Articles

Relative Efficiency in Rural Primary Health Care: An Application of Data Envelopment Analysis

Yueh-Guey Laura Huang and Curtis P. McLaughlin

This study applied data envelopment analysis (DEA) to the evaluation of rural primary health care programs, which are known to be very heterogeneous. DEA is a mathematical programming technique that optimizes the relative efficiency *ratio of current inputs over current outputs for each decision-making unit (DMU). It produces a summary scalar efficiency ratio for each DMU and identifies the amount of inefficiency. The data came from the National Evaluation of Rural Primary Health Care Programs. Despite the demands of the software used for homogeneous units and nonzero values, the efficiency analysis was useful to the evaluation. It assessed multiple inputs and multiple outputs simultaneously, and identified directly those units that are performing efficiently or inefficiently when compared to specific peer programs. This then allowed us to compare this efficient-inefficient classification with other data, first, to verify the classification and, second, to assist with the evaluation. DEA can contribute to the evaluation of heterogeneous health programs, especially when used in conjunction with other methods of analysis.*

Studies in the evaluation of rural or primary health care have been limited thus far by the representativeness of the medical practice and the

---

This study was supported by the Robert Wood Johnson Foundation, the U.S. Department of Health and Human Services, and the Health Services Research Center of the University of North Carolina at Chapel Hill.

Address correspondence and requests for reprints to Yueh-Guey Laura Huang, Dr.P.H., Assistant Professor, University of South Florida, College of Public Health, 13301 Bruce B. Downs Blvd., MHH-104, Tampa, FL 33612-3899. Curtis P. McLaughlin, D.B.A. is a Professor in the School of Business Administration and School of Public Health, University of North Carolina at Chapel Hill.

limited range of characteristics studied (Health Services Research Center 1983). Under constrained resources, an overall evaluation measure of efficiency is especially useful for program management and policymaking. Problems in conducting an overall evaluation of rural health programs' performance, however, are intensified by limitations of the conventional analytical methods: most existing efficiency measurement techniques in not-for-profit entities rely on regression and ratio analysis.

Data Envelopment Analysis (DEA), a mathematical programming technique developed by Charnes, Cooper, and Rhodes (1979), has been advanced as an appropriate and easy method for evaluating the relative efficiency of not-for-profit entities. Because it is able to handle multiple inputs and outputs simultaneously, DEA can generate relative-efficiency information not usually available from other methods, including the relative efficiency ratio and the amount and source of relative inefficiency in decision units (Charnes, Cooper, and Rhodes 1979, 1981; Bessent and Bessent 1980; Sherman 1984).

The technique has been used extensively to measure efficiency in not-for-profit firms and in governmental units, as well as in the service industries (Charnes, Cooper, and Rhodes 1981; Sherman 1984; Bessent, Bessent, Kennington, et al. 1982; Lewin, Morey, and Cook 1982; ORSA/TIMS 1984, 1987). However, it is not as well known to health services researchers. Up to now, five articles reporting the use of DEA in health services evaluation have been published (Nunamaker 1983; Conrad and Strauss 1983; Sherman 1984; Banker, Conrad, and Strauss 1986; Grosskopf and Valdmanis 1987). These studies, like the general DEA literature, emphasize the strengths of DEA in evaluating efficiency within relatively homogeneous groups of decision units. The challenge of our study is to examine whether DEA yields useful information when applied to extremely heterogeneous health activities, namely rural primary health care clinics.

The first section of this article provides an overview of DEA. Subsequently we describe the data set and input/output variables used in the empirical analysis, and present an illustration of the empirical model. The main empirical findings are then discussed, as well as the relationships between program efficiency and other variables, and comparisons of DEA results with those from other methods. The final section summarizes the analyses and presents conclusions.

AN OVERVIEW OF DEA

Data Envelopment Analysis (DEA) uses nonparametric deterministic mathematical programming to optimize the relative efficiency ratio in each decision-making unit (DMU) (e.g., organization, program, service) that utilizes similar inputs to produce similar outputs when compared to a peer group of DMUs. The theoretical base and mathematical model of DEA have been illustrated in many articles (Charnes, Cooper, and Rhodes 1979, 1981; Fare and Lovell 1978; Forsund, Lovell, and Schmidt 1980; Bessent and Bessent 1980; Charnes and Cooper 1980; Banker, Charnes, and Cooper 1984; Lovell and Schmidt 1986; Charnes, Cooper, and Thrall 1986).

