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TECHNICAL EFFICIENCY OF PRODUCTION IN AGRICULTURAL RESEARCH

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We define and model research production at Embrapa, the major Brazilian institution responsible for applied agricultural research. The main theoretical framework used is Data Envelopment Analysis – DEA. The economic interpretation of these models is explored to assess scale, congestion and cost efficiencies. Efficiency results are used to test for differences among types of research units and for the scale of operation. A further analysis of agricultural research in Brazil is carried out with the inclusion of three research centers in Argentina. Finally, DEA estimates are compared with the fit of a stochastic frontier.

Introduction

It is of importance to the administrators of research institutions to have at their disposal measures and procedures that make feasible an evaluation of the quantum of productivity as well as the technical efficiency of the production process of their institutions. In times of competition and budget constraints a research institution needs to know by how much it may increase its production, with quality, without absorbing additional resources. The quantitative monitoring of the production process allows for an effective administration of the resources available and the observation of predefined research patterns and goals. In this context we developed, at Embrapa, a production model based on the input-output data of its research units. The model serves the purpose to evaluate productivity, quantitatively, at relative and absolute levels. The theoretical framework for this model is the analysis of production frontiers. We make intensive use of DEA models described in *Seiford*,[12] *Färe*,[5] *Charnes*,[4] *Sengupta*,[13] and *Färe*.[6] DEA models are linear programming models that essentially generalize the notion of productivity. The dual problems of these models provide a rich economic framework relative to which it is possible to assess scale of production and input congestion. Our discussion of the subject is as follows. Firstly we detail the data envelopment models

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exploring the approach of *Färe*.[5] Then we introduce the input and output measures of Embrapa's production process and we present our empirical and statistical findings. These include a test for the scale of operation of the production process (constant returns vs. variable returns) and a test to investigate the existence of differences in technical efficiencies among the three types of research centers operating at Embrapa. The period covered in the analysis is 1996. The analysis is carried out for cost and quantity data. We augment the data with information from three major research units from Inta – Argentina and analyze Embrapa's research production from an international perspective. Finally we compare DEA results with the econometric fit of a stochastic frontier.

Data envelopment production models

Consider a production process composed of n decision making units (DMUs). Each DMU uses varying quantities of m different inputs to produce varying quantities of s different outputs. Denote by

$$Y = (y_1, y_2, \ldots, y_n)$$

the $s \times n$ production matrix of the n DMUs. The rth column of Y is the output vector of DMU r. Denote by

$$X = (x_1, x_2, \ldots, x_n)$$

the $m \times n$ input matrix. The rth column of X is the input vector of DMU r. The matrices $Y = (y_{ij})$ and $X = (x_{ij})$ must satisfy: $p_{ij} \geq 0$, $\Sigma_j p_{ij} > 0$ and $\Sigma_i p_{ij} > 0$ where p is x or y.

Definition 1 The measure of technical efficiency of production (under constant returns to scale) for DMU $o \in \{1,2,\ldots,n\}$, denoted $E^{CR}(o)$, is the solution of the linear programming problem

$$E^{CR}(o) = \max_{u,v} \frac{y_o' u}{x_o' v}$$

subject to (i) $x_o' v = 1$, (ii) $y_j' u - x_j' v \leq 0$, $j = 1,2,\ldots,n$ and (iii) $u \geq 0$, $v \geq 0$.

If we look at the coefficients u and v as input and output prices, we see that the measure of technical efficiency of production is very close to the notion of productivity (output income/input expenditure). Technical efficiency, in this context, basically, is looking for the price system (u, v) for which DMU o achieves the best relative productivity ratio.

An interesting motivation for the concept of technical efficiency obtains from the case $s = m = 1$. In this instance condition (ii) implies that

$$v = \frac{1}{x_o}$$

Let

$$R = \max_{j=1,\dots,n} \frac{y_j}{x_j}$$

be the largest output to input ratio (largest productivity) in the set of the n DMUs. Constraints (ii) and (iii) imply that

$$0 \le u \le \frac{1}{x_o R}$$

Hence,

$$E^{CR}(o) = \frac{y_o}{x_o R}$$

since the maximum is achieved when $u = (x_o R)^{-1}$. Thus we see that in the simple case of one input and one output the measure of technical efficiency is simply a normalization rule. In other words, the DMU with best productivity ratio has unit technical efficiency. Any other DMU has its efficiency evaluated dividing its productivity ratio by the best productivity ratio. It is interesting to observe that the quantity $E^{CR}(o)$, in this simple context, represents the proportional reduction one should apply to input quantity x_o in order to force o to achieve the best productivity ratio R. Equivalently, the reciprocal of technical efficiency define the proportional increase in output production necessary to obtain R. This is the essence of DEA models.

The dual problem of the linear programming problem of Definition 1 has an important economic interpretation, which we will explore. The features of the case $s = m = 1$ will be more evident in the context of the dual problem.

In matrix terms we may write the linear programming problem as

$$\max_{u,v,\delta} (y_o', 0, 0) \begin{pmatrix} u \\ v \\ \delta \end{pmatrix}$$

subject to the constraints

$$\begin{pmatrix} 0 & x_o' & 0 \\ Y' & -X' & I \end{pmatrix} \begin{pmatrix} u \\ v \\ \delta \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

where δ is a vector of slack variables and I is the identity of order n.

