Part III

Frontier Shifts and Efficiency Evaluations

Chapter 8

Estimating production frontier shifts: An application of DEA to technology assessment

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Evaluating the separate impacts of factors which affect the productive efficiency of organizations is difficult. This is because the impact of a factor is often contingent on other organizational, managerial or environmental characteristics. Standard econometric methods are limited in their ability to discriminate between efficient and inefficient units, and often impose considerable structure in parametrically specified functional forms. We show how a nonparametric data envelopment approach can be employed to focus on the best that can be achieved, with and without the key characteristic of interest. We illustrate the approach with real data from the service sector requiring the evaluation of the impact of a new information technology. The analytical technique estimates the annual savings in materials cost for an average store using the information technology to be over $4,000 (2.04% of materials cost), well in excess of the amortized annual cost for its installation. Establishing the separation in the production frontier in different regions, we show that the information technology had a substantially larger impact for the bigger stores. The savings were about 80% greater in the larger volume stores than in the smaller volume operations, an important consideration in setting the priorities for installation. The illustration underscores the flexibility of DEA in detecting different impacts of a new technology in different environments.

Keywords: Innovation impact, nonparametric estimation, efficiency analysis, data envelopment analysis, production frontier, cost-effectiveness.

1 Introduction

In many empirical applications, it is important to identify and evaluate the factors affecting the efficiency of individuals, teams or other operating units. Hypotheses regarding the sources and causes of inefficiency in organizations abound. They range from access to management, presence of a labor union, nature of decision-making process, method of compensation, extent of job security, and of automation.[1)] Unfortunately, it is difficult in practice to resolve such conjectures based on empirical data. This is especially true when the impact of a factor varies substantially across different demographic, competitive or other contingent or specific environments. Another difficulty arises because different operating units often exhibit different levels of efficiency and do not reap the full potential of the distinguishing characteristic.

Econometric methods have been commonly employed for evaluating factors affecting efficiency. They are, however, limited in their ability to discriminate between inefficient and efficient units. This is because they either rely on prices or subjective weights to tradeoff the relative importance of various outputs, or utilize optimal cost share conditions to estimate the model's parameters; the latter approach assumes that all of the units are operating efficiently.[2)] These methods also impose untested a priori structure in using parameter estimates, often yielding results that violate regularity conditions.[3)]

The flexibility provided by a nonparametric method like Data Envelopment Analysis (DEA) is important because the effect of a factor on productivity is often linked to the environment of an operating unit. For instance, in a branch banking network, an automatic teller machine (ATM) may improve productivity in large operations but not in small ones. The impact of new management procedures on hospital efficiency may depend on the hospital's teaching mission, its size (in terms of the number of beds), or the severity of its case mix. Therefore, the analytical tools used to evaluate such hypotheses must be able to distinguish between possibly different impacts in different environments.

The DEA approach models multiple outputs and multiple inputs directly without requiring any aggregation of outputs, or use of price data. Further, the Farrell (1957) radial contraction method is invariant to the scale used to measure the various inputs and outputs.[4)] It utilizes linear programs to estimate the maximum outputs that can be obtained from a given set of input resources, or alternatively, the minimum inputs needed to achieve a given level of outputs. This is in marked contrast to the multivariate regression approaches, which estimate the "average" amount of inputs required to produce given outputs. Furthermore, DEA can assess the (possibly different) impacts of a factor in different environments.

[1)] Banker and Datar (1987), for instance, examine the impact of a new incentive plan in a unionized plant, Banker and Kemerer (1989) study scale effects on productivity of software development project teams, Banker et al. (1990) study gains in efficiency from installing information technology, Bowlin (1989) studies efficiency of air force accounting offices, and Sinha, in the next chapter of this volume, studies high-technology manufacturing.

[2)] Alternative approaches, such as the one described by Banker et al. (1986) requires considerable additional structure.

[3)] See Caves and Christensen (1980), Barnett and Lee (1985), and Banker and Maindiratta (1988).

[4)] See Charnes and Cooper (1989) for a proof of the invariance.

In this paper, we employ DEA methodology to estimate the separation between two frontiers; this separation is then used as a key input in a cost effectiveness assessment.[5] For this purpose, we consider the DEA model of Banker, Charnes and Cooper (1984) that focuses on technical efficiency so that a decision making unit (DMU) is not penalized or rewarded for its actual scale of operation (as the scale size affects its average productivity, but is not within the DMU's control, at least in the short term).

Figure 1 depicts the basic intuition underlying our approach. The observed input consumption (x) is plotted against the observed output level (y) for several DMUs. The dummy variable reflects the two level of treatment: $w = 0$ denoting the level that is believed to improve productivity, relative to the one presented by $w = 1$.[6] We modify the DEA model to estimate the two frontiers (for $w = 1$ and $w = 0$). The flexibility of DEA allows us to identify where (if ever) the separation is large (for example, for the low output levels in figure 1).

