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A COMBINED DEA-STOCHASTIC FRONTIER APPROACH TO LATIN AMERICAN AIRLINE EFFICIENCY EVALUATIONS

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A COMBINED DEA-STOCHASTIC FRONTIER APPROACH TO LATIN AMERICAN AIRLINE EFFICIENCY EVALUATION

1. INTRODUCTION

This paper introduces some new approaches for evaluating efficiencies and identifying and estimating stochastic frontier production functions. These approaches are based on combinations of Data Envelopment Analysis - DEA (Charnes, Cooper and Rhodes, 1978) with regression and associated statistical analyses. Latin American Airlines are used to provide a concrete setting which is also of interest in its own right.

To start, we take advantage of a Delphi study which, as reported in Gallegos (1991), was conducted to identify goals and measures of performance used by Latin American airlines. The evidence from this study, showed no significant differences between the goals reported by private and state-owned Latin American airlines. This finding is used to justify including SOE and private airlines in a single study (a) to measure the relative efficiency of individual Latin American airlines without respect to ownership, while (b) retaining the option of examining whether our DEA analyses permit us to identify differences in the efficiencies displayed by private and public airlines. In an extension of these comparisons, U.S. airlines operating in Latin America will be brought into the picture and their performance compared with Latin American based airlines.

An important feature of this paper is that various methods are employed and then used in combination with each other. These methods include Data Envelopment Analysis (DEA) Ordinary Least Squares Regression (OLS), Goal

Programming Frontier Regression (GP/FR), and, finally, Generalized Linear Regression Models (GLM) and DEA combinations. Proceeding in this manner makes it possible to (a) cross check results from these various methodologies, (b) study possible discrepancies between these results, and, c) examine how these different techniques can be combined to obtain results that differ from what might be obtainable from any of them alone. In this development, we will also see how current difficulties frequently experienced by others may be resolved with increasingly satisfactory results form economics and management standpoints as more reined statistical methods are introduced.[1]

2. INPUT AND OUTPUT SELECTION AND DATA

To simplify matters and facilitate proposed comparisons and syntheses, we represent the production function of Latin american airlines in terms of a single output and three inputs. Reduction to a single output provides ready access to least squares regressions and other standard statistical techniques we will be using. We also want to maintain contact with other approaches to stochastic frontier model estimation, which have, by and large, been confined to the single output case.[2] We therefore conceptualize our study in terms of an "industry" production function which is interpreted as (a) a well defined function which generates a single output from designated inputs, and (b) is available to all firms in the industry. Using the results from our Delphi study (Cooper, Gallegos and Granof, 1990), we do not distinguish the private from the SOE production functions but rather we use the results secured from the archival data we now use to check further on whether dif-

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1 See, e.g., Varian (1990) who argues that is is "economic significance" rather than "statistical significance" what we should be seeking. See also Afriat (1972) who argues that "an Euclidean least squares metric is devoid of economic significance."

2 See Appendix B for a review of the Stochastic Frontier Production Function Literature.

ferences in efficiency appear between these 2 groups. Focusing on the production function allows us to avoid troubles we would encounter, as already noted, to deal with the prices that would need to be used with cost or profit functions. Additionally we also focus on technical and scale efficiency issues which are common to both.[3]

The single output we use, "ton-kilometers performed," as obtained from ICAO's (International Civil Aviation Organization) data base in Montreal, Canada, is a commonly used measure which combines passenger and freight traffic. We employ annual data which cover a period of eight years from 1981 to 1988, as recorded in the first column of the Appendix A. This measure of output is stated in physical units rather than the corresponding monetary units in order to avoid the need for dealing with the very high varying inflation and exchange rates, with related difficulties of treatment, that are prominent features in the majority of the 12 different countries included in our study.

To the extent possible we also confine ourselves to physical rather than value units for the input measures. Hence, the data for "labor" in column 2 of the Appendix A are stated in terms of total number of employees. Again we avoid breakdowns into more refined categories such as airport vs airline operation personnel, e.g., as in Banker et al. (1990) and Sickles et al. (1986). This is done because a major objective of this paper is to develop a new approach to stochastic frontiers. We therefore simplify matters as much as possible, while still retaining a production function which is meaningful, to obtain results that will also prove useful in the next chapter when further detail will be introduced via the multiple-input to multiple-output method of Data Envelopment Analysis.

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[3] For this notion of a production function, see Samuelson (1947), Chapter IV. Also see Carlson (1956) and Sato (1975) for a discussion of the relation between such industry functions and the functions which are applicable to a "representative firm."

A second input category we use is "fuel." Data on consumption of fuel in physical units are not available for the airlines we are studying. ICAO's Digest of Statistics - Series F - Financial provides data on expenditures for fuel and oil both in domestic currency and in U.S. dollars. For our purpose the latter is employed since (a) it is the unit in which fuel and oil are commonly traded internationally, and (b) it is already in a common unit of measure which makes possible the comparisons we are seeking. We do not need to adjust this for dollar inflation or deflation because our interest is in relative rather than absolute measures of efficiency; i.e. we will generally be studying the efficiency of each airline relative to the other airlines operating in Latin America in the same period of time. It must be noted, however, that although airlines from non- oil-producing countries are generally subject to the same world market prices for fuel (also generally denominated in U.S. dollars), airlines from oil-producing countries tend to purchase fuel at a substantial discount from their governments.[4]

Finally, for input of capital we use "available ton-kilometers" (i.e., a measure of capacity) as a surrogate. These data, as contained in column 4 of the Appendix A, represent the number of tons available for the carriage of passenger, freight and mail multiplied by the number of kilometers flown. Standard conversion factors are used to reduce these different types of carriage to a common unit as follows: the number of seat-kilometers available for passengers is multiplied by 90 kilos (= 198.4 pounds at 2.204 pounds per kilo). This multiplier allows for free and excess baggage in conformance with a widely used international standard which reckons a typical passenger at 75 kilos with 16 kilos of baggage on long-haul routes and 10 kilos of baggage on domestic or short-haul routes. Freight and mail ca-

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[4] As will be discussed later in the chapter, there appear to have been significant substitutions between fuel and the other inputs we are considering during the eight-year period of our study.

pacity is measured either in cubic meters or tons and is converted into tons by employing standard cargo-density and weight conversion factors.

3. PRODUCTION FUNCTION REGRESSION ESTIMATES

As a start, we use classical (interior point) least squares regressions to estimate our production function but our subsequent attention will be directed to adaptations for the study of stochastic frontiers. Studies focusing on frontier rather than central tendency estimates have become increasingly numerous and the reports from this research are scattered over many literatures.[5]

A Cobb-Douglas production function of the following form is used,

$$(1) \qquad y = a\, c^{\alpha}\, l^{\beta} f^{\gamma}\, \varepsilon$$

where y represents ton-kilometers transported, c represents capacity or available ton-kilometers, l represents labor, and f fuel consumed. The parameters to be estimated are a, α, β, and γ -- where the exponents, represent the output elasticities of each input. Finally ε is the error term representing statistical noise, which is assumed to follow a log-normal distribution.

Employing logarithms, (1) can be re-writen as

$$(2) \qquad \ln y = \ln a + \alpha \ln c + \beta \ln f + \gamma \ln l + \ln \varepsilon$$

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[5] For a review of this literature see Gallegos (1991)

As Heien (1968) notes, it is known from statistical distribution theory that if $\ln \varepsilon$ is normally distributed in (2), then ε is log-normally distributed in (1). This is the route we now follow to obtain access to classical statistical theory by assuming that $\ln \varepsilon$ is normally distributed. The usual, or ordinary, least squares approach was applied via (2) to the data recorded in columns (1) through (4) of Appendix A to obtain estimates of α, β, γ and a, with the results portrayed in column 1 of Table 1, where the following points stand-out:

- Positive and statistically significant values for capacity ($p < 0.001$) and labor ($p < 0.1$).
- The exponent for fuel in (2) is negative but not statistically significant.
- The constant a does not achieve statistical significance.
- A high R^2 is obtained, but
- A high condition number indicates the presence of collinearity.
- A low Durbin-Watson statistic indicates autocorrelation in the error term.[6]

Some of these results such as collinearity and autocorrelation are troublesome from a statistical standpoint. Others, like the negative value for fuel are troubling from an economic point of view in that lack of significance suggests $\gamma = 0$, which means that output is independent of the amount of fuel used. This is disturbing, to say the least, and the alternative of a negative gamma value would imply that output declines with fuel input, which would be even more disturbing.

For perspective and possible insight on what is happening, we next employ the following linear form,

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6 Since we are using a data set which combines cross sectional and time series data, the use of the Durbin-Watson statistic here is only indicative. Later in this chapter the Fuller and Batesse (1974) methods of estimation are employed to account for heteroscedasticity and autocorrelation.

TABLE 1
STOCHASTIC AND NOT STOCHASTIC MODELS
POOLED DATA 1981 - 1988

	WITHOUT EFFICIENCY ADJUSTMENTS			WITH EFFICIENCY ADJUSTMENTS	
TYPE OF PRODUCTION FUNCTION	(1) Cobb-Douglas OLS	(2) Linear OLS	(3) Cobb-Douglas GP	(4) Linear OLS	(5) Cobb-Douglas GP
Number of Observations	88	88	88 .	88	88
Parameters					
Constant a	1.28	12,452.00 *	0.162	- 1,221.3	1.644
Alpha (Capacity)	0.88***	0.52***	1.170	0.54***	0.689
Beta (Labor)	0.08*	5.28	- 0.110	7.24	0.145
Gamma (Fuel)	- 0.001	- 0.037***	- 0.029	0.38*	0.166
Returns to Scale	0.96		1.031		1.01
Regression Diagnostics					
R square	0.994	0.996		0.995	
Condition Number	110	18		17	
Durbin Watson	0.64	1.05		0.93	

*** statistically significant $p < 0.001$
** " " $p < 0.05$
* " " $p < 0.1$

$$(3) \qquad y = a + \alpha c + \beta l + \gamma f + \varepsilon,$$

and estimate its coefficients from the same data by OLS (ordinary least squares). This time, as shown in column 2 of Table 1, a positive and statistically significant value was found for capacity and a positive value for labor. Again, however, a negative value is found for fuel, and this time the situation is reversed. The labor coefficient does not attain statistical significance whereas the negative value estimated for the fuel coefficient in (3) is highly significant. The condition number and Durbin Watson statistic show an improvement, but this is not very reassuring given what was just said about the labor and fuel results. Finally, the very large intercept value shown for a in column 2 of Table 1, which is significant at less than $p=0.1$, suggests that the linear form is unsuitable since this intercept value implies an ability to deliver ton-kilometers of performance even when all inputs are zero.

We now turn to a mathematical (deterministic) approach along the lines of Aigner and Chu (1968) -- see also Farrell (1957) -- in order to explore whether the source of these troubles might lie in mixtures of efficient and inefficient behavior which are likely to be present in the interior points which these least squares regressions reflect. For this purpose we replace (1) with

$$(4) \qquad y_{it} = \frac{a\, c_{it}^{\alpha}\, l_{it}^{\beta}\, f_{it}^{\gamma}}{\delta_{it}}$$

and require $\delta_{it} \geq 1$ for all i and t so that $\ln \delta_{it} \geq 0$.

Note that δ_{it} can be regarded as the "distance" from any observation to the frontier. We have subscripted these δ_{it} values (which are to be estimated from the data in Appendix A). in a manner that will enable us to identify them with inefficiencies for each firm i in every period t relative to the industry production function that is obtained via our estimates of the parameters $A, \alpha, \beta,$ and γ, which are assumed to hold across all firms for the periods we are considering. Our objective is to obtain estimates

$$(5) \qquad \hat{y}_{it} = \hat{a}\, c_{it}^{\hat{\alpha}}\, l_{it}^{\hat{\beta}} f_{it}^{\hat{\gamma}}$$

which we can relate to the observations y_{it} via

$$(6) \qquad y_{it} = \frac{\hat{a}\, c_{it}^{\hat{\alpha}}\, l_{it}^{\hat{\beta}}\, f_{it}^{\hat{\gamma}}}{\hat{\delta}_{it}}$$

so that, with $\hat{\delta}_{it} \geq 1$, we will always have

$$(7) \qquad y_{it} \leq \hat{y}_{it}.$$

In other words, every estimate of $\hat{y}_{it}$ is to be at least as large as the corresponding observation, and thus, mathematically speaking, our estimates reflect the property of a production function -- viz, output is always maximal from every input combination utilized.[7]

For estimation purposes we apply a logarithmic transformation to (4) and obtain

$$(8) \qquad \ln y_{it} = \ln \hat{a} + \hat{\alpha} \ln c_{it} + \hat{\beta} \ln l_{it} + \hat{\gamma} \ln f_{it} - \ln \hat{\delta}_{it}$$

to represent the constraints which our estimates are to satisfy relative to these observations y_{it}. To determine these estimates we apply the following "goal programming" model to the data in appendix A.

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[7] See Chapter 1 in Rhodes (1978) for detailed discussions and reviews of the classical literature based on this definition of a production function as formalized in Samuelson (1947).

$$(9)\qquad \begin{aligned}&\min \sum_{i=1}^{n}\sum_{t=1}^{T} \ln \hat{\delta}_{it}\\ &\text{subject to:}\\ &\ln y_{it} = \ln \hat{a} + \hat{\alpha} \ln c_{it} + \hat{\beta} \ln l_{it} + \hat{\gamma} \ln f_{it} - \ln \hat{\delta}_{it}\\ &\ln \delta_{it} \geq 0, \quad i = 1, \ldots, n; \quad t = 1, \ldots, T\end{aligned}$$

This, it may be observed, yields a frontier function because only one-sided deviations are permitted via the condition $\ln \hat{\delta}_{it} \geq 0$ which is to be satisfied in each constraint.

As shown in Charnes, Cooper and Ferguson (1957), this problem of inequality constrained statistical estimation can be treated as an ordinary linear programming problem in order to obtain the desired coefficient estimates.[8] Interpreted in goal programming terms, the objective is to come "as close as possible" to all observations with $\ln \delta_{it} \geq 0$ ensuring that we will always have

$$(10)\qquad \ln y_{it} \leq \ln \hat{a}_t + \hat{\alpha} \ln c_{it} + \hat{\beta} \ln l_{it} + \hat{\gamma} \ln f_{it} = \ln \hat{y}_{it}$$

so that (7) is also satisfied by the estimates. In fact, via the constraints in (9),

$$(11)\qquad \ln y_{it} = \ln \hat{y}_{it} - \ln \hat{\delta}_{it}$$

and $\ln \hat{\delta}_{it} > 0$ is interpreted as an output shortfall associated with the observed y_{it}. That is, each such positive value is interpreted as an inefficiency in the output of firm i in period t relative to what it should have been able to obtain by reference to

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[8] In Charnes, Cooper and Sueyoshi (1988), this kind of goal programming formulation also extends to estimating simultaneous as well as single regression relations.

the industry production function which, under classical assumptions in economic theory, is hypothesized to be available to all firms in the industry.[9]

Via the inverse logarithmic transformation, $\ln \delta_{it} \geq 0$ gives

$$(12) \qquad \hat{\delta}_{it} y_{it} = \hat{y}_{it}$$

with strict inequality holding in (7) whenever $\hat{\delta}_{it} > 1$. Thus for the Cobb-Douglas functions, inefficiency, in natural units, is associated with $\hat{\delta}_{it} > 1$ in the performance of firm i in period t.

One purpose of our use of goal programming is to identify the presence of inefficiencies as a possible source of some of the troubles we have been encountering. Column 3 of Table 1 presents the results of this effort. Tests of statistical significance are not available for use with this approach and so none are reported. However, the estimates of the parameters for the industry production function are again unsatisfactory since the values of the exponents associated with labor and fuel are both negative.[10] We conclude that with all inefficiencies located in the output, this approach does not help to correct our troubles and so we turn next to the inputs.

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9 Cf. Sune Carlson (1956). An alternative interpretation of the industry production (and cost) functions, which is also classical, but allows for differences between firms, may be found in Sato (1975).

