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Probabilistic measures of efficiency and the influence of contextual variables in nonparametric production models: an application to agricultural research in Brazil

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Abstract

In a research institution it is important to identify which management practices have influence on production efficiency. In this paper we assess the statistical significance of contextual variables type, size, financial resources acquisition, intensity of partnerships, processes improvements and management change. The analysis is carried out for the Brazilian Agricultural Research Corporation over the period 1999–2006. The statistical analysis uses a balanced dynamic panel data model. We conclude that only financial resources acquisition is statistically significant. The association with the production process is positive. We also found the two lag inertial components of the conditional FDH to unconditional FDH ratio statistically significant, indicating a 2-year effort to improve efficiency.

Keywords: free disposal hull (FDH); contextual variables; agricultural research; two-stage inference.

1. Introduction

The Brazilian Agricultural Research Corporation (Embrapa) uses a production model to monitor its research production. Embrapa has 37 research centers, spread throughout the country.

The model has multiple objectives. Firstly, it allows the measurement of outputs and inputs in a systematic way. Proper qualification of inputs and outputs provides a quantitative basis that simplifies the understanding of the company's operations. Secondly, it provides a sound basis for decision making and strategic planning at the administration level. Thirdly, the computation of measures like productivity, economic efficiency and total factor productivity allows the identification of benchmarks and best procedures intended to increase overall performance and

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reduce differences within the organization. Finally, measures of variability in efficiency through time serve the purpose to assess the performance of the administration. In this context, the Embrapa's performance evaluation model is a decision support system.

This article is concerned with the identification of contextual variables external to the production process that may be affecting or causing efficiency. Typically these variables are under the control of the institution. The assessment of their effect is of importance, since they may serve as a tuning device to promote efficiency.

The use of technical efficiency as a performance and evaluation measure raises some questions within the organization. An important one is whether or not the process generates unwanted competition among the research centers. A typical criticism is that the evaluation system may inhibit partnerships.

The identification of causal factors of efficiency demands appropriate statistical modeling. In Embrapa, Data Envelopment Analysis (DEA) technical efficiencies have been computed since 1996 under constant returns to scale. Recently, Souza (2006) and Souza et al. (2007) assessed the influence of covariates on the DEA efficiency measurements using analysis of variance, dynamic panel data and maximum likelihood methods. A potential problem arises in this approach: the contextual variables used may affect the production frontier. This problem is pointed out in Simar and Wilson (2007) and may affect the nature of the statistical results.

In the search for an appropriate data-generating mechanism for efficiency measurements and for frontier assessment, with regard to the influence of contextual variables, we turn to the free disposal hull (FDH) measure of Deprins et al. (1984) and the extension of Daraio and Simar (2007). FDH has a probabilistic interpretation that facilitates the interpretation of the production frontier, when covariates are present, via the notion of conditional probability.

The article proceeds as follows. In Section 2, we introduce the concepts of unconditional and conditional FDH following Daraio and Simar (2007), and define the dynamic econometric model used to assess the influence of contextual variables. Section 3 introduces Embrapa's research production system. Section 4 presents statistical results. Finally in Section 5, we present conclusions and a summary of the main statistical results.

2. FDH unconditional and conditional measures of technical efficiency

The FDH measure of technical efficiency proposed in Deprins et al. (1984) does not impose convexity on the technology set and has an interesting probabilistic interpretation that allows the definition of a proper data-generating process in the presence of contextual variables affecting the production process. Only free disposability of inputs is imposed. A recent discussion on the issue may be found in Daraio and Simar (2007). If the technology is convex, both FDH and DEA are consistent estimators of the same population parameter, although the DEA convergence is faster. The concept is defined as follows.