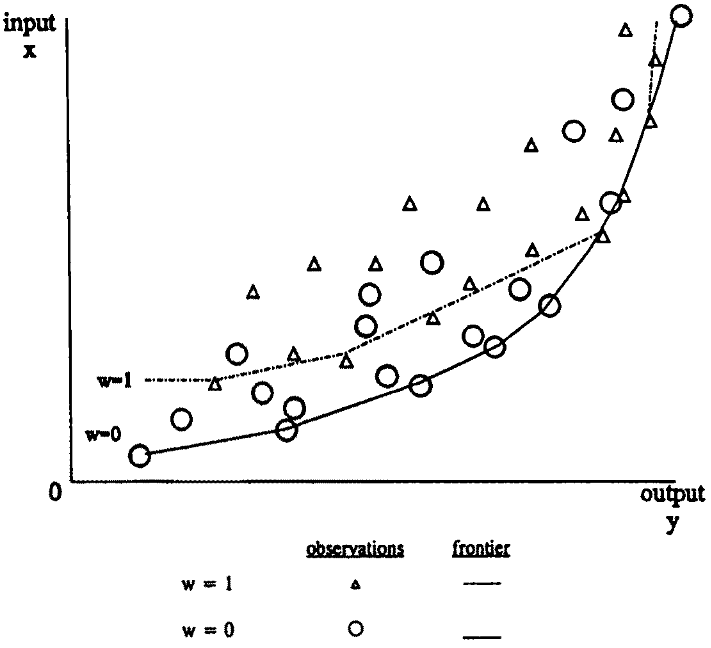

Figure 1. Separation of frontiers.

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[5] Other efforts involving a comparison of efficiency frontiers include Morey et al. (1992), Bowlin (1989), and Sinha in the next chapter of this volume.

[6] The reason for this choice becomes clear in constraint (2.2) of section 2; the basic motivation is that for an outlet without a new technology, its peer members can only come from other units that operate without the technology present. For units with the technology present, there is no restriction on the choice of peer members.

We illustrate our approach for evaluating such hypotheses with actual data obtained from Hardee's, a fast food chain based in Rocky Mount, North Carolina. This same data set was used in Banker et al. (1990), but the focus of that paper was on the results of various *formal statistical hypothesis tests*, where the store's dependence on breakfast sales was varied. The focus of this paper is very different. It discusses the estimation of the *degree of observed shifts in the production frontier* as the new technology is introduced. The extent of this shift or separation in the production frontier, due to the introduction of the new technology, will be shown to depend on the size (i.e., total of breakfast and other sales) of the store. More information on Hardee's, particularly from a site location decision perspective, can be found in Banker and Morey (1993).

The model described in this paper evaluates the impact of a new information technology (installed in a sample of outlets) on reducing the cost of materials (food and paper); such costs typically constitute about 35% of the sales. The equipment, known as Positran, is a computerized device attached to a cash register which utilizes CRT displays to aid the clerk in recording the order correctly and transmitting that order to the production side of the operation. This device is expected to reduce the possibility of an incorrect order, typically discarded, which contributes to materials "shrinkage".

The available data set consists of 89 company-owned restaurants, of which 48 had the technology in place,[7)] and 41 did not. Data on the quantities of the two outputs (dollar levels of breakfast sales, and other sales), the total cost of materials, and the presence or absence of the new technology, were collected for each outlet, for the same quarter of the same year. It is important to maintain the distinction between the two types of sales inasmuch as key variables such as profit margins, staffing requirements, and cost of materials are quite different for breakfast and other sales.

Summary statistics for the 89 restaurants are described in table 1. Total quarterly sales ranged between $74,200 and $291,900, with mean sales of $145,356. Of the 89 stores, 25% had sales below $112,800, and 25% had sales exceeding $174,900.

Table 1

Summary statistics for the 89 retail outlets. (All amounts are in thousands of dollars and are for one quarter.)

	Mean ($)	Standard deviation ($)	Minimum ($)	25th percentile ($)	Median ($)	75th percentile ($)	Maximum ($)
Total sales	145.5	41.0	74.2	112.8	136.4	179.2	291.9
Breakfast sales	36.2	9.1	8.2	28.2	36.0	41.8	59.3
Other sales	109.2	35.5	46.0	83.0	102.3	133.4	247.2
Materials cost	51.2	13.8	25.7	40.6	48.0	62.0	99.1

[7)] Only the 48 restaurants that had the Positran in place for at least one month before the quarter being studied were included in the sample in order to eliminate possible distortions due to degraded performance in the break-in period.

The remainder of this paper is structured as follows. Section 2 describes the problem at hand and our basic model. Section 3 reports the estimation results for the separation of frontiers for all stores and evaluates the cost-effectiveness of the Positran. Concluding remarks are presented in section 4.