10 It would be possible to introduce constraints to eliminate the possibility of such negative values, but our purpose here is oriented more toward the use of these goal programming models to locate possible sources of the troubles encountered in our statistical regression approaches.

4. A DEA EFFICIENCY THEOREM

Data Envelopment Analysis, as introduced by Charnes, Cooper and Rhodes (1978), provides a means for identifying both input and output values which are technically inefficient and it also provides formulas for effecting projections to an efficient frontier in a manner that eliminates any technical inefficiencies that may be present. A variety of DEA models are available for this purpose but here we focus on the following which is called the linear programming equivalent of the CCR ratio form:

$$\min\ \theta \quad - \quad \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

subject to

$$\begin{aligned}
(13) \qquad \theta x_{i0} &= \sum_{j=1}^{n} x_{ij}\lambda_j \quad + s_i^-, & i &= 1, \dots, m \\
y_{r0} &= \sum_{r=1}^{n} y_{rj}\lambda_j \quad - s_r^+, & r &= 1, \dots, s \\
0 &\leq \lambda_j, s_i^-, s_r^+ \quad \forall\, i,j,r
\end{aligned}$$

Here the x_{ij} and y_{rj} are input and output values, respectively, for each of $j = 1, \dots, n$ DMUs (= Decision Making Units)-- viz., the organization entities responsible for transforming the observed amounts of $i = 1, \dots, m$ inputs into the observed amounts of $r = 1, \dots, s$ outputs. x_{i0} and y_{r0} represent the observations for one of these n DMUs, which is designated as DMU_0, and positioned in the objective of (13) to have the technical efficiency of its performance evaluated relative to the performance of all of the DMUs (including itself) which are represented in the constraints.

The following two requirements are necessary and sufficient for efficiency:

$$(14)\qquad \begin{aligned} \theta^* &= 1 \\ s_i^{-*} = s_r^{+*} &= 0 \quad \forall\ i, r \end{aligned}$$

where the symbol "*" designates an optimal value. These requirements are related to the projection formulas we use, called the "CCR projection formulas" (Charnes, Cooper, and Rhodes, 1978), which are represented as follows

$$(15)\qquad \begin{aligned} \theta^* x_{i0} - s_i^{-*} &= \sum_{j=1}^{n} x_{ij}\lambda_j^* = \hat{x}_{i0} \\ y_{r0} + s_r^{+*} &= \sum_{j=1}^{n} y_{rj}\lambda_j^* = \hat{y}_{r0} \end{aligned}$$

with $\hat{x}_{i0} \le x_{i0}$ and $\hat{y}_{r0} \ge y_{r0}$ for every i and r. Strict inequality for some i or r, implies an input excess or an output shortfall, and can occur only when the conditions (14) are not fulfilled. Furthermore, as proved in Charnes, Cooper and Rhodes (1978), the $\hat{x}_{i0}$ and $\hat{y}_{r0}$ obtained via (15) represent points on a facet of an efficient frontier. That is, $\hat{x}_{i0}$, $\hat{y}_{r0}$ represent points on the efficient frontier obtained via projections of the original DMU_0 data. Hence the name CCR projection formulas given to (15).

The possibility of alternate optima makes it important to ensure that the slacks and θ values in (14) are both really optimal. This is accomplished by means of the non-Archimedean constant $\varepsilon > 0$.[11] This "very small" positive constant is used to ensure that the sum of the slacks in (13) are maximized without influencing the

[11] The choice of ε for this non-Archimedian constant conforms to common usage in the DEA literature and should not be confused with the earlier use of ε for the error term in the statistical models we discussed, which conforms to common usage in this discipline.

minimizing choice of θ. That is,the minimization of θ is given "preemptive" status relative to the maximization of the sum of the slacks.[12]

This preemption and its associated optimization may be accomplished in a variety of ways. Because we are using the IDEAS (Integrated Data Envelopment Analysis) code of Iqbal Ali (Ali, 1990), we find it advantageous to treat ε via the two stage approach which he uses as follows. In stage 1 we replace (13) with the following (ordinary) linear programming problem:

$$
\begin{aligned}
&\min \theta \\
&\text{subject to} \\
(16)\qquad &\theta x_{i0} \geq \sum_{j=1}^{n} x_{ij}\lambda_j, \qquad i = 1, \dots, m \\
&y_{r0} \leq \sum_{j=1}^{n} y_{rj}\lambda_j, \qquad r = 1, \dots, s \\
&0 \leq \lambda_j, \qquad j = 1, \dots, n
\end{aligned}
$$

After securing an optimum $\theta = \theta^*$ for (16), a second stage optimization is undertaken in which the sum of the slacks is maximized or, equivalently, their negatives are minimized in the following problem:

---

12 See Charnes Cooper and Ijiri (1963) for further discussion of preemptive versus relative and absolute priorities.

$$
\begin{array}{llll}
 & \min & -\sum_{i=1}^{m} s_i^- - \sum_{r=1}^{s} s_r^+ & \\
 & \text{subject to} & & \\
 & 0 = & x_{i0}\theta - \sum_{j=1}^{n} x_{ij}\lambda_j - s_i^-, & i = 1, \dots, m \\
(17) & y_{r0} = & \sum_{j=1}^{n} y_{rj}\lambda_j \quad - s_r^+, & r = 1, \dots, s \\
 & -\theta^* = & -\theta & \\
 & 0 \leq & \lambda_j, s_i^-, s_r^+, \forall i, j, r &
\end{array}
$$

As should be evident, the sum of slacks is maximized in (17) without allowing any alteration in the value of $\theta^* = \theta$ obtained from (16) because the constant in this constraint is imposed as a condition to be satisfied by any solutions to (17). Ali (1990) uses the above formulation to obtain a single condition for efficiency to replace the two conditions in (14). This is accomplished by introducing the following problem which is dual to (17):

$$
\begin{array}{llll}
 & \max & \sum_{r=1}^{s} \nu_r y_{r0} \quad - \alpha\theta^* & \\
 & \text{subject to} & & \\
(18) & 0 \geq & \sum_{r=1}^{s} \nu_r y_{rj} - \sum_{i=1}^{m} \mu_i x_{ij}, & j = 1, \dots, n \\
 & 0 = & \sum_{i=1}^{m} \mu_i x_{i0} \quad - \alpha & \\
 & 1 \leq & \nu_r, & r = 1, \dots, s \\
 & 1 \leq & \mu_i, & i = 1, \dots, m
\end{array}
$$

Via the dual theorem of linear programming we can relate the optimum solutions of (17) and (18) via

$$(19) \qquad -\sum_{i=1}^{m} s_i^{-*} - \sum_{r=1}^{s} s_r^{+*} = \sum_{r=1}^{s} v_r^* y_{r0} - \alpha^* \theta^*$$

From the constraint associated with α in (18) we have

$$(20) \qquad \alpha^* = \sum_{i=1}^{m} \mu_i^* x_{i0}$$

Hence, dividing (19) by α^* and rearranging terms gives

$$(21) \qquad \theta^* - \frac{\sum_{i=1}^{m} s_i^{-*} + \sum_{r=1}^{s} s_r^{+*}}{\sum_{i=1}^{m} \mu_i^* x_{i0}} = \frac{\sum_{r=1}^{s} v_r^* y_{r0}}{\sum_{i=1}^{m} \mu_i^* x_{i0}}$$

The expression on the right in (21) is in the form of a generalization of the usual science-engineering output-to-input ratio form for calculating efficiencies. The term on the left, which Ali (1990) symbolizes as ι (= iota), gives rise to the following single condition for efficiency:

(22) $\quad DMU_0$ is efficient if and only if $\iota^* = 1$,

where ι^* is an optimal value of iota as given by the differences between the two terms on the left of (21).

One may use either (14) or (22) to characterize the efficiency of any DMU_o but it needs to be recognized that the optimal ι^* is classificatory. That is, $\iota^* < 1$ means that DMU_o is not efficient, but the numerical value of this ι^* does not specify an amount of inefficiency that can be locate in any particular output or input. On the other hand the component values, as given in (14), may be used for this purpose as in (15) to obtain estimates of the amounts of inefficiency in each input and output via

$$(23)\qquad \begin{aligned} \Delta\hat{x}_{io} &= \theta^* x_{io} - \hat{x}_{io} \geq 0, & i &= 1, \ldots, m \\ \Delta\hat{y}_{ro} &= \hat{y}_{ro} - y_{ro} \geq 0, & r &= 1, \ldots, s. \end{aligned}$$

so that, alternately, $\Delta\hat{x}_{io} = s_i^{-*}$ and $\Delta\hat{y}_{ro} = s_r^{+*}$.

We wish to make use of the efficiency adjustments as represented in (23) for the further regression studies we will undertake in the next section. For this purpose we introduce the following theorem for use with the above models:

Theorem: At least one $\Delta\hat{x}_{io} = 0$ and at least one $\Delta\hat{y}_{ro} = 0$ in any optimum.

Proof: it will suffice to work with (16) and assume that we have an optimum solution so that

$$\begin{aligned} \theta^* x_{io} &\geq \sum_{j=1}^{n} x_{ij}\lambda_j^*, & i &= 1, \ldots, m \\ y_{ro} &\leq \sum_{j=1}^{n} y_{rj}\lambda_j^*, & r &= 1, \ldots, s \\ 0 &\leq \lambda_j^*, & j &= 1, \ldots, n \end{aligned}$$

Because $y_{ro} > 0$, all r, we must have some $\lambda_j^* > 0$. It is obvious that

$$\theta^* x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j^*$$

for at least one $i = 1, \ldots, m$. Similarly, we must have

$$y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j^*$$

for at least one $r = 1, \dots, s$. For suppose, on the contrary, that we could have

$$y_{r0} < \sum_{j=1}^{n} y_{rj}\lambda_j^*, \qquad r = 1, \dots, s.$$

But then we could choose a factor $0 < k < 1$ and obtain

$$y_{r0} \leq \sum_{j=1}^{n} y_{rj}\lambda_j^* k < \sum_{j=1}^{n} y_{rj}\lambda_j^*, \qquad r = 1, \dots, s$$
$$\theta^* x_{i0} \geq \sum_{j=1}^{n} x_{ij}\lambda_j^* > \sum_{j=1}^{n} x_{ij}\lambda_j^* k, \qquad i = 1, \dots, m$$

with strict inequality obtainable in all of the last $i = 1, \dots, m$ of these expressions because all terms are positive and the functions are continuous. It follows that we could then choose a new $\hat{\theta} < \theta^*$ such that

$$\hat{\theta} x_{i0} \geq \sum_{j=1}^{n} x_{ij}\lambda_j^* k, \qquad i = 1, \dots, n$$
$$y_{r0} \leq \sum_{j=1}^{n} y_{rj}\lambda_j^* k, \qquad r = 1, \dots, s$$

and hence θ^* could not have been minimal. Q.E.D. In fact, we can operationalize this by choosing

$$k = \max \left\{ \frac{y_{r0}}{\sum_{j=1}^{n} y_{rj}\lambda_j^*}, r = 1, \dots, s \right\}$$

which is permissible since $0 < y_{r0} < \sum^{n} y_{ij}\lambda_j^* \forall r$. With this choice we will have at least one of the output constraints satisfied as an equation. Hence we have proved that at least one $\Delta \hat{x}_{i0} = 0$ and at least one $\Delta \hat{y}_{r0} = 0$ in any optimum.

As a corollary to this theorem in the single output case we must always be on an efficient frontier with all output inefficiencies eliminated -- e.g., via the CCR projection in (15). In the next section we will therefore be able to concentrate on input inefficiencies which are the only kind of inefficiencies that can occur in the single output case. We can conclude this section by observing that the choice of λ values envelops DMU_0's input data from below, as is evident from the full collection of $i = 1, \dots, m$ constraints in (16), and its output data are enveloped from above. According to our theorem there is also a touching of these data from above and below, and this is also in the manner of an envelope, and hence justifies the name Data Envelopment Analysis given in Charnes, Cooper and Rhodes (1978).

5. DEA EFFICIENCY ADJUSTMENTS

We now employ the above DEA theorem, which in the single output case may be called the "no output inefficiency theorem," to obtain adjustments for use in a new approach to parametric regression estimation that will incorporate considerations of economic theory in our input choices. We then relate this approach to statistical principles that underpin the classical regression approaches we use.

Using the CCR model for DEA discussed in the preceding section, we obtain estimates of the inputs of labor, fuel, and ton-kilometers of capacity "required" to obtain the observed outputs that are recorded in column 1 of the appendix. These values, as recorded in columns 5, 6, and 7 of the table in the appendix, represent the input amounts required to obtain the observed outputs under efficient operations. In row 1, for example, which corresponds to Aeroméxico in 1981, only 9,036 personnel of all kind would have been used in place of the reported 10,532 persons if operations were at their DEA efficiency values. Similarly $32,505,000 of fuel and 999,930 ton-kilometers of capacity would replace the reported values of $36,264,00 for fuel and 1,111,570 ton kilometers of capacity (= capital) reported. No adjustment needs to be made for the observed output, viz., 661,213 ton-kilometers flown by AeroMéxico in this period since, by our "no output inefficiency theorem," this value will lie on the efficiency frontier associated with the thus adjusted inputs.

Replacing the observed inputs for all airlines by their efficiency adjusted values produces the new regression estimates noted in columns 4 and 5 of Table 1. As can be seen, satisfactory results appear both for the linear regression, using ordinary least squares, and a Cobb-Douglas form of production function with estimates obtained from the goal programming approach discussed in association with (4) ff. in section 4, above. Indeed, allowing for the fact that the intercept value is not significantly different from zero, the linear function intersects the origin as required in the classical economic theory of production.[13]

In the developments that are usual in economics, the achievement of technical efficiency is usually assumed to have been attained as a preliminary condition to examining other efficiencies such as efficiencies of scale, efficiencies of scope and allocative efficiency -- which are generally the topics of interest. Hence our approach conforms to the postulates of economics and it is conformance with these postulates that produces results which are also in conformance with what is to be expected in the behavior that is of economic interest.

To carry this analysis further, we go back to the Cobb-Douglas production function stipulated in (1) and reestimate it under a variety of approaches. In Table 2, column 1 simply recapitulates column 1 from Table 1 with the unsatis-

---

[13] Cf. Shephard (1970) for axioms. Koopmans (1951) refers to the zero intercept condition as the "Land of Cockaigne Impossibility Axiom" in the classical theory of production -- viz., zero amounts of all inputs result in zero output.

factory results we discussed earlier in the chapter. Column 2 records the parameter values secured after reestimating (1) to obtain the results shown in the "Combined DEA-SF" column which uses efficiency-adjusted input values. Since these estimates are secured via ordinary least squares we also use the corresponding statistical theory to note that the elimination of input inefficiencies yields parameter values which are all satisfactory and brings them into statistical significance ($p < 0.001$).

Our approach uses all of the data after effecting adjustments to obtain the efficient input amounts recorded in columns 5, 6 and 7 of the Appendix. This, however, is not the only way to deal with contaminations emanating from inefficiencies contained in the observed data. Thiry and Tulkens (1990), for example, follow Farrel (1957) to suggest an alternate approach in which all of the inefficient observations are discarded. Under this approach, the efficient carriers are first identified using a DEA-like method (as indicated by the "*" alongside the airline name and year in the tabulations included in the Appendix. The observations corresponding to inefficient carriers are then discarded. A "free of inefficiencies" production function is then obtained by employing only the efficient observations.

Following this approach, as suggested by Thiry and Tulkens, we employed ordinary least squares to obtain the estimates located under the column headed "Best Practice Frontier" in column 3 of Table 2. The results are not wholly satisfactory since, once more, the exponent associated with fuel consumption fails to achieve significance, and this may be occurring because of the reduced number of observations, from 88 to 30, that occurs when this method is used.