Consider production observations $(x_j, y_j),\ j = 1, \ldots, n$, of n producing units. The input vector x_j is a vector in R^p with nonnegative components with at least one strictly positive. The output vector y_j is a vector in R^I with nonnegative components with at least one strictly positive. The technical efficiency FDH of producing unit τ is taken relative to the frontier of free disposability (*free disposal hull*) of the set (1):

$$\psi = \left\{ (x, y) \in R_+^{p+l}, y \leqslant \sum_{j=1}^{n} \gamma_j y_j, x \geqslant \sum_{j=1}^{n} \gamma_j x_j, \sum_{j=1}^{n} \gamma_j = 1, \gamma_j \in \{0, 1\}, j = 1, \ldots, n \right\}. \tag{1}$$

The input-oriented FDH is given by (2) and the output-oriented FDH is given by (3):

$$\hat{\theta}(x_\tau, y_\tau) = \min\left\{ \theta; y_\tau \leqslant \sum_{j=1}^{n} \gamma_j y_j, \theta x_\tau \leqslant \sum_{j=1}^{n} \gamma_j x_j, \sum_{j=1}^{n} \gamma_j = 1, \gamma_j \in \{0, 1\} \right\}, \tag{2}$$

$$\hat{\lambda}(x_\tau, y_\tau) = \max\left\{ \lambda; \lambda y_\tau \leqslant \sum_{j=1}^{n} \gamma_j y_j, x_\tau \geqslant \sum_{j=1}^{n} \gamma_j x_j, \sum_{j=1}^{n} \gamma_j = 1, \gamma_j \in \{0, 1\} \right\}. \tag{3}$$

One can show the relations in (4):

$$\hat{\theta}(x_\tau, y_\tau) = \min_{j=1,\ldots,n}\left\{ \max_{i=1,\ldots,p}\left\{ \frac{x_j^i}{x_\tau^i} \right\} \right\}, \ \hat{\lambda}(x_\tau, y_\tau) = \max_{j=1,\ldots,n}\left\{ \min_{i=1,\ldots,l}\left\{ \frac{y_j^i}{y_\tau^i} \right\} \right\}. \tag{4}$$

In contrast to the Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models (Cooper et al., 2000), the FDH ensures that the efficiency measurements are only effected from observed performances. Additionally, the CCR model assumes constant returns to scale, i.e., if (x,y) is feasible, then $(\alpha x, \alpha y)$, $\alpha \geqslant 0$, is also feasible. The production frontiers determined by the BCC model are piece-wise linear and concave, which lead to variable returns to scale characteristics (increasing, decreasing and constant returns to scale).

The FDH measure as defined here does not impose any restrictions in regard to scale. It assumes variable returns. In this context, if the technology is convex, it is comparable to the DEA–BCC. As pointed out in Kerstens and Eeckaut (1999), it is possible to add one more restriction to the production set (1), to produce an FDH model comparable to DEA–CCR. In this case (1) becomes (5):

$$\begin{aligned}\psi = \Bigg\{ (x, y) \in R_+^{p+l}, y \leqslant \sum_{j=1}^{n} \gamma_j y_j, x \geqslant \sum_{j=1}^{n} \gamma_j x_j, \sum_{j=1}^{n} \delta_j = 1, \delta_j \in \{0, 1\}, \gamma_j \\ = \beta \delta_j, \beta \geqslant 0, j = 1, \ldots, n \Bigg\}.\end{aligned} \tag{5}$$

For more details regarding scale conditions in FDH, see Kerstens and Eeckaut (1999), Podinovski (2004), Soleimani-damaneh et al. (2006) and Soleimani-damaneh and Mostafaee (2009).

As pointed out in Cooper et al. (2000), the FDH measure may be computed as the solution of the mixed integer programming formulation (6):

$$\begin{aligned}
&\min \theta, \\
&\text{subject to} \\
&\theta x^o - X\gamma \geqslant 0, \\
&y^o - Y\gamma \leqslant 0, \\
&1\gamma = 1, \gamma \in \{0, 1\}.
\end{aligned} \tag{6}$$

Here X is the input matrix, Y the output matrix and (x^o, y^o) the input–output pair of the unit under analysis. FDH may be computed using the software Frontier Efficiency Analysis with R (FEAR) developed by Wilson (2008).