The corresponding dual problem is $\min_{\theta,\lambda} \theta$ subject to

$$\begin{pmatrix} 0 & Y \\ x_o & -X \\ 0 & I \end{pmatrix} \begin{pmatrix} \theta \\ \lambda \end{pmatrix} \geq \begin{pmatrix} y_o \\ 0 \\ 0 \end{pmatrix}$$

or, equivalently, $\min_{\theta,\lambda} \theta$ subject to (i) $Y\lambda \geq \theta y_o$, (ii) $X\lambda \leq \theta x_o$ and (iii) $\lambda \geq 0$, θ free.

The matrix products $Y\lambda$ and $X\lambda$ with $\lambda \geq 0$ represent linear combinations of the columns of Y and X, respectively. A sort of weighted averages of output and input vectors. In this way, for each λ, we can generate a new production relation, a new "pseudo" producer. Trivially the set of DMUs 1, 2,..., n are included among those new producers. Making allowance for these newly defined production relationships, the question that the dual intends to answer is: What proportional reduction of inputs θx_o it is possible to achieve for DMU o and still produce at least output vector y_o? The solution $\theta^*(x_o,y_o)$ is the smallest θ with this property. In this context the quantity $\theta^*(x_o,y_o)$ is known as a radial measure of technical efficiency. It is radial in the sense that the proportional reduction is applied uniformly to the entire input vector. The analogy with the case $s = m = 1$ is perfect. It is possible to define a non-radial measure of technical efficiency, see *Färe*,[5] but we will not consider it here.

Let (λ^*,θ^*) denote the solution of the dual problem. An inefficient DMU can be made more efficient by projection onto the isoquant, the set of efficient DMUs. This projection is defined by the mapping $(x_o,y_o) \rightarrow \theta^*(x_o,y_o)$. The projection will be Pareto efficient[+] when $X\lambda^* = \theta^* x_o$ and $Y\lambda^* = y_o$.

We can define the concept of technical efficiency of production in a context of fixed inputs instead of fixed outputs, i.e., in a program of output augmentation. In this environment the measure of technical efficiency of production of DMU o, under constant returns to scale, is $\phi^*(x_o,y_o) = \max_{\phi,\lambda}\phi$ subject to (i) $Y\lambda \geq \phi y_o$, (ii) $X\lambda \leq x_o$ and (iii) $\lambda \geq 0$, ϕ free.

[+]A production pair $w = (x,y)$ is Pareto efficient if we cannot find another production pair $z = (x_o,y_o)$ with $z \neq w$ such that $x_o \leq x$ and $y_o \geq y$.

In the output augmentation program the question we ask is what proportional rate ϕ can be uniformly applied to augment the output vector y_o without increasing the input vector x_o. The solution ϕ^* is the largest ϕ with this property. Projection onto the isoquant with fixed inputs is achieved with the mapping $(x_o,y_o)\rightarrow(x_o,\phi^* y_o)$. We have $\phi^* = 1/\theta^*$. Again the analogy with the case $s = m = 1$ is perfect.

One introduces the notion of scale of operation in DEA models imposing restrictions on the vector λ of nonnegative weights. The most general mode of operation is variable returns to scale (VR) which obtains imposing $\Sigma_i\lambda_i = 1$. Decreasing returns (DR) obtains imposing $\Sigma_i\lambda_i \leq 1$ and increasing returns obtains when $\Sigma_i\lambda_i \geq 1$. We can define a scale measure of technical efficiency as the ratio

$$\theta^*_{scale}(o) = \frac{\theta^*_{CR}}{\theta^*_{VR}}$$

A value $\theta^*_{scale}(o) < 1$ means inefficiency. If inefficiency holds and $\theta^*_{CR} = \theta^*_{DR}$ then DMU o operates in a region of increasing returns and y_o is too small for (x_o,y_o) to be efficient. If, on the other hand, $\theta^*_{CR} < \theta^*_{DR}$, then DMU o operates in a region of decreasing returns and x_o is too large for (x_o,y_o) to be efficient.

Input congestion implies the possibility of increasing inputs with actual reduction of the output level. A measure of congestion technical efficiency obtains considering the ratio

$$\theta^*_{cong}(o) = \frac{\theta^*_{VR}}{\theta^*_{g}}$$

where $\theta^*_g(x_o,y_o)$ solves the linear programming problem $\min_{\theta,\lambda}\theta$ subject to (i) $Y\lambda \geq \theta x_o$, (ii) $X\lambda = \theta x_o$ (iii) $\Sigma_i\lambda_i = 1$, $\lambda_i \geq 0$, and (iv) θ free. A value of $\theta^*_{cong} < 1$ indicates congestion. If such is the case, it is of interest to pinpoint which inputs, or combination of inputs, are responsible for the observed congestion. This is accomplished with the use of partial measures of technical efficiency. Let B be a subset of $\{1, 2,..., m\}$ with at least one element and B^c its complement. Suppose we want to investigate if the input set B^c causes congestion. Partition X and x_o according to the inputs in B. In other words, write

$$X = \begin{pmatrix} X^B \\ X^{B^c} \end{pmatrix} \text{ e } x_o = \begin{pmatrix} x_o^B \\ x_o^{B^c} \end{pmatrix}$$

Find the solution $\theta^*_{cong,B}(x_o,y_o)$ of the linear programming problem $\min_{\theta,\lambda}\theta$ subject to (i) $Y\lambda \geq y_o$, (ii) $X^B\lambda \leq \theta x^B_o$, (iii) $X^{B^c}\lambda = \theta x^{B^c}_o$ and (iv) $\Sigma_i\lambda_i = 1$, $\lambda_i \geq 0$; θ free. If $\theta^*_{cong,B}(x_o,y_o) = \theta^*_{VR}(x_o,y_o)$ the sub vector of inputs B^c congests production. Note that there is not uniqueness in the notion of congestion. The analysis has to be carried out for all possible subsets of the input list.