Finally, we have used the complement of the Thiry and Tulkens (1990) approach by using the ($58 = 88 - 30$) non-starred observations in the appendix to obtain what might be called an "Off-Frontier" (i.e., off-the-efficiency frontier) production function. As might be expected, the results which are shown in column (4)

TABLE 2
RESULTS FOR THE COBB-DOUGLASS MODEL
POOLED DATA 1981-1988

TYPE OF PRODUCTION FUNCTION	(1) Neoclassical Average Production Function	(2) Combined DEA-Stochastic Frontier	(3) Best Practice Frontier	(4) Off-Frontier Average Production Function
Number of Observ.	88	88	30	58
Parameters				
Constant a	1.28	1.78**	2.18**	0.57
	(1.28)	(1.20)		
Alpha (Capacity)	0.88***	0.75***	0.76***	0.97***
	(0.04)	(0.03)	(0.05)	(0.06)
Beta (Labor)	0.08*	0.16***	0.14***	0.04
	(0.03)	(0.02)	(0.04)	(0.05)
Gamma (Fuel)	- 0.001	0.09***	0.06	- 0.01
	(0.02)	(0.02)	(0.05)	(0.02)
Regression Diagnostics				
R square	0.996	0.996	0.993	0.997***
Condition Number	110	110	82	179
Durbin-Watson	0.64	0.87	1.05	0.80
Returns to Scale	0.96	1.00***	0.96	1.03
Ratios of Parameters				
Capacity/Labor	11.0	4.68	5.42	n.m.
Fuel/Labor	n.m.	0.56	n.m.	n.m.
Capacity/Fuel	n.m.	8.33	n.m.	n.m.

Number in ( ) indicates standard error
*** statistically significant $p < 0.001$
** " " $p < 0.05$
* " " $p < 0.1$
n.m.: not meaningful

of Table 2 are even less satisfactory than the results obtained in any of the other cases thereby suggesting that it is the mixture of efficient and inefficient observations that is a source of the troubles located in column 1 of Table 2.

Having already noted that our adjustments coincide with what is customarily postulated with respect to technical efficiency in economic theory, we next turn to the assumptions underlying the classical OLS regression approaches we have been using. Here, too, we can obtain support by noting that the independent variables -- i.e., the inputs -- are assumed to be free of error. Following R.A. Fisher (1922), the originator of this approach, the statistical errors are in the dependent variable. Stating this differently, the independent variables are to be chosen by the experimenter with all statistical errors located only in the dependent variable -- which in our case is represented by the output values. In this classical approach to statistical regression and experimental design the objective is to identify possible "causal" relations between these output values and the thus selected input values. In this way, as Fisher among others emphasized, it becomes possible to separate these causal relations from the statistical variations that generally accompany the kind of (controlled) experiments with which Fisher was concerned at the Rothamstead Agricultural Experimental Station in England.

Generally speaking social and management scientists do not have access to the experimental controls that formed the context in which Fisher developed these methods of regression estimation and testing. This has led to a variety of attempts to resolve these problems steming from applying experimental sciences' tools to non-experimental sciences, such as economics.[14] Here we have added a new alternative in which the data are adjusted to conform to the assumptions of production theory in economics.

It is pertinent now to discuss the use to be made of these estimates. The approach we are suggesting differs from the one used by Fisher (and his followers). In their case the choices were to be made from the input (= independent variables)

---

[14] Cf. e.g., C. Manski (1991) for a report on some of the developments in recent years.

side in conformance with the notions of causality and prediction which are of central interest to them. In conformance with the usual practices in management, however, we proceed in an opposite manner and effect our choices from the output side. That is, we select an output value -- or more precisely, an expected output -- and then designate the inputs to be used in securing this output. This leads to what we may refer to as a "control model" in order to distinguish it from the kind of "causal model" which formed the center of attention for Fisher and his followers. Issues such as collinearity are then of less concern than might otherwise be the case since, as is evident in Table 2, the values recorded for the condition numbers, and the Durbin-Watson statistic, indicate that collinearity and serial correlation are probably both present.

We return to this topic later in the paper. Here, however, we introduce Figure 1 to help clarify what we are suggesting and also to help tie things together. Consider a situation where we have 3 DMUs --which we associate with the coordinates of points P1, P2 and P3 in Figure 1. Our interest centers on the DEA evaluation of P2, with its respective input and output coordinates (2,1) relative to the corresponding inputs and outputs for P1 = (1,2) and P3 = (2,3). Applying (16) to these data produces

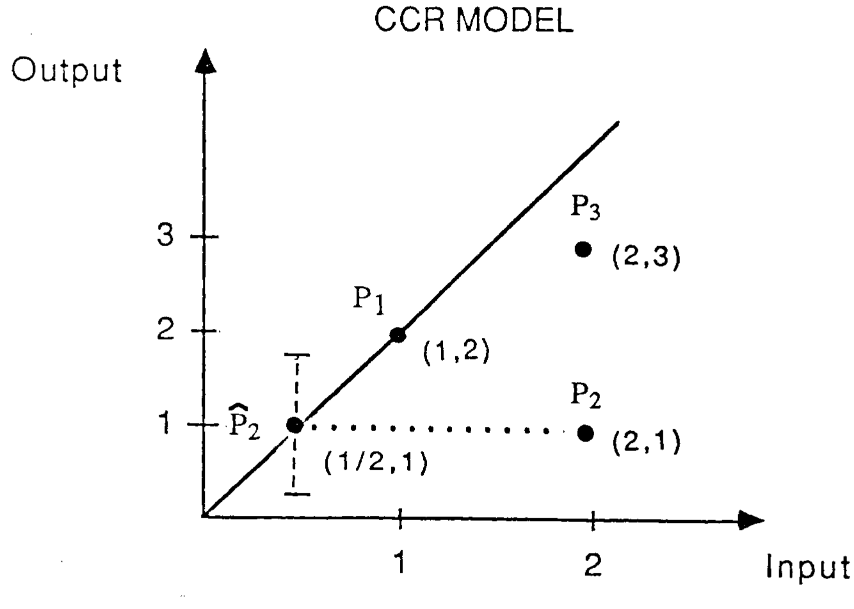
$$
\begin{aligned}
&\min \theta \\
&\text{subject to} \\
(24)\qquad &2\theta \geq 1\lambda_1 + 2\lambda_2 + 2\lambda_3 \\
&1 \;\leq 2\lambda_1 + 1\lambda_2 + 3\lambda_3 \\
&0 \;\leq \lambda_1, \lambda_2, \lambda_3
\end{aligned}
$$

which has an optimum with $\theta^* = 1/4$, $\lambda_1^* = 1/2$, and $\lambda_2^* = \lambda_3^* = 0$

Geometrically DMU 2 (= P2) which turns out to be inefficient at (2,1) is projected to the point (1/2, 1) which we associate with $\hat{P}_2$ at the intersection of the horizontal dotted line from (2,1) to the solid line from the origin through P1 = (1,2).

This solid line represents the portion of the DEA efficiency frontier that is relevant to the input decision needed to achieve the one unit of output we plan to make. That is, assuming that we are planning to obtain --i.e., expect to obtain -- one unit of output, we designate 1/2 unit of input for this planned output value. This input amount is controlled, i.e., its value is designated without statistical error. On the other hand, when production is undertaken we need to allow for statistical error in the output we will secure, and this is indicated by the brace which we use to represent the corresponding confidence interval limits for the vertical broken line above and below (1/2,1) -- with whatever confidence level we (or management) may select for this purpose. Just as we invoke the theory of hypothesis testing associated with our use of classical regression approaches, we also invoke the theory of estimation (including confidence intervals) that it also provides.

Figure 1
DEA EFFICIENCY PROJECTION
CCR MODEL



This statistical usage of our results conforms to what is sensible for a management approach --viz., inputs are selected to accord with expected outputs. In conformance with economic theory these inputs are required to be "technically efficient" input choices. Since these choices are at the disposal of the experimenter, as independent variables, the results are also in conformance with the canons of classical regression theory. We have not tampered with the output values where the statistical errors are to be found. Hence we also have access to the vast body of literature which has been developed for use when these canons are satisfied.

The topic of relations with classical regression theory is treated in more detail below in section 7. In the next section we will examine what is required to extend (or qualify) these DEA/SF combinations. Here we conclude by observing that Figure 1 refers to the case of a single output and a single input. Hence the input choice is unique. That is, in this case the choice of an output value on the efficiency frontier will uniquely designate a corresponding (efficient) input since the efficient frontier is monotonic and strictly increasing. However, this situation will not obtain when more than one input is to be selected. In such cases our point-to-point mapping gives way to a mapping into an entire isoquant, which is associated with all input combinations that can produce the desired output (= expected output) in a technically efficient manner. In such cases input prices, or some similar criterion of choice, must be invoked to attain a unique combination of inputs. We do not examine this topic in further detail, however, because we want to proceed to other matters which also need to be attended to in order to put our developments in better perspective.[15]

[15] See, e.g., Charnes, Cooper and Rhodes 91978) for a discussion of how this can be done.

Remark: As introduced by Charnes, Cooper and Rhodes (1978), DEA models admit of an input orientation and an output orientation.[16] Although different projections are thereby secured the results concerning whether performance is efficient or inefficient are the same. To clarify what this means we return to (16) which has an input orientation and replace it by the following which has an output orientation.

$$
\begin{aligned}
&\max \quad \psi \\
&\text{subject to} \\
(25) \qquad &\psi y_{r0} \leq \sum_{j=1}^{n} y_{rj}\lambda'_{j}, \qquad && r = 1, \ldots, s \\
&x_{i0} \geq \sum_{j=1}^{n} x_{ij}\lambda'_{j}, && i = 1, \ldots, n \\
&0 \leq \quad \lambda'_{j}, && j = 1, \ldots, n
\end{aligned}
$$

The optimal values of (16) and (25) are related as follows:

$$
(26) \qquad \psi^* = 1/\theta^*, \quad \lambda'^*_j/\theta^*, \quad \text{where } j = 1, \ldots, n
$$

with $\psi^* > 1$ when $\theta^* < 1$ but the conditions for efficiency are the same as in (14) when $\theta^* = \psi^* = 1$.

Although the efficiency characterizations are the same, the non-zero slack values associated with (25) will differ and the projection will be oriented toward maximizing output rather than minimizing input. The projections parallel to the input axis as in Figure 1 will be replaced by projections parallel to the output axis. As in the input orientation case, we will have no output efficiency in the single

[16] Input and output orientations have been developed for the CCR and the BCC models. See Banker, Charnes, Cooper, Swats and Thomas (1989) for a recent treatment of these topics.

output case but this may be accompanied with non-zero slacks with some inputs so that, again, input adjustments will be needed to achieve 100% efficiency.

Keeping this all in mind for reorientation when wanted, we will simplify matters by focussing on the input oriented case which was used in developing our no-output efficiency theorem. It is easy to go from one orientation to the other via (26) and so this is how we will continue to proceed.

6. CCR AND BCC MODEL COMPARISONS

The theorem we proved in the preceding section played a critical role in the approach we developed for estimating our parametric frontier production functions. As we indicated, the use of this new approach involves a reorientation from a causal to a control point of view in that the choice of the input values depends on the output -- or rather the expected output value -- that is desired. This reverses the reasoning in the customary causal approaches to statistical regressions. There is more than our mathematical development to justify this, however, since input efficiencies cannot be determined without reference to the output values with which they are to be associated. Hence the notion of efficiency itself requires us to proceed from output to input choices, as we have just done.

Unfortunately our theorem does not provide this same clear access in the case of multiple output and inputs. Indeed, it does not extend beyond the CCR DEA model which was used in the previous section. Thus, going from the CCR to the BCC model[17] -- viz.,

---

[17] As given in Banker, Charnes and Cooper, (1984) and Banker, (1984)

$$
(27)\quad
\begin{array}{llll}
\min & \theta & & \\
\text{subject to} & & & \\
0 & \leq \theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j, & & i = 1, \ldots, \\
y_{r0} \leq & \sum_{j=1}^{n} y_{rj}\lambda_j, & & r = 1 \ldots n \\
1 = & \sum_{j=1}^{n} \lambda_j & & \\
0 \leq & \lambda_j, & & j = 1, \ldots, n
\end{array}
$$

brings the applicability of the theorem into question. For, using the same data as in Figure 1 the following simple example suffices to show that the theorem fails to hold even in the case of one output and one input when the CCR model of (24) is replaced by the BCC model of (27):

$$
(28)\quad
\begin{array}{ll}
\min \theta & \\
\text{subject to} & \\
0 \leq 2\theta - 1\lambda_1 - 2\lambda_2 - 2\lambda_3 & \\
1 \leq \quad 2\lambda_1 - 1\lambda_2 - 3\lambda_3 & \\
1 = \quad \lambda_1 + \lambda_2 + \lambda_3 & \\
0 \leq \quad \lambda_1, \lambda_2, \lambda_3. &
\end{array}
$$

Here the optimum solution is $\theta^* = 1/2$, $\lambda_1^* = 1$ and $\lambda_2^* = \lambda_3^* = 0$. This evidently differs from the optimum solution secured from these same data in (24). The convexity condition associated with $1 = \lambda_1 + \lambda_2 + \lambda_3$ in (28) is the source of the difference. More importantly, this solution with $\lambda_1^* = 1$ gives $1 < 2\lambda_1^*$ so that a touching on the output side fails to materialize.

To clarify what is happening Figure 2 portrays the same 3 DMU situation as Figure 1. Unlike the CCR projection depicted in Figure 1, the BCC projection in Figure 2 does not bring the inefficient point P2 to the efficiency frontier by making only an input adjustment. The adjustment obtained from the optimum solution with $\theta^* = 1/2$ brings the input value only to the point (1,1). This point is on a portion of the frontier that is not efficient. Thus this shrinkage in input must be accompanied by an output expansion of one unit in order to reach the efficiency frontier at (1,2).

We can obtain further insight employing the following pair of dual linear programming problems to evaluate DMU P3, with coordinates (2,3), in Figure 2.

$$
\begin{array}{llll}
 & \min \theta & & \max 3v + \omega \\
 & \text{subject to} & & \text{subject to} \\
(29) & 0 \leq 2\theta - \lambda_1 - 2\lambda_2 - 2\lambda_3 & & 1 = 2\mu \\
 & 3 \leq \quad 2\lambda_1 + 1\lambda_2 + 3\lambda_3 & & 0 \geq \ -\mu + 2v + \omega_0 \\
 & 1 = \quad \lambda_1 + \lambda_2 + \lambda_3 & & 0 \geq -2\mu + v + \omega_0 \\
 & 0 \leq \quad \lambda_1, \lambda_2, \lambda_3. & & 0 \geq -2\mu + 3v + \omega_0 \\
 & & & 0 \leq \ \mu, v.
\end{array}
$$

With θ and ω otherwise unconstrained, the optimal solutions are

$$
\begin{array}{llll}
(30) & \theta^* = 1, \quad \lambda_3^* = 1 & & \mu^* = 1/2, v^* = 1/2 \\
 & \lambda_1^* = \lambda_2^* = 0 & & \omega^* = -1/2
\end{array}
$$

as is readily verified from the dual theorem of linear programming, viz.,

$$
(31) \qquad \theta^* = 1 = 3/2 - 1/2 = 2v^* + \omega^*
$$

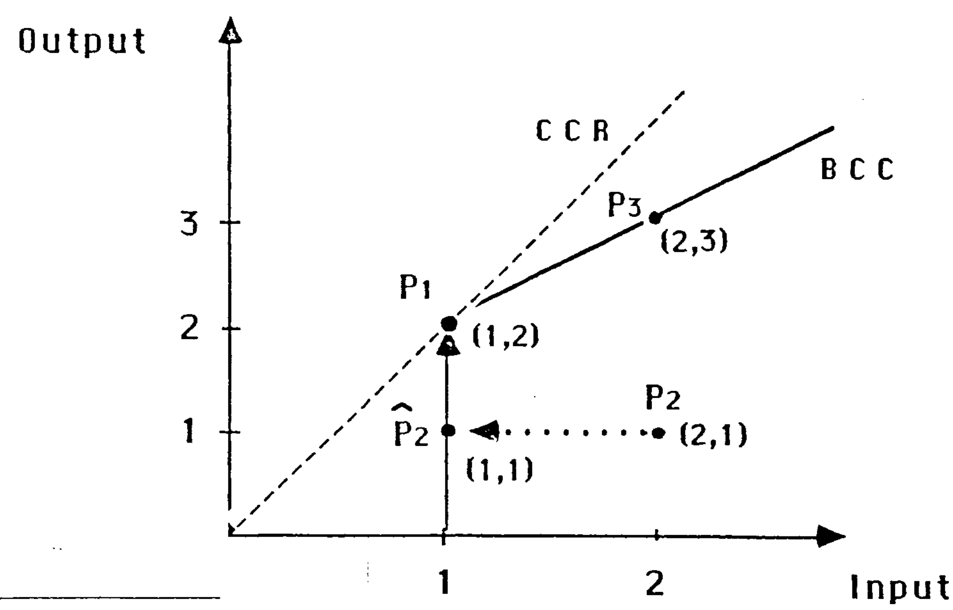
which shows this DMU to be efficient. The CCR optimum for P3, however, is

$$(32)\qquad \begin{array}{l} \theta^* = 3/4,\ \lambda_1^* = 3/2\ \omega^* = 1/2 \\ \lambda_2^* = \lambda_3^* = 0\ v^* = 1/4 \end{array}$$

which rates this DMU_0 as inefficient by reference to the CCR model -- which does not require satisfaction of the convexity condition in the left hand problem of (29) and does not contain the extra variable ω in the problem on the right.[18]

The value $\omega^* = -1/2 < 0$ in (30), identifies this point, viz. P3=(2,3), as being on a segment of the frontier which exhibits locally decreasing returns in the BCC model, whereas the CCR model exhibits constant returns to scale.