Using a nonlinear programming model, the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the ratio for every DMU be less than or equal to unity. Those programs with a positive efficiency ratio of less than 1 are defined as "inefficient" compared to programs with an efficiency ratio of 1. Those health programs with an efficiency ratio of 1, while not necessarily efficient in the absolute sense, represent the "best-practice" units when compared with other programs in their subset. A rural health program that is found to be relatively efficient, for instance, may still be able to innovate and improve its operating efficiency. In other words, a rural health program that is found to be inefficient will have inefficiencies at least as large as the amount determined by DEA. Hence, DEA methodology is considered conservative in measuring efficiency (Charnes, Cooper, and Rhodes 1979; Sherman 1984; Thompson and Thrall 1985).

This method uses the current values of chosen multiple inputs and outputs simultaneously in each DMU to generate efficiency boundaries (the reason for using the term "Data Envelopment"), and then compares the relative relationships between other DMUs and these boundaries. It produces a summary scalar efficiency ratio for each DMU in the study and also identifies the amount of inefficiency for each resource in each inefficient DMU.

One advantage of the DEA model is that each input and each output variable can be measured independently in any useful unit, without being transformed into a single metric, provided the same variables are utilized for every DMU (Charnes and Cooper 1980). Moreover, by not requiring a predetermined specific input-output relationship, the DEA model can use as inputs any factors that significantly affect the output variables. This avoids the problems associated with techniques used to convert and unify variables. The efficiency criterion employed is the maximization of relative efficiency for each rural health program rather than an arbitrary cutoff point; hence, each multiplier (weight) is generated, not a priori, but from actual data for each DMU.

EMPIRICAL APPLICATIONS OF DEA

Data from the National Evaluation of Rural Primary Health Care Programs, conducted by the Health Services Research Center, University of North Carolina at Chapel Hill, was used. This was a five-year (1978–1983), multidisciplinary evaluation of different organizational approaches to rural primary health care delivery. The data base included extensive reporting on program and provider characteristics, scope of services, provider stability and productivity, revenues and costs, and administrative and financial policies. Data were collected, by mail and telephone questionnaires, from 193 randomly selected programs. Secondary information was abstracted from Bureau of Community Health Services (BCHS) Common Reporting Requirements, and Bureau of Health Professions (BHP) Area Resource Files, from the Department of Health and Human Services (Health Services Research Center 1983; Sheps, Wagner, Schonfeld, et al. 1983).

OUTPUT AND INPUT VARIABLES

Since the delivery of rural primary health care has been so diverse, little agreement has been reached on its operational definition, or on the identification and measurement of inputs, outputs, or processes (Copp 1976).

In a DEA model, only two main categories are considered: input and output. Health programs that produce more outputs with given inputs are considered to be relatively more efficient. For our purposes, outputs can be any product of the rural health program, such as services provided and patients served. As mentioned previously, inputs can be any factors that affect significantly the production of outputs.

Potential input and output variables were identified and justified according to previous studies (Reinhardt 1973; Davis and Marshall 1977; Sheps, Wagner, Schonfeld, et al. 1983; Copp 1976; Ricketts, Konrad, and Wagner 1983; Bradham 1981; McLaughlin, Ricketts, and Bradham 1983). Correlation analysis was used to select nonredundant output variables. Taking these output variables as dependent variables, we selected input variables from the results of correlation and stepwise regressions. Those selected inputs and outputs were then classified into controllable (discretionary) and uncontrollable (nondiscretionary) inputs and outputs according to their relationship to managerial decisions.

The heterogeneity of rural primary health care programs was evident not only in their outputs but also in their inputs. Most of the variables used in this study had coefficients of variation (s.d./mean) greater than 100 percent (Huang 1986). Accordingly, all of the uncontrollable input variables were classified into two or three 0–1 categories in order to limit the range of peer programs that belonged to the same comparative group. The details of data selection and specification are described in Huang (1986).