We thus have the following decomposition

$$\theta^*_{CR}(o) = \theta^*_{scale}(x_o,y_o)\theta^*_{cong}(x_o,y_o)\theta^*_g(x_o,y_o)$$

It follows that a DMU is inefficient either due to scale problems, congestion or because it does not belong to the frontier of the problem leading to the solution $\theta^*_g(x_o,y_o)$.

To summarize we present the four main linear programming problems involved in the decomposition of the technical efficiency under constant returns to scale in primal form. These problems are known as multiplier problems and are handy for computational purposes. In general we are looking for

$$\max_{u,v,u^*} y'_o,u+u^*$$

subject to $x'_o v = 1$ and $Y'u-X'v+u^*1 \leq 0$. Imposing additional restrictions on the variables u, v and u^* we can generate all four linear programming problems:

1. constant returns: $u,v \geq 0$ and $u^* = 0$.
2. decreasing returns: $u,v \geq 0$ and $u^* \leq 0$.
3. variable returns: $u,v \geq 0$ and u^* free.
4. variable returns and congestion: $u \geq 0$ and u^*,v free.

If in addition to the quantity matrices Y and X a vector $p > 0$ of input prices is available for each DMU we may also compute a cost measure of technical efficiency. Our discussion will assume constant returns to scale. Let p_o and y_o denote prices and outputs for DMU o and let $C(p_o,y_o)$ be the solution of $\min_{\lambda,x}p'_o x$ subject to the conditions $Y\lambda \geq y_o$ and $X\lambda \leq x$, where x and λ are nonnegative. The measure of cost efficiency for DMU o is

$$\theta^*_{cost}(x_o,y_o) = \frac{C(p_o,y_o)}{p'_o x_o}$$

We see that the cost efficiency is given by the ratio of the minimum cost attainable to observed cost. Whenever $\theta^*_{cost}(o) < 1$, DMU o is spending more on inputs than is necessary to produce y_o. As in *Färe*,[5] the excess is due to either or both of two factors (i) using too much of all inputs, and (ii) using inputs in the wrong mix. The first factor is measured by $\theta^*_{CR}(x_o,y_o)$ and the second is measured by the allocative measure of cost efficiency. This is simply the ratio $A(x_o,y_o)$ of $\theta^*_{cost}(x_o,y_o)$ to $\theta^*_{CR}(x_o,y_o)$. It follows that

$$\theta^*_{cost}(x_o,y_o) = \theta^*_{CR}(x_o,y_o) \times A(x_o,y_o)$$

If only total input costs and output quantity data it is still possible to define a measure of technical efficiency. Let Q be the cost n vector. We now look for the minimum, in λ and x, both nonnegative, of $Q'\lambda$, subject to the condition $X\lambda \leq x$ and $Y\lambda \geq y_o$. We will not make use of this measure in this paper.

Statistical properties of DEA estimates

Suppose $m = 1$ (a single output) and assume the existence of a continuous frontier production function $g: \mathcal{K} \to \mathcal{R}$ defined on the convex and compact subset $\mathcal{K}$ of the positive orthant of $\mathcal{R}^s$. For each DMU o, the input observations x_o are points in $\mathcal{K}$. Let

$$\mathcal{K}^* = \left\{ x \in \mathcal{K}; x \geq \sum_{i=1}^{n} \lambda_j x_j, \lambda_j \geq 0, \ \sum_{i=1}^{n} \lambda_j = 1 \right\}$$

The DEA frontier production function is defined for $x \in \mathcal{K}$ by

$$g^*(x) = \sup_{\lambda} \left\{ \sum_{j=1}^{n} \lambda_j y_j ; x \geq \sum_{i=1}^{n} \lambda_j x_j, \lambda_j \geq 0, \sum_{i=1}^{n} \lambda_j = 1 \right\}$$

and it can be shown that for DMU o

$$g^*(x_o) = \frac{y_o}{\theta^*_{CR}(x_o, y_o)}$$

where we are assuming constant returns to scale.

Suppose that observations (x_o,y_o) are interior points to $\mathcal{K}$ and that they are generated in accordance with the (deterministic) statistical model

$$y_o = g(x_o) - \varepsilon_o$$

where

a. The inefficiencies ε_o are iid with a common density $f(\varepsilon)$, which is monotonically decreasing in $(0,+\infty)$.
b. The common distribution function $F(x)$ of the inefficiencies is strictly positive in $(0,+\infty)$.

c. The inputs x_o represent a random sample from a density $h(x)$ strictly positive in the interior of $\mathcal{K}$.
d. The inputs x_o and the inefficiencies are independent.

Then

e. $g^*(x_o)$ is the nonparametric maximum likelihood estimate of $g(x_o)$.
f. $g^*(x_o)$ is weakly consistent for $g(x_o)$.
g. Let M be any fixed subset of DMUs. If n is large the joint distribution of the estimated inefficiencies $\hat{\varepsilon}_j = y_j - g^*(x_j), j \in M$, is, approximately, the joint distribution of the true inefficiencies $\varepsilon_j, j \in M$.