Figure 2
DEA EFFICIENCY PROJECTION
BCC MODEL



[18] See Ahn, Charnes, and Cooper (1988), for a study of mathematical relations between DEA models.

For perspective on what is occurring we focus on the sign of the optimal value of ω^* and summarize the information on "returns to scale" which it provides as follows:[19]

1. Locally increasing returns to scale prevail if and only if $\omega^* > 0$ in all alternate optima.
2. Locally decreasing returns to scale prevail if and only if $\omega^* < 0$ in all alternate optima.
3. Locally constant returns to scale prevail if $\omega^* = 0$ in any optimum.

For the single output case, $s^* > 0$ -- i.e., non-zero output slack -- can occur only if $\omega^* > 0$, which is the case of locally increasing returns to scale. To see that this is so consider the following dual BCC pair:

$$
\begin{array}{llll}
 & \min \theta - \varepsilon\left(\sum_{i=1}^{m}\delta_i + s\right) & & \max vy_0 + \omega \\
 & \text{subject to} & & \text{subject to} \\
 & 0 = \theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j - \delta_i & & 0 \geq vy_j - \sum_{i=1}^{m} \mu_i x_{ij} + \omega \\
(33) & y_0 = \sum_{j=1}^{n} y_j\lambda_j - s & & 1 = \sum_{i=1}^{m} \mu_i x_{i0} \\
 & 1 = \sum_{j=1}^{n} \lambda_j & & \varepsilon \leq v \\
 & 0 \leq \lambda_j, \delta_i, s. & & \varepsilon \leq \mu_i,
\end{array}
$$

with $j = 1, \ldots, n$; $i = 1, \ldots, m$. At an optimum we have:

$$
(34) \qquad \theta^* - \varepsilon\left(\sum_{i=1}^{m}\delta_i^* + s^*\right) = v^* y_0 + \omega^*
$$

[19] Taken from R. Banker and R. M. Thrall (1991).

If $s^* > 0$ we will have $v^* = \varepsilon$. However, $1 = \sum_{j=1}^{n} \lambda_j^*$ and $x_{ij} > 0$ all i and j, implies $\theta^* > 0$ which is a real number. Thus we must have $\omega^* > 0$ since no multiple of $v^* = \varepsilon$ can equal a positive real number. This constitutes a proof of the following theorem which we complete by using the Extended Theorem of the Alternative, as given in Charnes and Cooper (1961) --[20] which asserts that we can have $\sum_{j=1}^{n} y_j \lambda_j^* > y_0$ in some optimum solution if and only if $v^* = \varepsilon$ in every optimal solution.

We formalize this all in the following

Theorem: For the single output case, an optimum with $s^* > 0$ implies locally increasing returns to scale with

$$(35) \qquad \omega^* = \theta^* - \varepsilon\left(\sum_{i=1}^{m} \delta_i^* + s^*\right) - v^* y_0$$

and

$$(36) \qquad re(\omega^*) = \theta^* > 0,$$

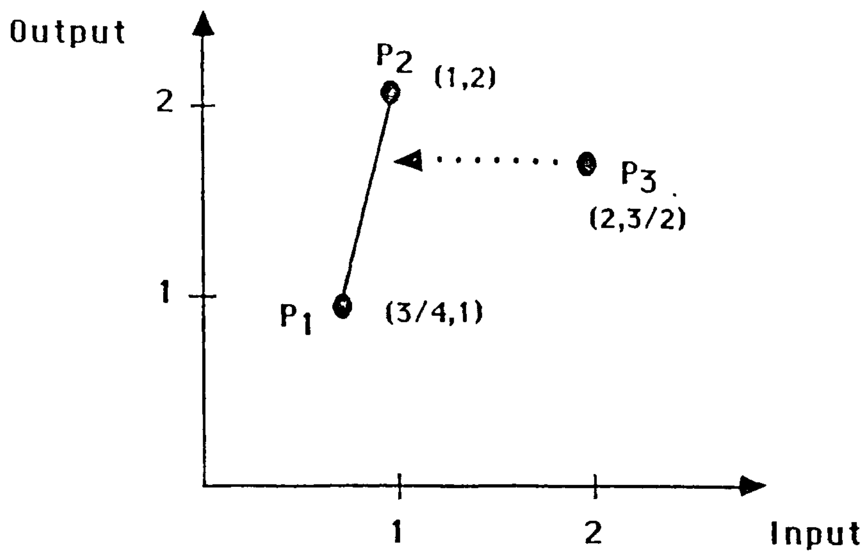
where $re(\omega^*)$ refers to the real part of ω^*. It follows from (35) that we must have $\omega^* > 0$ in (33) when $s^* > 0$.

The converse of this theorem is not true, however, since the presence of locally increasing returns need not imply $s^* > 0$. This is shown via the following dual BCC pair formed in accordance with (33) to evaluate P3 as portrayed in Figure 3.

---

[20] See Charnes and Cooper (1961), p. 441. The Extended Theorem of the Alternative is also called the SCSC (Strong Complementary Slackness Condition) as in Charnes, Cooper and Thrall "A Structure for Classifying and Characterizing Inefficiency in Data Envelopment Analysis," Journal of Productivity Analysis, (forthcoming).

Figure 3
BCC PROJECTION TO INCREASING
RETURNS EFFICIENCY FRONTIER



$$
\begin{array}{llcl}
 & \min \ \theta - \varepsilon\delta - \varepsilon s & \qquad & \max \ \ 3/2\nu + \omega \\
 & \text{subject to} & & \text{subject to} \\
 & 0 \ \leq 2\theta - 3/4\lambda_1 - \lambda_2 - 2\lambda_3 - \delta & & 1 = \ 2\mu \\
(37) & 3/2 = \qquad \lambda_1 + 2\lambda_2 + 3/2\lambda_3 - s & & 0 \geq -3/4\mu + \ \nu + \omega \\
 & 1 \ = \qquad \lambda_1 + \ \lambda_2 + \ \ \lambda_3 & & 0 \ \geq \ -\mu + \ 2\nu + \omega \\
 & 0 \ \leq \ \ \lambda_1, \lambda_2, \lambda_3 & & 0 \geq \ -2\mu + 3/2\nu + \omega \\
 & & & \varepsilon \leq \ \ \mu \\
 & & & \varepsilon \leq \qquad \nu
\end{array}
$$

The solutions to this dual pair are

$\theta^* = 7/16,\ \lambda_1^* = \lambda_2^* = 1/2$ $\qquad$ $3/2v^* + \omega^* = 7/16$

$\lambda_3^* = \delta^* = s^* = 0$ $\qquad$ $\mu^* = 1/2,\ v^* = 1/8,\ \omega^* = 1/4$

Thus, as this example shows, we must still rely on the ω^* values as given in (32) for returns to scale characterizations even in the single output case since $s^* > 0$ is sufficient but not necessary to show that locally increasing returns to scale are present.

A use of the BCC model of DEA for effecting efficiency adjustments evidently merits further attention when increasing returns to scale possibilities are present. We examine this topic further after first sharpening our interpretations and the corresponding uses we make of statistical theory and methods.

7. RELATIONS TO STATISTICAL THEORY

To start, we note that we have already observed that we are conforming to the customary assumption of economic theory that technical efficiency is always attained. In practice we are adjusting the reported inputs to their efficiency values as determined via DEA. Our interpretation is that the quantities actually used need not conform to the reported value of any input when the former (i.e. the amount actually used in productive effort) is less than the latter. Airline personnel employed and personnel actually used in productive effort can differ in this manner,for instance, and so can fuel and aircraft capacity.

Turning from economics to our statistical usages we follow the now widely used treatment first given on pp 54 ff. in Kempthorne (1952) and write our regression relations in the form

$$(38) \qquad y = X\beta + \varepsilon$$

where X, called the "design matrix," is an $n \times p$ collection of values of the independent variables used to generate y, an $n \times 1$ vector of observed values which are related to X via the p parameters represented in the $p \times 1$ vector, β. Finally, ε is an $n \times 1$ vector of error terms with components associated with the observed values, y, and <u>not</u> the design variables as represented by the chosen values represented in X[21]

To obtain estimates $\hat{\beta}$ of the parameters β, it is assumed that the components of ε, which we denote as ε_i are independently distributed around a mean of zero with variance σ^2. The least squares estimators are then obtained via

$$(39) \qquad S\hat{\beta} = X^T y$$

where X^T is the transpose of X and $S = X^T X$, which is symmetric. If S is nonsingular, we have

$$(40) \qquad E\hat{\beta} = E(S^{-1}S\beta + S^{-1}X^T\varepsilon) = \beta$$

where E symbolizes "expected value" and $ES^{-1}X^T\varepsilon = S^{-1}X^T E\varepsilon = 0$ since $E\varepsilon_i = 0, i = 1, \dots, n$ by the assumptions we associated with (38).

---

[21] As noted earlier we are here using ε in the sense of statistical error when referring to the statistics literature and as a non-Archimedean constant when referring to the DEA literature.

Via (38) we have our least squares values $\hat{\beta}$ as unbiased estimators of β Using * to denote efficiency values, we replace (38) by

$$(41) \qquad y = X^*\beta^* + \varepsilon$$

where X^* is our new design matrix with $X^* \leq X$ and the parameters in the vector β^* are associated with the efficient input-output relations. We now derive our new estimators $\hat{\beta}^*$ by applying least squares theory in the same manner as before, and obtain

$$(42) \qquad E\hat{\beta}^* = \beta^*$$

so that these estimators are also unbiased since, again, $ES^{*-1}X^{*T}\varepsilon = S^{*-1}X^{*T}E\varepsilon = 0$ because our adjustments are only on X and not on y or its associated errors ε.

Proceeding on the assumptions we have previously made, the covariance matrix associated with the estimators in (41) can be represented

$$(43) \qquad E(\hat{\beta} - \beta)(\hat{\beta} - \beta)^T = \sigma^2 S^{-1}$$

where σ^2 is the variance (assumed finite) of ε For our corresponding efficiency adjusted estimators $\hat{\beta}^*$ we have

$$(44) \qquad E(\hat{\beta}^* - \beta^*)(\hat{\beta}^* - \beta^*)^T = \sigma^2 S^{*-1}.$$

In short, σ^2 remains unaffected but the inverse S^{*-1} replaces S^{-1}.

We have not been able to establish relations of the form $S^{*-1} \leq S$ or $S^{*-1} \geq S$ which hold generally via the relation $S^* \leq S$. In the case where S^* and S are diagonal, or brought into diagonal form, e.g., via the use of Cochram's theorem in statistics,[22] we have

$$(47) \qquad S^{*-1} \geq S^{-1}$$

For $S^* \leq S$ means that the elements $s_{ii}^* \leq s_{ii}$, which are "all positive," and this implies that $1/s_{ii} \leq 1/s_{ii}^*$ all i and this establishes (47) when the matrices S and S^* are diagonal. In this case, which is of interest for its bearing on homoscedasticity, the substitution in (42) and (47) shows that the error estimates associated with $\hat{\beta}^*$ are at least as large as the error estimates associated with $\hat{\beta}$.

In any case we have a new class of estimators $\hat{\beta}^*$ which have the usual property of being BLUE (Best Linear Unbiased Estimators), under the usual "Gauss- Laplace-Markov" Conditions.[23] To obtain the usual tests of significance relative to hypothesized values β_0 we similarly replace

$$(48) \qquad (y - X\beta_0)^T(y - X\beta_0) = (\hat{\beta} - \beta_0)S(\hat{\beta} - \beta_0)$$

with

$$(49) \qquad (y - X\beta_0^*)^T(y - \beta_0^*) = (\hat{\beta}^* - \beta_0^*)S^*(\hat{\beta}^* - \beta^{0*})$$

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[22] See Kempthorne (1956), p. 57 ff.

[23] See Kempthorne (1952), p. 56 ff.

Here have replaced β_0 with β_0^* as the hypothesized values on the supposition that we are interested in the parameters associated with efficient production. We have thus responded to Varian (1990, p.126), who we cited earlier as arguing that "What matters for most purposes in economics is not whether a violation of an optimizing model is statistically significant but whether it is economically significant." And we have also responded to Afriat by showint that we can produce results which have economic meaning while adhering to classical least squares priciples and methods in statistics.

8.DEA/STOCHASTIC FRONTIER AND THE GENERALIZED LINEAR REGRESSION MODEL

So far we have been working with the ordinary least squares regression model which is based on somewhat restrictive assumptions regarding the error terms. In this section we will reestimate our results employing the Generalized Linear Regression Model (GLM) which is considerably more flexible and allows to attend explicitly to problems such as autocorrelation and heteroscedasticity in the data. Specifically, we will employ the approach suggested by Fuller and Battese (1974) to estimate regressions in cases such as ours which combine cross-section and time-series data.

To begin, consider the standard OLS model with "p" independent variables related to parameters β_k and an intercept a. Assuming "n" observations we write this as follows:

$$(50) \qquad y_i = a + \sum_{k=1}^{p} x_{ik}\beta_k + \varepsilon_i \quad , i = 1, \ldots , n$$

where the error term ε_i is assumed to satisfy the following conditions:

$$(51) \qquad \begin{array}{l} E(\varepsilon_i^2) = \sigma^2 \quad \forall \; i \\ E(\varepsilon_i \varepsilon_j) = 0 \quad \forall \; i \neq j \end{array}$$

This, of course, conforms to the assumptions we made with (36) in the preceding section. When pooling cross section and time series data, however, (50) is no longer an adequate representation since we then have not only "n" cross sectional units being observed for one period of time, but also for each one of them we now have observations extended over a period of time "T."

We follow Fuller and Battese (1974) to specify the regression model for these types of data. These authors conceptualize the error term as being composed of three independent components, one error component associated with time, another with the cross-sectional units and the third varying in both dimensions. This is done as follows. First we replace (50) with

$$(52) \qquad y_{it} = a_t + \sum_{k=1}^{p} x_{itk}\beta_k + \mu_{it}$$

$$i = 1, 2, \dots, n; \quad t = 1, 2, \dots, T$$

in which the random errors, μ_{it} have the following decomposition:

$$(53) \qquad \mu_{it} = v_i + e_t + \varepsilon_{it}.$$

where $v_i \sim N(0, \sigma_v^2)$, $e_t \sim N(0, \sigma_e^2)$, and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$

so that v_i, e_t and ε_{it} are all normally distributed with zero means and finite variances.

