Efficiency in Addiction Treatment:
A DEA of Clinic Efficiency in Maryland

Rafael A. Corredoira

The Wharton School - University of Pennsylvania - Philadelphia, PA
corredoi@wharton.upenn.edu

John R. Kimberly

The Wharton School - University of Pennsylvania - Philadelphia, PA
kimberly@wharton.upenn.edu

NOVEMBER 2006

WORKING PAPER
PLEASE DO NOT CITE WITHOUT AUTHOR PERMISSION

The authors thank ADAA – Maryland and Peter Luongo for access to the data; Chad Basham, Vickie Kaneko, and William Rusinko for generous data management and insightful discussions about the industry; Jon Chilingerian and David Guy for helpful comments and advice in early stages of this paper. Any errors and omissions remain our own. Rafael Corredoira would like to thank TRI for financial support received under grant #45771, funded by the Robert Wood Johnson Foundation.

Abstract

The addiction treatment industry is searching for a consensus on ways to measure how clinics perform. This is driven in part by the limited resources available compared to the sizeable number of potential patients. This study applies Data Envelopment Analysis (DEA), a methodology particularly apt to identify the most efficient units in context, where less of multiple inputs and more multiple outputs are preferred. DEA solves a linear optimization problem, identifies the firms on the efficient frontier and which of those firms are members of each inefficient unit reference set, and estimates efficiency scores and hypothetical efficiency outcomes for inefficient firms. DEA efficient scores can be utilized in a second stage to study antecedents of efficiency. The study presents an example of how DEA can be utilized in the addiction treatment industry. Data from Maryland's addiction treatment network, covering 373 clinics and more than 2005 patients during 2005 was utilized. We define efficiency as the ratio between two measures of performance (treatment completion, and no drug use at discharge) over number of patients in 18 classes, defined by level of care and addiction severity. Results show that of 353 clinics, 111 are on the efficient frontier (their performance cannot be improved by any other clinic or combination of clinics in the sample). We were also able to identify the group of firms each inefficient firm should utilize for benchmarking as well as the areas needing improvement (larger difference between actual and hypothetical efficient outcomes). In addition, a second stage utilizing clinic efficiency scores show that the number of patients treated is positively associated to clinic efficiency, while state funding and, apparently, patient social network and travel distance to the clinic have no impact on clinic efficiency.

Introduction.

The addiction treatment industry is searching for a consensus on ways to measure clinic performance (French, Homer, & Nielsen, 2006; Kimberly & McLellan, 2006; McLellan, Lewis, O'Brien, & Kleber, 2000). This is driven in part by the limited resources available compared to the sizeable number of potential patients. While federal and state governments are the main payees in the industry, officers administering the funds face pressure to justify their expenses and increase the efficiency of the treatments. In addition, new technological advances in recent years provide alternatives to old treatments. However, the adoption of new technologies is hindered by uncertainty about their performance. Suppliers of these new technologies can benefit from standards to measure the efficacy of new treatments in order to justify their adoption by addiction treatment centers. Efforts to understand the benefits of addiction treatment have resulted in a large body of research, not only from both a clinical (See McLellan et al., 2000) and an economic point of view (See French et al., 2006).

In this paper we introduce a relatively new methodology, Data Envelopment Analysis (DEA), which is particularly suited to estimate the efficiency of different units when processes involve multiple inputs and outputs (Banker, Charnes, & Cooper, 1984). DEA is able to identify the top performers in a set of units and estimate a relative efficiency score. This is done by comparing how efficient the transformation process is, treating it as a black box from inputs to output, and making the comparisons only between firms that have similar input profiles. In other words, in the case of the addiction treatment industry, DEA is able to identify the clinics that are more efficient and estimate the relative clinic efficiency by making comparisons between those that are similar and efficient. For example, the performance of clinics that treat alcoholism is only compared to those that treat alcoholics and not other types of addictions. DEA does not only estimate an efficiency score and rank units, it also identifies which are the referent clinics and estimate the output/input relation for a clinic to become efficient. This provides insights to

managers on aspects that should be improved to become as efficient as the most efficient firms in the reference group.

