A PARAMETRIC APPROACH FOR EVALUATING THE TECHNICAL EFFICIENCY OF THE BRAZILIAN AGRICULTURAL SECTOR

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In this study we assessed the technical efficiency of the 27 Brazilian states in the years 1995/96 and 2006. The data on land and labor were obtained from the agricultural census of the two considered periods. Data on credit for investment and running costs were obtained from the Brazilian Central Bank reports. In the analysis we used a DEA CCR model and a stochastic frontier with technical effects. The second model better fit the data, with 99% of correlation between predicted and observed values. The results show that Distrito Federal had the highest technical efficiency in agriculture in 2006 and the second highest in 1995/96. The lowest technical efficiency was found in Piauí in 2006 and in Tocantins in 1995/96. The estimated elasticities show that increases of 1% in per capita income would increase the technical efficiency by 0.77% in the North, by 0.76% in the Northeast, by 0.59% in the Center-west, by 0.56% in the South and by 0.49% in the Southeast region.

Palavras-chaves: Technical efficiency, Stochastic frontier, Elasticity, Agriculture

1. Introduction

Brazil is one of the most important countries in relation to agribusiness. Agribusiness represents about 25% of Brazilian GDP, 36% of its exports in 2008 and 37% of jobs in 2008.

The states of the South and Southeast historically and, more recently, the Center-west use more technology, such as improved varieties of plants, fertilizers, irrigation (Center-west), mechanization and chemicals. Brazilian agriculture differs regionally, due, primarily, to the differences in geographical area, such as climate and natural resources, and thus production characteristics. For example, in South region soybeans, maize, poultry and pork have particular significance, but in Northern region rubber (hevea), nuts, wood extraction are important activities. These regional differences can cause different agricultural performances among the regions.

Since there are regional variations regarding the way the agribusiness is organized in Brazil, it seems to be plausible that the technical efficiency shall also differ from state to state. The topic is delicate, since there are considerable differences among states, as can be seen, for instance, by the Human Development Index (HDI). In 2005 the HDI showed considerable differences: Distrito Federal (0.874), Santa Catarina (0.840), São Paulo (0.833) and Rio de Janeiro (0.832) were the states with higher HDI, while states like Alagoas (0.677) and Maranhão (0.683) had lower HDI (PROGRAMA DAS NAÇÕES UNIDAS PARA O DESENVOLVIMENTO, 2008).

As found by Battese and Broca (1997) for the case of wheat in Pakistan, in the case of Brazil the available data on agriculture and livestock may be not suitable for some models of efficiency analysis. Therefore, production data were extracted from the agricultural census of 1995/96 and 2006. Together with the production data, we used information on official credit used by farmers for investment and running costs in both mentioned years. These data were obtained from the Brazilian Central Bank reports.

In our analysis, both DEA and stochastic frontier models were used to estimate the technical efficiency of the agriculture and livestock production of the 27 Brazilian states. The second approach better fit the data. The literature on technical efficiency measures has some examples of studies using stochastic frontier models to assess the efficiency of agricultural activities, considering regional aggregation levels. In this frame, studies like Chen and Song (2008), Onishi et al. (2008), Kaneko et al. (2004), Bhattacharayya and Parker (1999), and Hofler and Payne (1995) can be mentioned.

2. Material and Methods

2.1. Stochastic Frontier Analysis

Basically, two approaches are available in the literature about efficiency analysis: the stochastic efficiency frontier analysis and the deterministic frontier analysis. In the context of deterministic frontiers, Data Envelopment Analysis (DEA) is by far the most used technique.

With a single output, for the stochastic frontier, typically, one specifies a parametric log cost function $C(\ln p, \ln y, \theta)$ dependent on log factor input prices $\ln p$ and log output level $\ln y$, and postulates the model (1), for cost data C_{it} for a panel of N producing units and T time periods.

$$\ln C_{it} = C(\ln p_{it}, \ln y_{it}, \theta) + v_{it} + u_{it} \quad i = 1,\ldots,N \quad t = 1,\ldots,T \tag{1}$$

For a production function one specifies (2), for log inputs $\ln x$.

$$\ln y_{it} = f(\ln x_{it}, \theta) + v_{it} - u_{it} \tag{2}$$

In these formulations, θ is an unknown parameter, $C(.)$ and $f(.)$ have known functional forms, and the stochastic components v_{it} and u_{it} represent random errors and inefficiency errors, respectively.

Typical parametric log cost families are provided by the Translog form (COELLI et al., 2005), the CES (GALLANT, 1982) and the Fourier Flexible Form (GALLANT, 1982). The latter endows the analysis with nonparametric properties. The random errors v_{it} are assumed to be uncorrelated across time and panel, and normally distributed with mean zero and variance $\sigma_v{}^2 > 0$. A flexible family of distributions to model the u_{it} (KUMBHAKAR, LOVELL, 2000; COELLI et al., 2005) is provided by truncation of the normal. In this context one may postulate $u_{it} = z_{it}\delta + w_{it}$, where z_{it} is a vector of specific inefficiency variables (covariates), δ is a vector of unknown coefficients of the firm specific inefficiency variables, and w_{it} is the truncation at $-z_{it}\delta$ of the normal with mean zero and variance σ_u^2. Here we use the production function approach. We will follow the production approach using the Cobb-Douglas representation (3), which leads to (4), where $\alpha = \alpha_0 + \alpha_1 dtime$.

$$y_{it} = \theta_0 x_{1it}^{\theta_1} x_{2it}^{\theta_2} x_{3it}^{\theta_3} x_{4it}^{\theta_4} \exp(v_{it}) \exp(-u_{it}) \tag{3}$$

$$\ln y_{it} = \alpha + \theta_1 \ln x_{1it} + \theta_2 \ln x_{2it} + \theta_3 \ln x_{3it} + \theta_4 \ln x_{4it} + v_{it} - u_{it} \tag{4}$$

Production is measured by total value of agricultural production (y) and the inputs are labor (x_1), capital (x_2), land (x_3) and other inputs (x_4, running costs like fertilizers, seeds, pesticides etc.) In (4), *dtime* is a dummy variable reflecting a time technological effect confounded with inflation. Since α_1 does not differ from zero significantly, we fit a model with current prices. It should be emphasized that a model with distinct elasticities for each period did not converge. In the next section we provide a more detailed explanation of the production variables.

