A DYNAMIC GMM APPROACH TO SUPPORT THE MANAGEMENT OF AGRICULTURAL RESEARCH CENTERS IN BRAZIL: A DEA APPLICATION

Geraldo da Silva e Souza
Eliane Gonçalves Gomes
Brazilian Agricultural Research Corporation (Embrapa)
Parque Estação Biológica, Av. W3 Norte final, Asa Norte, 70770-901, Brasília, DF, Brazil
{geraldo.souza; eliane.gomes}@embrapa.br

Abstract

In this paper, we measure the performance for each of the Brazilian Agricultural Research Corporation research centers by means of a Data Envelopment Analysis model. Performance data are available for a panel that covers the period 2002–2009. The approach is instrumentalist. We investigate the effects on performance of a set of contextual variable indicators related to the improvement in administrative processes, the quality of the reports on the impact of the technologies generated by the research centers, the intensity of partnerships and revenue generation. For this purpose, we propose a fractional regression nonlinear model and dynamic GMM estimation. We do not rule out the endogeneity of the contextual variables, cross-sectional correlation or autocorrelation within the panel. We conclude that partnership intensity and previous performance score are statistically significant and positively associated with actual performance. Improvement in administrative processes and revenue generation negatively affect performance.

KEYWORDS. Data envelopment analysis. Contextual variables. Panel Data. Fractional Regression. GMM.

Main area. DEA – Data Envelopment Analysis

RESUMO

Neste artigo foi medido o desempenho dos centros de pesquisa da Empresa Brasileira de Pesquisa Agropecuária com uso de modelo de Análise de Envoltória de Dados. Estão disponíveis dados em painel para o período 2002–2009. A abordagem é instrumentalista. São analisados os efeitos nas medidas de desempenho de um conjunto de variáveis contextuais relacionadas a melhoria de processos administrativos, qualidade dos relatórios sobre impactos das tecnologias geradas pela empresa, intensidade de parcerias e geração de receitas. Para tal, propõe-se o uso de um modelo não linear de regressão fracionada e estimação via GMM dinâmico. Não são descartados efeitos de endogeneidade das covariáveis, correlação serial e autocorrelação dentro dos painéis. Conclui-se que a intensidade de parcerias e o desempenho passado são estatisticamente significante e positivamente associados ao desempenho atual. Melhoria de processos e geração de receitas afetam negativamente o desempenho.

PALAVARAS CHAVE. Análise Envoltória de Dados. Variáveis contextuais. Dados em painel. Regressão Fracionada. GMM.

Área principal. DEA – Análise Envoltória de Dados

1. Introduction

The Brazilian Agricultural Research Corporation (Embrapa) has monitored the production processes of 37 of its 42 research centers since 1996, using a Data Envelopment Analysis (DEA) performance model with a single output and a three-dimensional input vector. This model provides a measure of technical efficiency (performance) for each research center. This article is concerned with the identification of the contextual variables, whether they are external to the production process or not, which may affect or contribute to efficiency. These variables are typically found in the control of the institution. The assessment of their effect is an issue of managerial importance, since they may serve as a tuning device to improve management practices, leading to more efficient units. Here, we are interested in studying the effects on the technical efficiency of indicators related to the improvement in administrative processes, the quality of reports on the impact of the technologies generated by the research centers, the intensity of partnerships and revenue generation.

The statistical identification of factors that influence DEA performance measures demands appropriate statistical modeling. The literature offers a number of parametric and semi-parametric statistical models for assessing the significance of covariates in DEA models; detailed discussions can be seen in, for instance, Simar and Wilson (2007, 2011), Gomes et al. (2008), Banker and Natarajan (2008, 2011) and Ramalho et al. (2010, 2011). These articles typically use statistical techniques such as analysis of variance, maximum likelihood, quasi-maximum likelihood and bootstrapping. The approach followed in most cases is based on a two-stage DEA. Efficiency (performance) measurements are computed in the first stage and are then regressed on a set of covariates in the second stage. This approach has been criticized in the literature, mainly by Simar and Wilson (2007, 2011).

Two main problems arise in this context: (a) the correlation between efficiency measurements in the first stage and (b) the endogeneity of the contextual variables, which may be involved in production decisions. The first problem, given that the contextual variables are indeed exogenous, does not seem to invalidate the approach, even in the presence of heteroskedasticity (e.g. Ramalho et al., 2010, 2011). There are cases in which the correlation is not at all a problem. For example, in an analysis of variance model with a single positive response, the standard statistical analysis for treatment comparisons is obtained by considering a simple DEA model with a unit input. In this instance, the correlation is induced by the division of a response observation by its maximum. F- and t-tests are invariant under location and scale transformations (for additional details, see Gomes et al., 2008). Ramalho et al. (2010, 2011) also do not see any apparent problems with this assumption.