TABLE 3
RESULTS ALLOWING FOR TIME SERIES AND CROSS-SECTIONAL ERROR TERMS - COBB-DOUGLAS MODEL
(Pooled Data 1981-1988)

	(1) WITHOUT EFFICIENCY ADJUSTMENTS	(2) WITH CCR EFFICIENCY ADJUSTMENTS	(3) WITH BCC EFFICIENCY ADJUSTMENTS
Constant (a)	1.71	2.71 ***	2.99 ***
	(1.50)	(1.19)	(1.38)
Capacity (alpha)	0.89 ***	0.67 ***	0.77 ***
	(0.05)	(0.02)	(0.04)
Labor (beta)	0.10**	0.22 ***	0.17 ***
	(0.04)	(0.02)	(0.03)
Fuel (gamma)	- 0.05 *	0.10 ***	0.01
	(0.02)	(0.01)	(0.02)
Variance Component Estimates			
For Cross-sections (σ_v^2)	0.0088	0.0006	0.0045
For Time Series (σ_e^2)	0.0007	0.0042	0.0017
For Error (σ_ε^2)	0.0051	0.0020	0.0031
Transformed Regression MSE	0.0051	0.0021	0.0033

Number in parenthesis indicate standard error.
*** Statistically significant at $p < 0.001$
** " " $p < 0.05$
* " " $p < 0.1$

Fuller and Battese's model (52), which we have employed to reestimate our "Combined DEA-Stochastic Production Functions," has the advantage of being able to account for heteroscedasticity and autocorrelation explicitly on the following assumptions. First, the composed errors μ_{it} are assumed to be homoscedastic with variance given by :

$$(54) \qquad Var(\mu_{it}) = \sigma^2 = \sigma_v^2 + \sigma_e^2 + \sigma_\varepsilon^2$$

so the error terms v, e and ε are additive and do not interact. In addition, the coefficient of correlation between two error components across two different points of time, μ_{it} and $\mu_{is}(t \neq s)$, is:

$$(55) \qquad \frac{Cov(\mu_{it},\mu_{is})}{\sqrt{Var(\mu_{it})Var(\mu_{is})}} = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_e^2 + \sigma_\varepsilon^2} \quad (t \neq s)$$

Model (52) in logarithmic form was applied to our data from the appendix and the results are shown in Table 3. The main results found under our previous OLS approaches to estimation continue to obtain under the GLM estimation employing (52). When calculated with unadjusted data, as shown in column (1), negative results for fuel were found under GML just as occurred with OLS in Table 2. This problem disappears when the input data are adjusted to account for inefficiency, as shown in column (2) of Table 3.

For comparison purposes we have included the parameter estimates obtained with efficiency adjusted data on the inputs using the BCC as well as the CCR models of DEA. As can be seen, the estimated parameter values in both cases differ from those portrayed in column (1). The BCC and CCR adjusted estimates are also relatively close to each other except for fuel which fails to attain statistical significance in the case of the BCC model. The regression mean square error for the CCR model is also smaller and so, on both statistical and economic grounds, the CCR model gives better results.

The important point to note here, however, is the fact that our results are robust across methods of estimation as well as across models. The statistical regressions, whether linear or Cobb-Douglas, did not give satisfactory results from either an economic or management standpoint when unadjusted input data were employed with OLS. This continues to be the case when goal programming/constrained regression (linear programming) and GLS methods are used. Our Combined DEA/SF approach, on the other hand, yielded more satisfactory results across all of these models and methods with the CCR model generally performing better than the BCC model for this purposes. In the sections that follow we therefore restrict ourselves to the use of CCR models for effecting our efficiency adjustments.

9. OWNERSHIP AND INTERNATIONAL COMPETITION

So far the developments in this chapter have been mainly methodological. Now we show how these tools can be used to gain some insights into two important policy problems for the Latin American airline industry. These are the effects on performance of (a) ownership regimes and (b) international competition. This section may also be regarded as a test of the DEA/SF method by demonstrating how it can be used in combination with other approaches to gain still further insights.

Over the last 5 years Latin American governments have been revising their air transport policies and in many cases they have decided to privatize their state-owned airlines. Lan Chile, Mexicana de Aviación, Aeroméxico, and VASP (Sao Paulo) have already been privatized and there are others, like Aerolíneas Argentinas and Aeroperú which are being considered for privatization by their governments. A main assumption underlying the privatization of these undertakings is that gains in efficiency will follow.

Two models of privatization have been implemented thus far. One approach, followed in the cases of VASP (Brasil) and Aeroméxico, consists of selling the SOE to a private national (domestic) individual or group, and the other approach, applied in the case of Lan-Chile, consists of selling part of the capital, and essentially integrating the company into the operations of an established international airline.

This section of the dissertation will proceed in a comparative fashion to examine the relative efficiency of Latin American carriers and attempt to provide some insights that may be useful in deciding the relative attractiveness of the strategy of using SOE privatization as far as gains in efficiency is concerned. Another aspect to be addressed is international competition. This can be conveniently accomplished because the Latin American airline industry is composed of three sets of firms. First, there are the Latin-American based airlines. These carriers, regardless of ownership status, enjoy significant government protection. Usually designated "flag carriers," they enjoy whatever access and flying privileges their governments are able to secure in bilateral negotiations with other governments -- usually on a reciprocal basis. Second, US-based airlines also operate in Latin America. The comparisons we seek are facilitated by the fact that the Latin American activities of these U.S. carriers (under the name of "Latin American entities") are separately identified and reported to ICAO.[24] A third group of airlines, which will not be included in this study, consists of European airlines flying in Latin America and, to a lesser extent, airlines from other regions. This group is not included in the present study because our main interest is in ascertaining the effect of international competition on performance and these additional airlines are not needed for this purpose. In addition, securing data for the Latin American operations of this group of airlines proved to be extremely difficult.

Airline regulation policies of most Latin American governments have been very tight historically and, naturally, they have also been protective of their do-

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24 International Civil Aviation Organization --the United Nations branch dealing with international aviation with headquarters in Montreal, Canada.

mestic carriers. As one ICAO study pointedly notes, these policies are "founded upon the belief that market forces cannot be counted on to produce a proper balance between the supply and demand for services" (ICAO, 1983, p.X). Because of the current focus on privatization as a possible strategy, the efficiency impacts and the potential gains from privatization will first be addressed without including the U.S. carriers. Next the possible liberalization of the current policies will be addressed by including the latter (i.e. U.S.) carriers.

For detailed study we use the following model in place of the Cobb-Douglas specification presented earlier in equation (1)

$$(56) \qquad y_i = \delta^{\mu_i} a c_i^{\alpha} l_i^{\beta} f_i^{\gamma} \varepsilon_i, \qquad i = 1, \dots, n,$$

$$\text{where} \quad \mu_i = \begin{cases} 1 & \text{when i = SOE} \\ 0 & \text{when i = PRI} \end{cases}$$

of course, $y, c, l, f, a, \alpha, \beta,$ and γ are defined as in (1) and ε_i is the statistical error term. δ is a dummy variable which, when estimated, will multiply the constant a. Thus, if $\delta > 1$ -- which results when $\ln \delta > 0$ and is statistically significant -- then SOEs are more efficient; and if $\delta < 1$ -- which means that $\ln \delta < 0$ and statistically significant -- then privately owned airlines are more efficient; finally, if δ fails to achieve statistical significance then SOE and privately owned airlines are equally efficient.

This characterization of the behavior of the dummy variable follows from the fact that the production function is otherwise the same --i.e., it is an "industry production function" -- for both classes of firms.[25] We could also test whether the

[25] See Malinvaud (1966) p. 517 ff. for a discussion of uses of "industry production functions" for statistical estimation.

production functions differ between SOE and privately owned airlines, of course, but the above development is both simpler and more in accord with our earlier discussions and so we here confine attention to this case.

For estimation purposes we use logarithms to replace (56) with

$$\ln y_i = \mu_i \ln \delta + \ln a + \alpha \ln c_i + \beta \ln l_i + \gamma \ln f_i + \ln \varepsilon_i, \quad i = 1, \ldots, n, \tag{57}$$

and this equation provides a way to determine whether $\ln \delta$ differs significantly from zero. Application to the data from the Appendix gives rise the the results portrayed in Table 4 when the regressions are estimated without and with efficiency adjusted input values.

Ignoring the reappearance of a negative exponent for fuel when observed rather than efficiency adjusted data are used, we note that type of ownership appears as statistically significant. In this case SOEs are expected to produce only 95% of the output that would be obtained by privately owned airlines with the same inputs. The efficiency adjusted data, however, produce the opposite result, i.e., no statistically significant difference due to ownership appears. As far as the models of privatization being implemented in the Latin American Airline industry is concerned, these results would indicate that there is, indeed, a potential gain in efficiency (5%) steming from transferring the SOEs to private (national) domestic individuals or groups.[26]

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[26] An analysis of the facet composition by ownership showed that the DEA efficient frontier is composed both by SOEs and private airlines. From the 88 DEA models run employing IDEAS, it was found that in average 53 % of the facet members were SOEs and 47 % were private airlines. This result is consistent with the fact that there is a single parametric efficient production function both for SOEs and private enterprises.

TABLE 4
OWNERSHIP DIFERENTIALS EMPLOYING DUMMY VARIABLES
LATIN AMERICAN BASED AIRLINES

	(1) WITHOUT EFFICIENCY ADJUSTMENTS (Interior Point)	(2) WITH EFFICIENCY ADJUSTMENTS (DEA/SF)
δ (Ownership Effect)	0.95 **	0.98
Constant	1.15	1.72 **
Capacity	0.91 ***	0.76 ***
Labor	0.07 *	0.15 ***
Fuel	- 0.01	0.08 ***
Returns to Scale	0.98	0.99

*** Statistically significant at $p < 0.001$
** " " $p < 0.05$
* " " $p < 0.1$

We need to probe this result a bit further since, in a sense, these regressions are responding to different questions.[27] The regression without efficiency adjusted data is responding positively to the question of whether SOEs are less efficient than private airlines as they have all been operated. The DEA/SF regression is responding to the question whether there are inherent efficiency differences when all airlines are operated efficiently. In the terminology introduced by Charnes Cooper and Rhodes (1978) -- in their discussion of the U.S. Office of Education sponsored "Program Follow Through," where they distinguish between schools participating and not participating in the Program -- we are distinguishing between "program efficiency" and "managerial efficiency."[28] This distinction is not made by

[27] See Charnes and Cooper (1990) on the need for attention to the way questions and interpretations change when different methodologies are employed.

[28] This is analogous to the distinction in economics between the choice of an efficient technology and the efficient use of that technology.

the regression in column (1) -- and cannot be made without eliminating or otherwise controlling for managerial inefficiencies, as we have done in column (2) by our use of DEA.

Our development thus provides a new way to distinguish between these types of efficiency in order to focus on program efficiency in contrast to the mixture of managerial and program inefficiency that is reflected in the regression protrayed in column (1) of Table 4. In sum, the comparison of state- and privately-owned Latin American airlines shows that there are potential efficiency gains from better management of the SOE airlines, and one way of accomplishing this would be through privatization following the VASP and Aeroméxico model which consists in selling the airline to private domestic individual or groups.

Proceeding in this manner leads very naturally to other questions. One such question is whether inclusion of other airlines, such as U.S. airlines with different modes of operation, will produce other effects. The results of such an analysis are shown in Table 5 where equation (57) is employed but the dummy variable δ is now indexed via

$$\text{(58)} \qquad \mu_i = \begin{cases} 1 & \text{when i = U.S.-based} \\ 0 & \text{when i = Latin-based} \end{cases}$$

As can be seen the situation in Table 5 reverses the one exhibited in Table 4. This time no statistically distinguishable difference is found between US-based and Latin American-based carriers when unadjusted data are employed, and there is a statistically significant class effect when efficiency adjusted data are employed, with the US-based carriers showing an efficient frontier of operation lower (96%) than that of Latin American carriers. This indicates an inherent competitive advantage of Latin- based airlines when compared with US-based airlines. However,

TABLE 5
CLASS DIFERENTIALS EMPLOYING DUMMY VARIABLES
US-BASED AND LATIN AMERICAN BASED AIRLINES

	(1) WITHOUT EFFICIENCY ADJUSTMENTS (Interior Point)	(2) WITH EFFICIENCY ADJUSTMENTS (DEA/SF)
δ (CLASS EFFECT)	0.95	0.96 *
Constant	0.96*	0.97
Capacity	0.97 ***	0.88 ***
Labor	0.02	0.06 ***
Fuel	- 0.001	0.07 ***
Returns to Scale	0.97	1.01

*** Statistically significant at $p < 0.001$
** " " $p < 0.05$
* " " $p < 0.1$

this advantage has not been realized by the Latin American carriers, which apear indistinguishable from the US carriers in their current level of operations.

At first these results appear to be counter intuitive since apriori it was expected to find U.S. airlines to be more efficient because of their greater fleet flexibility and larger size. It needs to be remembered, however, that all of these airlines operate in highly regulated environments. The regulations governing international air transport results from a myriad of bilateral agreements between governments which reflect the interests of both parties. Our results suggest that the current arrangement of regulations is more favorable for the Latin American airlines than to extra-regional (in this case US) airlines. In fact, the main purpose of some of the regulatory mechanisms currently in place such as restrictions in flight frequency and airplane size, in freedom to set fares and rates and other so called "freedoms of the air," is to protect the relatively smaller Latin American airlines from the potentially overwhelming strength of larger international carriers. Moreover, the fact that these regulations differ from one country to another introduces additional impediments to the operations of international carriers.

In the case of Table 4 we were able to explain the fact that the unadjusted and efficiency adjusted data were directed to different questions. Here we can exploit the availability of both results to show how they can be used in complementary fashion. Thus we observe that without the efficiency adjustments no statistically significant difference emerges in the case of Column (1) in Table 5. We thus conclude that in actual operations these carriers have all adjusted to one another with inefficiencies exhibited for both U.S. and Latin American carriers in our DEA adjustments. The fact that the significant difference between U.S. and Latin American carriers exhibited in column (2) does not also emerge in column (1) means that these opportunities have not been fully exploited by the latter -- even as domestically sheltered carriers in each of their countries. To help reinforce this interpretation we finally need to note that these data are all generated from activities conducted under these regulations.

It would be of interest to carry the analysis further to examine what might be expected by removal or alterations of these differing (by country) air transport regulations.[29] Instead we simply note that the issue of de-regulation is at least as important (and possibly more important) than the issues of privatization and/or the mergers or alliances with international airlines that are currently being considered both by airline managements and government officials in the countries involved in our study.

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[29] See Sinha (1991), for a "moving frontier analysis" in the context of a semiconductors manufacturing plant.

Our analysis has shown that under the current regulatory framework the efficient production frontier of Latin American airlines is higher than that of U.S. airlines operating in the region. Indeed, under fully efficient operations, U.S. airlines produce only 96 % of the output that can be obtained by Latin-American airlines from the same inputs. For this reason it appears that the model of privatization followed by Lan-Chile, which consists in associating with a large international carrier may not be conducive to gains in efficiency, if the current regulatory environment is maintained.

The analysis performed thus far has therefore served not only to ascertain specific characteristics of production functions and relative efficiencies by classes of firms in the Latin American airline industry, but it has also offered possibilities for addressing alternate questions that DEA/SF can offer when used both singly and in combination with interior point causal regressions. In the process we have cast light on current strategies being followed such as "privatization" and have also indicated the need for broadening the strategies to be considered by reference to the regulatory framework that is currently in place.

10.TECHNOLOGICAL CHANGE

In Gallegos (1991) DEA is used to check (and extend) the above findings by moving to the case of two outputs -- passengers and freight -- to ascertain what effects, if any, this may have on the results to this point. Here we proceed to check the validity of the methods used in this chapter in a different manner by applying our models and methods to see whether they produce results that are consistent with the fact that the airlines we are studying were moving to more fuel efficient planes.