The common major services in rural primary health care programs are medical services. Since no direct measure of quality of medical services was available in the data set, the provision of medical services was considered by type of provider, instead of an aggregated measure for all medical services. This study used three main types of health care providers: physicians, new health practitioners (NHPs, including nurse practitioners and physician assistants), and nurses.

In addition to the three medical output measures, "total encounters," the summation of medical, dental, and other encounters, was taken as an "uncontrollable" output in the DEA model. This procedure took total volume of the program into account in the efficiency comparisons and allowed consideration in the model of other nonmedical services that the center produced.

The input measures used in the model were: physician full-time equivalents (FTEs), NHP FTEs, nurse FTEs, medical technician FTEs, administrative FTEs, service area population size, age of program, and percentage of users under 4 years old. The five FTEs represent direct manpower inputs by disciplines and functions. The service area population size and the percentage of users under 4 years old were used as control variables of users' health need (or demand). The age of program is related to program performance since younger programs may have managerial strategies different from those of well-established programs.

The number of external primary care services in the area had been used as an index for competition. However, the relationship between competition and the quantity of output is ambiguous in the health care industry, in that more accessibility may induce, rather than reduce, demand for medical visits. The same problem was found between the variable of race distribution and the output of rural primary health care services. Both were dropped from the model.

THE EMPIRICAL MODEL OF DEA

Among 193 rural health programs in the data set, only 142 have complete data (including 0) for each chosen variable; further, only 77 of them provided services by physicians, NHPs, and nurses. Those programs that contained zero values in controllable input and output variables were not used due to technical difficulties in the software. Therefore, only 77 programs were used to test the applicability of DEA, since the representativeness of the programs is not an issue in DEA.

The empirical model for a primary rural health clinic k (DMU_k) can be presented as follows:

Objective:

$$\text{Max } h_k = \frac{\overset{\text{OUTPUTS}}{\left\{\begin{array}{ll} \text{controllable} & \text{uncontrollable} \\ u_1\text{MD encounters} & \\ u_2 \text{ NHP encounters} & + \; u_4 \text{ total encounters} \\ u_3 \text{ nurse encounters} & \end{array}\right\}}}{\underset{\text{INPUTS}}{\left\{\begin{array}{ll} v_1 \text{ administrative FTEs} & \\ v_2 \text{ Medical technician FTEs} & \\ v_3 \text{ MD FTEs} & v_6 \text{ population size} \\ v_4 \text{ NHP FTEs} & + \; v_7 \text{ program age} \\ v_5 \text{ nurse FTEs} & v_8 \text{ users' age} \\ \text{controllable} & \text{uncontrollable} \end{array}\right\}}}$$

Subject to:

$$\begin{array}{l} h_j \leq 1, j = 1, 2, \ldots, 77, \\ 0 < \epsilon \leq u_1, \ldots, u_4, \text{ and} \\ 0 < \epsilon \leq v_1, \ldots, v_8 \end{array}$$

where

h_j = the efficiency ratio for any DMU j;

$j = 1, 2, \ldots, 77$;

u's and v's = artificial weights generated from the model;

ϵ = a non-Archimedean infinitesimal.

This model, which sums up all medical services and takes physician, NHP, and nurse services into account separately, assesses the overall performance of a program. Alternative DEA models for each of those three medical professional services were also developed and interpreted, but are not reported here (Huang 1986).

RESULTS

This empirical model generates a scalar efficiency ratio and identifies a group of comparative DMUs for each program. Among the 77 programs, 29 had an efficiency ratio of 1 compared to a reference set of DMUs and no slacks; these were then classified as efficient. Thirteen were inefficient since their efficiency ratios were less than 1. The remaining 35 had an efficiency ratio of 1 without any comparative DMU generated: these were then called "self-evaluators." The large number of self-evaluators is a result of both the heterogeneity of the data set and the dimensionality of the model. For example, a six-input, two-output model of nursing efficiency produced 28 efficient DMUs, 33 inefficient DMUs, and only 16 self-evaluators using the same data set (Huang 1986). The fact that the self-evaluators are a disconcertingly large number did not prove to be a handicap in further analysis.