On the other hand, if the contextual variables are endogenous, as Simar and Wilson (2007) point out, we believe that the condition may invalidate the statistical analysis in a way similar to what happens with simultaneous equation models. In this case, it is appealing to consider instrumental variable estimation in the second stage. In order to lessen the covariates' effects causing interference on the production frontier, Daraio and Simar (2007) propose a measure based on the conditional FDH (Free Disposal Hull) in order to obtain insights into the effects of covariates. The correlation problem, however, is not addressed.

The model we propose here considers a panel data structure assuming a bounded nonlinear response function. The expected efficiency value is defined by a real valued monotonic function with values in [0,1], dependent on a linear construct defined by the set of covariates. Performance scores are viewed in the context of the instrumentalist approach described by Ramalho et al. (2010): DEA scores are treated as descriptive measures of the relative technical efficiency of the Decision-Making Units (DMUs) under analysis. This means that in a two-stage approach, DEA scores computed in the first stage can be treated as any other dependent variable in regression analysis. Therefore, as Ramalho et al. (2010) point out, "parameter estimation and inference in the second stage may be carried out using standard procedures". We assume the data follow a model in which the contextual variables may be endogenous. Endogeneity is accounted for through proper panel instrumentalization. Additionally, cross-sectional correlation and autocorrelation are also considered in the estimation process.

An earlier panel data analysis in the same context considered herein also appears in Souza et al. (2011). This latter article refers to the same production system (Embrapa) though differs from the present discussion in the following key aspects:

1. The contextual variables in the two articles are not the same. We now consider a new set of covariates of management interest that may be endogenous to the production process. The Souza et al. (2011) article considers only purely exogenous variables as factor effects (time and type dummies).
2. In the 2011 article an AR(1) process is imposed for the DEA measurements – the dependent observations – and fits the dynamic panel model proposed by Blundell and Bond (1998). Although this model is robust against second order autocorrelation, it does not take into account the correlation between the DMUs induced by DEA computations nor the potential endogeneity of the contextual variables. We propose different GMM methods here that are robust against endogeneity, crosssectional correlation and serial correlation.
3. No explicit assumption is made regarding the expected value of the DEA measurements in the 2011 paper other than the AR(1) evolution of the response. In order to better address this problem, we now propose combining the methods of fractional regression with GMM to produce a more adequate model to describe the response.

Our address is concerned with resolving the four main problems related to applied work involving DEA responses in two stage regressions which are recurrent in the modern literature on the subject, namely correlation between DMUs, endogeneity of contextual variables, serial correlation, and proper functional modeling of the response.

Our discussion proceeds as follows. In Section 2, we review Embrapa's performance process and the production variables used in the analysis, including the contextual variables. In Section 3, we discuss the estimation process that we recommend for panel data, overcoming the three problems related to DEA two-stage statistical models: endogeneity, cross-sectional correlation and autocorrelation. In Section 4, we present the statistical results. Finally, Section 5 summarizes our findings.

2. Embrapa's Performance Model

Embrapa's research system currently comprises 42 research centers, or DMUs. Five of these units were recently created (2010–2012) and these are not included in the evaluation system discussed here; hence, our sample consists of 37 DMUs. The input and output variables were defined from a set of performance indicators known to the company since 1991. The company routinely uses these indicators to monitor performance on an annual basis. With the active participation of the board of directors of Embrapa as well as the administration of each of its research units, 28 output and three input indicators were identified as being representative of production actions in the company. The performance measure computed within years is a technical efficiency DEA score based on one aggregated output and three input indices. These measurements are outside our control here. We are concerned with detecting the factors of managerial importancethat may influence the performance measurements (negatively or positively). Further details on the performance evaluation system carried out by Embrapa can be seen Souza et al. (2010) and Souza and Gomes (2013).

The output indicators are classified into four categories: scientific production; production of technical publications; development of technologies, products and processes; and diffusion of technologies and image. Scientific production entails the publication of articles and book chapters. The technical publications category groups publications produced by research centers that focus primarily on agricultural businesses and agricultural production. The development of technologies, products and processes category groups indicators that are related to the efforts made by a research unit to make its production available to society in the form of a final product. Only new technologies, products and processes are considered. Finally, the diffusion of technologies and image category includes production actions related to Embrapa's efforts to make its products known to the public and to market its image.

The input side of Embrapa's performance process is composed of three factors: personnel costs (salaries plus labor duties), operational costs (expenses resulting from the consumption of materials, travel and services, less income from production projects) and capital (measured by depreciation).

The company considers a system of dimensionless relative indices to be indicators (inputs and outputs) of the production process. These are all quantity indices that are computed on a within-year basis. The idea, from an output point of view, is to define a combined measure of output as a weighted average of the relative indicators (indices). The relative indices are computed for each production variable and for each research center by dividing the observed production quantity by the mean per research unit. We see that within a given year the base of the production indices is defined by the set of means per unit, as defined by the production and cost variables.

