

Brazilian Federal Universities: Relative Efficiency Evaluation and Data Envelopment Analysis*

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Summary: 1. Introduction; 2. Data envelopment analysis: a brief digression; 3. Applications; 4. Final comments.

Key words: universities; efficiency; data envelopment analysis.

This paper considers the issue of relative efficiency measurement in the context of the public sector. In particular, it considers the efficiency measurement approach provided by data envelopment analysis (DEA). The application considered the main Brazilian federal universities for the year of 1994. Given the large number of inputs and outputs, this paper advances the idea of using factor analysis to explore common dimensions in the data set. Such procedure made possible a meaningful application of DEA, which finally provided a set of efficiency scores for the universities considered.

Este artigo considera a questão da mensuração de eficiência relativa no contexto do setor público. Em particular, considera a abordagem de mensuração de eficiência fornecida pela análise envoltória de dados (AED). A aplicação considerou as principais universidades federais brasileiras para o ano de 1994. Dado o grande número de fatores de produção e produtos, este artigo lança a possibilidade de utilizar análise fatorial para explorar dimensões comuns no conjunto de dados. Tal procedimento possibilitou a aplicação da AED, a qual finalmente gerou um conjunto de *scores* de eficiência para as universidades consideradas.

1. Introduction

The study of multioutput nonprofit organizations is object of increasing interest in the empirical literature. The main difficulty associated with the

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assessment of those entities has to do with a precise characterization of their technologies. In this sense, several recent studies analyzed such organizations by means of flexible empirical approaches.

Universities and professional hierarchies constitute an influential example of the aforementioned issue, since its technology is characterized by multiple inputs and outputs and "strict profit maximization" is not the main organizing principle of conduct. Furthermore, their operations are guided by multiple missions/general objectives. Consequently, efficiency cannot be trivially defined and measurements of efficiency become a central research and management challenge, as they have been discussed by Façanha et alii (1996) among others. Examples of efficiency measurement in the context of universities include Davies and Verry (1976), Beasley and Wong (1990), Beasley (1990, 1995), Gamerman et alii (1992), Johnes (1992) and Johnes and Johnes (1993).

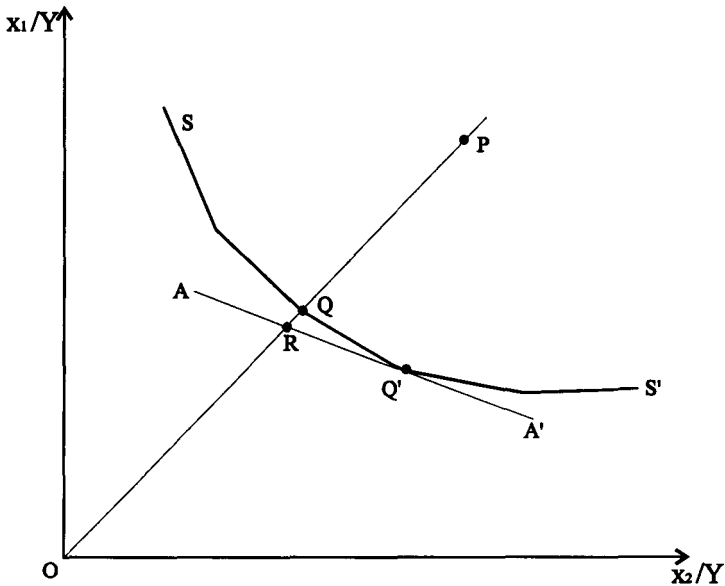
A leading flexible empirical approach for comparative efficiency measurement is the nonparametric method of data envelopment analysis (DEA). The yardstick for efficiency is not a theoretical concept or an ideal, but rather the achievement of other (comparable) organizations or decision making units (DMUs). "Efficiency is measured relative to the observed best practice" (Felder, 1995). Moreover, the methodology also handles difficulties brought in by unavailability/nonobservability of market prices, of inputs, of outputs, and of inputs and outputs. Universities are well-known examples of such complex managerial problems.

This paper intends to pursue a DEA approach in the context of the Brazilian federal universities. DEA can provide useful insights into critical resource allocation and management problems that constrain the DMUs considered in this paper. Federal universities are essential parts of the Brazilian Federal System of Higher Education, where those problems are certainly part of a much broader agenda that envisages reform and institutional consolidation, and calls for better evaluation, guidance and monitoring instruments as mandatory ingredients. The paper is organized as follows. The second section provides a brief digression on DEA. The third section presents a description of the information and variables used in the exercise, and an application of factor analysis for data preparation, which allowed us to obtain the basic result of DEA, the "efficient frontier" for the DMUs. Section 4 presents final comments.