2 The basic model

We consider observed cross-sectional data on two different outputs, breakfast sales (y_{1j}) and other sales (y_{2j}), the total input cost of materials (x_j), and the presence ($w_j = 0$) or the absence ($w_j = 1$) of Positran for each of the $j = 1,\ldots,89$ restaurants (see table 2 for raw data). Our choice in setting the value of the categorical variable w_j to be zero when the new technology is present at the jth outet will become clear in the linear programming formulation to follow. The input cost of materials is modeled as a function of the two outputs and the technology variable, and we write

$$x_j = f(y_{1j}, y_{2j}, w_j) + \varepsilon_j, \tag{1}$$

where ε_j is the *deviation* from the functional value for observation j. Our objective is to determine if $x^*(w = 0) \equiv f(y_1, y_2, w = 0)$ is strictly less than $x^*(w = 1) \equiv f(y_1, y_2, w = 1)$. That is, we are comparing the *best* that can be accomplished without the technology to the *best* that can be accomplished with the technology. This type of analysis is especially valuable if the implementation or training associated with the installation of the new technology was somehaw flawed in some situations. It is similar in spirit to the paper by Charnes et al. (1981), who assess the impact of the educational Program Follow Through (PFT), where some of the PFT executions were believed inefficient.

In the usual econometric methods, considerable additional structure is imposed on the relation in (1). Two important parametric assumptions are usually made. First, the function $f(\cdot)$ is specified using a parametric form. Furthermore, a specific parametric form is assumed for the probability distribution of ε in order to test the hypotheses of interest. Specifying a parametric form for the function $f(\cdot)$ requires that the same value for each parameter (especially those related to the impacts of the w_j variable) be estimated across *all* observations, unless variations in impacts across observations are known and modeled as such. But, in this setting, it is possible that Positran results in considerable benefits for some types of DMUs, but none for others. Such insights would be particularly valuable from a managerial viewpoint, especially in determining priorities in implementing the new information technology; hence, this possibility is explored via flexible methods in the next section.

Considerable attention has been paid in recent years to the econometrics literature, particularly that related to production economics, about the restrictiveness of the parametric specification of the production function. See, for instance, Hildenbrand (1981), Varian (1984), and Banker and Maindiratta (1988). Implicit in a parametric

Table 2

Raw data. (All amounts are in thousands of dollars).

Store no.	Quarterly breakfast sales	Quarterly other sales	Actual cost of sales	Presence of Positran (yes/no)
1	40.879	114.229	55.012	Y
2	26.375	74.834	36.061	N
3	32.698	153.780	68.158	N
4	111.459	57.400	57.400	Y
5	35.500	173.784	77.488	N
6	52.672	108.448	56.710	N
7	33.034	85.111	42.776	N
8	42.402	177.471	74.347	Y
9	50.002	66.303	44.564	N
10	29.746	83.038	43.215	N
11	42.123	132.799	61.042	N
12	54.245	149.541	70.261	Y
13	32.327	74.681	40.477	Y
14	39.601	137.539	59.068	Y
15	44.648	247.207	99.091	N
16	42.704	128.989	59.210	N
17	36.791	108.169	48.107	N
18	44.701	124.006	62.729	Y
19	40.361	104.301	42.704	Y
20	41.948	80.564	43.191	N
21	40.957	175.371	73.507	Y
22	36.295	93.826	47.073	N
23	29.025	45.989	25.672	N
24	27.592	76.046	37.744	N
25	25.692	101.165	41.633	Y
26	28.814	74.222	38.140	N
27	35.585	97.039	49.076	N
28	44.287	141.882	62.958	N
29	25.060	83.220	40.563	N
30	38.375	98.028	48.745	Y
31	41.799	111.336	54.098	N
32	40.977	75.968	39.650	N
33	25.974	105.448	45.546	N
34	26.943	90.568	44.452	Y
35	26.179	68.609	37.378	N
36	49.953	154.970	69.526	Y
37	38.789	66.301	37.322	Y
38	38.173	148.637	62.031	Y
39	41.322	102.247	52.617	N
40	35.195	83.948	40.745	N
41	26.470	63.822	32.534	N
42	26.454	133.664	67.782	Y
43	32.026	98.565	47.038	Y
44	34.817	61.282	34.040	N

. . . continues

Table 2 (continued)