For this purpose we divide our data into two sub-periods: 1981-1984 and 1985-1988. Applying our Cobb-Douglas model (1) to the data for our 17 airlines, as given in the Appendix, we obtain the results that are shown in Table 6, both for unadjusted and efficiency adjusted input data.

Evidently the value of γ, the output elasticity for fuel, increases for both cases -- i.e., with and without the efficiency adjustments -- in going from the earlier to the later period. The technological change reflected in these increases for the output elasticity for fuel is not "Hicks neutral." The capital (= capacity) to labor ratio increases when going from the earlier to the later periods in all cases, so that these technological innovations have been "labor saving" in this sense. In this case we also have a direct measure of technological change (as such) in the form of the marked increase in the output elasticity for fuel. Against this explicit measure of technological change, we can get another view by noting that the other output elasticities all decrease, as shown by the numerical values of the capacity/fuel and labor/fuel ratios, where, as seen at the bottom of Table 6, the labor to fuel ratio decreases more than the ratio for capacity to fuel.

The fact that the Allen elasticity of substitution for a Cobb-Douglas function is always unity makes it unprofitable to pursue this topic further. What we can say, however, is that the introduction of these more fuel efficient planes was accompanied by other changes which lowered the productivity of both labor and capacity with more effect on the former that the latter. From this one may conclude that there is less need for labor (e.g. maintenance labor) and less need for capacity (possibly because of stepped up flight schedules). In any case our models all reflect the known appearance of more fuel efficient planes between the two pe-

TABLE 6
STRUCTURAL CHANGES IN THE COMPOSITION OF THE PRODUCTION FUNCTION - ALL LATIN AMERICAN AND US AIRLINES COMBINED

	1981- 1984		1985- 1988	
	(1) Without Efficiency Adjustment	(2) With CCR Efficiency Adjustment (DEA/SF	(3) Without Efficiency Adjustment	(4) With DEA Efficiency Adjustment (DEA/SF)
Constant	0.84	1.31**	0.97	1.39**
Capacity	0.93***	0.80***	0.88***	0.74***
Labor	0.06***	0.10***	0.03**	0.06***
Fuel	- 0.01	0.08***	0.07**	0.19***
Returns to scale	0.98	0.98	0.98	0.99
R^2	0.990	0.997	0.991	0.996
Condition Number	90	97	93	105
DW	1.07	1.86	1.30	2.40
Number of Observations	68	68	66	66
Ratios of Parameters				
Capacity/Labor	15.5	8.0	29.3	12.3
Capacity/Fuel	n.m.	10.0	12.5	3.9
Labor/Fuel	n.m.	1.25	0.43	0.31

*** statistically significant p < 0.001
** " " p < 0.05
* " " p < .0.1
n.m. not meaningful

30 Note also the consistency of the returns to scale in all of our analyses. That is all the evidence points toward the Latin American airline industry as one which operates with constant returns to scale, or very close to it. This result is quite robust, and was obtained employing both various forms of DEA/SF and "interior point" specifications, and employing various methods of estimation such as goal programming/constrained regressions (see Table 1), a form of the generalized linear model (see Table 3.), and dummy variables (see tables 4 and 5).

11. SUMMARY AND CONCLUSION

This paper has presented some new approaches for estimating stochastic frontier production functions and has shown how these models and methods can be brought bear on issues of both public and managerial policy in new and interesting ways. For instance, our results comparing state- and privately-owned airlines (in Table 4) showed that even though a statistically significant difference appears that reflects the way these two classes of airlines have been operated, it is nevertheless the case that this difference is not inherent. In particular if both classes of airlines (SOE and private) are operated efficiently, this difference is eliminated (see Table 4).

We related the latter development to the distinction between "managerial efficiency" and "program efficiency" introduced by Charnes, Cooper and Rhodes (1978). Here the program difference takes the form of "SOE" vs. "privately owned" airlines as representing the different "programs" after eliminating the managerial inefficiencies observed in each program. Charnes, Cooper and Rhodes accomplished their program efficiency vs. managerial efficiency comparisons by separating the two programs in public school education they were considering and eliminating the managerial inefficiencies in each -- after which each of the two resulting program frontiers could be compared to obtain a program (as distinct from a managerial) efficiency evaluation. We could have followed the same route in our analyses since we had already effected the DEA computations. We proceeded via a different route, however, to introduce a new possibility for accomplishing this type of comparative analysis by first eliminating all managerial inefficiencies and then using dummy variables, as in a customary statistical analysis, to determine whether significant differences emerged. By doing so we have provided access to statistical inference procedures and tests of significance which are not available in the route followed by Charnes, Cooper and Rhodes (1978).

This was accomplished, of course, without eliminating opportunities like those suggested by Charnes Cooper and Rhodes (1978). For instance, our uses of DEA still allow us to identify efficient and inefficient managers operating within each class of airlines. In addition to making it possible to see where corrections might be used within each "program" (SOE or private enterprise) with resulting prospects of improvement, we can also uncover possibilities for switches in which efficient managers might best be transferred to produce even more efficient program-manager combinations.

These are possibilities that might be added to the current privatization vs. not-privatization alternatives that are currently being considered by a number of Latin American governments. Our discussion of Table 5 suggested still further possibilities in which deregulation for both public and privately owned airlines needs to be added to the set of alternative strategies to be considered for improving efficiency. Our introduction of new methods of analysis and control have thus brought these possibilities into view with accompanying statistically supported evidence to warrant their consideration.

What is especially satisfying from our point of view is that the supposed conflict between statistics and economics -- e.g. as in our quoted statements from Afriat (1972) and Varian (1990) -- seems to have disappeared in the above analyses. Indeed, the results obtained became increasingly satisfactory from an economics standpoint when statistical refinements were introduced by going from ordinary least squares to the generalized linear model of Fuller and Batesse (1974).

Reference to the appendix makes it clear that our focus on <u>input</u> efficiency adjustments differs from the other approaches to stochastic frontier analyses which have focussed on output efficiencies. The use of "composed error" terms in the latter publications have assumed that both statistical and managerial errors are to be found only in the observed outputs. In a sense we have returned to the earlier work of Feldstein (1968) who also focused on input inefficiencies in his study of British hospitals. Of course, Feldstein did not have access to procedures like DEA and hence used OLS (and like) approaches with troubles similar to those we encountered with those same approaches when using unadjusted data.[31]

Feldstein, we might add, also distinguished between input inefficiencies and "productive" use of inputs. Stated differently, this distinction allows for inefficiency in output resulting from a poor use of efficient amounts (and mixes) of inputs. To deal with possibilities of output as well as input inefficiency it would be necessary to apply one or more of the composed error approaches that now appear in the literature -- See Appendix E in Gallegos (1991) -- and to use them in combination with efficiency adjusted input values like those we have described.[32] It was not necessary to conduct such analyses here, however, since evidence of such output inefficiency was not present in the single output model that we are analyzing in this chapter.[33] Indeed, as the Appendix shows, no non-zero slack appeared in the BCC-DEA analysis for any airline in any year covered by our data and this is consistent with our statistical regressions which generally showed constant or slightly decreasing returns to scale.

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[31] Actually Feldstein noted the work by Farrel (1957), which is the basis for DEA, but rejected it in favor of the statistical approaches he used.

[32] See Cornwell, Schmidt and Sickles (1990) for an up-to-date treatment in the context of a stochastic frontier study of US airlines.

[33] See Gallegos (1991), Chapter IV which extends these analysis of output inefficiencies and shows how the latter appear in the context of a two-output DEA model.

We have now shown how our analyses can be used as an alternative or in combination with customary statistical approaches to yield new questions and obtain new insights into both managerial and public policy problems. This complementary sue of DEA and statistical regressions does not exhaust the possibilities, however, since as shown in Gallegos (1991) they can be extended and used to cross check their respective results.

APPENDICES

APPENDIX A

BASIC DATA FILES, EFFICIENCY ADJUSTMENTS AND DEA RESULTS

TABLE 1
INPUTS AND OUTPUTS - LATIN AMERICAN BASED AIRLINES

	OUTPUT	UNADJUSTED INPUTS			CCR EFFICIENCY ADJUSTED INPUTS		
	TON-KM PERFORMED (1)	LABOR (# of Employees (2)	FUEL (Thous. US $) (3)	CAPACITY (Ton-KM Available) (4)	LABOR (# of Employees (5)	FUEL (Thous. US $) (6)	CAPACITY (Ton-KM Available) (7)
AMEX81	661,213	10,532	36,264	1,115,570	9,036	32,505	999,930
AMEX82	633,889	10,800	40,936	1,148,781	10,722	40,642	1,137,307
AMEX83 *	715,514	10,703	52,416	1,230,262	10,703	52,416	1,230,262
AMEX84 *	802,602	11,700	62,953	1,413,615	11,700	62,953	1,413,615
AMEX85	836,012	11,548	89,434	1,473,836	7,248	89,381	1,472,966
AMEX86	774,424	11,688	75,353	1,392,741	8,427	68,737	1,270,458
AMEX87	724,250	12,524	84,570	1,382,357	7,326	69,695	1,139,214
AMEX88	363,549	3,752	35,621	706,566	3,330	31,610	627,014
ARGE81	768,720	10,176	365,574	1,588,697	7,352	236,028	1,147,849
ARGE82	649,848	9,835	237,991	1,417,993	7,169	170,796	1,033,646
ARGE83	645,480	9,822	291,098	1,386,259	7,935	144,365	1,119,945
ARGE84	757,875	10,303	106,047	1,320,666	9,677	99,608	1,240,475
ARGE85	765,795	10,276	146,546	1,432,758	7,728	117,682	1,150,562
ARGE86	801,754	10,323	110,685	1,363,462	8,980	96,285	1,186,076
ARGE87	874,234	10,283	109,586	1,491,265	8,910	94,957	1,292,196
ARGE88	882,954	10,372	140,290	1,430,859	8,920	111,971	1,230,524
ECUA81	111,086	1,055	29,210	187,307	986	27,306	175,096
ECUA82 *	100,054	1,023	20,028	168,252	1,023	20,028	168,252
ECUA83	77,882	1,045	12,249	154,439	938	10,993	138,598
ECUA84 *	98,202	1,010	12,617	208,618	1,010	12,617	208,618
ECUA85 *	119,904	988	11,124	220,665	988	11,124	220,665
ECUA86 *	137,771	1,088	11,098	269,056	1,088	11,098	269,056
ECUA87	147,862	1,165	12,935	297,142	1,044	11,586	266,159
ECUA88	148,696	1,187	11,001	289,335	1,139	10,557	277,666
LCHI81 *	256,733	1,423	63,678	468,803	1,423	63,678	468,803
LCHI82 *	209,938	1,487	46,529	405,690	1,487	46,529	405,690
LCHI83 *	169,337	1,372	32,789	325,350	1,372	32,789	325,350
LCHI84 *	173,633	1,046	30,935	320,817	1,046	30,935	320,817
LCHI85 *	190,631	851	31,600	347,580	851	31,600	347,580
LCHI86 *	220,794	1,013	26,600	381,196	1,013	26,600	381,196
LCHI87 *	259,854	1,028	26,950	443,207	1,028	26,950	443,207
LCHI88 *	310,889	1,261	31,670	513,098	1,261	31,670	513,098
MEXI81 *	843,804	11,555	38,775	1,280,848	11,555	38,775	1,280,848
MEXI82 *	701,821	11,957	43,627	1,257,990	11,957	43,627	1,257,990
MEXI83 *	860,876	11,882	58,486	1,495,193	11,882	58,486	1,495,193
MEXI84	812,735	12,439	72,771	1,703,551	11,530	67,453	1,458,348
MEXI85	855,541	13,117	110,576	1,750,772	7,502	94,234	1,492,025
MEXI86	834,460	13,759	102,226	1,764,630	9,140	78,070	1,347,648
MEXI87	902,437	14,615	116,781	1,760,357	9,366	91,419	1,378,043
MEXI88	999,074	13,027	108,938	1,744,491	10,048	100,305	1,606,240

	OUTPUT	UNADJUSTED INPUTS			CCR EFFICIENCY ADJUSTED INPUTS		
	TON-KM PERFORMED	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PERU81	110,554	1,567	23,449	247,810	1,121	16,781	177,338
PERU82	100,332	1,489	17,757	208,496	1,255	14,970	175,777
PERU83	109,627	1,695	21,604	227,137	1,418	18,069	189,971
PERU84	109,984	1,685	25,816	225,133	1,256	19,245	167,825
PERU85	100,485	1,681	21,322	208,942	1,013	15,419	151,098
PERU86	126,570	1,669	22,379	230,428	1,307	17,519	180,384
PERU87	147,188	1,691	25,675	254,066	1,416	16,981	212,717
PERU88	133,018	1,763	44,081	233,314	1,387	17,047	183,546
AVIA81	552,870	8,887	113,923	967,210	6,874	88,114	748,089
AVIA82	568,288	8,723	109,845	1,003,727	7,777	97,935	894,893
AVIA83	546,013	8,842	107,778	965,148	8,106	100,982	904,286
AVIA84	543,486	5,990	94,211	889,703	5,837	91,811	867,033
AVIA85	496,666	5,268	86,493	815,326	4,829	79,291	747,434
AVIA86	477,310	5,177	77,589	813,967	4,433	66,443	697,041
AVIA87	457,450	5,014	62,942	777,805	4,293	52,557	666,019
AVIA88	438,904	6,285	64,967	701,085	5,086	55,929	603,557
CRUZ81	207,776	4,238	53,452	407,602	2,652	31,315	276,884
CRUZ82	206,134	4,098	46,504	384,769	2,743	38,451	318,139
CRUZ83	200,590	4,061	35,324	399,456	2,985	29,746	336,374
CRUZ84	200,243	3,672	28,963	405,539	2,712	23,591	330,320
CRUZ85 *	222,193	3,513	20,296	459,326	3,513	20,296	459,326
CRUZ86 *	317,302	3,296	17,603	576,725	3,296	17,603	576,725
CRUZ87 *	310,390	2,535	18,215	593,789	2,535	18,215	593,789
CRUZ88 *	299,212	2,257	16,751	595,398	2,257	16,751	595,398
LACS81 *	77,796	993	11,725	103,672	993	11,725	103,672
LACS82 *	86,144	1,086	18,077	128,928	1,086	18,077	128,928
LACS83 *	74,379	1,100	17,965	120,801	1,100	17,965	120,801
LACS84 *	85,427	951	17,892	118,714	951	17,892	118,714
LACS85 *	89,357	944	15,120	126,552	944	15,120	126,552
LACS86 *	86,997	1,028	13,198	113,586	1,028	13,198	113,586
LACS87 *	98,077	1,107	11,652	134,217	1,107	11,652	134,217
LACS88 *	120,310	1,443	16,196	158,002	1,443	16,196	158,002
LADE81 *	55,810	485	19,519	85,783	485	19,519	85,783
LADE82 *	49,951	481	15,486	83,633	481	15,486	83,633
LADE83	45,540	474	14,403	89,339	446	9,370	84,072
LADE84	53,754	485	16,867	103,465	424	10,188	90,372
LADE85	52,684	490	15,143	101,661	408	8,831	84,558
LADE86	54,036	509	12,786	101,032	420	7,252	83,294
LADE87	66,093	658	14,120	126,690	523	7,393	100,701
LADE88	94,089	1,044	13,491	187,001	807	10,430	144,576
VARI81	1,273,239	16,793	289,675	2,500,518	13,047	225,060	1,942,752
VARI82	1,374,576	17,553	288,769	2,666,124	15,303	251,760	2,324,434
VARI83	1,312,406	16,745	244,201	2,623,762	15,023	219,087	2,353,934
VARI84	1,507,168	17,557	240,001	2,832,823	15,983	218,480	2,578,804
VARI85	1,624,970	19,383	232,733	2,988,422	15,134	208,112	2,672,277
VARI86	1,863,740	20,943	228,706	3,373,076	18,383	200,749	2,960,751
VARI87	1,882,317	23,356	227,767	3,558,728	19,141	186,662	2,916,484
VARI88	2,074,093	24,179	234,845	3,896,766	20,588	203,446	3,375,768