A very interesting interpretation of FDH arises when the production process is described by a probability measure, defined on the product space R_+^{p+l} by random variables (X, Y). In this case, for efficiency purposes, one is interested in the probability of dominance (7):

$$H(x, y) = \text{Prob}(X \leqslant x, Y \geqslant y) = \text{Prob}(X \leqslant x | Y \geqslant y)\,\text{Prob}(Y \geqslant y). \tag{7}$$

Let $F(x|y) = \text{Prob}(X \leqslant x | Y \geqslant y)$. The input-oriented measure of technical efficiency is defined by Daraio and Simar (2007), as (8):

$$\theta(x, y) = \inf\{\theta; H(\theta x, y) > 0\} = \inf\{\theta; F(\theta x|y) > 0\}. \tag{8}$$

The empirical version is given by (9), where $I(\cdot)$ denotes an indicator function. For each producing unit in the sample this quantity is precisely the input-oriented FDH measure of technical efficiency defined previously.

$$\hat{\theta}(x, y) = \frac{\sum_{j=1}^{n} I(X_j \leqslant x, Y_j \geqslant y)}{\sum_{j=1}^{n} I(Y_j \geqslant y)}. \tag{9}$$

A similar development may be considered for output orientation, leading likewise to the output-oriented FDH measure of technical efficiency.

Consider now a vector Z of covariates, with values in R^k, affecting the production process. The production observations are now viewed as realizations of the conditional distribution of (X, Y) given that $Z = z$. In this case, the conditional probability distribution generates the observations. The input-oriented measure of technical efficiency FDH conditional to $Z = z$ is defined by (10) and the corresponding sample estimate is (11):

$$\theta(x, y|z) = \inf\{\theta; H(\theta x, y|z) > 0\} = \inf\{\theta; F(\theta x|y, z) > 0\}, \tag{10}$$

$$\hat{\theta}(x, y|z) = \frac{\sum_{j=1}^{n} I(X_j \leqslant x, Y_j \geqslant y) K((z - z_j)/h)}{\sum_{j=1}^{n} I(Y_j \geqslant y) K((z - z_j)/h)}. \tag{11}$$

Notice that (10) is a straightforward extension of (8). Here we assume Z to be absolutely continuous. The function $K(\cdot)$ is a non-normal symmetric kernel concentrated in $[-1, 1]^k$. The quantity h is the corresponding bandwidth for nonparametric density estimation. The expression

(11) generalizes (9) and the presence of the kernel allows nonparametric estimation of the conditional density (Silverman, 1986).

In our application, we use as a kernel the probability in $[-1, 1]^k$ defined by the product of one-dimensional independent Epanechnikov kernels (Silverman, 1986).

One can show the relation in (12):

$$\hat{\theta}(x, y|z) = \min_{\{j | y_j \geqslant y, |z_j - z| \leqslant h\}} \left\{ \max_{i=1,\ldots,p} \left\{ x_j^i / x^i \right\} \right\}. \tag{12}$$

We see that the computation of the conditional measure of technical efficiency depends only on the kernel function through h. In our application, to compute conditional measures, we use Matlab and a software kindly provided by Cinzia Daraio and Léopold Simar.

For the assessment of the influence of Z in efficiency, Daraio and Simar (2007) suggested a nonparametric statistical analysis using the ratio (13) as the response variable.

$$q(x_j, y_j, z_j) = \frac{\hat{\theta}(x_j, y_j | z_j)}{\hat{\theta}(x_j, y_j)}. \tag{13}$$

As Daraio and Simar (2007) put it, if the smoothed nonparametric regression is increasing in a covariate z, it is an indication that the covariate is detrimental to efficiency. The covariate acts as an extra undesired output to be produced asking for the use of more inputs in production, and hence has a negative effect on production. On the other hand, if the smoothed nonparametric regression is decreasing in z, it is an indication of a factor favorable to efficiency. The contextual variable plays a role of a substitutive input in the production process, giving the opportunity to save inputs in the activity of production.