Store no.	Quarterly breakfast sales	Quarterly other sales	Actual cost of sales	Presence of Positran (yes/no)
45	26.470	88.795	43.058	N
46	26.454	47.745	27.464	N
47	33.263	91.503	45.293	N
48	44.359	126.443	60.998	N
49	21.926	81.385	36.738	N
50	41.560	100.484	48.195	Y
51	32.920	54.163	29.676	Y
52	24.492	102.847	46.428	Y
53	40.643	160.200	68.124	Y
54	51.996	127.689	64.048	Y
55	29.726	96.914	42.395	Y
56	22.714	165.672	69.124	Y
57	35.915	126.002	54.022	N
58	38.125	112.743	44.552	N
59	38.610	100.485	48.029	N
60	28.154	105.645	46.039	N
61	43.625	135.839	69.378	T
62	8.209	72.173	30.252	N
63	52.817	109.103	57.769	N
64	20.927	85.839	38.531	N
65	32.717	102.614	47.362	N
66	30.521	133.356	56.589	Y
67	38.897	136.013	62.041	N
68	33.311	130.533	57.071	Y
69	50.523	89.599	45.909	N
70	45.455	137.071	75.766	Y
71	50.788	150.627	70.788	Y
72	26.913	77.553	37.021	Y
73	39.584	145.039	61.972	N
74	31.812	72.658	37.227	Y
75	41.050	156.179	67.455	Y
76	37.807	102.271	48.204	Y
77	28.108	62.938	32.185	N
78	41.809	142.510	63.925	Y
79	40.245	113.638	54.989	Y
80	21.877	78.337	38.419	Y
81	30.393	89.254	41.408	Y
82	59.308	170.017	79.473	Y
83	37.388	83.689	42.060	Y
84	25.594	85.220	42.096	Y
85	27.057	80.505	39.157	Y
86	32.345	97.194	44.006	Y
87	29.885	95.073	43.184	Y
88	48.948	158.843	68.285	Y
89	28.205	99.394	44.592	Y

specification of the production frontier are maintained assumptions about its form, which can be tested only within the framework of a larger inclusive model. Any test of hypothesis, therefore, must be regarded as a joint test of the hypothesis of interest and implicit restriction on the form of the production function. In fact, in many instances the estimates of commonly employed parametric forms violate such regularity properties as monotonicity and convexity (or concavity), see Caves and Christensen (1980), and Barnett and Lee (1985).

An alternative approach, known as Data Envelopment Analysis (DEA) has been developed in the management science/operations research tradition. It imposes minimal and justifiable restrictions on the production function, and estimates it via a linear programming model. It is also flexible, and can be modified easily to suit specific settings such as exogenously fixed inputs (Banker and Morey (1986a)). Following the axiomatic framework of Banker (1993) and Banker, Charnes and Cooper (1984) (BCC), the production correspondence $f(\cdot)$ in (1) is specified to be monotone increasing and convex, and $\varepsilon_j \geq 0$ are distributed independently (but not necessarily identically) of each other and of (y_{1j}, y_{2j}).

DEA estimates the functional value $x_{j_0} = f(y_{1j_0}, y_{2j_0}, w_{j_0})$ for a DMU j_0 (j_0 is varied one at a time from 1 to 89) via the following linear program with two outputs, one controllable input, and one environmental variable:[8]

$$x^*_{j_0} = \min x \tag{2.0}$$

$$\text{subject to} \quad \sum_{j=1}^{89} y_{rj}\lambda_j \geq y_{rj_0} \qquad r = 1,\ 2, \tag{2.1}$$

$$\sum_{j=1}^{89} w_j\lambda_j \geq w_{j_0}, \tag{2.2}$$

$$\sum_{j=1}^{89} x_j\lambda_j \leq x, \tag{2.3}$$

$$\sum_{j=1}^{89} \lambda_j = 1, \tag{2.4}$$

$$x, \lambda_j \geq 0 \qquad (j = 1, 2, \dots, 89). \tag{2.5}$$

If it is assumed in addition that the e_j are distributed in accordance with a probability density function that is non-increasing, then Banker (1993) has shown that the above method yields maximum likelihood estimates of the residual deviations $\varepsilon_j = x_j - x^*_j$.

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[8] We remark that the LP formulation in (2.0)–(2.5) is a variation of the BCC model because it excludes any use of the non-Archimedean variable found in the standard DEA models. This is consistent with our focus on the minimum cost needed under two different scenarios involving whether the technology of interest is present or not.

The constraint in (2.2) embodies the assumption that the existence of a Positran will not lead to increased consumption of materials, and in fact may lead to a decrease. This constraint (2.2) permits all DMUs as referents when the Positran is present ($w_{j_0} = 0$), but only DMUs j without Positran (i.e., for which $w_j = 1$) when the DMU j_0 under consideration is in the more difficult environment ($w_{j_0} = 1$)[9] (see Banker and Morey (1986b)).

Since our objective is to assess whether or not proper installation and use of the Positran had an impact on reducing materials consumption, we need to compare the production frontier when the Positran technology is absent and with the frontier when it is present. In other words, we want to compare the DEA frontier estimates $x^*_{j_0}(w = 1) \equiv f(y_{1j_0}, y_{2j_0}, w = 1)$ with $x^*_{j_0}(w = 0) \equiv f(y_{1j_0}, y_{2j_0}, w = 0)$ to determine if the frontier shifts down when Positran technology is present. We can accomplish this by solving the optimization problem in (2) for each observation $j_0 = 1,\ldots,89$, first with the right-hand side of the constraint (2.2) set equal to one, and then with it set equal to zero, to yield the two values $x^*_{j_0}(w = 1)$ and $x^*_{j_0}(w = 0)$, respectively. We observe, of course, that it is possible that $x^*_{j_0}(w_{j_0} = 0) < x^*_{j_0}(w_{j_0} = 0)$ for some values of (y_{1j_0}, y_{2j_0}) but not for all.