These results are due to *Banker.*[1] Consistency can be extended to the multiple output case. See *Kneip.*[9]

The asymptotic properties of the $\hat{\varepsilon}_o$ serves as a basis for nonparametric hypothesis testing. An example would be testing for constant returns to scale. We perform this test comparing the distribution function of the $\hat{\varepsilon}_o$ under the assumptions of constant and variable returns to scale using Kolmogorov-Smirnov test. *Banker*[1] also suggests a parametric test to test two groups of DMUs for equality of their technical efficiencies. His approach assumes either an exponential or a half-normal distribution. *Brocket*[3] suggests a nonparametric approach that applies to more than two groups. This is the method we use. The three-step procedure follows:

1. Run DEA separately for each group and project inefficient units onto the frontier.
2. Run DEA with the adjusted production values of step (1).
3. Use Wilcoxon rank test to the values in step (2) to assess group differences in efficiency.

Embrapa's production system

Embrapa's research system comprises 37 units (DMUs) of research centers. Input and output actions have been defined from a set of performance indicators known to the company since 1991. The company uses routinely some of these indicators to monitor performance through annual work plans. With the active participation of the board of directors of Embrapa as well as the administration of each of its research units we selected 28 output and 3 input indicators as representative of production actions in the company.

We begin our discussion of Embrapa's production system with the output. The output indicators were classified into four categories. Scientific production, production of technical publications, development of technologies, products and processes and diffusion of technologies and image. By scientific production we mean the publication of articles and book chapters aimed mainly to the academic world. We require that each item be specified with complete bibliographical reference. Specifically the category of scientific production includes the following items.

1. Scientific articles published in refereed journals and book chapters – domestic publications.
2. Scientific articles published in refereed journals and book chapters – foreign publications.
3. Articles and summaries published in proceedings of congresses and technical meetings.

The category of technical publications groups publications produced by research centers aiming, primarily, agricultural businesses and agricultural production. Specifically,

1. Technical circulars. Serial publications, written in technical language, listing recommendations and information based on experimental studies. The intended coverage may be the local, regional or national agriculture.
2. Research bulletins. Serial publications reporting research results.
3. Technical communiqués. Serial publications, succinct and written in technical language, intended to report recommendations and opinions of researchers in regard to matters of interest to the local, regional or national agriculture.
4. Periodicals (document series). Serial publication containing research reports, observations, technological information or other matters not classified in the previous categories. Examples are proceedings of technical meetings, reports of scientific expeditions, reports of research programs, etc.
5. Technical recommendations/instructions. Publication written in simplified language aimed at extensionists and farmers in general, and containing technical recommendations in regard to agricultural production systems.
6. Ongoing research. Serial publication written in technical language and approaching aspects of a research problem, researches methodologies or research objectives. It may convey scientific information in objective and succinct form.

The category of development of technologies, products, and processes groups indicators related to the effort made by a research unit to make its production available to society in the form of a final product. We include here only new technologies, products and processes. These must be already tested at the client's level in the form of prototypes or through demonstration units or be already patented. Specifically,

1. Cultivars. Plant varieties, hybrids or clones.
2. Agricultural and livestock processes and practices.

3. Agricultural and livestock inputs. All raw material, including stirps, that may be used or transformed to obtain agricultural and livestock products.
4. Agro-industrial processes. Operations carried out at commercial or industrial level envisaging economic optimization in the phases of harvest, post harvest and transformation and preservation of agricultural products.
5. Machinery (equipment). Machine or equipment developed by a research unit.
6. Scientific methodologies.
7. Software.
8. Monitoring, zoning (agroecologic or socioeconomic) and mapping.

Finally, the category of diffusion of technologies and image encompasses production actions related with Embrapa's effort to make its products known to the public and to market its image. Here we consider the following indicators.

1. Field days. Research units organize these events. The objective is the diffusion of knowledge, technologies, and innovations. The target public is primarily composed of farmers, extensionists, organized associations of farmers (cooperatives), and undergraduate students. The field day must involve at least 40 persons and last at least 4 hours.
2. Organization of congresses and seminars. Only events with at least 3 days of duration time are considered.
3. Seminar presentations (conferences and talks). Presentation of a scientific or technical theme within or outside the research unit. Only talks and conferences with a registered attendance of at least 20 persons and duration time of at least one hour are considered.
4. Participation in expositions and fairs. Participation is considered only in the following cases:
   (a) With the construction of a stand with the purpose of showing the center's research activities by audiovisuals and distributing publications uniquely related to the event's theme.
   (b) Co-sponsorship of the event.
5. Courses. Courses offered by a research center. Internal registration is required specifying the course load and content. The course load should be at least 8 hours. Disciplines offered as part of university courses are not considered.
6. Trainees. Concession of college level training programs to technicians and students. Each trainee must be involved in training activities for at least 80 hours to be counted in this item.
7. Fellowship holders. Orientation of students (the fellowship holders). The fellowship duration should be at least six months and the work load at least 240 hours.