RELATIONSHIPS AMONG EFFICIENCY, ORGANIZATION FORMS, AND POPULATION SIZE

The rural primary health care programs in the data base had been classified, according to their operational characteristics, into four categories: organized group practices (OGPs), community health centers (CHCs), primary care centers (PCCs), and other programs (Sheps, Wagner, Schonfeld, et al. 1983). Using cost variables, previous studies had shown that organized group practices were the most cost efficient, community health centers were the least cost efficient, and primary care centers fell in between. Despite use of different variables and methods, findings in this study were consistent with the former evaluations. Table 1 shows that the OGPs have a higher proportion of efficient programs, the CHCs have a higher proportion of inefficient programs, and the PCCs are in between. Due to the small number of programs in some cells, the chi-square test could not be utilized to examine the significance of the variation.

Service area population size is related to the forms of organization. Most CHCs were located in comparatively populous service

Table 1: Chi-Square Test of the Relationship between Program Efficiency and Organization Form

Organization Forms	Number/Percent of Programs*		Total
	Efficient Programs	Inefficient Programs	
Organized group practices	9 90.00%	1 10.00%	10
Community health centers	5 45.45%	6 54.55%	11
Primary care centers	10 62.50%	6 37.50%	16
Total	24 64.86%	13 35.14%	37

Chi-square = 4.630; DF = 2; Prob = 0.0988.

*Over 20 percent of the cells have expected counts less than five. This table does not include self-evaluators.

Table 2: Distribution of Efficient Programs by Population Size and Organization Forms

Population Size	Organization Forms (number efficient programs/number programs)				
	OGP	CHC	PCC	Other	Total
Small	3/3	2/2	8/10	2/2	15/17
Medium	3/3	1/3	2/5	1/1	7/12
Large	3/4	2/6	0/1	2/2	7/13

areas, and most PCCs in communities with smaller populations. With the exception of two PCCs, all programs serving small populations were efficient, if not self-evaluators, regardless of their organizational form. The proportions of efficient and inefficient programs in medium and large population areas were similar.

Table 2 shows the distribution of efficient programs as related to population size and organization forms. The only two inefficient programs in small population areas were PCCs, and the only PCC in a large population area was also inefficient. While the only inefficient OGP was located in a large service area, four of six inefficient programs in large service area were CHCs. A logistic regression further confirmed that OGPs were more efficient than PCCs and CHCs, and that programs serving larger populations were more likely to be inefficient (Table 3).

Three cost-related ratios used in the earlier evaluations of program efficiency were also used for comparison with the DEA results. Average cost was calculated as the ratio of total costs (excluding dental costs) to total encounters (excluding dental encounters). This statistic is

Table 3: Logistic Regression Analysis for the Relationships between Organization Form, Population Size, and Program Efficiency

*Independent Variable**	*Beta*	*Standard Error*	*Chi-Square*	p	R
ORG1 (OGP)	2.46	1.30	3.54	0.060	0.179
ORG2 (CHC)	-0.79	1.16	0.47	0.492	0.000
POP1 (large)	-3.31	1.42	5.48	0.019	-0.269
POP2 (medium)	-2.23	1.11	3.99	0.046	-0.204

*Dependent variable: EFF (efficiency classification of DEA).

often used as an indicator of the cost efficiency of overall performance. Average medical cost was calculated as the ratio of total medical costs to total medical encounters. Total medical costs, when applicable, included the costs incurred in medical services, laboratory, x-ray, and pharmacy, as well as administrative costs, prorated by the ratio of medical encounters to total encounters. Total medical encounters excluded encounters for dental and other health-related services (social services, health education, mental health, etc.) from total encounters. This ratio emphasized the general performance of medical services. The self-sufficiency ratio—the ratio of total payments for services to total costs—was used as an indicator for the financial viability or stability of a program, excluding subsidies (Bradham 1981; McLaughlin, Ricketts, and Bradham 1983). The *t*-test results showed nonsignificant differences, except that the self-sufficiency ratios of OGPs were significantly higher than those of CHCs at the significance level of .05. However, the average total cost and average medical cost of OGPs were significantly lower than those of PCCs. These cost differences among population groups were not statistically significant.

