Cost Efficiency and Scale Economies in General Dental Practices in the U.S.: A Non-parametric and Parametric Analysis

Lei Chen
University of Connecticut

Subhash C. Ray
University of Connecticut

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Abstract

This paper uses both the non-parametric method of Data Envelopment Analysis (DEA) and the econometric method of Stochastic Frontier Analysis (SFA) to study the production technology and cost efficiency of the U.S. dental care industry using practice level data. The American Dental Association (ADA) 2006 survey data for a number of general dental practices in Colorado are used for the empirical analyses. The result shows that the average cost efficiency score is 0.79 for DEA and 0.87 for SFA, and the cost inefficiency comes mainly from the allocative inefficiency. The minimum average cost of production is 50.6 cents for each dollar of gross billing generated. The optimal output level for a dental practice to fully exploit the economies of scale is at $1.68 million. Both DEA and SFA provide generally consistent results.

Journal of Economic Literature Classification: I1,C2, D2

Keywords: Dental Care, Cost Efficiency, Economies of Scale, Data Envelopment Analysis, Stochastic Frontier Analysis

1. Introduction

Dentistry is a branch of medicine that is involved with the diagnosis, prevention and treatment of any disease of teeth, the oral cavity and associated structures. According to the Surgeon General's Report on Oral Health (2000), oral health can be considered a mirror reflecting an individual's general health or disease status. Also, oral health has a direct effect on a person's well-being and quality of life. Because of the above reasons, dental care has become an important component of general health care over the last 50 years throughout the world. For instance, the real total dental expenditure in the U.S. increased from $19.6 billion in 1960 to $101.2 billion in 2008, and the real total dental expenditure per capita in constant 2000 dollars increased from $50 in 1960 to $333 in 2008 (Source: National Health Expenditure Data from CMS).

There have been a number of studies in the recent literature that examine the cost of dental services. For examples, Bailit and Beazoglou (2008) found the high dental care expenditure is due to the persistent increase in the demand for dental services. Brown (2005) argued that the growth of US population, especially the increase of educated population contributed to the growth of dental expenditure. O'Keefe and Hochstein (1994) studied the trend of dental expenditures from 1962 to 1991 in Quebec, Canada and found that higher dental insurance coverage and disposable income caused the dental expenditures to increase. However, none of the above focused on the cost efficiency of dental practices, which could also be a critical factor determining total dental care expenditure. There is some literature that analyzes cost efficiency of dental services in European countries. For example, Linna *et al.* (2003) applied DEA to study the cost efficiency of dental care provision in Finnish health center. They showed that the average level of cost inefficiency is 20-30%. This meant, at least in principle, those dental care centers could save $90-100 million if they performed efficiently. There is, however, no study focusing on cost efficiency of dental services in the U.S. at practice level. This paper contributes to the literature of non-parametric and parametric analysis on cost efficiency of general dental practices in the U.S.

Although a significant body of research exists on various aspects of the U.S. dental care industry, few have investigated *productivity* or *efficiency* of dental practices. In neoclassical microeconomic theory, there are two ways to investigate a firm's production activity. One is the primal approach to production analysis. It reveals the direct relationship between the inputs and the corresponding outputs which belong to a given production possibility set. The other is the dual cost function approach to production analysis. Theoretically, a firm's cost minimizing activity will lead to the same optimal solution of input-output bundle that one can derive from the production optimization activity. Therefore, when market prices for inputs are available, we can recover the production information from the firm's cost function. In this paper, we follow the dual cost function approach on both non-parametric and parametric bases. The non-parametric DEA cost efficiency analysis provides us with the general information of how well each practice performs in terms of cost minimization. The parametric Cobb-Douglas cost function stochastic frontier analysis allows us to identify the nature of scale economies at any output level analytically from the fitted model.

This paper extends the literature in two important ways. First, it carries out cost efficiency analysis using private (for profit) dental practices and also seeks to cross validate the main findings using both DEA and SFA. Second, it is the very first paper that rigorously determines the regions of scale economies and diseconomies in dental care. The rest of the paper unfolds as the following. Section 2 introduces the methodologies we use in the study, followed by the empirical analysis in section 3. Section 4 concludes.