The final set of production variables is therefore reduced to one output y and a three-dimensional input vector $\left(x^1,\ x^2,\ x^3\right)$. For the period 2002–2009, we have balanced information on the vector $\left(x^1,\ x^2,\ x^3,\ y\right)$ for Embrapa's 37 research centers. Following the terminology of Ramalho et al. (2010), we see the DEA efficiency measures in the context of an instrumentalist approach rather than resulting from a true production process from which the research centers represent a sample.

Embrapa's performance system has been monitored since 1996. Measures of efficiency are calculated and used to ensure progress toward several managerial objectives. One of the most important is the negotiation of performance goals with the individual research units. The proper management of the evaluation system as a whole requires the identification of best practices and implementation of actions with a view to the improvement in overall performance and reduction in the variability in efficiency between research units. Parallel to this endeavor is the identification of non-production variables that may positively or negatively affect the system. It is of managerial interest to detect the controllable attributes that cause or contribute to the observed best practices.

We used the information for the period 2002–2009 to analyze the effect of the contextual variables on Embrapa's performance. In this context, we considered a vector of four covariates, which are indicators that correspond to improvements in processes (MPROC), the impact of technologies (IMP), the intensity of partnerships (PARC) and revenue generation (RECP). These are all measured on a within-year basis.

MPROC is intended to measure yearly changes in some administrative processes chosen by Embrapa's board of directors according to its priorities. These processes may vary by DMU. The values reflect the perception of management, on a 0–100 scale, regarding the successful implementation of certain processes.

IMPs are scores computed by Embrapa's administration that are intended to measure the quality of the reports on the impact of the technologies developed by the research centers. As a measure, it is concerned with the form and content of the reports and not with the importance of the technologies. Each research center selects three technologies to be evaluated in terms of their economic, social and environmental impacts. The evaluation methodology for a technology in each of these dimensions is a standard procedure that should be used by all research centers. The variable is not intended to facilitate the comparing of units in terms of the benefits generated by the technologies under evaluation. The importance of the score for management is simply to force DMUs to evaluate these technologies according to the criteria of managerial importance. IMP is measured on a 0–5 scale, 5 being the highest score.

RECP is a comparison of external and government funding. Each research unit negotiates with the board of directors an amount of external funds it expects to raise each year. The attainment of this goal is checked at the end of the evaluation period (a year) by the corporation's finance department. The measurement takes into account both direct and indirect funds. Direct funds are funds received from sales, contracts and credit from other public institutions, which are not part of Embrapa's budget. Indirect funds are those received from the private sector and other partners. RECP is the ratio between the sum of direct and indirect revenues raised by each research center and the amount of funds received from the national treasury. Managers expect that this indicator, over time, will show an upward trend, indicating reduced dependence on resources from the national treasury on the part of Embrapa's research centers.

PARC is a weighted index of the research or technology knowledge transfer actions (partnerships) scheduled by each research center and performed during the year being assessed. The weights are defined by the administration. Partnerships in a research program are entered into via projects (weight = 0.35), via scientific publications (weight = 0.15), via technical publications (weight = 0.15), via the development of technologies, products and services (weight = 0.15), via the attainment of final results (weight = 0.15) and via technology transfer and image promotion (weight = 0.20). External and internal partnerships are equally weighted. The score of partnerships is normalized by the number of researchers in each center.

As for scale orientation, we are aware that the use of ratios in DEA may pose convexity problems in the original scale of the production variables, as emphasized in Hollingsworth and Smith (2003) and Emrouznejad and Amin (2009). The problem is lessened in our application, in that we are dealing with a performance indicator and not a production function. We opted not to attempt to resolve this issue via a new programming problem (Emrouznejad and Amin, 2009) but instead impose the variable returns to scale assumption and interpret the DEA solution in the proper scale, as Hollingsworth and Smith (2003) suggest.

3. Statistical Model

Statistical inference derived from two-stage analysis in the context of DEA is hard to deal with. As we have already pointed out, covariates are typically entangled with the production process and therefore they may invalidate standard statistical procedures such as maximum likelihood and least squares because of the correlation of the independent variables with the error term. In addition, the DEA computations induce correlations between the DMUs being evaluated. Further to these comments, there is the necessity to model the DEA response properly, since the observations fall in the interval (0,1].

Ramalho et al. (2010) propose several approaches to deal with two-stage regressions when a DEA response is the dependent variable. The simplest formulation they consider that avoids the problems associated with linear and Tobit models — see Simar and Wilson (2007, 2011) and Ramalho et al. (2010) — is the fractional regression model (FRM) used by Papke and Wooldridge (1996). The only assumption required by the FRM is the correct specification of the conditional mean of the dependent variable (DEA score). In other words, it is assumed that the responses satisfy the moment condition $E\left(\phi_j^*\right)=F\left(\mu_j\right),\ \mu_j=l_j'\beta,$ where ϕ_j^* is the DEA score for the DMU j, l_j is the vector of observations on the contextual variables for DMU j, β is a vector of unknown parameters and F is some nonlinear function satisfying $0\leq F\left(\mu\right)\leq 1$. Typical choices for F are the distribution functions of the logistic, standard normal and inverse extreme value distributions. The idea is to estimate the model by using quasi-maximum likelihood methods, maximum likelihood or nonlinear least squares.