In sum, most programs in small service areas were efficient, and most of the efficient programs were located in small service areas. Most PCCs were located in communities of small population, while most CHCs were in large population areas. Hence, in terms of population size, rural health programs performed more efficiently in small population areas regardless of organization form. In terms of organization form, the OGPs were generally the most efficient of the three, regardless of the size of the community; the CHCs were least efficient, especially when located in large service areas; and the PCCs performed more efficiently if they were located in small service areas.

Further effort was made to search for the reasons underlying the negative relationship between population size and program efficiency. Variables of community involvement—such as number of functions in which the board of directors was involved or had final authority, and the factor of competition measured by the number of primary care services in the area—were brought into a logistic regression model using efficiency as the dependent variable. A similar examination was conducted for the variable, single- versus multiple-site programs. However, none of these variables was found to affect program efficiency significantly.

THE SOURCES AND AMOUNT OF INEFFICIENCY

The DEA model also generates an adjusted value for each variable, suggesting the amount by which the inefficient programs can adjust and become efficient (by reducing inputs or increasing outputs at least to the amount suggested by DEA). For example, Program 4 in Table 4 can become efficient if it reduces its staff to 5.83 administrative FTEs, 4.0 paramedical FTEs, 3.5 physician FTEs, 0.94 NHP FTEs, and 1.65 nurse FTEs. It also can allocate the additional capacities indicated in the output slack column. These input "values if efficient" are obtained by multiplying the efficiency ratio of 0.94 by the current values and then subtracting the slack (Bessent, Bessent, Kennington, et al. 1982).

Table 4: A DEA Output Sample (Program no. 4: Efficiency Ratio = 0.94; Reference DMUs: 7, 10, 22, 42, 65)

Output	*Current Value*	*Value if Efficient*	*Slack*
Physician encounters	16856	17875	1019
NHP encounters	2299	2311	12
Nurse encounters	358	1789	1431
Total encounters	22913	22913	0
Input	*Current Value*	*Value if Efficient*	*Slack*
Controllable			
Administrative FTEs	8.0000	5.8282	1.7128
Medical technician FTEs	4.2500	4.0062	0.0000
Physician FTEs	3.7300	3.5160	0.0000
NHP FTEs	1.0000	0.9426	0.0000
Nurse FTEs	1.7500	1.6496	0.0000
Uncontrollable			
Users' age index	0.0000	0.0000	0.0000
Population index 1	1.0000	0.2875	0.7125
Population index 2	1.0000	0.7581	0.2419
Age of program	1.0000	0.2441	0.7559

COMPARISONS OF THE RESULTS FROM DEA AND OTHER METHODS

The individual result for each program was compared to that obtained from ratio analysis and simple linear regression analysis.

Comparison of DEA Results with Ratio Analysis

The rural clinics were ranked from efficient to inefficient by each of the three cost-related ratios used in previous rural health studies: average cost, average medical cost, and self-sufficiency ratio. Then the DEA rankings were compared with these rankings. In general, the results from DEA and the three cost-related ratios paralleled each other. Most of the efficient programs had low costs and high self-sufficiency ratios. Most of the inefficient programs had high costs and low self-sufficiency ratios (details shown in Huang 1986).

Another common ratio used in evaluating program efficiency is productivity, defined as the ratio of the output of a certain type of staff to the FTEs of that type of staff in the program. Usually, the higher the productivity, the more efficient the program. The DEA multiple-output model results generally paralleled the rankings of productivity for each type of personnel, although less closely than in the cost-ratio comparisons. The least efficient programs had the lowest productivity and the most efficient programs had higher productivity. A *t*-test (shown in Table 5) confirmed the difference in average productivity for each type of personnel between efficient and inefficient programs assessed by DEA.