2. Methodologies

2.1 Non-parametric DEA

The nonparametric method of Data Envelopment Analysis (DEA) was first introduced by Charnes, Cooper, and Rhodes (CCR) (Charnes *et al.* 1978) and later modified by Banker, Charnes, and Cooper (BCC) (Banker *et al.* 1984). In subsequent years, it has been widely used to analyze efficiencies of production units in various industries. DEA requires no parametric specification of the production frontier and relies on a number of fairly general assumptions about the nature of the underlying production technology. Using a sample of actually observed input-output data and the assumptions, it derives a benchmark output quantity with which the actual output of a firm can be compared for efficiency measurement.

The basic assumptions in DEA about the production technology are:

(i) All actually observed input-output combinations are feasible;

(ii) The production possibility set is convex;

(iii) Inputs are freely disposable;

(iv) Outputs are freely disposable.

Consider the simplest case with one input and one output. If we let (x, y) represent an input-output bundle, then based on above assumptions, the production possibility set (PPS) can be defined as:

$$S = \{(x, y): x \geq \sum_{j=1}^{N} \lambda_j x_j; y \leq \sum_{j=1}^{N} \lambda_j y_j;\ \sum_{j=1}^{N} \lambda_j = 1;\ \lambda_j \geq 0; (j = 1, 2, \ldots, N)\}, \tag{1}$$

where x_j is the input quantity and y_j is the output level observed at firm j. The corresponding input requirement for any output level (y) that corresponds to S in equation (1) is:

$$V(y) = \{(x): x \geq \sum_{j=1}^{N} \lambda_j x_j; y \leq \sum_{j=1}^{N} \lambda_j y_j;\ \sum_{j=1}^{N} \lambda_j = 1;\ \lambda_j \geq 0; (j = 1, 2, \ldots, N)\}. \tag{2}$$

For any production possibility set, one can define the input requirement set $V(y)$ for any specific output bundle y. For a target output level y^0 and a given input price w^0, the minimum cost under the VRS assumption is:

$$c^* = min\ w^0 x: x \in V(y^0). \tag{3}$$

Now if we consider the case with multiple inputs and one output, the DEA linear programming model under the VRS assumption can be specified as (Ray 2004):

$$\begin{aligned} & min\ \sum_{i=1}^{I} w_i\, x_i \\ & s.t.\ \ \sum_{j=1}^{N} \lambda_j y_j \geq y_t; \\ & \qquad \sum_{j=1}^{N} \lambda_j x_{ij} \leq x_i;\ (i = 1, 2, \ldots, I); \\ & \qquad \sum_{j=1}^{N} \lambda_j = 1; \\ & \qquad \lambda_j \geq 0;\ (j = 1, 2, \ldots, N). \end{aligned} \tag{4}$$

Here w_i is the price of input x_i; I is the number of inputs; N is total number of firms; t is one firm among the N firms. Let $c^* = \sum_{i=1}^{I} w_i\, x_i^*$ be the minimum total cost for firm t, and then the cost efficiency of firm t can be measured by $\gamma = \frac{c^*}{C_0}$, where C_0 is the actual total cost of firm t.

The cost efficiency measured can be decomposed into technical efficiency and allocative efficiency[1] (also called price efficiency). The relation can be expressed as:

$$\gamma = \theta \cdot \mu, \tag{5}$$

where γ is the cost efficiency; θ is the input-oriented technical efficiency; μ is the allocative efficiency. Note that both θ and μ lie in the [0, 1] interval. The overall cost (γ) measures the factor by which the cost can be scaled down if the firm selects the optimal input bundle x^* and performs at full technical efficiency. When technical efficiency is eliminated, all inputs are scaled down by the factor θ, and that by itself would lower the cost of the factor. The allocative efficiency factor μ shows how much the cost of the firm can further scaled down when it selects the input mix that is most appropriate for the input price ratio faced by the firm in a given situation[2].

2.2 Econometric SFA

Stochastic Frontier Analysis (SFA) models were first developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), simultaneously. These models allow for technical inefficiency, but also acknowledge the fact that random shocks outside the control of producers can affect output.

In the econometric analysis in this study, we first assume that there exists a cost frontier, which can be expressed as

$$C \geq c(y, w; \beta), \tag{6}$$

where $C = \sum_{i=1}^{I} w_i \, x_i$ is the total expenditure of a firm associated with the production of output level y, w is the vector of input prices in the market (we assume firms are price takers), β is the vector of technology parameters to be estimated, and $c(y, w; \beta)$ is the cost frontier to all firms. Notice that the cost frontier $c(y, w; \beta)$ here is a deterministic frontier; it does not involve any random shock. Any deviation of C from $c(y, w; \beta)$ is treated as inefficiency.