TABLE 2
INPUTS AND OUTPUTS - LATIN AND US BASED AIRLINES

	OUTPUT	UNADJUSTED INPUTS			CCR EFFICIENCY ADJUSTED INPUTS		
	TON-KM PERFORMED (1)	LABOR (# of Employees (2)	FUEL (Thous. US $) (3)	CAPACITY (Ton-KM Available) (4)	LABOR (# of Employees (5)	FUEL (Thous. US $) (6)	CAPACITY (Ton-KM Available) (7)
AMEX81	661,213	10,532	36,264	1,115,570	9,036	32,505	999,930
AMEX82	633,889	10,800	40,936	1,148,781	10,692	40,525	1,137,259
AMEX83	715,514	10,703	52,416	1,230,262	10,703	52,416	1,230,262
AMEX84	802,602	11,700	62,953	1,413,615	11,700	62,953	1,413,615
AMEX85	836,012	11,548	89,434	1,473,836	7,248	89,381	1,472,966
AMEX86	774,424	11,688	75,353	1,392,741	8,427	68,737	1,270,458
AMEX87	724,250	12,524	84,570	1,382,357	7,326	69,695	1,139,214
AMEX88	363,549	3,752	35,621	706,566	483	31,189	618,662
ARGE81	768,720	10,176	365,574	1,588,697	7,352	236,028	1,147,849
ARGE82	649,848	9,835	237,991	1,417,993	7,094	135,817	1,022,841
ARGE83	645,480	9,822	291,098	1,386,259	7,661	147,717	1,081,324
ARGE84	757,875	10,303	106,047	1,320,666	9,615	98,962	1,232,432
ARGE85	765,795	10,276	146,546	1,432,758	7,728	117,682	1,150,562
ARGE86	801,754	10,323	110,685	1,363,462	8,972	96,204	1,185,080
ARGE87	874,234	10,283	109,586	1,491,265	8,910	94,957	1,292,196
ARGE88	882,954	10,372	140,290	1,430,859	8,862	110,951	1,222,526
ECUA81	111,086	1,055	29,210	187,307	966	26,753	171,553
ECUA82	100,054	1,023	20,028	168,252	1,006	19,686	165,380
ECUA83	77,882	1,045	12,249	154,439	911	10,676	134,609
ECUA84	98,202	1,010	12,617	208,618	878	10,966	175,213
ECUA85	119,904	988	11,124	220,665	988	11,124	220,665
ECUA86	137,771	1,088	11,098	269,056	1,003	10,230	248,008
ECUA87	147,862	1,165	12,935	297,142	1,044	11,586	266,159
ECUA88	148,696	1,187	11,001	289,335	648	10,461	275,126
LCHI81	256,733	1,423	63,678	468,803	1,348	60,318	444,064
LCHI82	209,938	1,487	46,529	405,690	1,372	42,917	374,200
LCHI83	169,337	1,372	32,789	325,350	1,262	30,155	299,211
LCHI84	173,633	1,046	30,935	320,817	957	28,293	293,419
LCHI85	190,631	851	31,600	347,580	785	29,137	320,486
LCHI86	220,794	1,013	26,600	381,196	976	25,617	367,107
LCHI87	259,854	1,028	26,950	443,207	1,028	26,950	443,207
LCHI88	310,889	1,261	31,670	513,098	1,227	30,400	499,388
MEXI81	843,804	11,555	38,775	1,280,848	11,555	38,775	1,280,848
MEXI82	701,821	11,957	43,627	1,257,990	11,957	43,627	1,257,990
MEXI83	860,876	11,882	58,486	1,495,193	11,882	58,486	1,495,193
MEXI84	812,735	12,439	72,771	1,703,551	11,374	66,540	1,433,379
MEXI85	855,541	13,117	110,576	1,750,772	7,502	94,234	1,492,025
MEXI86	834,460	13,759	102,226	1,764,630	9,140	78,070	1,347,648
MEXI87	902,437	14,615	116,781	1,760,357	9,366	91,419	1,378,043
MEXI88	999,074	13,027	108,938	1,744,491	4,312	99,380	1,591,429
PERU81	110,554	1,567	23,449	247,810	1,081	16,181	170,999
PERU82	100,332	1,489	17,757	208,496	1,233	14,706	172,672
PERU83	109,627	1,695	21,604	227,137	1,391	17,726	186,364
PERU84	109,984	1,685	25,816	225,133	1,244	19,059	166,209

	OUTPUT	UNADJUSTED INPUTS			CCR EFFICIENCY ADJUSTED INPUTS		
	TON-KM PERFORMED	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PERU85	100,485	1,681	21,322	208,942	1,013	15,419	151,098
PERU86	126,570	1,669	22,379	230,428	1,297	17,391	179,068
PERU87	147,188	1,691	25,675	254,066	1,416	16,981	212,717
PERU88	133,018	1,763	44,081	233,314	1,379	16,918	182,557
AVIA81	552,870	8,887	113,923	967,210	6,862	87,970	746,870
AVIA82	568,288	8,723	109,845	1,003,727	7,775	97,904	894,612
AVIA83	546,013	8,842	107,778	965,148	8,106	100,982	904,286
AVIA84	543,486	5,990	94,211	889,703	5,706	89,751	847,584
AVIA85	496,666	5,268	86,493	815,326	4,792	78,681	741,686
AVIA86	477,310	5,177	77,589	813,967	4,375	65,572	687,900
AVIA87	457,450	5,014	62,942	777,805	4,293	52,557	666,019
AVIA88	438,904	6,285	64,967	701,085	4,551	55,820	602,379
CRUZ81	207,776	4,238	53,452	407,602	2,652	31,315	276,884
CRUZ82	206,134	4,098	46,504	384,769	2,743	38,451	318,139
CRUZ83	200,590	4,061	35,324	399,456	2,985	29,746	336,374
CRUZ84	200,243	3,672	28,963	405,539	2,712	23,591	330,320
CRUZ85	222,193	3,513	20,296	459,326	3,513	20,296	459,326
CRUZ86	317,302	3,296	17,603	576,725	3,296	17,603	576,725
CRUZ87	310,390	2,535	18,215	593,789	2,535	18,215	593,789
CRUZ88	299,212	2,257	16,751	595,398	2,257	16,751	595,398
LACS81	77,796	993	11,725	103,672	993	11,725	103,672
LACS82	86,144	1,086	18,077	128,928	1,086	18,077	128,928
LACS83	74,379	1,100	17,965	120,801	1,100	17,965	120,801
LACS84	85,427	951	17,892	118,714	951	17,892	118,714
LACS85	89,357	944	15,120	126,552	944	15,120	126,552
LACS86	86,997	1,028	13,198	113,586	1,028	13,198	113,586
LACS87	98,077	1,107	11,652	134,217	1,107	11,652	134,217
LACS88	120,310	1,443	16,196	158,002	1,443	16,196	158,002
LADE81	55,810	485	19,519	85,783	485	19,519	85,783
LADE82	49,951	481	15,486	83,633	472	10,403	81,995
LADE83	45,540	474	14,403	89,339	416	9,882	78,463
LADE84	53,754	485	16,867	103,465	391	10,236	83,475
LADE85	52,684	490	15,143	101,661	390	8,586	81,006
LADE86	54,036	509	12,786	101,032	407	7,331	80,794
LADE87	66,093	658	14,120	126,690	523	7,393	100,701
LADE88	94,089	1,044	13,491	187,001	608	10,283	142,528
VARI81	1,273,239	16,793	289,675	2,500,518	12,672	218,586	1,886,866
VARI82	1,374,576	17,553	288,769	2,666,124	15,081	248,096	2,290,600
VARI83	1,312,406	16,745	244,201	2,623,762	14,449	210,714	2,263,966
VARI84	1,507,168	17,557	240,001	2,832,823	15,442	211,090	2,491,581
VARI85	1,624,970	19,383	232,733	2,988,422	15,134	208,112	2,672,277
VARI86	1,863,740	20,943	228,706	3,373,076	18,248	199,281	2,939,096
VARI87	1,882,317	23,356	227,767	3,558,728	19,141	186,662	2,916,484
VARI88	2,074,093	24,179	234,845	3,896,766	7,889	201,445	3,342,568
AMER81	366,023	916	80,166	704,300	897	78,543	690,038
AMER82	340,408	768	69,668	670,688	768	69,668	670,688
AMER83	352,904	930	66,602	648,208	930	66,602	648,208
AMER84	358,004	874	59,619	629,326	874	59,619	629,326

	OUTPUT	UNADJUSTED INPUTS			CCR EFFICIENCY ADJUSTED INPUTS		
	TON-KM PERFORMED	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)	LABOR (# of Employees	FUEL (Thous. US $)	CAPACITY (Ton-KM Available)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AMER85	374,594	848	57,236	650,156	848	57,236	650,156
AMER86	413,027	973	48,026	712,184	973	48,026	712,184
AMER87	463,989	1,471	53,719	830,306	1,449	47,860	817,611
AMER88	503,370	1,619	53,857	920,699	1,456	46,789	827,920
CONT81	21,820	61	6,228	50,553	50	5,021	41,225
CONT82	22,459	87	6,076	55,914	68	4,605	43,473
CONT83	49,071	72	11,432	106,798	72	11,432	106,798
CONT84	56,731	91	11,644	117,669	91	11,644	117,669
CONT85	67,507	101	10,748	134,685	101	10,748	134,685
CONT86	81,897	113	8,624	146,578	113	8,624	146,578
CONT87	130,391	361	13,123	241,805	356	12,930	238,243
CONT88	220,194	1,133	16,972	414,950	774	16,330	399,257
DELT81	57,477	174	12,835	112,573	165	12,200	107,004
DELT82	63,149	168	14,049	133,189	156	12,931	123,794
DELT83	66,542	162	11,469	122,656	162	11,469	122,656
DELT84	77,260	139	11,878	140,088	139	11,878	140,088
DELT85	81,610	151	14,194	165,119	143	12,804	155,902
DELT86	88,164	136	9,959	167,767	128	9,344	157,414
DELT87	165,681	68	16,786	322,394	68	16,786	322,394
DELT88	221,135	251	18,776	377,866	251	18,776	377,866
EAST81	299,960	532	66,185	575,075	532	66,185	575,075
EAST82	360,684	1,520	81,852	746,044	1,394	74,109	684,100
EAST83	491,134	1,409	99,819	910,344	1,394	93,121	900,367
EAST84	464,755	2,126	113,763	889,616	1,877	81,063	785,522
EAST85	453,010	1,389	97,460	851,446	1,267	69,696	776,944
EAST86	473,012	1,218	78,981	889,777	1,116	55,009	815,525
EAST87	572,923	1,227	92,740	1,111,587	1,161	58,672	1,052,073
EAST88	567,606	1,365	80,348	1,078,705	1,202	50,746	949,606
PNAM81	780,640	3,539	155,999	1,485,757	3,374	148,734	1,416,565
PNAM82	706,900	3,482	147,262	1,482,833	3,184	134,665	1,355,991
PNAM83	590,424	3,093	127,845	1,258,631	2,623	108,410	1,067,294
PNAM84	571,505	2,990	103,263	1,061,905	2,735	94,455	971,325
PNAM85	549,896	2,465	97,249	1,086,712	2,114	83,395	931,899
PNAM86	847,028	2,961	100,513	1,642,322	2,658	90,244	1,474,526
PNAM87	878,362	3,097	111,199	1,780,108	2,698	90,572	1,550,777
PNAM88	932,369	3,223	103,359	1,677,939	2,929	87,730	1,525,045
WEST81	159,436	1,014	32,271	318,251	892	28,404	280,115
WEST82	91,383	650	21,043	214,832	521	16,872	172,248
WEST83	97,819	534	19,482	209,088	453	16,526	177,367
WEST84	100,981	549	18,689	226,357	435	14,809	179,363
WEST85	96,829	512	17,667	204,978	412	14,226	165,059
WEST86	93,262	474	10,486	178,514	428	9,477	161,330

TABLE 3
"t" TESTS FOR THE DIFFERENCE BETWEEN
MEAN EFFICIENCY RATINGS

GROUPS	Number of Cases	Mean.	Standard Error	t value	P >| t |
SOE - Latin American Privately-owned Latin American	48 40	.884 .895	.013 .014	- 0.57	0.57
SOE - Latin American USA -owned	48 46	.884 .930	.013 .010	- 2.82	.006 **
Privately-owned Latin American USA - owned	40 46	.895 .930	.014 .010	- 2.08	0.041 **
Combined SOE & Pri Latin Am. USA - Owned	88 46	.889 .930	.010 .010	- 2.75	0.007 **

*** Statistically significant at P < 0.001
** " " P < 0.05
* " " P < 0.1

TABLE 4
SLACK INFORMATION

	CCR MODEL SLACKS			BCC MODEL SLACKS			
	Personnel '(1)	Fuel '(2)	Capacity '(3)	Ton-Km Performed '(4)	Personnel '(5)	Fuel '(6)	Capacity '(7)
AMEX81	404	0	0	0	406	188	0
AMEX82	0	0	3,214	0	0	0	8,249
AMEX83	0	0	0	0	0	0	0
AMEX84	0	0	0	0	0	0	0
AMEX85	4,293	0	0	0	0	0	0
AMEX86	2,235	0	0	0	0	0	0
AMEX87	2,995	0	0	0	3,711	0	0
AMEX88	0	0	0	0	824	0	0
ARGE81	0	28,103	0	0	0	173,801	0
ARGE82	0	2,688	0	0	0	71,319	0
ARGE83	0	90,810	0	0	0	174,963	0
ARGE84	0	0	0	0	0	0	0
ARGE85	524		0	0	931	15,036	0
ARGE86	0	0	0	0	0	0	0
ARGE87	0	0	0	0	0	0	0
ARGE88	0	8,677	0	0	0	0	0
ECUA81	0	0	0	0	0	3,622	0
ECUA82	0	0	0	0	0	0	0
ECUA83	0	0	0	0	0	0	0
ECUA84	0	0	0	0	0	0	0
ECUA85	0	0	0	0	0	0	0
ECUA86	0	0	0	0	0	0	0
ECUA87	0	0	0	0	0	0	0
ECUA88	0	0	0	0	0	0	0
LCHI81	0	0	0	0	0	0	0
LCHI82	0	0	0	0	0	0	0
LCHI83	0	0	0	0	0	0	0
LCHI84	0	0	0	0	0	0	0
LCHI85	0	0	0	0	0	0	0
LCHI86	0	0	0	0	0	0	0
LCHI87	0	0	0	0	0	0	0
LCHI88	0	0	0	0	0	0	0
MEXI81	0	0	0	0	0	0	0
MEXI82	0	0	0	0	0	0	0
MEXI83	0	0	0	0	0	0	0
MEXI84	0	0	120,708	0	0	0	159,849
MEXI85	3,677	0	0	0	0	0	12,866
MEXI86	1,368	0	0	0	0	0	0
MEXI87	2,075	0	0	0	2,829	0	0
MEXI88	1,947	0	0	0	0	0	0
PERU81	0	0	0	0	0	0	0
PERU82	0	0	0	0	113	0	32,973
PERU83	0	0	0	0	0	0	0
PERU84	0	0	0	0	0	0	0
PERU85	202	0	0	0	158	0	0
PERU86	0	0	0	0	0	45	0
PERU87	0	4,515	0	0	0	5,190	0
PERU88	0	17,632	0	0	0	17,974	0

	CCR MODEL SLACKS			BCC MODEL SLACKS			
	Personnel '(1)	Fuel '(2)	Capacity '(3)	Ton-Km Performed '(4)	Personnel '(5)	Fuel '(6)	Capacity '(7)
AVIA81	0	0	0	0	117	69,702	0
AVIA82	0	0	0	0	0	0	0
AVIA83	178	0	0	0	419	61,321	0
AVIA84	0	0	0	0	0	0	0
AVIA85	0	0	0	0	0	0	0
AVIA86	0	0	0	0	0	13,709	0
AVIA87	0	1,339	0	0	0	6,183	0
AVIA88	325	0	0	0	1,607	0	0
CRUZ81	227	4,995	0	0	370	23,475	0
CRUZ82	645	0	0	0	705	980	0
CRUZ83	434	0	0	0	458	5,249	0
CRUZ84	279	0	0	0	0	0	0
CRUZ85	0	0	0	0	0	0	0
CRUZ86	0	0	0	0	0	0	0
CRUZ87	0	0	0	0	0	0	0
CRUZ88	0	0	0	0	0	0	0
LACS81	0	0	0	0	0	0	0
LACS82	0	0	0	0	0	0	0
LACS83	0	0	0	0	0	0	0
LACS84	0	0	0	0	0	0	0
LACS85	0	0	0	0	0	0	0
LACS86	0	0	0	0	0	0	0
LACS87	0	0	0	0	0	0	0
LACS88	0	0	0	0	0	0	0
LADE81	0	0	0	0	0	0	0
LADE82	0	0	0	0	0	0	0
LADE83	0	4,184	0	0	0	0	0
LADE84	0	4,544	0	0	0	0	0
LADE85	0	3,765	0	0	0	0	0
LADE86	0	3,289	0	0	0	0	0
LADE87	0	3,830	0	0	0	0	0
LADE88	0	0	0	0	0	0	0
VARI81	0	0	0	0	0	0	0
VARI82	0	0	0	0	0	0	0
VARI83	0	0	0	0	0	0	0
VARI84	0	0	0	0	404	0	0
VARI85	2,199	0	0	0	0	0	0
VARI86	0	0	0	0	0	0	0
VARI87	0	0	0	0	0	0	0
VARI88	358	0	0	0	0	0	0

APPENDIX B

A SUMMARY OF STOCHASTIC FRONTIER STUDIES

Farrel (1957)

Scope: Agricultural Production in the U.S., 1952.