Comparison of DEA Results with Regression Analysis

The regression model used for this comparison utilized inputs and outputs identical to those of the DEA model. However, the simple regression model took the continuous values of the input variables as the measures for independent variables. And the number of total medical encounters, which included physician, NHP, and nurse encounters, was used as the measure for dependent variables, since multiple output variables are not allowed in the simple regression model. The resulting regression model was:

$$
\begin{aligned}
\text{Total medical encounters} = & - 6{,}811 \\
& + 6{,}393 \quad \text{physician FTEs} \\
& + 2{,}237 \quad \text{NHP FTEs}
\end{aligned}
$$

+	544	nurse FTEs
-	483	administrative FTEs
+	239	medical technician FTEs
+	324	program age in years
+	0.055	population of service area
+	181	percentage of users <4 years.

The R-square for this model was 0.96. The coefficient of every independent variable was significant ($p < .05$), except for "population of service area" ($p = .18$).

The simple linear regression model was then used to classify programs under a commonly used criterion of "efficiency." In a personal communication with A. Lewin (1986), the expected number of medical encounters was defined as the value between the regression line plus 1/2 standard deviation and the regression line minus 1/2 standard deviation, that is, predicted value ± 1/2 s.d. The programs with actual

Table 5: Test of Productivity Difference between Efficient and Inefficient Programs

	Efficient Programs (N = 29)		*Inefficient Programs (N = 13)*			
*Productivity**	*Mean*	*s.d.*	*Mean*	*s.d.*	t	p
Physician	5089	1395	3925	1171	2.62	.012
NHP	2734	869	2139	731	2.15	.038
Nurse	1329	1893	337	239	2.77	.010
Administration	4310	2483	2690	1272	2.21	.033
Medical technician	6187	7966	2706	1104	2.30	.028

*Productivity = number encounters/number FTEs for each category.

Table 6: The Comparison of the Results from DEA versus Regression

	Results from Regression			
	Programs above Average	*Programs below Average*	*Programs within Average*	*Total Programs*
DEA Results		*Number of Programs*		
Efficient	18	8	3	29
Inefficient	1	10	2	13
Total	19	18	5	42

medical encounters above that range were considered to be "efficient" in the regression analysis, and the programs below the average were considered to be "inefficient." Then the results from this regression analysis and from the DEA were matched, as shown in Table 6.

Table 6 shows that 18 efficient and 10 inefficient programs had the same results as in DEA, while 9 programs gave contradictory results. Eight programs that were identified as efficient in DEA were below the regression criterion, and only one inefficient program in DEA was above the range. These inconsistent programs were further examined for their rankings in cost-related ratio analyses. Among those eight efficient programs, five were found to have low costs (ranks < 30) and high self-sufficiency ratios (ranks < 22). Moreover, seven of these eight programs were found to be located in a service area with small population, which was taken into account in the relative efficiency comparison of DEA. The inefficient program that fell above the average was found to have a very low self-sufficiency ratio (rank no. 62), high average cost, and relatively high average medical cost (ranks no. 56 and 43), which meant that this program was indeed more likely to be inefficient. These results tended to validate the DEA analysis.

CONCLUSION

DEA identified the relatively more efficient primary health care programs in a manner confirmed by other methods of analysis. DEA can provide the basis for carrying out detailed field studies to find out what the efficient programs are doing differently than the others. It also can point toward issues of organizational change and its implementation.

DEA was suitable for a portion of the evaluation even for programs as heterogeneous as rural primary health care clinics. The technical problems—production of numerous self-evaluators and the inability to handle zero values—reportedly have been solved since this study was done (Charnes, Cooper, and Thrall 1986; Sueyoski and Chang 1987).

The encouraging result was our ability to use the classification of efficient and inefficient cases in further analyses. Earlier analyses were often defeated by the inability to use a multi-output model—and the single metric of dollar costs was not the answer. With DEA's assistance we have been able to gain new insights into the relationships between relative efficiency, organizational form, and size of the service area. When adjusted for differences in output and size of service area, CHCs and PCCs are not significantly more likely to be efficient, but OGPs are. The PCCs with their predominantly NHP staffing are effective for use in small, remote service areas. It appears that much of the observed cost inefficiency of the CHCs relates to their being oversized in terms of both staffing and total size.