2. Data Envelopment Analysis: A Brief Digression

The study of empirically determined efficiency frontiers has its roots on the seminal paper by Farrell (1957), who considered a data derived approximation to a representative unit isoquant with respect to which deviations would characterize inefficiency. Consider a firm that produces one unit of a single output upon two inputs, x_1 and x_2 , according to a production function $f(x_1, x_2)$. Figure 1 illustrates the main ideas.

Figure 1
Graphical description of efficiency measurement



The two coordinates of figure 1 represent the quantities of the two inputs in securing their per-unit output level. AA' represents a slope equal to the ratio of the two input prices. At a general conceptual level, Farrell distinguishes two components of the productive inefficiency: the technical inefficiency, given by the ratio OQ/OP , and the allocative inefficiency, provided by OR/OQ . Finally, OR/OP indicates the total efficiency. It should be noted that the unit isoquant representation above relies on the potentially restrictive assumption of constant returns to scale. In the previous example the DMUs, Q and Q' , are technically efficient, and P is inefficient at both the technical and allocative criteria. Q' represents the unique point at which both forms of efficiency are

attained. A feasible empirical counterpart for a theoretical smooth isoquant will display the piece-wise linearity as above, and consists on the consideration of the free disposal convex hull of the observed input-output ratios that would be obtained by linear programming procedures. The data envelopment analysis (DEA) literature may be thought as inspired on Farrell's concepts, and considers multi-output multi-input, as well as variable returns to scale extensions. It is worth mentioning that DEA differs from the econometric methods in two fundamental aspects:

- a) the production efficiency frontier is obtained in a nonparametric fashion, as the solution to a fractional linear programming problem;
- b) the focus is on relative efficiencies, in contrast with the econometric approach, that considers central tendencies or average planes that would be adjusted and assumed to hold for each decision making unit, DMU (Seiford & Thrall, 1990).

Leibenstein (1966) advanced the possibility of non-allocative forms of inefficiency, the x-inefficiency, that may arise, among other factors, due to sub-optimal effort levels within a principal-agent relationship. Frantz (1988, 1992) and Leibenstein and Maital (1992) defend the properness of DEA to assess the degree of x-inefficiency of a given DMU. In addition, such technique imposes no functional forms restrictions on the underlying technology; the basic structure imposed refers to the convexity and piece-wise linearity of the technology.

DEA has been object of increasing popularity, with a wide range of applications in different areas (see Seiford, 1994, for an extensive bibliography), and its consolidation as an influential approach can be illustrated by the publication of a comprehensive textbook in the matter by Charnes et alii (1994); some general introductions to that approach appear in Seiford and Thrall (1990) and Boussofiane et alii (1991).

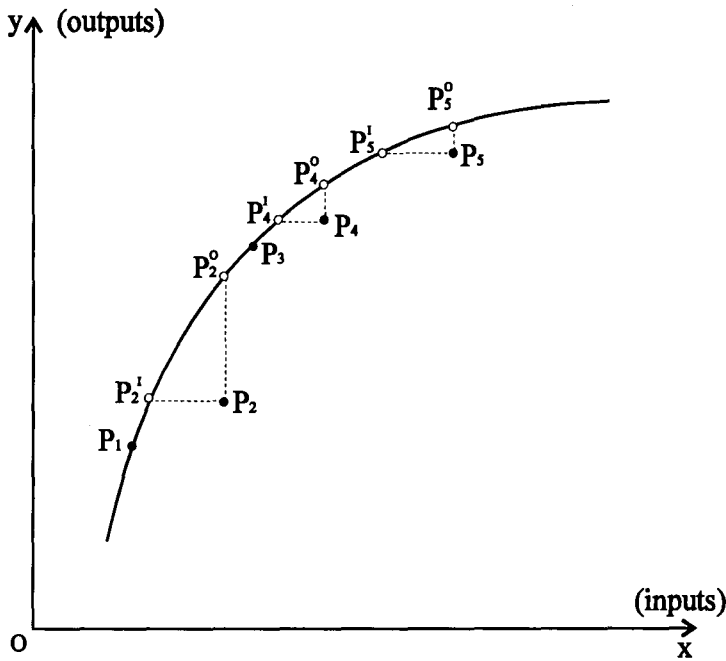
There are two classes of DEA models that are most commonly applied, and for which a brief description will follow. It should be noted that the general idea underlying DEA models is the comparison of a virtual output measure (that aggregates output measures) with a virtual input measure (that aggregates input measures), such that the corresponding weights are chosen in a way to represent a given DMU in the most efficient characterization

consistent with the data and with the restriction that no DMU can be beyond the efficiency envelopment surface.