8. Folders. Only folders inspired by research results are considered. Reimpressions of the same folder and institutional folders are not counted.
9. Videos. Videos should address research results of use for Embrapa's clients. The item includes only videos of products, services and processes with a minimum duration time of 12 minutes.
10. Demonstration units. Events organized to demonstrate research results – technologies, products, and processes, already in the form of a final product, in general with the co-participation of a private or government agent of technical assistance.
11. Observation units. Events organized to validate research results, in space and time, in commercial scale, before the object of research has reached its final form. Observation units are organized in cooperation with producers, cooperatives, and other agencies of research or private institutions. The events may be organized within or outside the research unit.

The input side of Embrapa's production process is composed of three factors. Personnel, operational costs (consumption materials, travel and services less income from production projects), and capital measured by depreciation.

Input and output indexes

As indicators (inputs and outputs) of the process we consider a system of dimensionless relative indexes. These are all quantity indexes. The idea, from the output point of view, is to define a combined measure of output as a weighted average of the relative indicators (indexes) in the system. The relative indexes are computed for each production variable and for each research unit within a year dividing the observed production quantity by the mean per research unit. Only research units that can potentially exercise the production activity related to the production variable in question are included in the computation of the mean. We see that, within a given year, the base of our system of production indexes is defined by the set of means per unit defined by the production variables. In case of inputs the means use all 37 cases. In principle DEA assumes quantity data. We use the number of employees to represent the personnel factor. Division of money expenses by their respective means will produce a quantity index under the assumption of a common price to all research units. This is a reasonable assumption for operational and capital expenses considering the interest rate as the relevant price. The input indexes are indicated by x_i^o, $i = 1, 2, 3$. These quantities represent relative indexes of personnel, operational expenditures, and capital expenditures, respectively. A combined measure of inputs x_o is defined as the simple average of the three quantities x_i^o.

Output measures per category are defined as follows. The output component y_i, $i = 1, 2, 3, 4$ of each production category is a weighted average of the relative indexes composing the category. If o is the DMU (research unit) being evaluated then

$$y_i^o = \sum_{j=1}^{k_i} a_{ji}^o y_{ji}^o ; 0 \le a_{ji}^o ; \sum_{j=1}^{k_i} a_{ji}^o = 1$$

where a_{ji}^o, $j = 1, \ldots, k_i$ is the weight system for DMU o in the category of production i, k_i is the number of production indicators comprising i and y_{ji}^o is the relative index of production j. The weights, in principle, are supposed to be user defined and should reflect the administration perception of the relative importance of each variable to each DMU. Defining weights is a hard and questionable task. In our application in Embrapa we followed an approach based on the law of categorical judgment of Thurstone. See *Torgerson*[14] and *Kotz.*[8] The model is competitive with the AHP method of *Saaty*[11] and is well suited when several judges are involved in the evaluation process. Basically we sent out about 500 questionnaires to researchers and administrators and asked them to rank in importance – scale from 1 to 5, each production category and each production variable within the corresponding production category. A set of weights was determined under the assumption that the psychological continuum of the responses projects onto a lognormal distribution.

DEA models implicitly assume that the DMUs are comparable. This is not strictly the case in Embrapa. To make them comparable it is necessary an effort to define an output measure adjusted for differences in operation and perceptions. At the level of the partial production categories we induced this measure allowing a distinct set of weights for each DMU. In principle one could go ahead and use DEA with multiple outputs. This would minimize the effort of defining weights leaving to DEA the task of finding these coefficients. The problem with such approach is that there is a kind of dimensionality curse in DEA models. As the number of factors (inputs and outputs) increases, the ability to discriminate between DMU's decreases, i.e, as *Seiford*[12] put it "given enough factors, all (or most) of the DMUs are rated efficient. This is not a flaw of the methodology, but rather a direct result of the dimensionality of the input/output space relative to the number of DMUs". In our case with 4 separate measures of output we found that more then 60% of the DMUs were efficient. In this context we found convenient to extend the weight system to produce a single measure of output y_o. This further established a common basis to compare research units and avoided the incidence of zero output (shadow) prices, another common occurrence in multiple output models (and also a disturbing fact for management interpretation!). A single output also allows the use of the statistical tests described in the previous section.

The (combined) measure of productivity for DMU o is given by the ratio Prod(o) $= y_o/x_o$. We call a research unit productive when its productivity measure is greater than or equal to one.

Data analysis I

We performed a DEA analysis with 34 of the 37 research centers of Embrapa for the year 1996. Three research centers were eliminated from the analysis due to the particular nature of their operation. In Tables 1 and 3 these are coded as UD35, UD36, and UD37. The research units of Embrapa's system are classified into 3 types according to their missions and research objectives. Ecoregional research units (E, total of 13 units), product oriented (simply referred as product), research centers (P, total of 15 units) and thematic research centers (T, total of 9 units). As described before the production system comprises 28 output items and 3 inputs. The output variables are reduced to a single output measure with the use of a weight system variable per research unit. The only production category where one can observe major differences in perception among research units is development of technologies, products and processes. The basic data is shown in Table 1.

Table 2 shows the results of DEA. Of the four efficient units only UD33 is Pareto efficient. Shadow prices (not shown) also indicate that units are more efficient in the use of operational expenses than personnel and capital. The location of operation relative to the efficient frontier is as follows. Research units UDs 07, 12, 17, 24, 25, and 26 show decreasing returns to scale. The others, with the exception of the four technical efficient, show increasing returns. Congestion measures are particularly low for UDs 01, 03, 07, 08, and 17. In all these research units the congestive component is operational expenses. UD08 also shows capital congestive.