In addition, efficient scores derived from DEA analysis can and have been utilized to test how different factors affect unit's efficiency, factors such us internist age (Jon Arsen Chilingerian, 1989), internist specialization and affiliation (Jon Arsen Chilingerian, 1989), rules and regulations (Ostroff & Sckmitt, 1993), provider experience (Ozcan, Watts, II, & Wogen, 1998), mergers (Harris, Ozgen, & Ozcan, 2000), among others. DEA also provides tests for returns-to-scale, and recent developments also allow the study of technological evolution as well as to detect technological improvements in longitudinal studies.

The rest of the paper is organized as follows: the next section discusses DEA and its application to estimate clinic efficiency in treating addiction in the state of Maryland. Results are presented and its application on benchmarking is discussed in the following next section. We conclude with a discussion of how DEA results can be utilized to test the impact of treatments and technologies on outcomes, and the technological evolution of the industry.

Data Envelopment Analysis and Addiction Treatment Clinics.

Outcomes in addiction treatment have been studied by two streams of research, which resulted in two distinctive type of measurement: clinical outcome and economic outcome. The clinical studies pay attention to how treatment should be delivered, and which technologies should be administered according to a clinical diagnosis (McLellan et al., 2000). On the other hand, health economics studies have focused on the economic benefits that are derived from treatment (Cartwright, 2000). For addiction treatment, this is particularly important because the economics benefits, unlike most of other type of services, accrue mostly to others but the patient (reduced criminality, lower unemployment rates, lower job absenteeism, etc.) (French et al., 2006). In this study, we develop a DEA model that utilizes clinical performance measures as the

output of the treatment and, in order to control for the patient mix, a combination of ASAM treatment levels (Mee-Lee, 1996) and severity of the addiction as the inputs.

DEA extends the from the work of Farrell (1957) on single input single output technical efficiency estimation to multiple input multiple output by means of linear programming optimization. Originally introduced by Charnes, Cooper, Rhodes (1978), a multitude of models have been developed to assess efficiency and compare from educational departments to health care (hospitals, clinics) and prisons, from agricultural production to banking and armed forces, and have been applied to market research and benchmarking (For a bibliography see Emrouznejad, 2001).DEA is a non-parametric method for efficiency frontier estimation and ranking. It has the ability to handle multiple inputs and outputs simultaneously, and it does not require the assumption of a functional form linking inputs to outputs. It compares the efficiency of units against a peer or combination of peers. Among the limitations of the method we find that estimated unit efficiency is relative to its peers and not an absolute number, and is very sensitive to outliers.

In order to evaluate and compare the relative efficiency of clinics in Maryland, we take and agnostic view of the treatment of addiction and only consider the patient mix and two measures of treatment efficiency: completion of treatment and no use of drugs at time of patient discharge. DEA estimates efficiency as the ratio of a linear combination of output over a linear combination of inputs. In order to calculate the efficient solution, the DEA solution can take an output orientation (holding input constant and maximizing output) or input orientation (holding outputs constant and minimizing the amount of input utilized). Our DEA model provides information about how well clinics are doing when compared to their peers. Estimations can be done assuming Constant Returns-to-Scale (CRS), which implies that input increase leads to a proportional increase of outputs, or Variable Returns-to-Scale (VRS), which implies that input increase leads to changes in outputs in a different proportion. DEA models assume that, in the

decision making process, less inputs and more outputs are better. We adopt a CRS, an output orientation DEA model. (See Appendix A for a detailed discussion of the models)

Different types of addition lead to different outcomes. For example, abstinence is different for alcohol than for opiates. Severity is also associated to how easy to treat and how complete the treatment for addiction patients are. In Maryland patients are allocated to clinics and provided ASAM levels of care based on type of addiction. By taking into account the number of patients treated by ASAM levels and addiction severity, our model compares how well each clinic performs with those other clinics in the sample that provide similar treatments for patients with similar severity. In this way, we avoid estimating the relative efficiency of clinics based on comparisons between qualitatively different processes. The number of patients that completed treatment is utilized as an output measure, since it is a measure correlated to desired outcomes. For example, treatment completion is associated to lower arrest rates and increased likelihood of finding a job.(ADAA, 2006) Therefore, a clinic's ability to retain the patient until completion is an important factor in delivering the treatment to achieve valued outcomes. We also measure the number of patients that do not use drugs at time of discharge. (See figure 1) Both of these variables, number of patients that completed treatment and that do not use drugs at time of discharge, are a reflection of treatment effectiveness and, as assumed by DEA models, larger numbers are preferred over smaller ones.