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[1] First introduced by Farrell (1957).

[2] See Ray (2004) page 210 for detailed discussion.

To consider the effect of a noise in the model, we can apply the stochastic cost frontier in the form of

$$C = c(y, w; \beta) \cdot e^{v+u}, \tag{6a}$$

where v is a two-sided normally distributed random factor and u is a one-sided nonnegative half-normally distributed cost inefficiency component. Here $c(y, w; \beta) \cdot e^{v}$ is the stochastic frontier which moves up or down based on whether v is positive or negative. But $u \geq 0$ ensures that $C \geq c(y, w; \beta) \cdot e^{v}$. Therefore, the cost efficiency of firm j under stochastic cost frontier defined above can be expressed as

$$CE_j = \frac{C*}{C_j} \equiv \frac{c(y,w;\beta) \cdot e^{v}}{C_j} = e^{-u} \leq 1. \tag{7}$$

where $C_j = \sum_{i=1}^{I} w_i \, x_{ij}$ is the total expenditure of firm j associated with the production of output level y_j. If we assume that the stochastic cost frontier has the log-linear Cobb-Douglas functional form, we have

$$ln\, C = \beta_0 + \beta_y ln\, y + \sum_{i=1}^{I} \beta_i ln\, w_i + v + u, \tag{8}$$

A required property of a valid cost frontier is that $c(y, w; \beta)$ is homogeneous of degree 1 in w_i. To impose this restriction we scale both the total expenditure and the price indices for all other inputs by one arbitrarily selected price w_k. Equation (8) thus is modified as

$$ln\, \widetilde{C} = \beta_0 + \beta_y ln\, y + \sum_{i \neq k}^{I} \beta_i ln\, \widetilde{w}_i + v + u, \tag{9}$$

where $\tilde{C} = \frac{C}{w_k}$ and $\widetilde{w}_i = \frac{w_i}{w_k}$.

Based on equation (9), we can identify the nature of returns to scale, which is indicated by scale elasticity

$$\frac{\partial(ln\, \tilde{C})}{\partial(ln\, y)} = \beta_y. \tag{10}$$

Note that when $\frac{\partial(ln\, \tilde{C})}{\partial(ln\, y)} < 1$, the marginal cost is less than the average cost so that the average cost is declining. This implies locally increasing returns to scale. Similarly constant returns to scale or diminishing returns to scale holds when $\frac{\partial(ln\, \tilde{C})}{\partial(ln\, y)} = 1$ or $\frac{\partial(ln\, \tilde{C})}{\partial(ln\, y)} > 1$. Therefore, the production technology exhibits increasing (diminishing) returns to scale if β_y is strictly less (greater) than 1, and constant returns to scale if β_y is equal to 1. Because we assume that the cost frontier has the log-linear Cobb-Douglas cost functional form, whenever β_y is different from 1, the production technology exhibits increasing or diminishing returns to scale at any output levels. This implies that the average cost curve will be either downward sloping or upward sloping at all output levels, so long as $\beta_y \neq 1$.

To circumvent this problem, we follow the model introduced by Nerlove (1963) and revise equation (9) by include a quadratic term of $(ln\, y)$, so the new model becomes:

$$ln\, \widetilde{C} = \beta_0 + \beta_y ln\, y + \beta_{yy}(ln\, y)^2 + \textstyle\sum_{i \neq k}^{I} \beta_i ln\, \widetilde{w}_i + v + u. \quad (11)$$

Then the scale elasticity is given by

$$\frac{\partial(ln\, \widetilde{C})}{\partial(ln\, y)} = (\beta_y + 2\beta_{yy} ln\, y). \quad (12)$$

Now the scale elasticity is no longer a constant. Instead, it depends on the output level (y). If, for some output level, $(\beta_y + 2\beta_{yy} ln\, y)$ is less than 1, then the production technology exhibits increasing returns to scale at that certain output. Similarly, if $(\beta_y + 2\beta_{yy} ln\, y)$ is greater than 1 at some other output level, the production technology exhibits diminishing returns to scale at that output level. The production technology exhibits constant return to scale only when $(\beta_y + 2\beta_{yy} ln\, y)$ is equal than 1, from which we can identify what is the optimal output level where the average cost of production is at its minimum. Consequently, the optimal output level that leads to minimum average production cost can be calculated as

$$y^* = exp(\frac{1-\beta_y}{2\beta_{yy}}). \quad (13)$$

Given that all inefficiency is captured by the one-sided (positive) random term u, the cost efficiency of firm j can be defined as