The DEA models admit two orientations: output augmentation (output orientation) or input conservation (input orientation). In the former, efficiency refers to obtaining the maximum output level, given a fixed utilization of inputs, whereas in the latter efficiency alludes to securing the minimum employment of inputs, given the output level.¹ In the case of constant returns to scale, the efficiency frontier hyperplane would be linear and pass through the origin; in this case, the two orientations would produce the same efficiency scores. When there are variable returns to scale, this is no longer the case. However, empirical practice seems to show that the choice of inputs and outputs to be used in the analysis is the crucial choice, rather than the orientation choice (Charnes et alii, 1994).

Figure 2 illustrates some basic ideas.

Figure 2
Efficiency frontier



¹For a generic discussion of such distinction, outside the realms of DEA, see Fare & Lovell (1978).

Once the efficient frontier is defined, one can project an inefficient DMU (such as indicated by points P_2 , P_4 , and P_5) to the frontier, in the sense of making salient the gap between the actual and the best practice. For example, consider DMU 2. According to an output orientation, one would compare P_2 with P_2^0 by defining a constant level of input use. One could, on the other hand, consider an input orientation and define a constant level of output; in this case, DMU 2 could have saved inputs for this given level of production, given the gap between P_2 and P_2^I . For the DMUs 1 and 3, no further output augmentation or input conservation would have been possible, as they are situated on the efficiency frontier.

The seminal contribution in DEA was advanced by Charnes, Cooper and Rhodes (1978) — from here on mentioned as CCR — and addressed the constant returns to scale case. The basic setup considers m inputs (indexed by subscript i), s outputs (indexed by subscript r) and n DMUs (indexed by subscript j). Additionally, it is assumed that $x_{ij} > 0$ and $y_{rj} > 0$, which refer to strictly positive values of inputs and outputs from the j -th DMU, respectively.

CCR consider the following fractional linear programming problem:

$$\max_{u,v} h_k = \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}} \quad (1)$$

subject to:

$$\sum_{r=1}^s u_r y_{rj} / \sum_{i=1}^m v_i x_{ij} \leq 1 \quad (\text{for } j = 1, 2, \dots, k, \dots, n) \quad (2)$$

$$u_r \geq 0 \quad (\text{for } r = 1, \dots, s) \quad v_i \geq 0 \quad (\text{for } i = 1, \dots, m). \quad (3)$$

The problem above is to be solved for each DMU taken as reference, such that there would be n mathematical programming problems to be solved, and the solution would generate optimal input and output shadow prices, given the constraints that no DMU can operate beyond the efficiency frontier (constraint 2) and that the referred weights should be non-negative (constraint 3). As it stands, the above problem is complex. However, CCR have shown that it can be transformed into an equivalent linear programming problem.

Specifically, one can obtain the following program:

$$\max_{u,v} w_k = \sum_{r=1}^s u_r y_{rk} \quad (4)$$

subject to:

$$-\sum_{i=1}^m v_i x_{ij} + \sum_{r=1}^s u_r y_{rj} \leq 0 \quad \text{for } j = 1, \dots, n \quad (5)$$

$$\sum_{i=1}^m v_i x_{ik} = 1 \quad (6)$$

$$u_r \geq 0 \quad \text{for } r = 1, \dots, s \quad v_i \geq 0 \quad \text{for } i = 1, \dots, m. \quad (7)$$