This model estimates the relative efficiency of the clinics, assigning an efficiency value of 1 to those clinics in the efficient frontier, which achieve results that are not or cannot be improved by any other clinic or combination of clinics working with comparable set of inputs. At the same time, the efficiency of those clinics that are not in the efficiency frontier is calculated as a percentage of the efficient achievable by a combination of those clinics in the efficient frontier. It also provides for each inefficient clinic a reference group and the "efficient outcome." The reference group is composed by those clinics in the efficient frontier that are comparable to the focal clinic. They serve as a benchmarking group, since a theoretical combination of those firms

is able to improve the clinics actual outcome. The “efficient outcome” is the outcome of the theoretical combination and provides information to the clinic about what areas should be improved. Figure 2 illustrates how DEA works for one input and one output. It plots input vs. output for 18 units. Units A, B, C, D, E, and F have extreme output-input ratios and define the efficient frontier (a convex line that “envelops” all the other output-input ratios). The rest of the units are less efficient in transforming inputs into outputs. There is always a combination of units in the efficient frontier that is able to outperform the inefficient units. The reference group for inefficient units is composed by the closest units in the efficient frontier (in this example, C and D are the reference group for unit X). DEA with output orientation maximizes outputs with constant inputs. In this case, the efficient hypothetical output is the weighed sum of actual outputs for C and D (with weights equal to the dual values estimated by the linear optimization). In our example, O_x* is the efficient output for X and the difference between O_x* and O_x divided by O_x* is a measure of X inefficiency.

Data.

Our data were provided by the Maryland Alcohol and Drug Abuse Administration (ADAA) and were collected by the Substance Abuse Management Information System (SAMIS). All Maryland Department of Health and Mental Hygiene (DHMH) certified or Joint Committee on Accreditation of Healthcare Organization (JCAHO) accredited alcohol and drug abuse treatment programs are required to SAMIS. Data was collected for 2005 and include 375 treatment programs operating in the state of Maryland (the complete treatment network). Due to incomplete data 22 treatment programs were dropped from the analysis. Information on patients in treatment is gathered by ADAA. Clinics submit a report to ADAA with information about the case at each admission or discharge. From these data we derived the following variables utilized in the model:

Input variables.

For each clinic, the count of patients assigned to each one of the 13 ASAM levels of care in each one of the three severity levels (High, Moderate and Low) are the variables utilized as inputs. The 8 ASAM levels of care that account for only 18% of the patients treated were collapsed into 1 category (OtherCare). This resulted in a total of 18 categories (6 ASAM levels * 3 Severity levels).

Output variables.

As measures of successful treatment we utilized two variables: *Completion* and *NoUse*. *Completion* is the count of patients that completed treatment at time of discharge, while *NoUse* is the count of patients that were not using drugs at the time of discharge.

Results.

Results of DEA analysis provide valuable information to understand in what areas the clinic is inefficient and identify the clinics that are the top performers in the field. Table 1 presents the reference group and efficient outcome for a few selected cases. Two of the clinics are on the efficiency frontier (id30 and id51). Their estimated efficiency is 1.0 and the actual and efficient number of patients completing the treatment and without using drugs at time of discharge are the same (12, 21, 56, and 58, respectively). The analysis resulted in locating 41 of the 354 clinics in the efficiency frontier. For the rest of the clinics, DEA estimates a relative efficiency score ranging from 0.0 to 1.0, and a reference group. The other 4 clinics presented in Table 1 (id23, id45, id111, and id32) are not in the efficiency frontier and their estimated efficiency score range from 0.644 to 0.993. The clinics in the reference group are those that belong to the efficiency frontier. As we can see, id30 (efficient clinic) is the only referent for clinic ID45. In addition, a comparison between actual and efficient output shows that clinic ID45 has to improve completion by almost 30% in order to achieve a performance as efficient as ID30. On the other hand, clinics ID23, ID111 and ID32 have to improve NoUse at discharge by 2%, 8%, and 44%, respectively, in order to achieve efficient performance. Clinic ID23 has 4 clinics in

its reference group, while clinics ID111 and ID32 share the same 3 clinics in their reference group. A study and deep understanding of the practices and treatments applied by the clinics in the reference group may provide the clinic with valuable insight about how to improve its performance.