Here we propose a variant of this approach. For observations on a balanced panel (x_{jt}, y_{jt}, z_{jt}), $j = 1, \ldots, n$, $t = 1, \ldots, T$, of n producing units over T time periods, we postulate (14), following Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998):

$$\begin{aligned} R_t\big(q(x_{jt}, y_{jt}, z_{jt})\big) = {} & c + \alpha R_{t-1}\big(q(x_{jt-1}, y_{jt-1}, z_{jt-1})\big) + \gamma R_{t-2}\big(q(x_{jt-2}, y_{jt-2}, z_{jt-2})\big) \\ & + \sum\nolimits_{f=1}^{k} \beta_f R(z_{jt}^f) + \upsilon_j + \varepsilon_{jt}. \end{aligned} \tag{14}$$

The transformation $R_t(\cdot)$ denotes rank of the argument in period t. The quantities c, α, γ and β_f are unknown parameters, υ_j are specific random effects of the panel, the ε_{jt} i.i.d. errors with common variance σ_ε^2. The panel-level effects may be correlated with the covariates. The statistical analysis is carried out using Generalized Method of Moments (GMM; Greene, 2007) and is robust to the presence of serial correlation of first order in the residual structure. The use of ranks lends nonparametric properties to the analysis (Conover, 1998).

3. Embrapa's production model

Embrapa's research system comprises 37 units (DMUs) of research centers. Input and output variables have been defined from a set of performance indicators known to the company since 1991. The company routinely uses 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.

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 aimed primarily at 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. Plants varieties, hybrids or clones.
2. Agricultural and livestock processes and practices.
3. Agricultural and livestock inputs. All raw materials, 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, postharvest 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 (agro ecologic or socioeconomic) and mapping.

Finally, the category of diffusion of technologies and image encompasses production actions related to 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 h.
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 1 h 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; and (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 h. 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 h to be counted in this item.
7. Fellowship holders. Orientation of students (the fellowship holders). The fellowship duration should be at least 6 months and the workload at least 240 h.
8. Folders. Only folders inspired by research results are considered. Re-impressions 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 min.
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:

1. Personnel costs. Salaries plus labor duties.
2. Operational costs. Expenses with consumption materials, travel and services, less income from production projects.

3. Capital. Measured by depreciation.

As indicators (inputs and outputs) of the process, we consider a system of dimensionless relative indices. These are all quantity indices. The idea, from the output point of view, is to define a combined measure of output as a weighted average of the relative indicators (indices) in the system. The relative indices 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 indices 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.

The input indices are indicated by x_i^o, $i = 1, 2, 3$. These quantities represent relative indices 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 indices composing the category. If o is the DMU (research unit) being evaluated then $y_i^o = \sum_{j=1}^{k_i} a_{ji}^o y_{ji}^o$; $0 \leqslant a_{ji}^o$; $\sum_{j=1}^{k_i} a_{ji}^o = 1$, 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, 1958; Kotz and Johnson, 1989). The model is competitive with the AHP method of Saaty (1994) 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.

The efficiency models implicitly assume that the production units are comparable. This is not strictly the case in Embrapa. To make them comparable, an effort to define an output measure adjusted for differences in operation and perceptions is necessary. At the level of the partial production categories, we induced this measure allowing a distinct set of weights for each production unit. In principle, one could go ahead and use multiple outputs. This would minimize the effort of defining weights. The problem with such approach is that there is a kind of dimensionality curse in efficiency models. As the number of factors (inputs and outputs) increases, the ability to discriminate between units, i.e., as Seiford and Thrall (1990) 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 units. This approach further established a common basis to compare research units.

Thus the set of production variables monitored by Embrapa comprises an output y and a three-dimensional input vector (x^1, x^2, x^3). For the period 1996–2006, we have balanced information on the vector (x^1, x^2, x^3, y) for all 37 Embrapa's research centers.

Embrapa's production system has been monitored since 1996. Measures of efficiency and productivity are calculated and used for several managerial objectives. One of the most important is the negotiation of production goals with the individual research units. A proper management of the production system as a whole requires the identification of good practice and the implementation of actions with a view to improve overall performance and reduce variability in efficiency among research units. Parallel to this endeavor is the identification of non-production variables that may affect the system positively or negatively. It is of managerial interest to detect controllable attributes causing the observed best practices.