Finally, the precedent program is a linear programming problem and, therefore, admits a dual representation, which is given by:

$$\min \theta \quad (8)$$

$$-\sum_{j=1}^n x_{ij} \lambda_j + \theta x_{ik} \geq 0 \quad \text{for } i = 1, \dots, m \quad (9)$$

$$\sum_{j=1}^n y_{rj} \lambda_j \geq y_{rk} \quad \text{for } r = 1, \dots, s \quad (10)$$

$$\lambda_j \geq 0 \quad \text{for } j = 1, \dots, n. \quad (11)$$

A potentially limiting assumption of the CCR model concerns the constant returns to scale. Banker (1984) and Banker, Charnes and Cooper (1984) — from here on mentioned as BCC — extended the CCR model by incorporating the possibility of variable returns. The notion of variable returns is defined as follows. Let the production possibility set be given by $T = \{(X, Y) : \text{the output vector } Y \geq 0 \text{ can be produced from the input vector } X \geq 0\}$. Then, returns to scale at a point (X, Y) on the efficient surface of T can be expressed in terms of the following formulation:

$$\rho = \lim_{\beta \rightarrow 1} \frac{\alpha(\beta) - 1}{\beta - 1} \quad (12)$$

where $\alpha(\beta) = \max\{\alpha : (\beta X, \alpha Y) \in T\}$, $\beta > 0$.

The idea is to observe how proportionate changes in the input vector reflect in terms of changes in the output vector. Specifically, if $\rho > 1$, one would have a situation of increasing returns to scale, as a change in the inputs (maintaining the input mix fixed) leads to a more than proportionate change in the outputs (keeping the output mix constant). Similarly, one can characterize a

situation of decreasing and constant returns to scale when $\rho < 1$ and $\rho = 1$, respectively. Furthermore, one can define the notion of a most productive scale size (mpss), that would indicate the most efficient scale for given input and output mixes. Obviously, a mpss is a boundary point, but it also maximizes the average productivity per input for its given input and output mix. The main result obtained by the aforementioned authors is that aggregate efficiency can be factored in terms of technical efficiency and scale efficiency, where the latter would capture deviations of the actual scale from the mpss (Banker, 1984). In other words, the efficiency score obtained from the CCR model (that assumes constant returns to scale) is equal to the product of the technical efficiency score obtained from the BCC model (that contemplates variable returns to scale) multiplied by the scale efficiency score.

The BCC model extends the previous DEA analyzes by imposing more structure in the production possibility set, so as to capture scale effects. Most importantly, a convexity restriction is added to the CCR model. More precisely, convexity requires that if $(X_j, Y_j) \in T$ for $j = 1, \dots, n$, and $\lambda_j \geq 0$ are non-negative scalars such that $\sum \lambda_j = 1$, then $(\sum \lambda_j X_j, \sum \lambda_j Y_j) \in T$. The basic modification of the CCR model accounts for introducing the constraint $\sum \lambda_j = 1$ into the mathematical programming problem given by equations 8–11.

BCC consider the following problem:

$$\min \theta \tag{13}$$

$$- \sum_{j=1}^n x_{ij} \lambda_j + \theta x_{ik} \geq 0 \quad \text{for } i = 1, \dots, m \tag{14}$$

$$\sum_{j=1}^n y_{rj} \lambda_j \geq y_{rk} \quad \text{for } r = 1, \dots, s \tag{15}$$

$$\lambda_j \geq 0 \quad \text{for } j = 1, \dots, n \tag{16}$$

$$\sum \lambda_j = 1. \tag{17}$$

The intuition underlying the usefulness of convexity is that it would secure that any composite unit extrapolated is similar in size to the reference unit, and not merely an extrapolation of another composite unit operating at a different scale size. Therefore, the restriction ensures that all DMUs are evaluated taking the convex combination of inputs and outputs as reference (Sawkins & Accam, 1994).

3. Applications

3.1 Data description

This paper makes use of a new data set concerning federal universities in Brazil for the year of 1994. Most of the data was obtained from MEC/ANDIFES (1995), which covers 52 federal institutions of higher education (*instituições federais de ensino superior — IFES*). The information was carefully collected and audited by a special commission during 1995, as part of a promising follow-up activity ushered by the Ministry of Education, MEC, and the Higher Education Federal Institutions Managers' Association, ANDIFES. Each IFES will be treated as an individual DMU. The data also includes information about current expenses (OCC), obtained from a public report released by ANDIFES. OCC is the initial budget, allocated to each IFES according to a "model" that privileges "historical OCC" (with a weight of 90%), "input" data (with around 9% weight), and "output" data.

The exercise will take full advantage of all the information available, avoiding the risky consequences of delimitting the data set with *a priori* criteria and/or of making use of popular (however useful and/or convenient) measures of performance, like the ratios academic staff per student, total expenses per student, and others. Stronger reasons to adopt the more exploratory procedure can be found in Marinho (1996), and are related to the nature of returns of scale of the (implicit, unobservable) "technology" that prevails in such cases. Moreover, the main objective of the special commission was to provide good information for better management and to improve the "model" of initial budget allocation that is currently used among the IFES. In any case, the reader can assess some of these comments by examining the list of variables that is presented next.