DEA efficiency scores and Antecedents of clinic inefficiency.

DEA efficiency scores can also be utilized to test whether different factors are antecedents of clinic efficiency or not. The attribution bias (the tendency to attribute successful outcomes to own skills but blame unsuccessful ones to uncontrollable factors) has been well documented in managers (Bettman & Weitz, 1983; Gioia & Sims, 1985; Ingram & Frazier, 1983; Staw, McKechnie, & Puffer, 1983; Zuckerman, 1979). There is also an actor-observer difference in attribution, where observers suffer the fundamental attributional bias (the observer's tendency to attribute an actor's performance to the actor's characteristics) that might blame managers' poor performance stemming from situational factors on managers' attributes.

DEA can provide a way to test whether clinic inefficiency can be explained by a DMU's characteristics (technology, practices, demographics) or factors outside the DMU's control (Jon A. Chilingerian, 1995) by means of multi-factor Tobit regression. As an exemplar of applying this method to substance abuse clinics, we regress inefficiency [(1/DEA efficiency score)-1] on 2 environmental variables and 2 variable under manager control (for model description see Appendix B). Poor performance in treating patients is frequently attributed to patients' lack of supporting social network and difficulty in completing treatment. For environmental variables, we utilize county income per capita as a proxy for social network support, and the number of clinics per county square mile as a proxy for how difficult it is for patients to access the clinic and continue their treatment. For variables under manager control we utilize the number of patients treated, a proxy for learning and experience, and state funding as a proxy for market pressure on the clinic. Results from Tobit regression (See table 2) show that number of patients treated per

year is associated with lower inefficiency ($\beta_{patients}$=-0.0009, *p*-value= 0.02), while income per capita, state funding and number of clinics per square mile are not associated to clinic inefficiency (*p*-vlaues > 0.05). This is an indication that larger clinics are more efficient than smaller ones, and that markets and the state of Maryland impose similar demands regarding performance per dollar. The lack of significant effects of income and clinics per square mile could indicate that the effects of supporting networks or ease of travel to the clinic do not impact clinic efficiency. This should be taken cautiously because our variables may not be good proxies for the factors we are trying to test.

Conclusion

In this paper we have built the argument for increased attention to clinic performance and efficiency. Budget restrictions are likely to pressure clinics to perform at higher levels of efficiency. The view that the American people have about the addiction problem forces legislatures to limit and justify funding of substance abuse treatment programs (French et al., 2006). The industry needs ways to estimate performance and identify the most efficient ways to treat addiction. Our study applies DEA methodology to estimate relative efficiency of the clinics. It is based in the comparison of each clinic with the set of similar clinics in the population (which makes comparisons fair) and an estimation of the performance based on a combination of outcomes (which makes the process of "playing" the system more unlikely). Among the advantages of DEA are that it does not assume any production function; it identifies a reference set of efficient firms for each inefficient clinic, and estimates a theoretical efficient outcome for the clinic.

By not assuming a production function, DEA limits data needs to inputs and outputs, not about the process itself. DEA also provides valuable information for benchmarking by identifying

the reference sets (which are the clinics that should be looked at for best practices) and a theoretical efficient outcome (which highlights the areas where the clinic should improve).

Another advantage of the method is that it requires identifying the adequate input and output variables. This process is about how to classify patients and resources, and which variables are indicators of good performance. By being able to handle various output measures simultaneously, it generates an overall measure of performance. This is a clear advantage over methods that only handle one output at a time, which demands aggregating each variable into an overall performance and eliminating the politics of defining the weights for this formula.

DEA also identifies the most efficient clinics in the population, a necessary first step in the study of best practices. Our study made no assumption about what treatment, practice, or technology was better, and is thus unbiased about the best outcomes that could be expected. The most efficient clinics are found by looking at the relationship between inputs and outputs, without any other information about how that transformation is achieved. This reduces the possibility of researcher bias. By focusing attention to outcomes and efficiency, it creates a situation where industry players have to justify the selection of the variable based on reasons other than the technology driving it. Decisions should be based on variables associated with clear benefits for patients, payees and other stakeholders. For example, our selection of treatment completion is based on the fact that completion is associated with decreased unemployment and lower arrest rates.