Two points are overlooked in this process: endogeneity and the dependence of DMU scores. None of the proposals in Ramalho et al. (2010) covers these conditions simultaneously. Simar and Wilson (2007) impose strong assumptions (separability) on the production process to avoid endogeneity, while Banker and Natarajan (2008) assume the exogeneity of the covariates. The best approach to overcome the problem of endogeneity seems to be the conditional FDH of Daraio and Simar (2007) and Badin et al. (2012). The latter, however, do not address the correlation induced by the FDH measures in a way similar to what happens with DEA. Our proposal is to combine the moment condition of the FRM with GMM (Generalized Method of Moments) when instruments are available for estimation. Because the GMM allows a test of the specification and of the validity of the instruments, it simultaneously takes into account endogeneity, correlation between units and time series errors. It is thus ideal for the instrumentalist approach. For information on the GMM estimation as presented here, see Gallant (1987), Davidson and MacKinnon (1993), Greene (2011) and StataCorp (2012).

We have panel data in which the expected value of a DEA performance response has been modeled as a nonlinear function of the contextual variables. First, the DEA performance measures may be contemporaneously correlated and might show heteroskedasticity. Second, for each DMU, the performance measures may also be correlated over time. Finally, the contextual variables may be endogenous. In such a context, we postulate that efficiencies ϕ_j^* satisfy the FRM $\phi_{jt}^* = F\left(l_{jt}'\beta\right) + \varepsilon_{jt}$, where l_{jt} is an observation of a vector of the independent covariates that may include strictly exogenous variables, endogenous independent variables, lagged endogenous variables and time and panel dummies. The subscript t stands for time and j for a panel member, or DMU. The panel is complete in our application. The vector of constants β, which is the same for all panels, defines the parameters to be estimated. ε_{jt} are stochastic errors with mean zero. They may be contemporaneously correlated, serially correlated and heteroskedastic. We use panel-style instruments. For each point in time, we use a different set of instruments, defined by the lagged values of the variables appearing in the model plus the fixed effects. Two lags are used to guarantee no correlation dynamically with the residuals. Indeed, the matrix of instruments used here is of the following form:

$$Z = \begin{pmatrix} z_1 & 0 & \dots & 0 \\ 0 & z_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & z_T \end{pmatrix}$$

where Z is a block diagonal matrix and z_t is the matrix of instruments for period t, of dimension 37 by 12, including lagged two values of the contextual variables, six time dummies and a column of ones. Notice that the jth row of z_t is $z_{jt} = (l_{jt-2}^1, \cdots, l_{jt-2}^5, d_{jt})$, $d_{jt} = (1, time3_{jt}, \cdots, time8_{jt})$. Here *time3–time8* are time dummies (2004–2009). The next section further specifies the 37 instruments considered in our analysis.

Let $\varepsilon_t = q\left(\phi_t^*, l_t, \beta\right)$, where, for each t, ε_t is a vector of dimension 37 with the typical element ε_{jt}. The function q has dimension 37 with the typical element $\phi_{jt}^* - F(l_{jt}'\beta)$. We assume $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t') = \Sigma$. Moreover, $E(\varepsilon_t \otimes vec(z_t)) = 0$, where $\otimes$ denotes the direct product of matrices. The moment conditions are defined by

$$E\left(\frac{1}{6}\sum_{t=3}^{8} m(\phi_t^*, l_t', \beta)\right) = 0, \;\; m(\phi_t^*, l_t', \beta) = q(\phi_t^*, l_t', \beta) \otimes vec(z_t).$$

In the GMM estimation, one looks for the vector β minimizing

$$S(\beta, V) = [\sum_{t=3}^{8} m(\phi_t^*, l_t', \beta)]' V^{-1} [\sum_{t=3}^{8} m(\phi_t^*, l_t', \beta)]$$

where V is a weight matrix positive definite. The optimal matrix V is the variance-covariance matrix of the moment functions:

$$V = E\left(\left(\sum_{t=3}^{8} \varepsilon_t \otimes vec(z_t)\right)\left(\sum_{s=3}^{8} \varepsilon_s \otimes vec(z_s)\right)'\right)$$

$$= \sum_{t=3}^{8}\sum_{s=3}^{8} E\left[\left(\varepsilon_t \otimes vec(z_t)\right)\left(\varepsilon_s \otimes vec(z_s)\right)'\right]$$

As an initial estimate of the parameter vector, we use $W = \frac{1}{6} I_{37} \otimes \sum_{t=3}^{8} vec(z_t) vec(z_t)'$.