$$CE_j = \exp\{-u_j\}. \quad (14)$$

We apply the maximum likelihood techniques, as described in Kumbhakar and Lovell (2000) to estimate the stochastic Cobb-Douglas cost frontier. Because we cannot directly estimate u, we use the procedure suggested by Battese and Coelli (1998) to measure the cost efficiency for each firm in the following way:

$$CE_j = E\left(\exp\{-u_j\} \middle| \varepsilon_j\right) = \left[\frac{1-\Phi(\sigma_* - \frac{\mu_{*j}}{\sigma_*})}{1-\Phi(-\frac{\mu_{*j}}{\sigma_*})}\right] \cdot \exp\{-\mu_{*j} + \frac{1}{2}\sigma_*^2\}, \quad (15)$$

where $\mu_{*j} \equiv -\frac{\varepsilon_j \sigma_u^2}{\sigma^2}$, $\sigma_*^2 \equiv \frac{\sigma_u^2 \sigma_v^2}{\sigma_u^2 + \sigma_v^2}$, $\varepsilon_j \equiv v_j + u_j$, $\sigma^2 \equiv \sigma_u^2 + \sigma_v^2$, and σ_u^2 and σ_v^2 are the variance of *u* and *v* respectively[3].

3. Empirical Analysis

3.1 Data

In the empirical analysis we use a sample of practice level data collected by the American Dental Association (ADA) through a 2005-2006 survey of general dental practices located in Colorada[4]. This survey data set contains detailed information on hours worked by dentists, hours worked by hygienists, hours worked by staff, employee's annual salary, space of dental office, expenditure on laboratory supplies, total number of visits, annual gross billing, service-mix fees for different procedures, etc. for any participating practice. From this information we can construct the quantities of outputs and inputs for each practice in the sample. We include one output and eight inputs in our analysis. The output of each practice is measured as its annual gross billings. A general dental practice performs a variety of procedures for which different fees are charged. Value aggregation of the individual outputs into a single scalar measure, gross billing, is not inappropriate given that fees for specific procedures do not vary much across practices. The eight inputs are dentist hours, hygienist hours, chair-side assistant hours, other staff hours, square feet of dental office space, number of operatories, laboratory expense, and supply expense. All the inputs are in annual measures. The first four are labor inputs and the rest are capital inputs. We include in all 117 practices for which complete data were available.

The hourly wage for dentists, hygienists, and chair-side assistants are constructed from

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[3] See Kumbhakar and Lovell (2000) page 78 for detailed discussion.

[4] For a report of the ADA study, see Beazoglou *et al.* (2009).

the information provided from the survey. For price index of other staff working hours, we get the average annual wage for receptionists in dental office by zip code from a commercial website[5], and then we convert it into hourly wage by assuming a full-time employee works 2000 hours per year. For the price indices of capital inputs, we use the rent per square feet of dental office space from the survey. Annual cost per equipped operatory is assumed to be constant for all practices at $10,000. The laboratory expense and supply are measured in dollars, so the price for them has effectively been normalized to one.

[insert Table 1 here]

The summary statistics (i.e., minimum, maximum, mean, median, and standard deviation) of the data included in the cost DEA model are shown in Table 1. Nearly 70% of the dental practices in the sample are solo practices. The median number of operatories a practice has is 4. The median space of dental office is 1,800 square feet. The smallest practice has one dentist with only one operatory and 800 square feet of office space. Whereas the largest practice accommodates 5 dentists with 20 operatories and 13,000 square feet of office space. The output (gross billing) varies from $178,920 to $3,490,280 with the median at $748,000. For the price indices, the average hourly wage is $131.51 for dentists, $37.28 for dental hygienists, $19.31 for chair-side assistants, and $17.01 for other staff (mainly receptionists). The average annual rent for one square feet of dental office space is $24.37.

3.2 Non-parametric Analysis

Using the non-parametric model specified in equation (4) and efficiency decomposition in equation (5), we estimate the DEA cost efficiency as well as its decomposition of technical efficiency and allocative efficiency for each dental practice in the sample. We impose an additional integer constraint on number of operatories because practically it can change only as a discrete variable. The results are shown in Table 2.