The second stage of our analysis makes clear that the number of patients treated is associated with increased efficiency. This is an indication of the existence of returns to scale and consolidation opportunities in the industry. Future research should explore this area and identify where benefits of scale come from. It also shows that state funding makes no difference compared to other types of funding. This shows that the state of Maryland is behaving as well or as poorly as markets in providing incentives for better performance. Lack of data has impeded us to study resource allocation efficiency. With financial data, this methodology can incorporate the

amount of money spent per patient as one of the variables in the efficiency estimation. Our findings show that county income per capital and the numbers of clinics per square mile in each county have no significant effect on efficiency. This could be because, despite the differences between counties, the population of patients in each county has the same support network and difficulty of travel (independent of income per capita or clinics per square mile), or because these factors are of no relevance for the performance of the clinic. Further research should clarify this point.

Finally, we see DEA as a methodology that has the potential to provide a measure of efficiency that would help the field to advance in its understanding of the causal relationships between treatment, practices and outcomes. It also provides a framework to facilitate the dialog between industry participants, and guidance about what to do to improve the performance of inefficient clinics. We hope that the needed refinement of the DEA model presented in this paper will increase our understanding of the industry, technologies and practices, which is crucial to improve our ability to deal with this serious social problem.

Figure 1: DEA model to estimate Clinic Performance

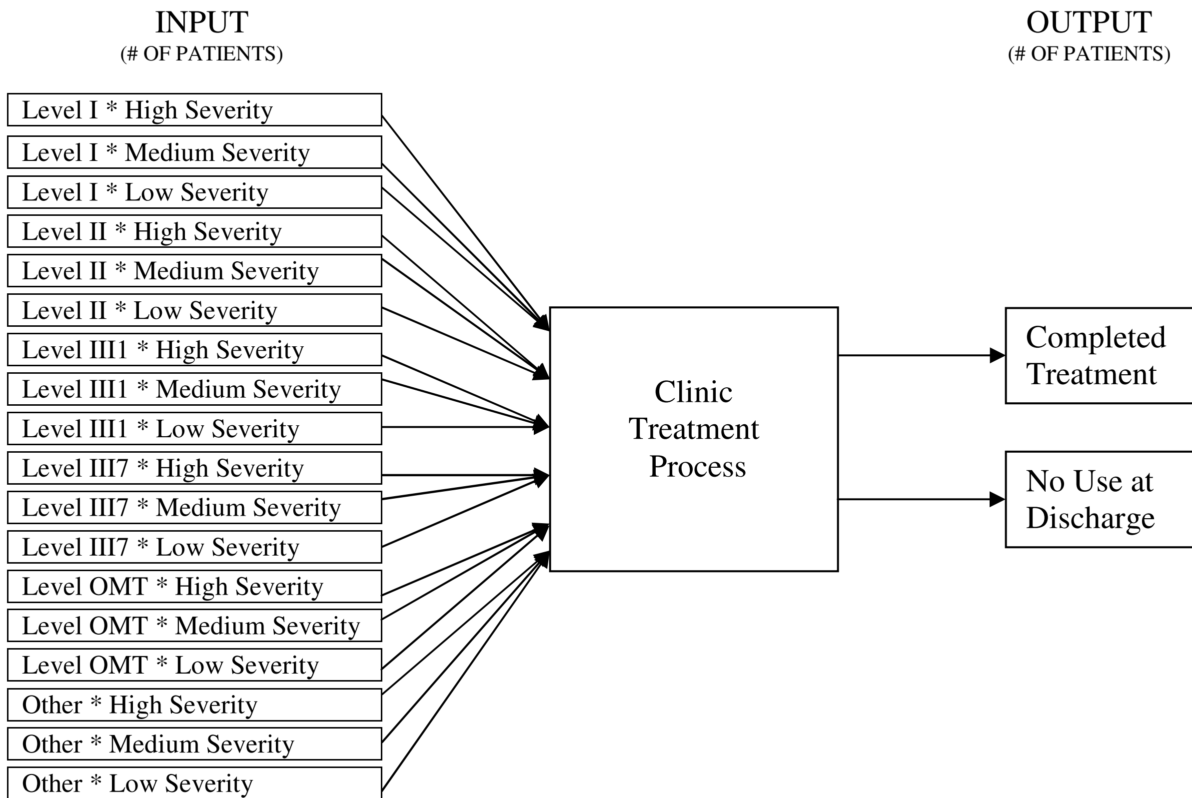

Figure 2. DEA, efficient frontier, comparison group and efficient output.