Input variables:

- a) area of buildings — AREA;
- b) area of hospitals — ARHOSP;
- c) area of laboratories — ARLAB;
- d) total number of students — ALU;
- e) academic staff with doctoral degree — DD;
- f) academic staff with master degree — DM;

- g) academic staff with specialization degree — DE;
- h) academic staff with undergraduate degree — DG;
- i) academic staff of second and first degree teaching — DSG;
- j) administrative personnel at support level — TECADAP;
- k) administrative personnel with high school degree background — TECAMED;
- l) administrative personnel with undergraduate degree or higher — TECADS;
- m) budget for current expenses — OCC;
- n) incoming students at undergraduate level — ING;
- o) incoming medical residents — MATRMED.

Output variables:

- a) number of undergraduate courses — NGRAD;
- b) number of graduate courses — master degree level — NCMEST;
- c) number of graduate courses — doctoral degree level — NCDOUT;
- d) certificates issued — undergraduate degree — NDI;
- e) certificates issued — medical schools residence — DIPRMED;
- f) number of master degree thesis approved — NTM;
- g) number of doctoral dissertations approved — NTD;
- h) weighted average of MEC's evaluation: master degree courses — CAPESM;
- i) weighted average of MEC's evaluation: doctoral degree courses — CAPESD.

The last two variables were conventionally defined. The rank of each course — A, B, C, D, or E — was transformed into 10, 8, 6, 4, or 2, respectively, and the weights were defined by the number of courses in each category of evaluation.

Before performing the application of DEA, a close examination of the data recommended that some observations (DMUs) should be suppressed on grounds of notorious specialization. Moreover, for the IFES whose graduate

courses were not evaluated. we attributed the average grades from the remaining sample. This procedure can be justified on assumption that new courses are expected to possess at least average quality, otherwise they wouldn't obtain official support. The IFES for which graduate courses were not available received grades of 0. After taking into account the previous remarks, we ended with 38 DMUs to be compared.

Though sensible in principle, this procedure has a cost. The final number of DMUs resulted small *vis-à-vis* the number of variables selected. This fact complicates the application of DEA as a discriminant and ranking technique. The intuitive reason is that with too many dimensions, most DMUs become special cases of efficiency. With most of DMUs becoming an efficiency standard in its own way, the objective of creating "best practice standards" is impaired. A possible approach is then to treat DMUs in different years as distinct DMUs (Marinho, 1996). In the present situation, while the updated information (for 1995 and for 1996) is not yet officially available, the resort to multivariate statistical analysis, MSA, is a natural device. To the best of our knowledge, MSA has not been applied in the context of DEA, despite its notorious usefulness. Factor analysis, FA, was then used to explore the presence of common dimensions in the data set, so as to allow a reduction on the number of variables considered. Next, we will describe such application.

In the factor model (see Manly, 1994, as a good introductory reference), a random vector, \underline{X} , of observed characteristics, with p components, mean \underline{u} and covariance matrix E , is linearly related to some nonobserved random variables, $F_1 \cdots F_m$, ($m < p$), called "common factors", as well as to errors or "specific factors", $e_1 \cdots e_p$, as follows:

$$\underline{X} - \underline{u} = \underline{L}\underline{F} + \underline{e}$$

where L denotes the $(p \times m)$ matrix of factor loadings, whose typical element, l_{ij} , is the "factor load" of variable i over factor j , and $\text{Cov}(F_i, e_i) = 0$ for $i = 1 : p$. The method of principal components was used to obtain the loads and the variance explained by Factor j is given by $l_{1j}^2 + \cdots + l_{pj}^2/p$. Factor analysis was applied first to reduce the dimension of "input variables", and then to reduce the dimension of the "output variables", with the results — loads of variables over factors and correlations of variables among themselves through the factors — displayed in the next subsection.

3.2 Empirical results

Tables 1 and 2 present the factor matrix respectively for input and output variables.