Before discussing the results for all 89 DMUs in the next section, in table 3 we describe the results for two DMUs: DMU 22 and DMU 34, the first without the Positran, and the other with the Positran. DMU 22 had breakfast sales of \$36,295, other sales of \$93,826, and actual materials cost of \$47,073. Since it did not have the Positran, its reference group (from constraint (2.2)) was forced to be composed of only DMUs without the Positran, and actually included outlets 17, 23, and 69.

The efficient cost without Positran is estimated to be $x^*_{22}(w = 1)$ or \$43,295, compared to actual cost of \$47,073. When the Positran is present, the efficient consumption of materials is estimated to be $x^*_{22}(w = 0) = \$42{,}719$, a further reduction of \$576 from the efficient consumption in the absence of the Positran. Also, its reference group, when the Positran is available, actually consisted of stores both with and without the Positran.

To complete table 3, next consider the case fro DMU 34, one that did indeed have the Positran present. The efficient materials cost $x^*_{34}(w = 0)$ is \$38,760 versus $x^*_{34}(w = 1) = \$40{,}211$, when the Positran is assumed to be absent, for a frontier separation of \$1,451.

3 Discussion of estimation results

The data envelopment analysis models described in section 2 provide two sets of frontier values $x^*_{j_0}(w = 0)$ and $x^*_{j_0}(w = 1)$ for each observed vector (y_{1j_0}, y_{2j_0}) which

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[9] If it is not known a priori which category has an advantage, then we may want the selection of referent DMUs to be restricted to only those having the same distinguishing characteristic. This is accomplished easily by changing the constraint (2.2) to $\Sigma_{j=1}^{89} (w_j - w_{j_0})\lambda_j = 0$, or equivalently $\Sigma_{j=1}^{89} w_j \lambda_j = w_{j_0}$.

Table 3

Data and results for two stores.

		Actuals Store 22		*Actuals* Store 34
Total sales		$130,121		$117,511
Breakfast sales		$ 36,295		$ 26,943
Other sales		$ 93,826		$ 90,568
Breakfast/total sales		27.9%		22.9%
Materials cost		$ 47,073		$ 44,452
Positran		not present		present
	Frontier if Positran assumed not available			
Referent group	DMU #	Weight	Store #	Weight
	17	0.713	17	0.583
	23	0.207	23	0.099
	69	0.080	62	0.318
Frontier materials cost		$42,719		$40,211
	Frontier if Positran assumed present			
Referent group	DMU #	Weight	Store #	Weight
	17	0.713	17	0.583
	23	0.207	23	0.099
	69	0.080	62	0.318
Frontier materials cost		$42,719		$38,760
Separation in frontiers	$576 ($43,295 – $42,719)		$1,451 ($40,211 – $38,760)	
Percent separation	1.33% ($576/$43,295)		3.61% ($1,451/$40,211)	

correspond to the frontier with and without Positran, respectively. The linear programs for estimating the frontier were infeasible for 16 of the 89 units, all with Positran actually present, if the Positran was assumed *not* to be available.10) Hence, although we can estimate what the efficient cost is when the Positran is present, it is impossible to estimate what the cost would have been if there had been no Positran for these 16 stores.11)

10)Infeasibility occurs in the above cases because it is not possible to envelope (from above) the observed outputs for a DMU which actually had a Positran with a *convex* combination of observed outputs of only 41 of the 89 units (i.e., λ_j's in the linear program (2.0)–(2.5) were allowed to be strictly positive for only 41 of the 89 DMUs) that were *without* the Positran.

11)The sixteen stores, all with Positran, for which reference group members could not be found (when limited to only stores *without* a Positran) were characterized as very large stores with a mean of $204.81 thousand, compared with an overall mean of $145.5 thousand.

As a consequence, the results described in table 4 are *averaged across the remaining 73 feasible separations*. They indicate that the separation ($\Delta_{j_0} = x^*_{j_0}(w = 1) - x^*_{j_0}(w = 0)$) between the two frontiers is \$1,046, which is about 2.04% of the actual average materials cost. For 5 of the 73 feasible cases, the frontier values were the same for $w = 1$ and $w = 0$. The average separation between the frontiers for the remaining 68 observations was \$1,123, which is 2.19% of the actual average materials cost.

The separation between the two frontiers is not uniform across all outlets with different sales volumes (see table 4). For example, the mean of the frontier separation for the 44 stores with the lowest total sales is \$815, compared to the mean separation of \$1.046 overall. Also, the average of the percent separation (i.e., the separation between the two frontiers divided by the frontier level without the Positran present) is 2.05% for the smaller stores versus 2.54% for the larger stores. Because the larger stores tend to have more confusion to manage, with more demanding matching of orders and production delivery, the installation of Positran results in greater gains in the larger outlets.