[insert Table 2 here]

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[5] http://www.simplyhired.com/a/salary/search/q-Dental+Receptionist/ (most recently accessed on 04/15/10)

The average cost efficiency across all practices in the sample is 0.793. This means on average a practice can lower its total cost by 20.7% without lowering its output level. As mentioned earlier, the cost inefficiency of a practice comes from either technical inefficiency, or allocative efficiency, or both. For instance, practice #100 has cost efficiency 0.931, which is all contributed by its allocative inefficiency because its technical efficiency is one. Practice #133, on the other hand, exhibits both technical inefficiency and allocative inefficiency. The technical efficiency and allocative efficiency of practice #133 are 0.857 and 0.835 respectively. Its cost efficiency is the product of the two, which is equal to 0.715. In fact, the average input-oriented technical efficiency across all dental practices in the sample is 0.978 whereas the average allocative efficiency across all dental practice in the sample is 0.810. Obviously, on average, the cost inefficiency of a dental practice comes mainly from allocative inefficiency.

3.3 Parametric Analysis

In the parametric analysis, we use the same data set to estimate the cost frontier. However, because the price indices for operatory, lab expense, and supply expense do not vary across dental practices, we have to drop at least two of them from the model to avoid multicollinearity[6]. We choose to combine the costs from these three inputs and define it as operating expense with price index equal to one. Thus, in the empirical analysis based on the modified log-linear Cobb-Douglas stochastic cost frontier with quadratic term specified in equation (11), we consider gross billing as the single output and assume that the total expenditure consists of labor cost on dentists, hygienists, chair-side assistants, and other staff, and capital cost on office space and operating expense (including cost of operatories, lab expense and supply expense). We normalize the price indices by dividing all other input prices by the price of operating expense. The result of the estimated coefficients is shown in Table 3.

[insert Table 3 here]

Table 3 shows that all variables except for hourly wage of chair-side assistant are statistically significant at the 5% level. Also, from the estimated model, we can calculate the

[6] Note that lack of variation in one or more prices is not a problem in DEA cost efficiency models.

marginal cost of generating one more dollar of gross billing at average output level. The result shows that the marginal cost at the sample mean of output is 63.5 cents.

We estimate the cost efficiency for each dental practice in the sample under the Cobb-Douglas stochastic cost frontier using equation (15). To compare the results relative to the stochastic cost frontier with the cost efficiency score we get for each dental practice relative to the deterministic DEA frontier, we list the DEA cost efficiency scores along with the SFA cost efficiency scores in Table 4.

[insert Table 4 here]

Table 4 shows that the cost efficiency score measured under the stochastic cost frontier is in general higher than that under the DEA deterministic frontier. In fact, the average efficiency across the sample practices is 0.871 from SFA estimation and 0.793 from DEA estimation. This is as expected because the DEA efficiency measures how far away the actual cost of a practice is from a deterministic cost frontier, while the SFA efficiency measures that from a stochastic cost frontier where a two-sided random shock may shift the frontier up or down and the cost efficiency is captured by a non-negative one-sided random term. Nonetheless, both measures are effective approaches and provide us with reasonably consistent results. In fact, the simple correlation between cost efficiency scores derived from two methods is 0.73.

Because average cost efficiency for a dental practice in the U.S. is 0.79 from DEA and 0.87 from SFA, in theory dental practices can on average reduce their cost of production by 13~21%. This provides a benchmark target for cost reduction.

3.4 Economies of Scale

As stated above, one important objective of this study is to identify the optimal output level where economies of scale have been fully exploited but diseconomies have not yet set in. This is the output level where the average cost reaches a minimization. In DEA, if we use the average price index across the sample dental practices as the market price for each individual input, we estimate the average cost of production at different output level. We thus can derive the average cost curve for the general dental practices in the sample and plot it on a graph.

[insert Figure 1 here]

Figure 1 shows the average cost curve of the general dental practices in our data for various output levels where the cost is estimated at the sample mean of the individual input prices. The break-even point is approximately at output level of $300,000 where the average cost of producing one unit of output (one dollar of revenue) is one dollar. Very few practices in the sample are operating below that output level. The lowest point on the curve is at output level of approximately $1,677,000. According to neoclassical microeconomic theory, practices that face market input prices and produce at this output level fully exploit the economies of scale. After this point, the average cost of production rises. So beyond this level diseconomies of scale prevail.

From the parametric stochastic cost frontier model with quadratic term of output included, as specified in equation (11), we also empirically estimate the optimal output level that leads to lowest average cost of production. Using equation (13), we find that at the average cost of production is lowest at output level of approximately $1,890,000. It is broadly consistent with what was found above from DEA. From Table 1 we know that the average output level among the sample practices is about $851,000, and that only 9 practices are having output level higher than $1,677,000, among which only 6 practice are having output level higher than $1,890,000. From both non-parametric and parametric methods, the results suggest that more than 90% of the dental practices in the sample are experiencing increasing returns to scale at their current output levels. They could have expanded their production to further exploit the economies of scale.