Table 1
Factor matrix for input variables

Variable	Factor 1	Factor 2	Factor 3
ALU	0.94	0.13	-0.01
AREA	-0.06	0.20	-0.59
ARHOSP	0.82	-0.32	-0.13
ARLAB	0.48	-0.32	0.21
DD	0.90	-0.32	0.06
DE	0.57	0.77	-0.03
DG	0.81	0.47	-0.04
DM	0.94	0.22	-0.01
DSG	0.05	0.30	0.76
ING	0.91	0.14	0.02
MATRMED	0.66	-0.19	0.24
OCC	0.97	-0.07	-0.01
TECADAP	0.68	-0.01	-0.22
TECADMED	0.96	-0.14	0.00
TECADS	0.87	-0.27	-0.11
Var. explained	59.0%	9.7%	7.5%

This intermediate step of the exercise deserves some attention, because it adds relevant information about the data set and concerning the IFES. As stressed before, FA explores common and unobservable dimensions in the data, and extracts the common factors from the covariance matrix. In a positive sense, the factor reveal correlations among the variables (that may not be observable in pairwise computation), and new information is provided for the analysis. Some supression of new information is implied when some of the factors are discarded, on the basis of their contribution to the total variance. In the present case, the factors selected (responsible for 76.2% of the total input variance, and for 83.5% of the total output variance) will not imply the rejection of any of the original variables. All the available information about

inputs and outputs will be taken into account in the DEA application that follows, and the variables can be individually recovered in possible extensions of the results. Each factor (and all DMUs) will receive a score based on linear combinations of the observed values of variables, and the correlations are weights of the factor scores.

Table 2
Factor matrix for output variables

Variable	Factor 1	Factor 2	Factor 3
CAPESD	0.72	0.34	0.40
CAPESM	0.51	0.57	0.50
DIPRMED	0.44	-0.43	0.30
NCDOUT	0.93	-0.31	0.05
NCMEST	0.97	0.01	-0.03
NDI	0.73	0.40	-0.43
NGRAD	0.67	0.11	-0.61
NTD	0.84	-0.43	0.08
NTM	0.94	-0.09	-0.02
Var. explained	59.5%	12.1%	11.9%

Therefore, the correlations are more important than the scores themselves, and a closer inspection of some of the results (the outstanding ones are in bold type) shown by tables 1 and 2, will clarify the previous remarks and the meaning of the factors. Table 1 shows that the total number of students (ALU), area of hospitals (ARHOSP), area of laboratories (ARLAB), academic staff at all degree levels (DD, DE, DG, DM), incoming medical residents (MATRMED), administrative personnel at all professional levels (TECADP, TECADMED, TECADS), and budget for current expenses (OCC) have high loads over (and are strongly correlated among themselves through) factor 1. The revealed common dimension of these variables and factor 1 can be reasonably interpreted as the “main management and coordination problem” of the IFES’ inputs. Factor 2 shows that there are DMUs with higher percentages of academic staffs of specialization degree (DE) and of undergraduate degree (DG) *vis-à-vis* the academic staff of doctoral degree (we observe negative load of

DD over factor 2). In those cases, area of laboratories is less important *vis-à-vis* the total area. Factor 3 selects (and correlates) total area (with negative loads) and academic staff of second degree teaching (DSG), pointing out that these last activities are relatively less important in “bigger” IFES (technical schools were suppressed from the sample). The negative load of area over factor 3 also means that its scores “penalize” larger areas IFES.

The meaning attributed to factor 1 in table 1 could be extended to factor 1 in table 2. As can be seen, all output variables have high (positive) loads over factor 1. This phenomenon represents and emphasizes the interrelated and complementary dimensions of IFES’ outputs. Factor 2 and factor 3 address DMUs with specialized activities. In the case of factor 2, the loads (and correlations) point out that there are IFES with good evaluations of master degree courses (CAPESM) that do not have outstanding performance on doctoral courses and activities (CAPESD), and/or on medical activities (DIPRMED). On its turn, factor 3 puts emphasis on IFES with high score evaluations of doctoral and master degree courses, and high number of certificates issued for medical residence, which do not privilege undergraduate activities (CAPESD, CAPESM, DIPRMED are positively correlated through factor 3, and NGRAD is negatively correlated with this factor, and with those variables). The results also tell that MEC’s evaluations (and the financial support of graduate activities, that is not subsumed under OCC) are relatively independent of the “management and coordination problem” revealed by factor 1.