This insight is confirmed by regressing the frontier separation (D_j) against total sales ($y_{1j} + y_{2j}$) for the 73 observations: $D_j = -1.467 + 0.019(y_{1j} + y_{2j})$; $R^2 = 0.333$. The standard error of the coefficient related to total sales (namely, 0.019) is 0.003, indicating that the coefficient is statistically significant at the 1% level. (We caution the reader that this inferential interpretation may not be appropriate if the distributional assumptions of the regression are not valid.) Thus, each increase of \$1,000 in total quarterly sales is associated with a \$19 increase in the separation between the frontiers. Notice that the flexibility of DEA models has enabled us to identify a specific characteristic of DMUs (namely its total sales) which experienced greater gains from the installation of the Positran technology than other DMUs.

Next, to enable us to assess the cost-effectiveness of a Positran deployment, consider the following simplified cost-benefit analysis of the Positran unit. Its cost (in 1986) was about \$2,500 per installation, over and above the cost of standard cash registers. The useful life of the Positran (for depreciation purposes) was 7 years, and Hardee's internal opportunity cost of capital was 15% per annum at that time. Hence, the amortized annual cost of a Positran installation was about \$732, comprising a straight line annual depreciation of \$357 (\$2500/7), plus the annual opportunity cost of capital of \$375 ($0.15 \times \$2500$). Thus, in order for the equipment to be cost-effective, the annual savings in the cost of materials would need to be at least \$732 annually, or \$183 per quarter. Because the average quarterly materials cost averaged \$51,161 (ranging between \$25,652 and \$77,488), the break-even percent savings for the average store is about 0.36% (i.e., \$183/\$51.161).

Recall that average quarterly savings (i.e., the difference between the two frontiers) is \$1,046 (or 2.04% of the average quarterly materials cost), which is about 5.7 times the break-even threshold for the average store. Therefore, it appears from this "back-of-the-envelope" analysis that the Positran is very cost-effective. Alternatively, we observe that the payback period for the \$2500 investment is only about 2.4 quarters.

Table 4

Estimated technically efficient frontier values with and without Positran for each store, and the estimated separation. (All dollar amounts are in thousands.)

Store no.	Presence of Positran	Actual total sales	Actual cost of materials	Estimated efficient cost of materials without Positran	Estimated efficient cost of materials with Positran	Estimated separation between the two efficient frontiers
1	yes	155.110	55.012	51.486	50.705	0.581
2	no	101.210	36.061	33.874	33.874	0.976
3	no	186.48	68.158	62.157	62.378	5.78
4	yes	161.22	57.400	54.994	32.888	2.106
5	yes	209.78	77.488	infeasible	70.300	NA
6	no	161.12	56.710	56.710	53.970	2.74
7	no	118.14	42.776	39.610	39.002	0.608
8	yes	219.81	74.347	infeasible	73.36	NA
9	no	116.310	40.564	40.564	50.564	0.00
10	no	112.780	43.215	38.250	37.324	0.926
11	no	174.922	61.042	58.807	57.450	1.357
12	yes	203.790	70.261	infeasible	68.709	NA
13	yes	107.010	40.477	35.967	35.562	0.405
14	yes	177.140	59.068	60.314	58.251	2.063
15	yes	291.560	99.091	infeasible	99.091	NA
16	no	171.693	59.210	56.611	56.379	0.232
17	no	144.960	48.107	48.107	47.568	0.539
18	no	168.710	62.729	56.500	55.383	1.117
19	yes	144.662	52.407	48.114	47.473	0.641
20	no	122.512	43.19	40.560	40.415	0.145
21	yes	216.328	73.507	infeasible	72.243	NA
22	no	130.121	47.073	43.295	42.719	0.576
23	no	75.014	25.672	25.672	25.672	0.00
24	no	103.638	37.744	35.469	34.488	0.981
25	yes	126.857	41.633	43.553	41.633	1.92
26	no	103.036	38.14	35.103	34.311	0.792
27	no	132.624	49.076	44.143	43.496	0.647
28	no	186.169	62.958	62.758	61.158	1.8
29	no	108.280	40.563	37.364	36.175	1.189
30	yes	136.403	48.745	45.248	44.733	0.515
31	no	153.12	54.098	50.747	50.242	0.505
32	no	116.950	39.650	38.791	38.691	0.1
33	no	131.422	45.546	45.070	43.318	1.752
34	yes	117.511	44.452	40.211	38.760	1.451
35	no	84.780	37.378	32.687	31.985	0.702
36	yes	204.923	69.526	infeasible	61.897	NA
37	yes	105.090	37.322	35.028	35.019	0.009
38	yes	186.810	62.031	infeasible	61.897	NA
39	no	143.569	52.617	47.453	47.089	0.364
40	no	119.143	40.745	39.796	39.325	0.444
41	no	90.469	32.534	31.176	30.628	0.548
42	yes	160.118	67.782	infeasible	59.673	NA
43	yes	130.591	47.038	43.921	42.840	1.081
44	no	96.099	34.040	32.279	32.217	0.062