Let $\tilde{\beta}$ minimize $S(\beta,W)$. The GMM estimate of β, $\hat{\beta}$, minimizes $S(\beta,\hat{V})$, where $\hat{V}=\frac{1}{6}\sum_{t=3}^{8} q(\phi_t^*,l_t,\tilde{\beta})q(\phi_t^*,l_t,\tilde{\beta})'\otimes\sum_{t=3}^{6} vec(z_t)vec(z_t)'$. This is a two-step estimator. The variance-covariance of $\hat{\beta}$ is estimated by

$$\left[\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)'\hat{V}^{-1}\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)\right]^{-1}$$

$$\times\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)'\hat{V}^{-1}S\hat{V}^{-1}\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)$$

$$\times\left[\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)'\hat{V}^{-1}\left(\sum_{t=3}^{8} Q(\phi_t^*,l_t,\hat{\beta})\otimes vec(z_t)\right)\right]^{-1}$$

where $Q(\phi_t^*,l_t,\hat{\beta})=\dfrac{\partial q(\phi_t^*,l_t,\hat{\beta})}{\partial\beta'}$ is the 37 by 5 Jacobian matrix of $q(\phi_t^*,l_t,\hat{\beta})$ (Gallant, 1987). The matrix S endows the standard error robustness relative to serial correlation. It corresponds to Newey–West corrections and is given by

$$S=\frac{1}{6}\sum_{t=3}^{8}\left(\hat{\varepsilon}_t\otimes vec(z_t)\right)\left(\hat{\varepsilon}_t\otimes vec(z_t)\right)'+$$

$$\frac{1}{6}\sum_{g=1}^{L-1}\sum_{i=g+1}^{8} K(g,L)\left\{\left(\hat{\varepsilon}_t\otimes vec(z_t)\right)\left(\hat{\varepsilon}_{t-g}\otimes vec(z_{t-g})\right)'+\left(\hat{\varepsilon}_{t-g}\otimes vec(z_{t-g})\right)\left(\hat{\varepsilon}_t\otimes vec(z_t)\right)'\right\}$$ Ou

$$K(g,L)=1-\frac{g}{L+1}.$$

r choice is $L=2$.

Finally, Hansen's (1982) J test of over-identifying restrictions (goodness of fit and validity of instruments) is given by $37\times S(\beta,\hat{V})$, which is chi-square with 31 degrees of freedom for our application.

4. Statistical Results

Table 1 shows the data for 2009. Figure 1 shows the performance evolution by DMU over time. Units 7, 19, 25 and 37 are fully efficient during the analyzed period. The medians per period vary within the range 0.4–0.6 and the box-plots do not indicate any clear trend in the data (Figure 2).

The distribution of each of the contextual variables by year is shown in Figure 3. The upward trend in partnerships is clear (Figure 3(a)), reflecting the concerns of Embrapa's administration regarding potential competition between research centers.

The units' efforts to obtain external funding are depicted in Figure 3(b) and these show a downward trend over time. This should be a point of concern for the company's administration and it may be one of the reasons for the absence of an upward trend in efficiency.

The distribution of process improvements by year is shown in Figure 3(c). There is no trend in the series. This may reflect local actions rather than the enacting of consistent policies by the administration.

The distribution of the impact of technologies over time is shown in Figure 3(d). The series seems to be stationary around an overall median of about 4.0. There are several outliers in the series that in some cases reflect the research units' non-responses, with those units subsequently penalized in the evaluation process.

Table 1. Production data and contextual variables. Inputs are X1, X2 and X3. Output is Y. The contextual variables are process improvements (MPROC), impact (IMP), partnerships (PARC) and revenue (RECP). Year = 2009.