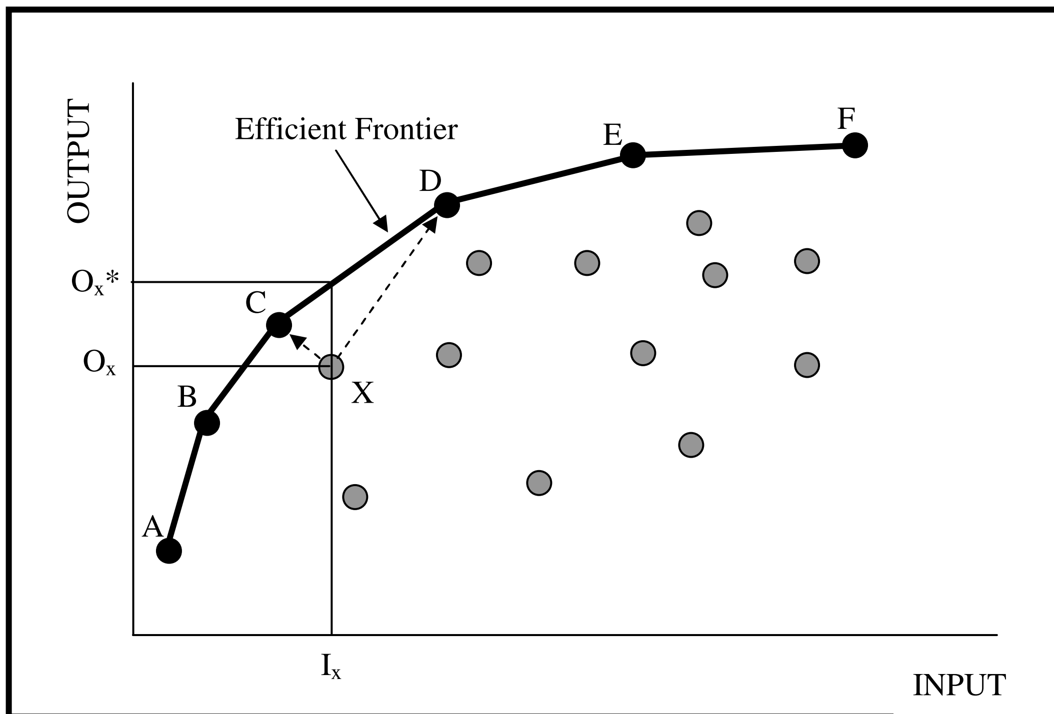

Table 1. Reference Group and Efficient Outcome for selected clinics.

			Actual		Efficient	
Clinic	Efficiency	Reference Group	Completion	No Use	Completion	No Use
⋮	⋮	⋮	⋮	⋮	⋮	⋮
id30	1.000	id30	12	21	12	21
id51	1.000	id51	56	58	56	58
⋮	⋮	⋮	⋮	⋮	⋮	⋮
id23	0.993	id8 id77 id124 id222	355	361	355	369.55
id45	0.952	id30	7	16	9.14	16
⋮	⋮	⋮	⋮	⋮	⋮	⋮
id111	0.556	id93 id234 id199	20	21	20	22.78
⋮	⋮	⋮	⋮	⋮	⋮	⋮
id32	0.644	id93 id234 id199	45	43	45	62.08
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Number of Clinics: 354
Number of Clinics in the efficient frontier: 41

Table 2. Tobit regression of inefficiency on income per capita, clinics per square mile, state funding, and number of patients treated per year (SAS V.9)

The LIFEREG Procedure

Model Information

Data Set	WORK.TOBIT
Dependent Variable	lower
Dependent Variable	y
Number of Observations	351
Noncensored Values	246
Right Censored Values	0
Left Censored Values	105
Interval Censored Values	0
Name of Distribution	Normal
Log Likelihood	-631.535918

Number of Observations Read	369
Number of Observations Used	351
Missing Values	18

Algorithm converged.