. . . continues

Table 4 (continued)

Store no.	Presence of Positran	Actual total sales	Actual cost of materials	Estimated efficient cost of materials without Positran	Estimated efficient cost of materials with Positran	Estimated separation between the two efficient frontiers
45	no	115.265	43.508	39.520	38.064	1.456
46	no	74.199	27.464	25.979	25.979	0.00
47	no	124.766	45.293	41.801	41.045	0.756
48	no	170.802	60.998	57.276	56.078	1.198
49	no	103.311	36.738	36.115	35.139	0.976
50	yes	142.044	48.195	46.941	46.584	0.357
51	yes	87.083	29.676	29.427	29.423	0.004
52	yes	127.339	46.428	43.894	42.295	1.599
53	yes	200.845	68.124	infeasible	66.689	NA
54	yes	179.685	64.048	infeasible	59.888	NA
55	yes	126.64	42.395	42.982	41.596	1.386
56	yes	188.386	69.124	infeasible	67.012	NA
57	no	161.917	54.022	54.022	53.177	0.845
58	no	150.868	55.551	50.106	49.516	0.57
59	no	139.095	48.029	46.114	45.622	0.492
60	no	133.795	46.039	45.562	43.917	1.645
61	yes	179.464	69.378	60.481	58.944	1.537
62	no	80.382	30.252	30.252	30.252	0.00
63	no	161.92	57.769	57.769	54.403	3.366
64	no	106.766	38.531	37.408	36.314	1.094
65	no	135.33	47.362	45.420	44.403	1.017
66	yes	163.877	56.589	57.764	54.461	3.303
67	no	174.91	62.041	59.463	57.523	1.94
68	yes	163.844	57.071	56.328	54.143	2.185
69	no	140.122	49.909	45.909	45.909	0.00
70	yes	182.526	75.766	infeasible	72.542	NA
71	yes	201.415	70.778	infeasible	66.810	NA
72	yes	104.466	37.021	35.837	34.771	1.066
73	yes	184.593	61.972	64.199	60.945	3.254
74	yes	104.48	37.227	35.188	34.779	0.409
75	yes	197.229	67.455	infeasible	65.341	NA
76	yes	140.078	48.204	46.471	44.95	0.521
77	yes	91.041	32.185	31.173	30.607	0.566
78	yes	184.419	63.925	63.128	60.635	2.493
79	yes	153.883	54.989	51.071	50.503	0.568
80	yes	100.214	38.419	35.082	34.221	0.861
81	yes	119.657	41.408	40.470	39.448	1.022
82	yes	229.325	79.473	infeasible	79.473	NA
83	yes	121.077	42.060	40.299	39.938	0.361
84	yes	111.814	42.096	38.345	37.011	1.334
85	yes	107.572	39.157	36.859	35.697	1.162
86	yes	129.54	44.006	43.526	45.51	1.016
87	yes	124.959	43.184	42.317	41.079	1.238
88	yes	207.791	68.285	infeasible	68.285	NA
89	yes	127.600	44.592	43.439	41.881	1.558

Table 5

Differences in frontier separation for large and small volume stores.

	High total sales (> \$136,000)	Low total sales (< \$136.000)
Number of stores*	44	44
Mean separation	\$1,482	\$815
Mean percentage separation**	2.54%	2.05%

[*] It was feasible to estimate separation for only 29 of the 44 high volume stores. The standard deviation of the separation between the two frontiers was \$1,301 for the high volume stores and \$541 for the low volume stores.

[**] The standard deviation of the percentage separation between the two frontiers was 1.40% for the high volume stores and 1.26% for the low volume stores.

We have also observed that the mean of the frontier separation for the 44 low volume stores is \$815, still well in excess of the \$183 break-even point. At the same time, the mean of the frontier separation for the 44 high volume stores is \$1,482, nearly 82% more than that for the smaller stores. Hence, while ultimately the Positran should be installed in all stores, the highest priority is for the larger stores.

4 Concluding remarks

Based on the results of some pilot installations of Positran, Hardee's was interested in determining the extent of the impact of the Positran technology in reducing the cost of materials. Since the Positran device costs about \$2,500 more than a standard cash register, and Hardee's operated about 2,600 stores at the time of the study, at risk was a possible \$6.5 million investment in information technology. Of particular interest was the setting of managerial priorities, since Hardee's was interested in identifying whether the benefits of Positran were linked to particular characteristics of the stores. The conclusion of our analysis, namely that the savings were much more pronounced for larger stores, was particularly useful to the management in planning the investment and installation of Positran in the approximately 700 stores owned by Hardee's and in advising its franchisees.

There are some caveats associated with the DEA method described here to assess the impact of a specific factor. Important among them is its sensitivity to outliers and measurement errors. More recent work, such as Banker (1989), Banker and Maindiratta (1992), Retzlaff-Roberts and Morey (1993) have provided useful extensions to address situations where the deviations ε_j result from both inefficiencies *and* random factors, which parallels similar work in econometrics (see Aigner et al. (1977)). These methods are not discussed here, but the basic ideas extend directly.