	X1	X2	X3	Y	MPROC	IMP	PARC	RECP
DMU1	1.9491	2.3100	2.7117	1.5779	71.38	1.42	3.45	71.30
DMU2	0.9475	0.7801	0.6516	0.8873	45.88	4.27	3.64	36.50
DMU3	0.6054	0.6833	0.7612	1.5432	88.38	3.53	5.65	61.20
DMU4	1.3058	1.1456	1.1190	0.5541	72.79	4.20	7.65	17.70
DMU5	1.0482	1.1079	1.1601	1.3029	88.88	2.86	3.09	21.00
DMU6	0.6746	0.8532	0.6409	0.7294	58.50	3.86	8.15	21.40
DMU7	0.4377	0.5439	1.0545	1.8501	58.42	2.22	3.81	142.60
DMU8	1.0210	0.7785	0.7123	1.0453	80.68	4.61	3.91	44.40
DMU9	0.9175	0.9185	1.8102	0.7664	80.92	3.94	4.09	95.10
DMU10	1.3485	0.9039	1.5332	0.7837	95.13	4.10	4.15	262.70
DMU11	0.9720	1.0944	1.0455	0.7466	85.88	3.75	5.17	51.50
DMU12	1.0433	0.7983	1.0437	1.0598	57.75	4.10	6.17	7.30
DMU13	1.0481	1.0375	0.7269	1.2256	70.04	4.91	4.42	29.30
DMU14	1.4299	1.4462	1.4492	1.0583	81.88	4.07	7.40	74.80
DMU15	0.9104	0.7062	0.7744	1.0922	73.63	3.32	2.51	56.40
DMU16	0.8805	0.8380	0.9973	0.6600	79.48	4.54	3.18	76.30
DMU17	1.3737	1.7809	1.5852	1.1443	47.43	4.72	5.43	195.40
DMU18	1.0264	0.9054	0.9540	0.9172	76.50	4.47	5.75	72.90
DMU19	0.5765	0.5647	0.6141	1.8501	92.25	4.96	4.55	21.00
DMU20	0.6892	0.9250	1.0699	0.7055	76.38	4.02	6.10	31.30
DMU21	1.2903	1.1155	0.8306	0.5272	73.38	3.91	6.44	14.70
DMU22	1.7702	1.7286	1.5338	0.5682	85.38	4.22	5.16	56.70
DMU23	1.6006	1.7150	1.8198	1.1389	84.08	3.16	7.46	91.00
DMU24	0.7749	1.1940	0.6730	0.6848	85.40	3.84	6.87	19.10
DMU25	0.5078	0.4727	0.2901	0.4944	73.00	1.41	13.71	16.70
DMU26	0.7037	0.5547	0.4159	1.1163	0.00	3.10	15.39	34.00
DMU27	0.6122	0.5341	0.6379	1.4728	50.17	3.73	12.89	15.90
DMU28	1.1706	1.0919	0.8334	0.5575	2.50	1.77	7.03	95.10
DMU29	0.6368	0.7740	0.5731	0.6497	73.88	4.51	16.09	24.40
DMU30	0.7758	0.5738	0.6142	0.8509	86.54	4.85	4.90	9.70
DMU31	1.0206	0.9173	0.6094	1.2273	95.50	2.71	9.53	21.50
DMU32	1.3446	1.3243	1.1444	0.6782	65.14	4.32	5.70	49.60
DMU33	2.3904	2.1439	1.5218	0.8324	83.13	4.32	7.11	40.30
DMU34	0.6753	0.6457	0.7747	0.9863	83.80	4.35	5.55	61.50
DMU35	0.4118	0.4548	0.5033	1.5013	18.88	4.67	11.4	21.60
DMU36	0.7590	0.8277	1.0633	1.8501	90.25	3.04	4.45	46.70
DMU37	0.3500	0.8103	0.7465	0.7627	0.00	4.26	2.42	121.80

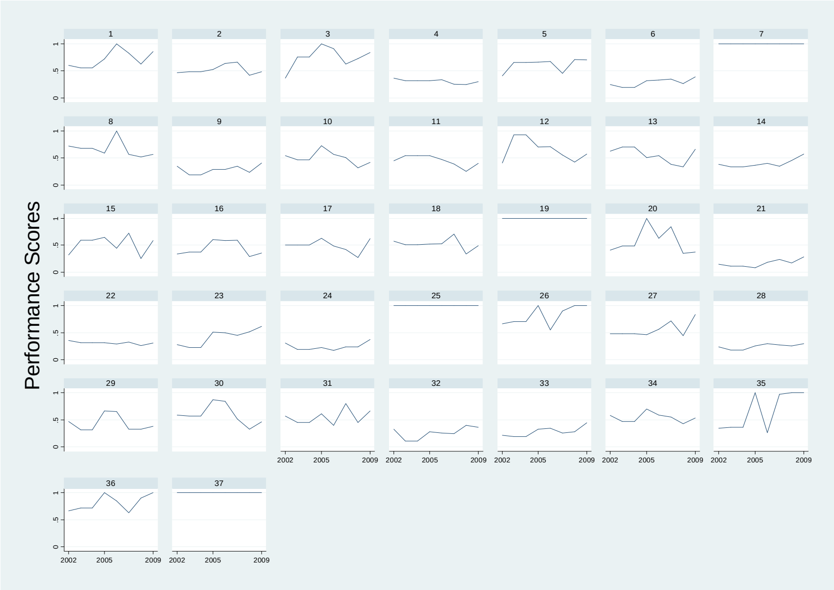

Figure 1. Evolution of *effic* (performance scores) by year and DMU.