However, we have to be careful for policy recommendation. Our analyses are based on the supply side of the market only, so there may not be sufficient demand for dental services in the local market if a dental practice expands its output level. In addition, a practice's output level may also be constrained by other factors such as the practicing dentist's willingness to hire dental auxiliaries to delegate certain procedures, or to work with other dentists in the same practice. Furthermore, the optimal output level for economies of scale is estimated by assuming perfect competitive market. But the market of dental care services in the U.S. should be regarded as monopolistic competitive. Practically it is not a free-entry market because a dentist's license is required for practicing. Also, each dental practice has some degrees of monopoly power within the local market it serves. Therefore, if we consider US dental practices facing monopolistic competition, we should expect them choosing output levels lower than the optimal output level that leads to minimum average cost, which is exactly what we discover from the sample.

4. Conclusion

Using both non-parametric DEA method and parametric SFA method, we study the production technology and cost efficiency of the U.S. dental care industry at practice level. The empirical analyses are based on the ADA 2006 survey data for a number of general dental practices located in one state. The results show that the average cost efficiency is between 0.79 and 0.87, and the cost inefficiency comes mainly from the allocative inefficiency. The minimum average cost of production is 50.6 cents for each dollar of gross billings generated, whereas the marginal cost of production at average output level is 63.5 cents. The optimal output level for a dental practice to fully exploit the economies of scale is approximately at $1,677,000 from DEA estimation or $1,890,000 from SFA estimation. Both DEA and SFA provide quite consistent results, which suggest that dental practices in the U.S. should expand their services if demand is not a constraint.

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Table 1: Summary Statistics of Output and Inputs Quantities and Input Prices

	Variables	Min	Max	Mean	Median	Std. Dev.
	Gross Billings	178920	3490280	851482	748000	532739
Inputs	Dentist hrs	800	9214	2120	1700	1142
	Hygienist hrs	400	8820	2353	1840	1472
	Chair-side hrs	360	11210	3085	2976	1838
	Other Staff hrs	400	16400	3187	2600	2403
	Square Feet	800	13000	2156	1800	1534
	Operatories	1	20	4.6	4	2.48
	Lab Expense	5278	200000	57390	50000	36891
	Supply Expense	3676	236816	49525	41600	34614
Input Prices	Dentist	25.39	717.06	131.51	115.74	79.74
	Hygienist	18.79	65.10	37.28	37.20	8.00
	Chair-side	10.00	62.12	19.31	18.00	6.70
	Other Staff	13.50	19.50	17.01	17.50	1.31
	Square Feet	5.16	116.67	24.37	20.00	15.57
	Operatories	10000	10000	10000	10000	0
	Lab Expense	1	1	1	1	0
	Supply Expense	1	1	1	1	0

