Weight	Insolvent	Asset Size ($000)
1 (2)	.108	30.2	No	109,944.19
2 (111)	.083	34.8	Yes	110,151.08
3 (3)	.071	30.1	Yes	105,051.73
4 (5)	.060	26.4	No	106,265.57
5 (17)	.042	21.9	No	165,583.46
6 (4)	.036	23.8	Yes	151,896.44
7 (30)	.036	28.4	No	357,485.51
8 (21)	.022	12.3	Yes	110,788.75
9 (7)	.022	18.4	No	938,474.15
10 (Not Ranked)	.022	7.4	No	122,101.30

APPENDIX

The sample of Savings and Loan institutions used in this study included all institutions with total assets greater than $100,000,000 for which we could obtain complete data on the factor inputs (labor, branches, and desposits). The accounting balances were obtained from the Federal Home Loan Bank Board quarterly financial reports from June, 1987 through March, 1988. The asset and liability data were computed as average holdings over four quarters June, 1987 through March, 1988. The mean, maximum, and minimum values for all the continuous variables are reported in Table A.1.

Total assets:

ASSET86, total assets. Two forms of total assets were used in the analysis. Our first measure of total assets adjusts, in some sense, for credit problems in an S&Ls portfolio and treats the "performing" assets as our measure of total output. For the tests of the Weak Axiom of Cost Minimization (WACM) and Weak Axiom of Profit Maximization (WAPM), valuation allowances for mortgage loans, non-mortgage loans, real estate owned, service corporations, investment securities, fixed assets, and other assets were subtracted from the total book value of assets held. These valuations are the original issue discount or premium on purchased assets and adjustments in valuation to recognize credit losses. Total assets were scaled by 100 million in the Probit and Tobit analyses.

The output classes are as follows:

Assets held as service corporations and subsidiaries. The included assets are subsidiary corporations in which the primary assets are junk bonds or equity participations in real estate. Wholly owned finance subsidiaries are not included in this variable.

Assets held as real estate obtained through foreclosure, from deed in lieu of foreclosure, or real estate acquired from a debt restructuring.

Assets held as consumer loans and commercial loans. These include loans on deposits, home improvement loans, education loans, auto loans, retail mobile home loans, revolving loans secured by one to four family dwelling units, credit cards and other open ended credit extended to consumers. These include secured loans for farming operations, for commercial properties nonmortgage, retail auto loans for commercial use, loans to service corporations. It also includes unsecured loans such as unsecured construction loans to builders for new residential property, loans for the improvement of multifamily properties, commercial lines of credit, and for farming operations.

Assets held as insured and uninsured mortgage backed securities. Includes securities issued by Federal National Mortgage Association (FNMA), the Federal Home Loan

Mortgage Corporation, (FHLMC), the Government National Mortgage Association, (GNMA) and private issuers.

Assets held as residenial mortgages. These include mortgages on five plus dwelling units. where a dwelling unit is defined as a unit designed for the residence by one family and mortgages on one to four dwelling units.

Assets held as cash and noninterest earning deposits.

Two flow lines of business were also included in the analysis. These were computed as the total flow over four quarters. These are:

Dollar value of all mortgage sales including sales to federal agencies and sales to trusts issuing MBS. This variable was also divided by 100,000,000.

Dollar value of mortgage loans serviced for others. This variable was also divide by 100,000,000.

The input quantities and average input prices used in the efficiency analysis include:

FUNDS, Federal Home Loan Bank Advances, fixed maturity deposits, money market accounts, NOW, super NOW, and other transaction accounts, and passbook accounts. The Federal Home Loan Bank quarterly financial statements no longer distinguish the interest rates paid on term and demand deposits. Thus, we were unable to treat term and demand deposits as separate inputs as in previous papers (Mester, 1989; 1990)

FNDRATE, the average unit interest rate paid on the funds as defined above.

Two other factor inputs were included: labor and physical capital. The number of full time employees was obtained from the Dun and Bradstreet, *Million Dollar Directory.* Obtaining good employment data was a major obstacle and many S&Ls were excluded because of lack of available information. Average expenditure on labor (AVWAGE) was computed as total labor expenditures divided by total number of employees. We recognize that the employment data probably over estimates average expenditures because we were unable to obtain information on part-time employees in the institutions. The number of branches was obtained from the Rand McNally, *U.S. Savings and Loan Directory.* The average expenditure per branch was computed as total office occupancy expenses divided by number of branches.

Revenue was measured as the sum of the total operating income over the four quarters.

Insolvent institutions were identified as S&Ls in operation in June of 1986 that were either taken over by the RTC or were unable to meet their capital requirements as of December 7, 1989. The capital requirements mandated by FIRREA and regulators went into effect on

December 7, 1989. The requirements under FIRREA were that an S&L must have tangible capital equal to at least 1.5 percent of assets. Tangible capital is real assets minus liabilities. They were required to have core capital (mainly common equity, retained earnings, a certain amount of good will, and non-cumulative preferred stocks) equal to at least 3% of assets. Insolvent institutions were identified using lists obtained from the Resolution Trust Corporation.

TABLE A.1
Summary Statistics for the Sample
Four Quarters from July 1987 - March, 1988.
(N = 951)

VARIABLES	MEAN	MAXIMUM	MINIMUM
Average assets in service corporations	$16,679,960	$756,634,900	0
Average assets in Real Estate Owned (Foreclosed Real Estate)	$13,333,280	$685,403,840	0
Average assets in consumer and commerical loans, vacant land, and commerical Real Estate Loans	$53,599,160	$1,762,360,280	0
Average assets in insured and uninsured mortgage backed securities	$95,972,060	$2,854,234,830	$1,387,310
Average assets in mortgages on 1-4 and 5+ dwellings	$513,230,310	$21,872,244,860	$228,088,200
Average assets in cash	$9,773,690	$348,769,330	$116,206
Average total assets	$806,197,090	$28,480,385,200	$100,024,020
Total dollar value of loans and participations sold	$74,437,180	$4,459,143,790	0
Total dollar value of mortgage servicing	$914,498,430	$70,437,532,680	0
Average total Income (REVENUE)	$70,436,020	$2,446,433,470	-$22,063,700
Total branches	13.5	294	1
Total full time employees	252	6000	2
Total Deposits and FHLB Advances	$668,810,740	$22,905,308,290	$57,126,030
Average Branch Expenditures	$239,475	$8,956,600	$25,317
Average Wage Rate	$29,599	$67,092	$3,742
Average funds rate	.0699	.0983	.0558
Total costs	$57,036,790	$1,841,694,000	$5,592,170

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