Several attempts are in course in Embrapa to evaluate the effects of contextual variables in production efficiency. It is worth mentioning Souza (2006) and Souza et al. (1999, 2007); these studies are based on DEA and have studied, for distinct periods, the effects of rationalization of costs, processes improvement, intensity of partnerships, type and size. We now combine information for the period 1999–2006 and analyze the effect of these variables on the conditional FDH through (12). In this context, we consider a vector of covariates $(z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8)$. Components (z_1, z_2, z_3) correspond to process improvement (mproc), financial resources acquisition (rec) and partnership (par). These are considered continuous covariates. Process improvement and intensity of partnerships are indices. All continuous covariates are normalized by the maximum for each time. The definition of these scores can be seen in Embrapa (2006). The subvector $(z_4, z_5, z_6, z_7, z_8)$ is formed by indicator variables and corresponds to management change (adm), type and size. Two dummies are used to describe three levels for size and three levels for type, respectively. The vector of categorical variables is assumed to be exogenous to the production process and it was not included in the computations of (12). Not enough replications are available for this purpose within each year of analysis.

3.1. Statistical analysis

Figures 1 and 2 show the evolution of measures FDH, FDH conditional and DEA under variable returns to scale (DEA–BCC). We see from Fig. 1 that in some instances FDH and DEA–BCC differ significantly, indicating non-convexity of the underlying technology. Figure 2, on the other hand, shows significant differences between FDH and its conditional form, suggesting that the production frontier may indeed be affected by the covariates. These observations lead naturally to FDH methods.

Table 1 shows the statistical results derived from (14). The test for the presence of second autocorrelation is not significant with a *p*-value of 45% and the Sargan test for overidentifying restrictions does not reject the model either with a *p*-value of 76%. The instruments used in the analysis are first- and second-order differences of the response, first-order differences of the ranks of processes improvements, financial resources acquisitions, partnerships, the two type indicators, the two size indicators, management change indicator and a constant term.

The effects size and type are not statistically significant with joint *p*-values of 84% and 86%, respectively. Processes improvements, financial resources acquisition and management change have negative signs. But only financial acquisition resources are statistically significant. Therefore the response is a decreasing function of these factors. Following the interpretation of Daraio and Simar (2007), this is a case of favorable (to the production process) covariates. The intensity of