We will leave to the reader further explorations of results of FA, and the exercise will turn now to the application of DEA, using the factors that now represent inputs and outputs of the DMUs. It should be remembered that it is usual to observe negative factors when FA is applied. After all, negative correlations have a meaning. But they present a problem to DEA’s application because of the demanded positivity of inputs and outputs. The procedure advanced by this paper is to consider an affine transformation of the scores of factors (scores are linear combinations of variables with loads as weights), so as to generate positive values consistent with the constraints of the DEA model. This procedure has two motivations. The first is conceptual: in the seminal paper of Charnes, Cooper and Rhodes (1978:430), the authors emphasize: “we can, however, replace some or all of these observations by theoretically determined values if we wish (and are able) to conduct our efficiency evaluations in that manner”. The second motivation is a technical one.

We are able to apply an affine transformation of the data without altering the “efficient frontier” of DEA. Ali & Seiford (1990), has shown that the BCC model is translation invariant. The combination of the two motivations justify our approach of using factor analysis as an intermediate stage in DEA applications, what was not considered before in the DEA literature. The results from the DEA approach are presented next.

Table 3 presents the final ranking of the DMUs obtained from the BCC formulation. Those DMUs with 100% efficiency scores constitute the “efficient frontier”. It is worth mentioning that the exploration of common dimensions in the data set, by means of factor analysis, was instrumental to enable a proper discrimination of the DMUs. In fact, most of the previous DEA applications made use of a very restricted number of variables.

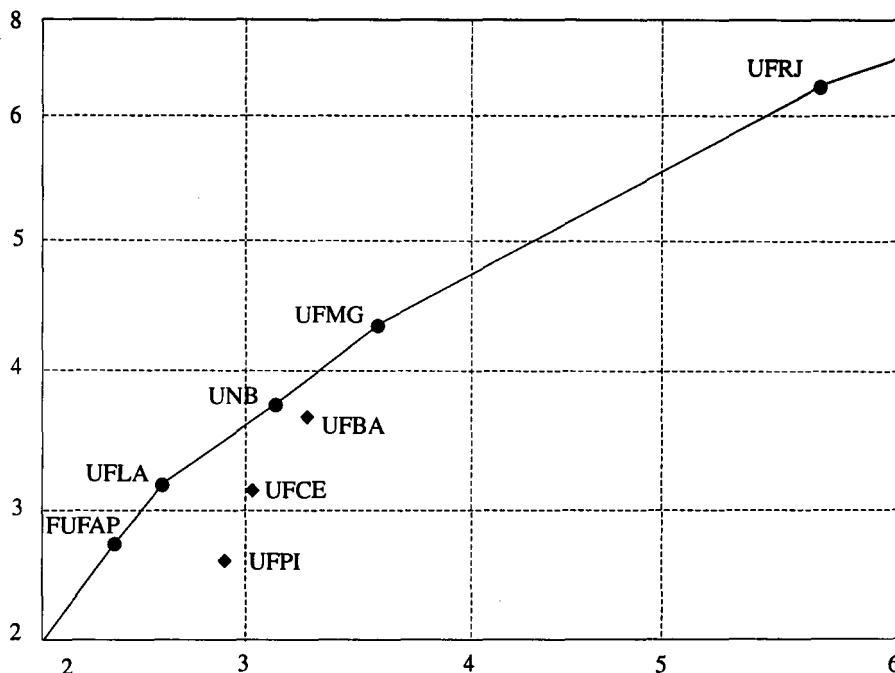
Table 3
DEA efficiency scores achieved by IFES

University	Effic.value
FUFAC — Fund. Univ. Federal do Acre	77.08
FUFRO — Fund. Univ. Federal de Rondônia	78.18
FUFRR — Fund. Univ. Federal de Roraima	79.22
UFPI — Fund. Univ. Federal do Piauí	79.24
UFJF — Univ. Federal de Juiz de Fora	82.06
FUAM — Fund. Univ. do Amazonas	82.64
FUNREI — Fund. de Ensino Superior de São João del Rei	82.71
FUFMS — Fund. Univ. Federal de Mato Grosso do Sul	84.07
FUOP — Fund. Univ. Federal de Ouro Preto	84.69
UNIRIO — Fund. Univ. do Rio de Janeiro	87.75
UFRN — Univ. Federal do Rio Grande do Norte	88.03
UFSE — Fund. Univ. Federal de Sergipe	88.81
UFRPE — Univ. Federal Rural de Pernambuco	88.96
FUFUB — Fund. Univ. Federal de Uberlândia	89.18
UFGO — Univ. Federal de Goiás	89.29
UFES — Univ. Federal do Espírito Santo	91.33
FUFPEL — Fund. Univ. Federal de Pelotas	93.79
UFBA — Univ. Federal da Bahia	96.03
UFCE — Univ. Federal do Ceará	96.10