This and other caveats notwithstanding, the separation-in-frontiers approach provides a fresh approach for assessing impacts, especially when improper use or management of resources may result in inefficiencies, and when then impact of the factor of interest may depend on the environment or other characteristics of the DMUs.

Acknowledgements

The authors are grateful to Mr. John C. Wilson, formerly Senior Vice President and Chief Financial Officer of Hardee's Food Systems, Rocky Mount, North Carolina, for his help and support for this research and for providing access to data. Financial support was provided in part by the National Science Foundation Grant No. SES709044 at Carnegie-Mellon University.

References

Aigner, D.J., C.A.K. Lovell and P.J. Schmidt, Formulation and estimation of stochastic frontier production function models, Journal of Econometrics, July 1977, 21–37.

Banker, R.D., Econometric estimation and Data Envelopment Anaysis, Research in governmental and nonprofit accounting, 1989, 231–244.

Banker, R.D., Stochastic Data Envelopment Analysis, Working Paper Series, Carnegie-Mellon University, 1989.

Banker, R.D., Maximum likelihood, consistency and Data Envelopment Analysis: A statistical foundation, Management Science 39, 1993, 1265–1273.

Banker, R.D., A. Charnes and W.W. Cooper, models for the estimation of technical and scale inefficiencies in Data Envelopment Analysis, Management Science, September 1984, 1078–1092.

Banker, R.D., R.F. Conrad and R.P. Strauss, A comparative application of DEA and translog methods: An illustrative study of hospital production, Management Science, January 1986, 30–44.

Banker, R.D. and S.M. Datar, Accounting for labor productivity in manufacturing: An application, in *Accounting and Management: Field Study Perspectives*, W. Burns and R. Kaplan, eds., Harvard Business School Press, Boston, 1987.

Banker, R.D., R.J. Kaufman and R.C. Morey, Measuring gains in operational efficiency from information technology: A study of the Positran deployment at Hardee's Inc., Journal of Management Information Systems 7, 1990, 29–54.

Banker, R.D. and A. Maindiratta, Nonparametric analysis of technical and allocative efficiencies in production, Econometrica, November 1988, 1315–1332.

Banker, R.D. and A. Maindiratta, Maximum likelihood estimation of monoton increasing and concave production frontiers, Journal of Productivity Analysis, December 1992, 401–416.

Banker, R.D. and R.C. Morey, Efficiency analysis for exogenously fixed inputs and outputs, Operations Research, July/August 1986a, 1613–1627.

Banker, R.D. and C.F. Kemerer, Scale economies in new software development, IEEE Transactions on Software Engineering, October 1989, 1197–1205.

Banker, R.D. and R.C. Morey, Data Envelopment Analysis with categorical inputs and outputs, Management Science, December 1986b, 1613–1627.

Banker, R.D. and R.C. Morey, Integrated system design for service sector outlets vis allocative efficiency analysis, Journal of Operation Management 11, 1993, 81–89.

Barnett, W.A. and Y.W. Lee, The global properties of the minflex Laurent, generalized Leontief and translog flexible functional forms, Econometrica, 1985, 1421–1437.

Bowlin, W.F., An intertemporal assessment of the efficiency of U.S. Air Force accounting and finance offices, Research in Governmental and Non-Profit Accounting 5, 1989.

Caves, D.W. and L.R. Christensen, The relative efficiency of public and private firms in a competitive environment: The case of Canadian railroads, Journal of Political Economy, October 1980, 958–976.

Charnes, A. and W.W. Cooper, Management science relations for evaluation of management accountability, Journal of Enterprise Management 2, 1980, 143.

Charnes, A., W.W. Cooper and E. Rhodes, Measuring the efficiency of decision making units, European Journal of Operational Research 2, 1978, 429–444.

Charnes, A., W.W. Cooper and E. Rhodes, Project evaluation and managerial efficiency: An application of Data Envelopment Analysis to program following through, Managemetnt Science, 1981, 668–697.

Farrell, M.J., The measurement of productivity efficiency, J.D. Royal Statistical Society 120, Series A, part III, 1957.

Hildenbrand, W., Short-run production functions based on microdata, Econometrica 49, 1981, 1095–1125.

Morey, R.C., D.J. Fine, S.W. Loree, D.L. Retzlaff-Roberts and S. Tsubitami, The tradeoff between hospital costs and quality of care, Medical Care 30, 1992.

Retzlaff-Roberts, D. and R.C. Morey, A goal programming methodology stochastic allocative Data Envelopment Analysis, European Journal of Operational Research, December 1993, 379–397.

Sinha, K.K., Moving frontier analysis: An application of Data Envelopment Analysis for competitive analysis of a high-technology manufacturing plant, Annals of Operations Research, Chapter 9, this volume.