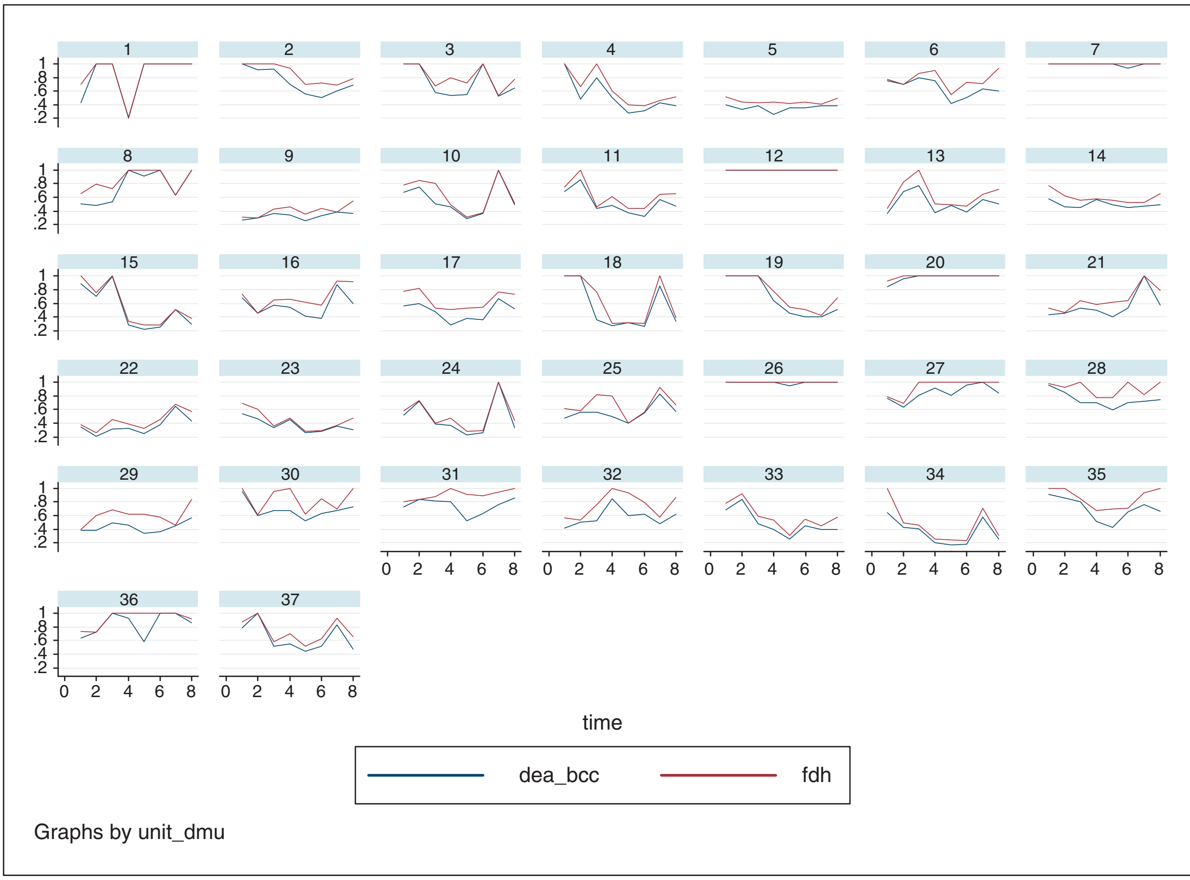

Fig. 1. Panel data plots of FDH and DEA–BCC results.

partnerships is detrimental to the production process, but it is not statistically significant. The lag 2 negative and statistically significant component of the response provides indication of an effort for improvement. Two periods are necessary for that to be achieved. These results are not in agreement with the analysis carried out by Souza et al. (2007), notably with respect to financial resource acquisition and management change. The differences are due more to the response used than to the statistical methods used. The DEA–BCC frontier at Embrapa is similar to the FDH, suggesting convexity of the technology.

3.2. *Final considerations*

The statistical assessment of the effects of contextual variables on Embrapa's production system is carried out when the response of interest is the conditional FDH measure of technical efficiency with input orientation. The conditional FDH has an interesting probabilistic interpretation when one assumes the production model generated by a joint probability measure defined by outputs, inputs and the contextual variables. Conditioning on the absolutely continuous contextual