Table 2 also shows cost efficiencies. Prices for capital and operational expenses factors were considered constant (unit) for all DMUs and the price for personnel is an index computed from the average year salary of each unit. The basis is the company average salary. These indexes are shown in Table 1. We see that inefficiencies come much more from spending too much on all inputs than due to a poor allocation of resources. It is interesting to note that of the four units technical efficient only one, UD27, is cost efficient.

Table 1
Production indexes – Y (combined), Y1 (scientific production), Y2 (technical publications), Y3 (diffusion), Y4 (technologies, products, and processes). Input indexes – X1 (personnel), X2 (other expenses), X3 (capital) and P (wages)

ID	Type	Y	Y1	Y2	Y3	Y4	X1	X2	X3	P
UD01	E	0.449	0.309	0.848	0.397	0.175	1.382	0.875	1.139	0.727
UD02	E	0.536	0.748	0.492	0.448	0.444	1.415	1.005	1.233	1.045
UD03	E	1.568	1.576	2.463	1.197	0.937	2.713	3.003	1.280	1.132
UD04	E	0.252	0.045	0.524	0.308	0.060	0.343	0.409	0.385	0.938
UD05	E	0.573	0.421	1.185	0.481	0.080	0.912	0.812	0.764	0.906
UD06	E	0.571	0.213	1.318	0.342	0.450	0.762	0.922	0.627	0.948
UD07	E	1.193	1.695	1.007	1.364	0.375	2.125	1.217	2.112	0.991
UD08	E	1.432	0.970	1.729	0.754	2.976	1.923	1.277	1.165	0.827
UD09	E	0.459	0.250	0.760	0.493	0.271	0.390	0.391	0.434	0.959
UD10	E	0.714	0.144	1.477	0.472	0.918	0.475	0.609	0.583	1.008
UD11	E	0.827	0.366	1.537	0.661	0.800	0.564	0.591	0.626	1.010
UD12	E	1.924	1.470	1.046	3.557	0.835	1.806	1.094	1.737	0.957
UD13	E	1.127	0.790	0.872	0.400	3.384	0.569	1.064	0.953	1.140
UD14	P	0.655	1.316	0.360	0.590	0.299	1.105	1.217	0.987	0.988
UD15	P	0.607	0.377	1.248	0.619	0.281	0.964	0.896	0.697	1.007
UD16	P	0.621	0.780	0.014	0.491	1.089	1.143	0.798	1.366	0.884
UD17	P	0863	0.670	0.404	1.771	0.673	1.820	1.095	1.304	0.925
UD18	P	0.712	0.724	0.632	0.550	0.904	0.959	0.960	1.496	0.744
UD19	P	0.505	0.419	0.223	0.752	0.622	0.607	0.638	0.863	0.954
UD20	P	1.523	1.339	0.474	2.392	1.858	1.401	1.583	2.266	0.953
UD21	P	0.901	1.008	1.448	0.892	0.337	0.738	0.885	1.000	1.185
UD22	P	2.422	2.044	0.242	4.404	2.971	1.810	2.121	0.983	0.978
UD23	P	1.486	2.317	0.756	1.584	1.194	1.636	1.015	1.085	0.909
UD24	P	1.056	1.109	1.262	1.389	0.543	0.705	0.891	0.720	0.969
UD25	P	0.817	0.335	0.937	1.088	0.966	0.710	0.460	0.972	0.815
UD26	P	1.586	1.789	1.963	1.559	1.083	1.086	0.945	1.024	1.126
UD27	P	2.008	1.769	1.701	1.292	3.119	1.110	1.250	0.602	0.949
UD28	P	0.748	0.487	0.666	0.418	1.361	0.513	0.389	0.351	0.925
UD29	T	0.606	0.665	0.214	0.536	0.998	0.616	0.859	0.920	1.307
UD30	T	0.866	1.002	0.696	1.020	0.656	0.738	1.539	0.554	1.279
UD31	T	1.068	1.359	1.425	0.675	0.409	0.668	0.871	1.485	1.088
UD32	T	1.206	1.246	0.811	0.594	2.102	0.649	0.909	1.504	1.227
UD33	T	2.638	3.665	2.649	2.193	0.952	1.293	2.069	1.872	1.373
UD34	T	1.253	1.952	0.359	0.671	1.378	0.654	0.822	0.890	0.892
UD35	T	1.501	1.172	1.687	0.726	2.603	0.249	0.401	0.407	1.170
UD36	T	1.518	0.048	0.676	0.454	6.333	0.315	0.676	0.352	1.478
UD37	T	0.500	0.411	0.057	0.278	1.376	0.132	0.447	0.267	1.223

Table 2
Technical efficiencies – CR (constant returns), DR (decreasing returns), Scale, Congestion, Cost and Allocative (cost allocative)