Model: Cobb-Douglass

$$K = X_1^{\alpha_1} X_2^{\alpha_2} X_3^{\alpha_3} \varepsilon$$

where:

K = output, X_i = inputs (labor, land, and capital), and ε = statistical error.

Error term assumptions

$\varepsilon \sim N(0, \sigma^2)$

Assumptions about the independent variables

- "All inputs and outputs are correctly measured." (p.254).
- Admits "small error of obsevation" (p.263).

Estimation Methods

- OLS

Comments

- Error terms discussed by J.A.C. Brown (p.287), and Farrel referred to it as a "knotty little problem" (p.290).
- Discusses the method of estimation from a statistical point of view (p.263).
- Estimates "best practice" parametric frontier employing 100% efficient DMUs only.
- Having only 9 fully efficient observations he states "the the paraphernalia of regresion analysis is clearly unjustified" (p. 277). Nevertheless he estimates the "best practice" frontier for illustration purposes.

Aigner, Amemiya, and Poirier (1976)

Scope: US metals industry and artificial data.

Model: Cobb-Douglas

$$x_0 = x_1 x_2^{b_2} x_3^{b_3} \varepsilon$$

where:

x_0 = output, x_i = inputs, $i = 1, 2, 3$, b^i are the parameters to be estimated and ε is statistical error.

Error term assumptions

Different weights are assumed for positive and negative residuals.

$$\varepsilon_i = \begin{cases} \dfrac{\varepsilon_i^*}{\sqrt{1-\theta}} & \text{if } \varepsilon_i^* > 0 \qquad \dfrac{\varepsilon_i^*}{\sqrt{\theta}} \quad \text{if } \varepsilon_i^* \leq 0 \end{cases}$$

where:

$\varepsilon_i^* \sim N(0, \sigma^2)$ for $0 < \theta < 1$ and $\varepsilon_i^* \sim$ truncated normal (with mean $\pm$ 0.798 sigma, and variance $0.363\sigma^2$), positive when $\theta = 0$ and negative when $\theta = 1$, respectively.

Assumptions about the independent variables

Values for the inputs are given: they are "exogenous" and assumed to be free of statistical error. See expression for x_i above. in the model formulation

Estimation Methods

- OLS = Ordinary Least Squares
- Corrected OLS
- ML = Maximum Likelihood

Comments

- Precursor of Aigner, Lovell and Schmidt (1977) which is reported here.
- Unified treatment of frontier and average production functions, and ordinary least squares

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Aigner, Lovell and Schmidt (1977)

Scope: US Metals Industry 1957-58; US Agriculture 1960-65.

Model: Cobb-Douglas, which is logarithmically transformed into

$$y_t = X\beta + \varepsilon_t$$

$$\varepsilon_t = v_t + \mu_t$$

where:

y_t = output, X = vector of inputs, and β a vector of coefficients with parameter values to be estimated and ε_t is the error term, which is composed by μ_t, the inefficiency component and v_t, random error component.

Error term assumptions

$\varepsilon_t = v_t + \mu_t$ where

$\mu_t = -|\mu^*|$, $\mu^* \sim N(0, \sigma_\mu^2)$

$v_t \sim N(0, \sigma_v^2)$

v_t and μ_t are independent

Assumptions about the independent variables

- X is a vector of exogenous variables implicitly assumed to be free of observational error.

Estimation Methods

- OLS
- ML

Comments

- Seminal piece on stochastical frontiers.

Meeusen and Van den Broeck (1977-a)

Scope: Ten French Manufacturing Industries.

Model: Cobb-Douglas

$$y_t = A\prod_{j=1}^{n} x_{t_j}^{\beta_j} e^{-Z_t} e^{-V_t}$$

where:

y_t represents output at time "t," x_{tj} represents amount of input j, $j = 1, \ldots, n$, at time "t," and A, and the β_j are the parameters to be estimated. e^{-Z_t} is the efficiency error component, and e^{-V_t} is the statistical error component.

Error term assumptions

$e^{-Z_t} \sim -Z_t$ has an exponential distribution

$e^{-V_t} \sim -V_t \sim N(0, \sigma^2)$

Assumptions about the independent variables

The independent variables x_{tj} are "free of error," both managerial and statistical error.

Estimation Methods

- ML

Comments

- Independently introduced the composed error model.
- Builds on Afriat (1972), and Richmond (1974)
- In a related piece, Meeusen and Van den Broeck (1977-b), the authors study the correlation of X_t, the matrix of independent variables (i.e., the inputs) with the inefficiency error component, e^{-Z_t}, but the study is seriously deficient because it continues to assume that the independent variables are free of both statistical and managerial error in the estimation method employed. In addition, this later piece incurs in a contradiction: assumes independent variables for estimation purposes "free of error," but then studies input inefficiencies such as labor and capital inefficiencies as derived from this statistical analysis.

Lee and Tyler (1978)

Scope: Brazilian Manufacturing firms

Model: Cobb-Douglas, which is logarithmically represented by

$y = X\beta + \varepsilon$

$\varepsilon = v - \mu$

where:

in logarithmic units, y is an output vector, X is a vector of inputs, β is a vector of parameters to be estimated and ε is an error term with components $\varepsilon = (v - \mu)$ representing statistical noise and inefficiency, respectively.

Error term assumptions

$v \sim N(0, \sigma_v^2)$ $\mu \sim$ "a one-sided, non-positive error, which is derived from a normal $(0, \sigma^2)$ distribution truncated from above" (p. 386).

Assumptions about the independent variables

- Assumes "independence of μ and the inputs in X" (p.387), however contradicts this asssumption when asserting "μ is reflected in, e.g., poor managerial skills, work stoppages, material bottlenecks, and low employee effort." (p. 386), which implies that these inefficiencies are reflected in X, y, or both.
- No explicit assumption about errors (or lack of thereof) in the independent variables.

Estimation Methods

- OLS
- ML

Comments

- Employs firm-level data
- Builds upon Aigner, Lovell and Schmidt (1977).

Van den Broeck, Forsund, Hjalmarsson , and Meeusen (1980)

Scope: Swedish dairy industry, 1964-1973.

Model: Cobb-Douglas

$$x = A \ L^{\alpha_L} \ K^{\alpha_K} \ e^{-\beta x}$$

where:

x represents tons of milk, L represents labor, K represents capital, α_L and β_K represent the scale function parameters to be estimated, and $e^{-\beta x}$ is the error term component of $-Z_0 - Z_1$, where Z_0 is statistical and Z_1 is managerial error or inefficiency.

Error term assumptions

Adopts a "composed error" model in which $e^{-\beta x} = e^{-Z0-Z1}$, where $Z0 \sim N(0, \sigma)$ is the random noise component, and $Z1 \sim h_{Z1}(z1) = (1 + \alpha)e^{-(1+\alpha)Z1}$ is the efficiency component, which is assumed to follow an exponential distribution.

Assumptions about the independent variables

- "The input structure of each unit observed is given." (p. 136).

Estimation Methods

- LP
- ML

Comments

- Compares deterministic (linear programming) and stochastic frontiers
- Analysis combines cross section and time series data.
- Production frontier found to be a neutral shift of the average (interior points OLS) production functions.
- Empirically the same DMUs appear above the frontier in 3 consecutive years. This would appear to contradict the assumptions that they are randomly distributed (i.e., contradicts the statistical error assumption that these observations will fall above and below the frontier randomly).
- Effective use of graphs to interpret production functions, elasticity curves, isoquants, etc., and good discussion about aggregate efficiency.
- Defines optimal scale output as $x = (1 - \alpha)/\beta$. Where α and β, are the "scale function parameters" previously defined by (α_{I}, β_{K}).

Kopp and Smith (1980)

Scope: US Electric Plants 1969-1973

Models: Cobb-Douglas, Translog, and CES (Constant Elasticity of Substitution).

The three models are specified in terms of the following translog function which specializes to the other two functions on certain assumptions.

$$\ln Q_k = \alpha_0 + \sum_{i=1}^{2} \alpha_i \ln X_{ik} + \frac{1}{2} \sum_{i=1}^{2} \sum_{j=1}^{2} \gamma_{ij} \ln X_{ik} \ln X_{jk} - \varepsilon_k$$

where:

Q_k = observed output of the kth unit
X_{ik} = vector of input levels (i = 1,2) for kth unit
$\gamma_{11} + \gamma_{22} - 2\gamma_{12} = 0$ --> CES restrictions.
$\gamma_{11} = \gamma_{12} = \gamma_{22} = 0$ --> Cobb-Douglas restrictions.

Error term assumptions

Adopts the composed error model, $\varepsilon_i = v_i + \mu_i$, where v and μ are statistical noise and inefficiency, respectively, with

$\varepsilon_i \sim (\mu, \sigma^2)$ with $\varepsilon_i \geq 0$ for all i

$\varepsilon_i = v_i + \mu_i$

where: $v_i \sim (0, \sigma^2)$, $\mu_i \sim$ truncated normal, and μ and v are independent.

$$E(\varepsilon_i) = E(\mu_i) = (\sqrt{2} / \sqrt{\pi})\sigma_u$$

$$V(\varepsilon_i) = V(\mu_i) + V(v_i) = [(\pi - 2)/\pi]\sigma_u^2 + \sigma_v^2$$

Assumptions about the independent variables

- All error is assumed to be in the dependent variable (see above expression).

Estimation Methods

- Linear Programming
- Corrected OLS
- ML

Comments

- Interest centers on comparing results from the 3 functional forms and 3 methods of estimation

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Kopp and Mullahi (1990)

Scope: Electricity Generation Plants

Model: Cobb-Douglas

$$y_t = \alpha + x_{1t}\beta + v_t + \mu_t = x_t\delta + v_t + \mu_t$$

where:

y_t, in logarithmic units, is a scalar measure of cost; α is a scalar, β a a vector of slope parameters to be estimated, x_{1t} is a vector of input prices and output; v_t and μ_t, represent statistical error and inefficiency, respectively; and $\delta = (\alpha, \beta)$.

Error term assumptions

- μ_t and v_t are assumed to be uncorrelated with x_t
- $f_u(\mu_t)$, the distribution of inefficiencies, is correctly specified
- v_t, the statistical error component, is conditionally symmetric around zero with well behaved higher order moments.

Assumptions about the independent variables

- Assumes that the independent variables represented in x are free of error and free of inefficiencies (see the way the model is written).

Estimation Methods

- Generalized Method of Moments - GMM

Comments

- This is the first paper which deviates from other studies in which the noise component is assumed to be iid normal.
- Develops a test to determine whether the data are consistent with a asymmetrically distributed inefficiency component (p. 173).
- The paper aims to show that moment based estimates are more robust than maximum likelihood estimators in response to misspecificaqtion of the symmetric error assumed for μ.
- The authors employ 3 different data sets and apply tests to see if they conform to underlying assumptions about the error terms. From the 3 data sets two "pass" the test. The third fails and for this data set "the results of the symmetry test suggest that there is little hope of separating the errors due to inefficiencies from simple random noise." P. 179.
- The authors note that COLS (Corrected Ordinary Least Squares) frontier estimation is also a moment-based method.

Cornwell, Schmidt and Sickles (1990)

Scope: US Airlines 1970-1981

Model: Translog

$$Y_{it} = X_{it}B + W_{it}\delta_i + V_{it} + \varepsilon_{it}$$

where:

Y_{it} and X_{it} represent output "i" on period "t," respectively. W_{it} contains an intercept plus time and time squared which are individually-varying and Z_{it}

Error term assumptions

$$\varepsilon_{it} = V_{it} + \mu_{it}$$
$$\mu_{it} = \theta_{i1} + \theta_{i2} + \theta_{it}t^2$$
$$W_{it} = [\theta_{i1},\theta_{i2},\theta_{i3}] = [1, t, t^2], \delta_i$$

Assumptions about the independent variables

- No explicit assumption is made about errors (or lack of thereof).
- Correlations between efficiency term and X_i are admisible.

Estimation Methods

- Generalized LS
- ML

Comments

- Introduces a procedure to estimate firm-specific inefficiencies. Relaxes the assumption that firm inefficiencies are time invariant.
- Overcomes problems associated with the distributional assumptions of the composed error model by using panel data.
- Single output model

Greene (1990)

Scope: US Electric Utility Industry

Model: Translog

$$\ln(Cost/P_f) = \beta_0 + \beta_1 \ln Q + \beta_2 \ln^2 q + \beta_3 \ln(P_1/P_f) + \beta_4 \ln(P_k/P_f) + \varepsilon$$

$$\varepsilon = v + \mu$$

where:

$Q =$ is output; P_1,P_k and P_f are the three factor prices corresponding to labor, capital and fuel. ε is the error term, composed of v and μ, the statistical noise and inefficiency components, respectively.

Error term assumptions

$\mu \sim G(\Theta, P)$ and $v \sim N(0, \sigma^2)$
where G regers to the gamma and N to the normal distribution, respectively.

Assumptions about the independent variables

- Interest is in the effect of errors of measurement on the dependent variable (p. 142).
- Implicitly assumes that independent variables are free of error.

Estimation Methods

- Corrected OLS
- ML

Comments

Argues advantages of Gamma distribution for representing μ versus use of half normal and exponential distributions.

Thiry and Tulkens (1990).

Scope: Belgian Urban Transit Companies 1977-1985

Model: Translog

$$\log Y = \alpha_0 + \sum_{i=1}^{3} \alpha_i \log X_i + \sum_{i=1}^{3} \sum_{j} i\alpha_{ij} \log X_i \log X_j + \varepsilon$$

where:

Y = output (seats-km), X_i for $i = 1, 2, 3$ inputs (energy in kwh, labor in hours of work, and seat-vehicles).

Error term assumptions

- Normally distributed

Assumptions about the independent variables

- Recognizes presence of inefficiencies by eliminating the observations containing them.

Estimation Methods

- OLS

Comments

- Follows approach introduced by Farrel (1957) to estimate "best practice" production function in two stages. First, employing the "Free Disposal Hull (FDH) method to identify efficient DMUs, the authors separate those units located on the efficiency frontier and those located below the frontier; second, the latter group are discarded and the "best practice" frontier is estimated by OLS employing only the set of "efficient units" located on the frontier.

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