Whether one uses DEA or some other technique will depend on the purpose of the analysis, the size of the sample, the perceived reliability of the data, the homogeneity of the units being evaluated, and the emphasis on hypothesis testing versus emphasis on managerial evaluation. DEA has its shortcomings—a deterministic basis and the need for homogeneity, for complete and accurate data, and for modeling simplicity. What we did in combining deterministic models with statistical approaches reflects a direction that evaluative research seems to be taking (Charnes, Cooper, and Sueyoshi 1988), but not without spirited debate (Evans and Heckman 1988). All we can say is that, had we had the DEA technique and its results on hand at the time the evaluation data were being collected, we could have focused on those sites that presented anomalies and/or extremes in terms of both cost and relative efficiency. We then could have used our resources to obtain additional information on the factors accounting for these extreme cases. Since such tools are now available to program evaluators, DEA should become an important part of each health evaluator's tool kit in the future.

ACKNOWLEDGMENTS

The authors would like to acknowledge Professor A. Y. Lewin, Duke University, and Performance Analysis Corporation, Chapel Hill, North Carolina, for their technical support in carrying out this study. Comments on this article from Professors W. W. Cooper, A. Charnes, R. M. Thrall, and T. Chirikos are also very much appreciated.

REFERENCES

Banker, R. D., A. Charnes, and W. W. Cooper. "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis." *Management Science* 30, no. 9 (September 1984):1078-92.

Banker, R. D., R. F. Conrad, and R. P. Strauss. "A Comparative Application of Data Envelopment Analysis and Translog Methods: An Illustrative Study of Hospital Production." *Management Science* 32, no. 1 (January 1986):30-44.

Bessent, A. M., and E. W. Bessent. "Determining the Comparative Efficiency of Schools through Data Envelopment Analysis." *Educational Administration Quarterly* 16, no. 2 (Spring 1980):57-75.

Bessent, A. M., E. W. Bessent, J. Kennington, and B. Reagan. "An Application of Mathematical Programming to Assess Productivity in the Houston Independent School District." *Management Science* 28, no. 12 (December 1982):1355-67.

Bradham, Douglas D. "A Cost Structure Analysis for Subsidized Rural Primary Care Practices." Ph.D. diss., University of North Carolina, Chapel Hill, 1981.

Bradham, Douglas D., C. P. McLaughlin, and T. C. Ricketts. "The Ability of Aggregate Data to Predict Self-Sufficiency Levels in Subsidized Rural Primary Care Practices." *The Journal of Rural Health* 1, no. 2 (July 1985):56-68.

Charnes, A., and W. W. Cooper. "Auditing and Accounting for Program Efficiency and Management Efficiency in Not-for-Profit Entities." *Accounting, Organizations and Society* 5, no. 1 (1980):87-107.

Charnes, A., W. W. Cooper, and E. Rhodes. "Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through." *Management Science* 27, no. 6 (June 1981):668-97.

______. "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research* 2, no. 6 (1978):429-44. (See also "Corrections." *European Journal of Operational Research* 3, no. 4 [1979]:339.)

Charns, A., W. W. Cooper, and R. M. Thrall. "Classifying and Characterizing Efficiencies and Inefficiencies in Data Envelopment Analysis." *Operations Research Letters* 5, no. 3 (August 1986):105-10.

Charns, A., W. W. Cooper, and T. Sueyoshi. "A Goal Programming/Constrained Regression Review of The Bell System Breakup." *Management Science* 34, no. 1 (January 1988):1-26.

Conrad, R. F., and R. P. Strauss. "A Multiple-Output Multiple-Input Model of the Hospital Industry in North Carolina." *Applied Economics* 15, no. 3 (June 1983):341-52.

Copp, J. H. "Diversity of Rural Society and Health Needs." In *Rural Health Services*. Edited by E. W. Hassinger and L. R. Whiting. Ames, IA: Iowa State University Press, 1976.