ID	Type	CR	DR	Scale	Congestion	Cost	Allocative
UD01	E	0.266	0.266	0.600	0.556	0.197	0.741
UD02	E	0.277	0.277	0.717	0.897	0.216	0.780
UD03	E	0.367	0.367	0.914	0.402	0.330	0.899
UD04	E	0.394	0.394	0.394	1.000	0.325	0.825
UD05	E	0.396	0.396	0.807	0.998	0.340	0.859
UD06	E	0.403	0.403	0.683	0.930	0.363	0.901
UD07	E	0.509	0.538	0.945	0.538	0.322	0.633
UD08	E	0.582	0.652	0.893	0.652	0.490	0.842
UD09	E	0.694	0.694	0.694	1.000	0.555	0.800
UD10	E	0.784	0.784	0.798	0.997	0.632	0.806
UD11	E	0.845	0.845	0.917	1.000	0.685	0.811
UD12	E	0.913	1.000	0.913	1.000	0.612	0.670
UD13	E	0.971	0.971	0.971	1.000	0.656	0.676
UD14	P	0.332	0.332	0.785	0.963	0.292	0.880
UD15	P	0.388	0.388	0.761	0.961	0.350	0.902
UD16	P	0.404	0.404	0.829	0.899	0.276	0.683
UD17	P	0.409	0.417	0.980	0.417	0.303	0.741
UD18	P	0.439	0.439	0.874	0.900	0.299	0.681
UD19	P	0.479	0.479	0.718	0.885	0.352	0.735
UD20	P	0.600	0.600	0.998	0.885	0.426	0.710
UD21	P	0.653	0.653	0.901	0.998	0.515	0.789
UD22	P	0.739	1.000	0.739	1.000	0.727	0.984
UD23	P	0.760	0.845	0.900	0.845	0.590	0.776
UD24	P	0.791	0.791	0.915	0.998	0.671	0.848
UD25	P	0.923	0.935	0.987	0.935	0.558	0.605
UD26	P	0.932	0.993	0.939	0.993	0.767	0.823
UD27	P	1.000	1.000	1.000	1.000	1.000	1.000
UD28	P	1.000	1.000	1.000	1.000	0.884	0.884
UD29	T	0.500	0.500	0.717	0.976	0.386	0.772
UD30	T	0.630	0.630	0.833	0.756	0.464	0.737
UD31	T	0.827	0.827	0.942	0.878	0.528	0.638
UD32	T	0.944	0.944	0.977	0.966	0.601	0.637
UD33	T	1.000	1.000	1.000	1.000	0.776	0.776
UD34	T	1.000	1.000	1.000	1.000	0.773	0.773

Table 3
Production indexes – Y (combined), Y1 (scientific production), Y2 (technical publications), Y3 (diffusion), Y4 (technologies, products, and processes). Input indexes – X1 (personnel), X2 (other expenses), X3 (capital)

ID	Y	Y1	Y2	Y3	Y4	X1	X2	X3
A01	2.816	4.199	0.227	1.0427	2.302	1.145	0.499	1.523
A02	3.733	0.715	2.326	2.4317	5.294	1.530	1.154	0.432
A03	1.105	1.322	2.118	0.210	0.971	0.399	0.224	0.099
UD01	0.484	0.293	0.981	0.381	0.323	1.380	0.901	0.708
UD02	0.565	0.695	0.414	0.426	0.658	1.413	1.035	1.130
UD03	1.120	1.466	0.855	0.988	1.091	2.708	3.094	1.320
UD04	0.236	0.043	0.531	0.354	0.096	0.343	0.421	0.308
UD05	0.588	0.396	1.423	0.547	0.096	0.910	0.837	0.722
UD06	0.871	0.200	2.160	0.389	0.778	0.760	0.950	0.549
UD07	1.000	1.577	1.062	1.254	0.196	2.121	1.254	1.918
UD08	1.329	0.907	1.259	0.677	2.260	1.919	1.315	1.063
UD09	0.472	0.231	0.666	0.542	0.499	0.390	0.403	0.336
UD10	0.730	0.137	1.634	0.525	0.695	0.474	0.628	0.605
UD11	0.777	0.346	1.273	0.660	0.866	0.563	0.609	0.436
UD12	1.582	1.375	0.808	4.327	0.553	1.802	1.127	2.191
UD13	0.518	0.735	0.722	0.411	0.200	0.568	1.096	0.710
UD14	0.628	1.207	0.545	0.523	0.193	1.103	1.254	1.071
UD15	0.504	0.356	0.821	0.617	0.305	0.962	0.924	0.586
UD16	0.533	0.730	0.014	0.417	0.859	1.140	0.822	1.608
UD17	0.582	0.628	0.057	1.449	0.386	1.816	1.128	2.165
UD18	0.721	0.682	0.996	0.562	0.635	0.957	0.989	1.575
UD19	0.462	0.395	0.596	0.711	0.245	0.605	0.658	0.970
UD20	1.527	1.240	0.448	2.263	2.223	1.398	1.631	1.975
UD21	0.890	0.943	1.855	0.754	0.108	0.737	0.912	1.066
UD22	2.188	1.898	0.057	5.379	2.091	1.807	2.185	1.043
UD23	1.512	2.151	0.926	1.739	1.214	1.633	1.046	1.783
UD24	0.847	1.025	0.995	1.368	0.184	0.704	0.918	0.590
UD25	0.904	0.309	1.123	1.200	1.106	0.709	0.474	1.091
UD26	1.327	1.703	1.262	1.544	0.857	1.084	0.974	1.012
UD27	1.802	1.669	0.670	1.270	3.266	1.108	1.288	0.494
UD28	0.710	0.456	0.556	0.412	1.302	0.512	0.400	0.443
UD29	0.487	0.621	0.382	0.520	0.320	0.615	0.885	0.881
UD30	0.731	0.940	0.379	0.697	0.737	0.737	1.585	0.972
UD31	0.805	1.275	0.718	0.562	0.112	0.666	0.898	1.371
UD32	1.253	1.145	0.699	0.529	2.542	0.648	0.936	1.482
UD33	2.416	3.343	2.419	1.804	0.928	1.291	2.132	2.163
UD34	1.219	1.782	0.527	0.363	1.404	0.652	0.846	0.679
UD35	1.696	1.086	2.288	0.688	2.843	0.249	0.413	0.329
UD36	3.114	0.046	2.504	0.487	11.54	0.314	0.696	0.463
UD37	0.275	0.375	0.057	0.285	0.321	0.131	0.460	0.139