UFPE — Univ. Federal de Pernambuco	97.46
UFSM — Univ. Federal de Santa Maria	97.51
UFF — Univ. Federal Fluminense	99.61
UFRJ — Univ. Federal do Rio de Janeiro	100.00
UFPA — Univ. Federal do Pará	100.00
UNB — Fund. Univ. de Brasília	100.00
FURG — Fund. Univ. do Rio Grande	100.00
FPB — Univ. Federal da Paraíba	100.00
UFAL — Univ. Federal de Alagoas	100.00
UFMG — Univ. Federal de Minas Gerais	100.00
UNIFESP — Escola Paulista de Medicina	100.00
FUSCAR — Fund. Univ. Federal de São Carlos	100.00
UFRGS — Univ. Federal do Rio Grande do Sul	100.00
FUFUV — Fund. Univ. Federal de Viçosa	100.00
UFRRJ — Univ. Federal Rural do Rio de Janeiro	100.00
UFPR — Univ. Federal do Paraná	100.00
FUFAP — Fund. Univ. Federal do Amapá	100.00
UFSC — Univ. Federal de Santa Catarina	100.00
UFLA — Escola Superior de Agricultura de Lavras	100.00

The ranking of DMUs according to efficiency scores is one of DEA's most remarkable and well-known accomplishments. Nonetheless, there are useful extensions to be explored, and one of them will be selected to illustrate another dimension of the model's potentialities. Figure 3 synthesizes the motivation, and it was drawn up with a particular choice of variables. Input values are actual scores of factor 1, defined by the correlations and loadings of the original input variables, and output values were taken from the scores of factor 1, defined by the original output variables. The high percentage of variance explained by factor 1 (in either case) turns the choice made a non-arbitrary device to portray the DMUs, as well as the inner meaning of this common factor. As explained before, factor 1, either as a common dimension of input variables, or as a common dimension of output variables, suggests the complementary (in the sense of e.g., Milgrom & Roberts, 1992: chap. 4) dimensions, and the importance of Universities' management activities.

Figure 3
Efficiency frontier



Some of the efficient DMUs were then plotted, as well as some of the inefficient cases. The important point to stress is that the frontier can be taken as a reference and orientation to the inefficient DMUs (and to the efficient ones), as shown by Marinho (1996). In fact, DEA provides targets for each input and output (when inputs and outputs are factors, it is a trivial task to define the targets for the original variables), and the menu can serve as a support information to DMU's planning and monitoring activities. It should not be assumed that the targets are rigid goals and will be self-imposed as a standard of performance. They are simply an indication of how the bundle of inputs and how the bundle of outputs could be more efficiently adjusted as a whole. DEA can be especially useful for comparative efficiency measurement and can constitute, therefore, an important tool of management. Relative efficiency measurement becomes important as it provides a useful yardstick. This feature is particularly welcome in the realm of complex organizational systems' characterized by multiple inputs and outputs (even if the technology is not well known), and where budgetary and financial support call for stronger coordination and monitoring instruments.

4. Final Comments

This paper had two initial objectives. The first one was to develop a preliminary application of data envelopment analysis, DEA, to new data about Brazilian federal universities. The authors undertook an experiment using DEA in UFRJ, as part of its budgeting and institutional evaluation activities, and the exercise had both challenging and positive motivations. In fact, the exercise could manage a broad and comprehensive data set, overcoming difficulties associated to the definition of variables as emphasized before. A ranking for the DMUs could be generated without arbitrary selection of the informations available. Additionally, the most outstanding feature of the methodology could also be exemplified. DEA explores diversity, instead of trying to “adjust” the observations (DMUs) to prespecified parametric constructions. A remarkable result is that most of the prominent and well-known IFES were assessed as efficient DMUs.

These more “technical” achievements reinforced the second thrust of the paper; to motivate the systematic application of DEA as a subsidiary policy instrument. This objective was not completely attended — new information and inventories (as described in Façanha et alii, 1996) will certainly improve the results of DEA applications — but the authors think that the pioneering job done by the special comission (see section 1) and its explicit objective of improving evaluation and monitoring activities will merit the readers’ consideration.

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