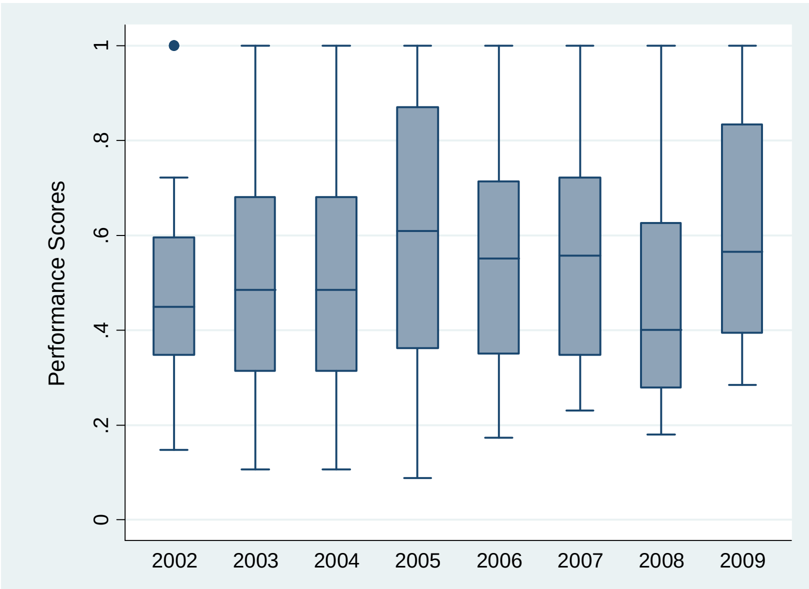

Figure 2. Distribution of effic (performance scores) by year.

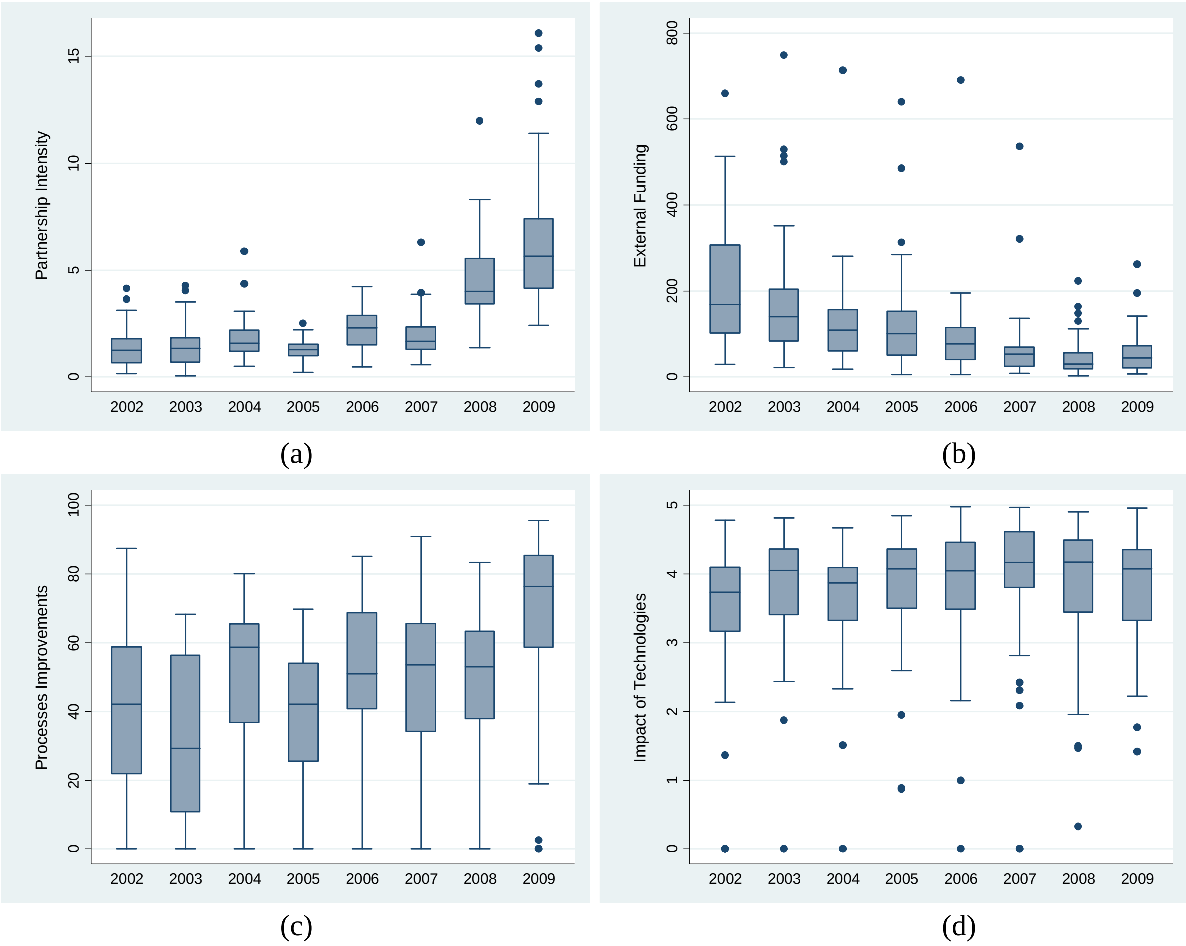

Figure 3. Distribution of PARC – partnership intensity (a), RECP – external funding (b), MPROC – process improvements (c) and IMP – impact of technologies(d) by year.