Table 2: DEA Cost Efficiency and Its Decomposition

Practice Survey ID	Cost Efficiency	Technical Efficiency	Allocative Efficiency	Practice Survey ID	Cost Efficiency	Technical Efficiency	Allocative Efficiency	Practice Survey ID	Cost Efficiency	Technical Efficiency	Allocative Efficiency
100	0.931	1	0.931	240	0.758	1	0.758	395	0.912	1	0.912
102	0.854	1	0.854	242	0.824	1	0.824	397	0.766	1	0.766
104	0.908	1	0.908	246	0.834	1	0.834	399	0.849	1	0.849
106	0.681	1	0.681	247	0.935	1	0.935	406	0.760	1	0.760
109	0.972	1	0.972	250	0.829	1	0.829	412	0.597	0.800	0.746
121	0.895	1	0.895	251	0.889	1	0.889	415	0.615	0.857	0.717
128	0.922	1	0.922	262	0.911	1	0.911	419	0.670	1	0.670
130	0.770	1	0.770	274	0.810	1	0.810	420	0.787	1	0.787
133	0.715	0.857	0.835	276	0.857	1	0.857	422	0.930	1	0.930
136	0.807	1	0.807	277	0.840	1	0.840	428	0.614	0.875	0.702
138	0.855	1	0.855	279	0.738	1	0.738	431	0.793	1	0.793
139	0.867	1	0.867	280	0.686	1	0.686	432	0.960	1	0.960
142	0.737	0.800	0.921	285	0.769	1	0.769	438	1	1	1
143	0.808	1	0.808	286	0.775	1	0.775	442	0.860	1	0.860
149	0.815	1	0.815	290	0.737	1	0.737	444	0.732	1	0.732
154	0.898	1	0.898	293	0.781	1	0.781	453	0.967	1	0.967
155	0.740	1	0.740	294	0.806	1	0.806	460	0.763	1	0.763
157	0.690	1	0.690	295	0.463	0.625	0.740	463	0.705	0.857	0.822
165	0.824	1	0.824	297	0.764	1	0.764	466	0.684	1	0.684
170	0.741	1	0.741	306	0.692	1	0.692	468	0.696	1	0.696
173	1	1	1	310	0.805	1	0.805	474	0.727	1	0.727
175	0.758	1	0.758	313	0.825	1	0.825	475	0.647	1	0.647
176	0.761	1	0.761	315	0.605	1	0.605	479	0.615	1	0.615
187	0.784	1	0.784	318	0.853	1	0.853	482	0.827	1	0.827
196	0.844	1	0.844	324	0.857	1	0.857	486	0.810	1	0.810
197	0.759	1	0.759	328	0.785	1	0.785	487	0.895	1	0.895
200	0.745	1	0.745	330	0.820	1	0.820	493	0.870	1	0.870
202	0.818	1	0.818	333	0.636	0.800	0.796	494	1	1	1
206	0.786	1	0.786	339	0.813	1	0.813	500	0.778	1	0.778
210	1	1	1	348	0.841	1	0.841	504	0.799	1	0.799
215	0.751	1	0.751	352	0.822	1	0.822	505	0.876	1	0.876
217	0.742	1	0.742	359	0.640	0.857	0.746	512	0.838	1	0.838
218	0.853	1	0.853	366	0.598	0.875	0.683	520	0.861	1	0.861
219	0.638	0.750	0.851	367	0.901	1	0.901	521	0.751	1	0.751
222	0.631	0.833	0.757	378	0.640	0.833	0.767	527	0.718	1	0.718
228	0.748	1	0.748	380	1	1	1	529	0.888	1	0.888
229	0.621	0.800	0.777	381	0.833	1	0.833	533	0.880	1	0.880
238	0.838	1	0.838	385	0.612	1	0.612	535	0.719	1	0.719
239	0.822	1	0.822	393	0.765	1	0.765	537	0.987	1	0.987

Table 3: Estimated Coefficients of Stochastic Cost Frontier

Dependent Variable: $ln\ C$

Independent Variables	Est. Coef.	Std. Err.	t-ratio
Constant	25.036	4.949	5.06***
ln(Gross Billings)	-2.892	0.726	-3.98***
$[\ln(\text{Gross Billings})]^2$	0.135	0.027	5.08***
ln(Dentist hourly wage)	0.262	0.026	9.94***
ln(Hygienist hourly wage)	0.131	0.056	2.34**
ln(Chair-side hourly wage)	-0.046	0.040	-1.14
ln (Other Staff hourly wage)	0.331	0.144	2.30**
ln(Square Feet rent)	0.067	0.024	5.06***
σ_u^2	0.013842		
σ_v^2	0.000002		