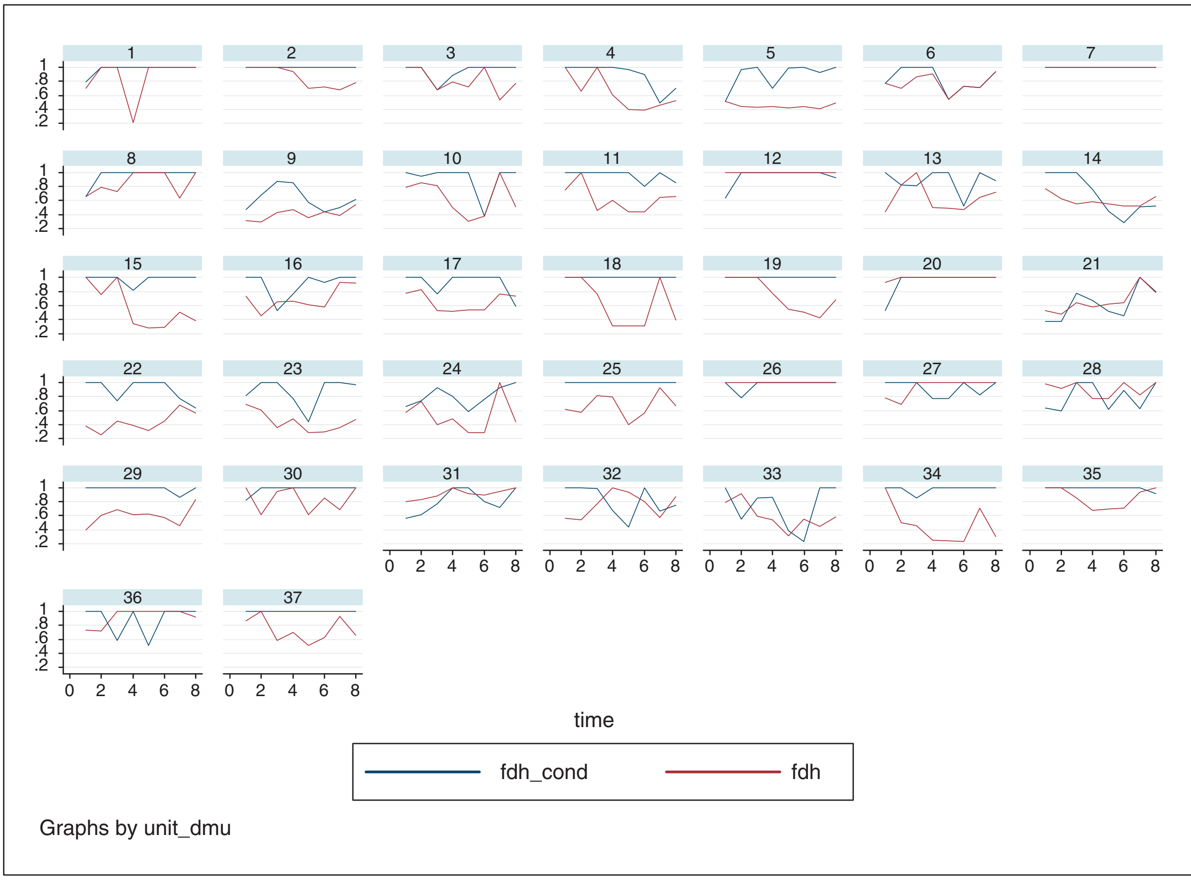

Fig. 2. Panel data plot of FDH vs. conditional FDH results.

Table 1
Dynamic panel statistical model

Variable	Coefficient	Standard error	z	$P>\|z\|$	95% confidence interval	
Lag1	0.0377	0.2152	0.18	0.861	– 0.3841	0.4595
Lag2	– 0.2694	0.0905	– 2.98	0.003	– 0.4468	– 0.0920
Z1 (mproc)	– 0.0108	0.0418	– 0.26	0.796	– 0.0928	0.0712
Z2 (rec)	– 0.2011	0.0977	– 2.06	0.040	– 0.3929	– 0.0096
Z3 (par)	0.0025	0.0453	0.05	0.956	– 0.0863	0.0913
Z4 (adm)	– 0.5931	1.4980	– 0.40	0.692	– 3.5292	2.3429
Z5 (type2)	31.7611	102.2497	0.31	0.756	– 168.6446	232.1668
Z6 (type3)	– 83.7362	153.0349	– 0.55	0.584	– 383.6790	216.2067
Z7 (medium)	23.7291	75.5381	0.31	0.753	– 124.3228	171.7810
Z8 (large)	46.7976	94.9387	0.49	0.622	– 139.2788	232.8741
Intercept	32.3361	46.9948	0.69	0.491	– 59.7719	124.4442

Response is rank of $q(x_j, y_j, z_j)$, the ratio of conditional to unconditional FDH measures of technical efficiency.
Z1, Z2 and Z3 are ranks of processes improvement (mproc), financial resources acquisition (rec) and partnership (par). Variables Z4–Z8 are indicators.

variables, one obtains the conditional FDH. The ratio of the conditional to the unconditional FDH produces a response that can be investigated as a function of the continuous covariates and other indicator variables strictly exogenous to the production process. In this context, we use a dynamic panel data model and GMM to assess the effects of contextual variables. The analysis is nonparametric. The contextual variables of interest are improvements of processes, acquisition of financial resources, management change, type and size.

We conclude that the production process has a strong inertial component. The research centers try to improve from negative results with a 2-year time lag. The contextual variables processes improvements, acquisition of financial resources and management change are favorable to the production process, but only acquisition of financial resources is statistically significant. Intensity of partnerships, size and type do not show statistically significant effects.

The statistical results differ markedly from the analyses carried out with DEA measures elsewhere.

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