Kolmogorov–Smirnov test for constant returns to scale yields $D = 0.235$, which is non-significant. There is no evidence of separate frontiers for each type of research unit since Wilcoxon chi-square for the corresponding null hypothesis is $\chi^2_2 = 4.09$ with a p-value of 0.129.

Table 4
Efficiencies from stochastic frontiers – half-normal (U), truncated normal (V), and exponential (W).

ID	U	V	W
UD01	0.400	0.409	0.382
UD02	0.421	0.429	0.408
UD03	0.525	0.530	0.531
UD04	0.438	0.446	0.429
UD05	0.518	0.524	0.523
UD06	0.497	0.503	0.499
UD07	0.634	0.637	0.642
UD08	0.749	0.750	0.753
UD09	0.673	0.676	0.680
UD10	0.715	0.718	0.719
UD11	0.793	0.795	0.793
UD12	0.929	0.929	0.923
UD13	0.712	0.716	0.714
UD14	0.453	0.461	0.447
UD15	0.520	0.525	0.524
UD16	0.517	0.523	0.520
UD17	0.562	0.566	0.570
UD18	0.515	0.522	0.517
UD19	0.526	0.532	0.530
UD20	0.658	0.662	0.663
UD21	0.663	0.667	0.669
UD22	0.855	0.855	0.852
UD23	0.857	0.856	0.854
UD24	0.762	0.764	0.763
UD25	0.840	0.841	0.836
UD26	0.926	0.926	0.920
UD27	1.000	1.000	1.000
UD28	0.946	0.946	0.944
UD29	0.514	0.521	0.516
UD30	0.528	0.533	0.532
UD31	0.718	0.721	0.719
UD32	0.762	0.766	0.760
UD33	0.855	0.858	0.848
UD34	0.863	0.864	0.857

Data analysis II

The inclusion of three research centers, coded A01, A02, and A03, from Inta, the institution similar to Embrapa in Argentina, leads to the data in Table 3. The information in Table 3 is important since it provides an international standard relative to which one may evaluate agricultural research in Brazil. To construct this table we had to restrict the output analysis to similar products, which left out production activities from both sides. This puts a restriction on DEA analyses since we do not know what proportion of total input can be attributed to those activities. In spite of this we notice that the Argentine research centers are very competitive from Brazilian standards. A01 dominates scientific publications, A02 dominates development of technologies products and processes and A03 is highly productive since it operates at very low costs.

Final remarks

The recent literature in DEA suggests that DEA estimates are inconsistent if the production frontier is stochastic. See *Löthgren.*[10] To look for evidence in this direction we fitted a stochastic frontier to the data in Table 1.

A single equation stochastic frontier model, *Bauer*,[2] has the form

$$\log y_t = \alpha + \beta_1 \log x_{1t} + \beta_2 \log x_{2t} + \beta_3 \log x_{3t} + v_t - u_t$$

where we choose the response (true stochastic frontier) in the Cobb-Douglas family, the residuals v_t are normally distributed with mean zero and variance s, the residuals u_t are nonnegative and distributed as a half-normal, truncated normal or exponential distribution with variance σ_v^2. The errors $\varepsilon_t = v_t - u_t$ are assumed independent across research units. Let $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_v$. Assuming a half-normal distribution for u_t a measure of production inefficiency is given by

$$E(u/\varepsilon) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\varepsilon\lambda/\sigma)}{1-\Phi(\varepsilon\lambda/\sigma)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right]$$

Here $\phi(.)$ and $\Phi(.)$ are the density and distribution function of the standard normal, respectively. See *Greene*[7] for the other formulas of this quantity under the assumptions of truncated normal and exponential distributions for the component u_t. We used LIMDEP to fit the Cobb-Douglas function via maximum likelihood assuming, in turn, each of the 3 distributions mentioned above. Ordinary least squares produced a fit with $R^2 = 0.47$ and a significant F statistic. Ordinary least squares residuals for the Cobb-

Douglas fit are negatively skewed – an important property for mle estimation of stochastic production function frontiers. The parametric estimates of technical efficiencies above cannot be shown to be consistent for cross section data, but we used them anyway to compare with the nonparametric efficiency measures. To make the measurements comparable we inverted the stochastic frontier estimates and normalized dividing by the maximum. The final results are shown in Table 4. The hypothesis of constant returns is not rejected in any of the 3 fits. Although individual efficiencies may differ, Spearman and Pearson correlation coefficients with DEA-CR are on the order of 90%. Between stochastic frontier fits the correlations are on the order of 99%. On the average inefficiencies are lower in the nonparametric case but in many cases we have a reasonable agreement between the two methods. It is worth mentioning that, independently of the residual distributional assumption, the important variable in the stochastic frontier fit is operational expenses, which has an elasticity estimate of about 0.69 with a standard error of 0.25.

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