Davis, K., and R. Marshall. "Primary Health Care Services for Medically Underserved Areas." *Papers on the National Health Guidelines: The Priorities of Section 1502*. USDHEW Publication No. (HRA) 77-64. Washington, DC: Government Printing Office, 1977.

Evans, D. S., and J. J. Heckman. "Rejoinder: Natural Monopoly and The Bell System." *Management Science* 34, no. 1 (January 1988):27-38.

Fare, R., and C. A. K. Lovell. "Measuring the Technical Efficiency of Production." *Journal of Economic Theory* 19, no. 1 (1978):150-62.

Farrell, M. J. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society, Series A*. 120, no. 3 (1957):252-81.

Forsund, F. R., C. A. K. Lovell, and P. Schmidt. "A Survey of Frontier Production Functions and of Their Relationship to Efficiency Measurement." *Journal of Econometrics* 13, no. 1, Supplement (1980):5-26.

Grosskopf, S., and V. Valdmanis. "Measuring Hospital Performance: A Non-Parametric Approach." *Journal of Health Economics* 6, no. 2 (1987):89-107.

Health Services Research Center. *Report of National Evaluation of Rural Primary*

Health Care Programs. Chapel Hill, NC: University of North Carolina, November 1983.

Huang, Yueh-Guey L. "An Evaluation of Efficiency in Rural Primary Health Care Program: An Application of Data Envelopment Analysis." Ph.D. diss., University of North Carolina, Chapel Hill, 1986.

Lewin, A. Personal communication, 1986.

Lewin, A. Y., R. C. Morey, and T. J. Cook. "Evaluating the Administrative Efficiency of Courts." *OMEGA* 10, no. 4 (1982):401-11.

Lovell, C. A. K., and P. Schmidt. "A Comparison of Alternative Approaches to the Measurement of Productive Efficiency." In *Application of Modern Production Theory: Efficiency and Productivity*. Edited by A. Dogramaci and R. Fare. Boston: Kluwer-Nijhoff, 1986.

McLaughlin, C. P., T. C. Ricketts, and D. D. Bradham. "Productivity and Rural Primary Care Clinics." Working paper, University of North Carolina, Chapel Hill, 1983.

Nunamaker, T. R. "Measuring Routine Nursing Service Efficiency: A Comparison of Cost per Patient Day and Data Envelopment Analysis Models." *Health Services Research* 18, no. 2, Part I (Summer 1983):183-205.

ORSA/TIMS. *ORSA/TIMS Bulletin*, no. 18, Dallas Meeting. Baltimore, MD: ORSA/TIMS, 26-28 November 1984.

______. *ORSA/TIMS Bulletin*, no. 23, New Orleans Meeting. Baltimore, MD: ORSA/TIMS, 4-6 May 1987.

Reinhardt, U. E. "Manpower Substitution and Productivity in Medical Practice: Review of Research." *Health Services Research* 8, no. 3 (Fall 1973):200-27.

Ricketts, T. C., T. R. Konrad, and E. H. Wagner. "An Evaluation of Subsidized Rural Primary Care Programs: II. The Environmental Contexts." *American Journal of Public Health* 73, no. 4 (April 1983):406-13.

Sheps, C. G., E. H. Wagner, W. H. Schonfeld, et al. "An Evaluation of Subsidized Rural Primary Care Programs: I. A. typology of Practice Organizations." *American Journal of Public Health* 73, no. 1 (January 1983):38-49.

Sherman, H. D. "Hospital Efficiency Measurement and Evaluation." *Medical Care* 22, no. 10 (October 1984):922-38.

Sueyoski, T., and Y. L. Chang. "A Special Algorithm for the Additive and Multiplicative Models in Data Envelopment Analysis." Working paper, Ohio State University, 1987.

Talukdar, R. B., and C. P. McLaughlin. "Comparing the Productivity of Family Planning Operations: An American Experience." *The Journal of Health Administration Education* 5, no. 1 (Winter 1987):45-61.

Thompson, R. G., and R. M. Thrall, eds. "Normative Analysis in Policy Decisions, Public and Private." *The Annals of Operations Research*, Vol. 2. Basel, Switzerland: J. C. Baltzer A. G. Scientific Publishing Company, 1985.