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
Income	1	0.2784	0.5977
clinic_sqmile	1	0.6912	0.4057
Funded	1	0.2244	0.6357
patient	1	5.0943	0.0240

Analysis of Parameter Estimates

Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	0.8599	0.7563	-0.6223	2.3422	1.29	0.2555
Income	1	-0.0059	0.0111	-0.0276	0.0159	0.28	0.5977
clinic_sqmile	1	0.2651	0.3189	-0.3599	0.8901	0.69	0.4057
Funded	1	-0.1259	0.2658	-0.6469	0.3951	0.22	0.6357
Patients	1	-0.0009	0.0004	-0.0017	-0.0001	5.09	0.0240
Scale	1	2.2793	0.1069	2.0792	2.4987		

Appendix A. Data envelopment analysis for addiction treatment clinics (For details see Banker et al., 1984; Charnes et al., 1978)

DEA is a non-parametric method to estimate decision making unit's efficiency. Developed by Charnes, Cooper and Rhodes (1978) the model, known as CCR, extended the one input-one output efficient frontier analysis by Farrell (Farrell, 1957) to multiple input-multiple output settings and applied to situation with constant returns of scale. Banker, Charnes and Cooper (1984) model, known as BCC, extended the CCR model to accommodate variable returns of scale. While the CCR model estimates overall technical efficiency and scale efficiency, the BCC model does measures pure technical efficiency.

Both models, the most frequently utilized, solve a linear programming problem without identifying the production function utilizes to transform inputs into outputs. They can have output or input orientation. In this paper, we assume that there are constant returns-to-scale. This implies that treating 100 patients is the same as treating 10 or 1000, and outputs will vary proportionally. The set-up of our paper justifies this decision because the input we are considering is patients with addiction problems, the output is patient without addiction problems and we are not including in our study any type of economic efficiency. We also adopt an output maximization orientation because we are interested in increasing the number of patients without addiction problems for the patients that entered into the system. For these reasons we utilize a CCR model with output maximization and solve (with SAS v9, PROC LP) the following optimization problem:

Maximize $$E_k = \sum_{r=1}^{R} u_r Y_{rk}$$

s.t. $$\sum_{s=1}^{S} v_s X_{sk} = 1,$$

$$\sum_{r=1}^{R} u_r Y_{rj} - \sum_{s=1}^{S} v_s X_{sj} \leq 0,$$

$$v_1, \ldots, v_S > 0,$$
$$u_1, \ldots, u_R > 0$$

Where:

E_k is the measure of efficiency for clinic k

Y_{rk} is the known amount of output r produced by clinic k during 2005,

X_{sk} is the known amount of input s produced by clinic k during 2005.

Y_{rj} is the known amount of output r produced by clinic j during 2005,

X_{sj} is the known amount of output s produced by clinic j during 2005,

u_r is the coefficient assigned to output r computed in the solution to the DEA model,

v_r is the coefficient assigned to input s computed in the solution to the DEA model,

S is the number of inputs used the clinics

R is the number of outputs produced by the clinics

The objective function for this model maximizes the Efficiency rating for the clinic k. This is subject to constraint that when the same set of coefficients U and V are applied to all other clinics being compared, the linear combination of the output will not be less than the linear combination of inputs (no efficiencies about 100% allowed), the linear combination of inputs for clinic k is equal to 1 (output orientation) and all the coefficients (u and v) are greater than zero. This model is solved for every one of the 353 clinics in the sample.

Appendix B. Tobit regression of DEA efficiency scores on efficiency antecedents

We utilized clinic's DEA efficiency scores to explore whether a set of factors are antecedents of clinic efficiency or not. Efficiency scores are bounded between 0 and 1. For this reason and following Chilingerian (1995), we utilize the following function to transform efficiency scores into a measure of inefficiency (derived from the radial distance to the efficient frontier from the firm production point (Banker, 1993)) :

$$y^* = (1/Efficiency) - 1.$$

y^* is now a left-censored continuous variable and amicable to use in a Tobit regression model. The Tobit model takes the form:

$$\begin{cases} y_i^* = \beta X_i + \varepsilon_i & \text{if } y_i^* > 0; \\ y_i^* = 0 & \text{otherwise;} \end{cases}$$

where β is the vector of unknown parameters to be estimated,

X is a vector of known values for county's income, county's clinics per squared mile, state funding, and number of patients treated, and

ε_i is an independent and normally distributed error term.