** significant at 5% level, *** significant at 1% level

Table 4: SFA vs. DEA Cost Efficiency Scores

Practice Survey ID	SFA Cost Effi.	DEA Cost Effi.	Practice Survey ID	SFA Cost Effi.	DEA Cost Effi.	Practice Survey ID	SFA Cost Effi.	DEA Cost Effi.
100	0.959	0.931	240	0.919	0.758	395	0.975	0.912
102	0.886	0.854	242	0.922	0.824	397	0.899	0.766
104	0.968	0.908	246	0.924	0.834	399	0.899	0.849
106	0.695	0.681	247	0.819	0.935	406	0.906	0.760
109	0.967	0.972	250	0.918	0.829	412	0.762	0.597
121	0.947	0.895	251	0.958	0.889	415	0.815	0.615
128	0.926	0.922	262	0.964	0.911	419	0.817	0.670
130	0.882	0.770	274	0.935	0.810	420	0.926	0.787
133	0.872	0.715	276	0.941	0.857	422	0.921	0.930
136	0.936	0.807	277	0.845	0.840	428	0.733	0.614
138	0.907	0.855	279	0.905	0.738	431	0.915	0.793
139	0.930	0.867	280	0.728	0.686	432	0.951	0.960
142	0.850	0.737	285	0.799	0.769	438	0.969	1
143	0.903	0.808	286	0.870	0.775	442	0.932	0.860
149	0.948	0.815	290	0.809	0.737	444	0.829	0.732
154	0.884	0.898	293	0.892	0.781	453	0.956	0.967
155	0.910	0.740	294	0.921	0.806	460	0.891	0.763
157	0.851	0.690	295	0.574	0.463	463	0.892	0.705
165	0.898	0.824	297	0.886	0.764	466	0.838	0.684
170	0.891	0.741	306	0.833	0.692	468	0.797	0.696
173	0.746	1	310	0.883	0.805	474	0.861	0.727
175	0.907	0.758	313	0.917	0.825	475	0.792	0.647
176	0.852	0.761	315	0.740	0.605	479	0.785	0.615
187	0.906	0.784	318	0.925	0.853	482	0.915	0.827
196	0.834	0.844	324	0.907	0.857	486	0.942	0.810
197	0.894	0.759	328	0.900	0.785	487	0.858	0.895
200	0.890	0.745	330	0.842	0.820	493	0.963	0.870
202	0.941	0.818	333	0.832	0.636	494	0.954	1
206	0.880	0.786	339	0.952	0.813	500	0.904	0.778
210	0.961	1	348	0.924	0.841	504	0.946	0.799
215	0.863	0.751	352	0.901	0.822	505	0.938	0.876
217	0.919	0.742	359	0.812	0.640	512	0.850	0.838
218	0.883	0.853	366	0.768	0.598	520	0.928	0.861
219	0.806	0.638	367	0.948	0.901	521	0.837	0.751
222	0.850	0.631	378	0.814	0.640	527	0.890	0.718
228	0.884	0.748	380	0.913	1	529	0.955	0.888
229	0.715	0.621	381	0.936	0.833	533	0.938	0.880
238	0.931	0.838	385	0.744	0.612	535	0.788	0.719
239	0.911	0.822	393	0.885	0.765	537	0.934	0.987

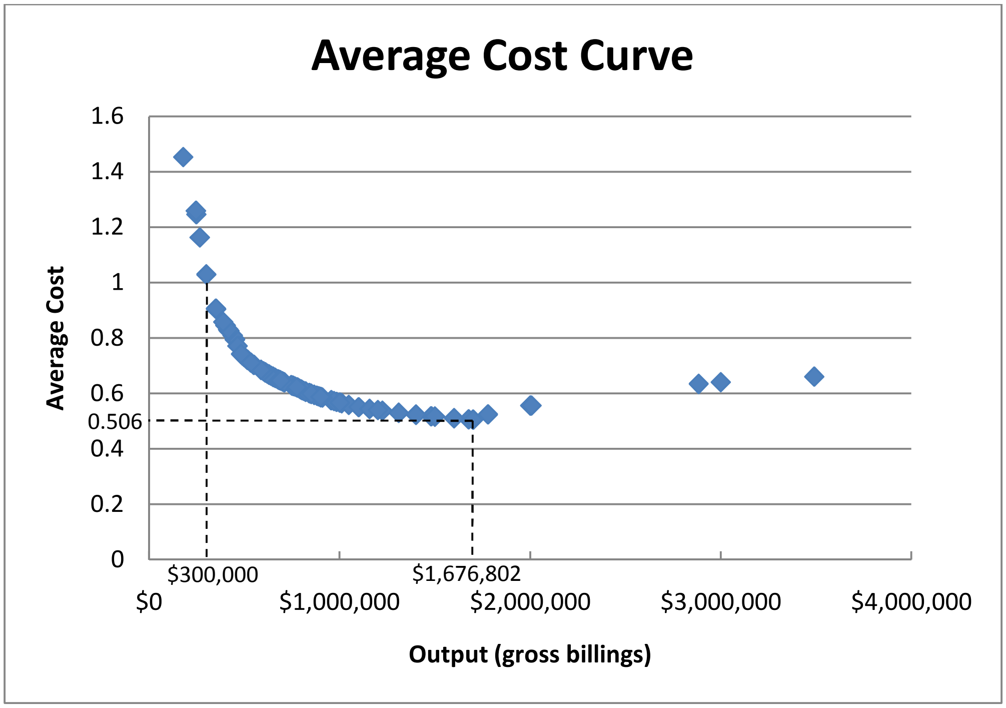

Figure 1: Average Cost Curve of the Practices in the Sample

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