Our statistical analysis begins by defining the exogenous variables and instruments to be used in the GMM analysis. The model considers the within-year rank transformations of PARC, RECP, MPROC and IMP as well as lagged ranked DEA efficiency as exogenous variables. The instruments are of the panel data type. For each point in time, we consider as instruments lag two values of all exogenous variables, a column of ones and six dummies for the time effects. Time 1 and Time 2 are lost. Therefore, there are 37 instruments.

Table 2 shows the final GMM-FRM estimates under cross-sectional and serial correlations for the logistic response. Three models were considered: logistic, normal and inverse extreme value. The corresponding minimum chi-square values are 34.104, 34.336 and 34.967. The logistic is the best model, followed by the normal and the inverse extreme value. The J test statistic for over-identifying restrictions is 34.104 (p-value 0.3207) and does not invalidate the model specification or the instruments. The inclusion of all time dummies and DMU effects does not lead to a sensible model in the sense that the corresponding parameters are either non-significant or the GMM does not converge.

The variable IMP is not statistically significant. MPROC and RECP show a strong negative impact on efficiency. PARC and the lagged ranked efficiency score exert positive effects on performance. This is an important result for management. A criticism of the performance evaluation model used here is that it may cause unwanted competition between research units. The evidence found that DMUs engaged in more intense peer partnerships, whether internal or external, perform better. Further, a persistent effect is related to DMUs. Previous performance positively affects actual performance.

Table 2. Stata12 output. The GMM nonlinear regression of DEA performance (*effic*) on the contextual variables RMPROC (b1), RIMP (b2), RPARC (b3), RREC (b4) and L.REFFIC (b5). The response is defined by the logistic distribution, and the standard errors take into account cross-sectional and serial correlations.

	Coefficient	HAC standard error	z	P>|z|	[95% confidence interval]	
b0	-1.315480	0.156923	-8.38	0.000	-1.623043	-1.007917
b1	-0.017324	0.005136	-3.37	0.001	-0.027389	-0.007258
b2	-0.002338	0.004201	-0.56	0.578	-0.010571	0.005896
b3	0.011585	0.005084	2.28	0.023	0.001621	0.021548
b4	-0.013416	0.003240	-4.14	0.000	-0.019767	-0.007076
b5	0.106168	0.005412	19.62	0.000	0.095561	0.116775

HAC (heteroskedasticity- and autocorrelation-consistent) standard errors based on Bartlett's kernel with two lags.
Instruments for equation 1 [efic:efic - exp({b0} + {b1}*rmproc + {b2}*rimp + {b3}*rparc + {b4}*rrecp + {b5}*L.refic)/(1+ exp({b0}+{b1}*rmproc+{b2}*rimp+{b3}*rparc+{b4}*rrecp+{b5}*L.refic))]:
XT (panel data)-style: L2(rimp rmproc rparc rrecp reffic)
Standard: time_3 time_4 time_5 time_6 time_7 time_8 _cons

The effort to generate external funding does not translate into a performance increase. The message here is that the company may not be effectively enforcing its policy on external funding. Relatively, the effect of increasing external funding decreases performance. The negative impact of MPROC seems to reinforce the impression Figure 5 created. The policies on process improvements seem to be casuistic and not directly aimed at improving production.

The non-significance of IMP in the model is the result of the stationarity of the series. We should emphasize here that the computation of the IMP score is controversial, since it does not involve an implicit measure of quality. For production performance purposes, however, it has no effect.

5. Summary and Conclusions

We fit a panel data model for performance data generated by Embrapa's research centers during the period 2002–2009. A single combined output with a three-dimensional input vector was used to compute a performance score. The measure of performance is DEA under variable returns to scale. The panel data model postulates that performance is a nonlinear function of the contextual variables 'process improvements', 'quality of the impact report on the generated technologies', 'intensity of partnerships', 'external revenue generation' and 'past DEA performance'. The GMM estimation was used as a way to overcome the endogeneity of the covariates, cross-sectional correlations and serial correlations of the DMUs.

We found statistically significant effects for all contextual variables, with the exception of the 'impact of technologies'. The association between the intensity of partnerships and past performance with the response is positive. The other statistically significant covariates show negative associations.

We conclude that Embrapa's administration should not insist on the form of impact reports and on minor local changes to administrative processes as a way to motivate the higher performance of its research centers. Funding from external sources other than the government is decreasing over time, which may be the main reason why this indicator does not imply higher performance. The company should also continue to enforce its policy on partnerships. Increasing the values of this indicator would improve performance in a given year and through the persistency effect for the future.

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