The model is solved using PROC LIFEREG in SAS version 9.

References

ADAA. (2006). *Outlook and Outcomes: 2005 Annual Report*: Maryland Alcohol and Drug Abuse Administration.

Banker, R. D. (1993). Maximum likelihood, consistency and Data Envelopment Analysis: A statistical foundation. *Management Science, 39*(10), 265-1273.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technological and Scale Inefficiencies in Data Envelopment Analysis. *Management Science, 30*(9), 1078-1092.

Bettman, J. R., & Weitz, B. A. (1983). Attributions in the Board Room: Causal Reasoning in Corporate Annual Reports. *Administrative Science Quarterly, 28*(2), 165-183.

Cartwright, W. S. (2000). Cost-benefit analysis of drug treatment services: review of the literature. *The Journal of Mental Health Policy and Economics, 3*(1), 11-26.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Chilingerian, J. A. (1989). Investigating Non-Medical Factors Associated with the Technical Efficiency of Physicians in the Provisions of Hospital Services: A Pilot Study. *Academy of Management Proceedings*, 85-89.

Chilingerian, J. A. (1995). Evaluating physician efficiency in hospitals: A multivariate analysis of best practices. *European Journal of Operational Research, 80*(3), 548-574.

Emrouznejad, A. (2001). *An Extensive Bibliography of Data Envelopment Analysis (DEA), Volume I: Working Papers.*Unpublished manuscript, Coventry CV4 7AL, England.

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society, 120*(3), 253-290.

French, M. T., Homer, J. F., & Nielsen, A. L. (2006). Does America spend enough on addiction treatment? Results from public opinion surveys. *Journal of Substance Abuse Treatment, 31*(3), 245-254.

Gioia, D. A., & Sims, H. P. (1985). Self-serving Bias and Actor-Observer Differences In Organizations: An Empirical Analysis
doi:10.1111/j.1559-1816.1985.tb00919.x. *Journal of Applied Social Psychology, 15*(6), 547-563.

Harris, J., II, Ozgen, H., & Ozcan, Y. (2000). Do Mergers Enhance the Performance of Hospital Efficiency? *The Journal of the Operational Research Society, 51*(7), 801-811.

Ingram, R. W., & Frazier, K. B. (1983). Narrative disclosures in annual reports. *Journal of Business Research, 11*(1), 49-60.

Kimberly, J. R., & McLellan, A. T. (2006). The business of addiction treatment: A research agenda. *Journal of Substance Abuse Treatment, 31*(3), 213-219.

McLellan, A. T., Lewis, D. C., O'Brien, C. P., & Kleber, H. D. (2000). Drug Dependence, a Chronic Medical Illness: Implications for Treatment, Insurance, and Outcomes Evaluation. *JAMA, 284*(13), 1689-1695.

Mee-Lee, D. (Ed.). (1996). *ASAM (American Society of Addiction Medicine) patient placement criteria for the treatment of substance-related disorders* (2nd ed.). Chevy Chase, Md.: American Society of Addiction Medicine.

Ostroff, C., & Sckmitt, N. (1993). Configurations of organizational effectiveness and efficiency. *Academy of Management Journall, 36*(6), 1345.

Ozcan, Y. A., Watts, J., II, J. M. H., & Wogen, S. E. (1998). Provider Experience and Technical Efficiency in the Treatment of Stroke Patients: DEA Approach. *The Journal of the Operational Research Society, 49*(6), 573-582.

Staw, B. M., McKechnie, P. I., & Puffer, S. M. (1983). The Justification of Organizational Performance. *Administrative Science Quarterly, 28*(4), 582-600.

Zuckerman, M. (1979). Attribution of success and failure revisited, or: The motivational bias is alive and well in attribution theory. *Journal of Personality, 47*(2), 245-287.