DEA, on the other hand, assumes a deterministic frontier. Typical statistical models for which DEA is optimal do not assume the presence of the stochastic component v_{it}.

Let r denote the vector of log inputs, q the log output and θ the production function parameter vector. As Coelli et al. (2005) put it; much of stochastic efficiency analysis is directed towards the prediction of inefficiency (efficiency) effects. The most common output-oriented measure of technical efficiency for firm o is estimated in the stochastic frontier case by (5), where $\varepsilon_{it} = q_{it} - w_{it}\theta, \mu_{*it} = (-\varepsilon_{it}\sigma_u^2 + \mu_{it}\sigma_v^2)/\sigma_S^2, \mu_{it} = z_{it}\delta, \sigma_S^2 = \sigma_u^2 + \sigma_v^2, \sigma_* = \sigma_u\sigma_v/\sigma_S$.

$$E\left[\exp(-u_{it}) \mid \varepsilon_{it}\right] = \left\{ {[1 - \Phi(\sigma_* - \mu_{*it}/\sigma_*)]} \big/ {\Phi(\mu_{*it}/\sigma_*)} \right\} \exp(-\mu_{*it} + 0.5\sigma_*^2) \tag{5}$$

Assuming a normal-truncated normal specification the parameters are obtained maximizing the log likelihood function (BATTESE, COELLI, 1995) as in (6), where $d_{it} = \mu_{it}/\sigma_u$, $d_{*it} = \mu_{*it}/\sigma_*$, $\sigma_* = \sigma_u\sigma_v/\sigma_S$.

$$-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{\ln(2\pi)+\ln(\sigma_S^2)\right\}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{\ln(2\pi)+\ln(\sigma_S^2)\right\}$$
$$-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{[(q_{it}-r_{it}\theta)+z_{it}\delta]/\sigma_S^2\right\} \quad (6)$$
$$-\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{\ln\Phi(d_{it})-\ln\Phi(d_{it}^*)\right\}$$

A convenient model re-parameterization, making $\gamma = \sigma_u^2/\sigma_S^2$, leads to the log likelihood as a function $L(\beta,\delta,\gamma,\sigma_S^2)$, where $\sigma_u^2 = \gamma\sigma_S^2$, $\sigma_*^2 = \gamma(1-\gamma)\sigma_S^2$. A classical production model is implied by $\gamma = 0$.

Elasticity for firm *i* in period *t* relative to a contextual variable measured in logs with parameter estimate *b* is computed using the formula (7).

$$b\left(1-d_{it}\phi(d_{it})\Phi(d_{it})+[\phi(d_{it})]^2/[\Phi(d_{it})]^2\right) \quad (7)$$

In the DEA context, if X^t and Y^t represent the input and output matrices, the efficiency estimate of firm *i* in period *t*, under constant returns to scale and output orientation, is given by the solution of the linear programming problem Min φ, subject to $X^t\lambda \le x_i^t$, $Y\lambda \ge \varphi y_i^t$, $\lambda \ge 0$ (CHARNES et al., 1978). Here x_i^t and y_i^t represent the input vector and the output used by firm *i* in period *t*. The effect of contextual variables may be studied in a second stage regression using the efficiencies computed in the first stage, as proposed in Simar and Wilson (2007), Souza and Staub (2007) and Banker and Natarajan (2008). The stochastic and deterministic specifications underlying these approaches did not provide a good fit for our data. Thus the classical stochastic frontier with technical effects was our choice of model.

2.2. Data

In this model we used the value of agricultural production as dependent and land, labor, capital and running costs as independent variables. We used data on value of agricultural and livestock production of all 27 Brazilian states in the years 1995/96 and 2006. The two years correspond to the two last available agricultural census data in Brazil. The output variable used was the total value of Brazilian agricultural and livestock production in the years 1995/96 and 2006 (total value of production; R$). The inputs of the model were: total land area used (planted area; hectares), labor force (employment in agriculture and livestock; number of persons), investment and running costs (in monetary value, R$).

The data on area, labor force and value of production were obtained from the agricultural census (INSTITUTO DE PESQUISA ECONÔMICA APLICADA, 2008). Credit data on investments (or capital) and running costs (or other inputs) were extracted from the “Anuários Estatísticos do Crédito Rural” (BANCO CENTRAL DO BRASIL, 1995, 2006), representing all official credit taken by farmers in all 27 states in both evaluated years.

The credit for running costs includes annual expenditures on annual and permanent crops, as well as livestock. Those expenditures are used for maintenance and field operations (annual and permanent crops, and extractivism activities) and for livestock related activities. These expenditures include costs of seeds, fertilizers, pesticides, and field operations (seeding/planting, spraying, fertilizing, harvesting etc.). In livestock production, the running expenditures include maintenance of pastures, vaccines, salt and medicaments. Depending on the state, the running expenditures for agriculture and livestock are composed by different crops and livestock types.

Agricultural credit for running costs of livestock activities include the costs of keeping wild animals (emus, ostrich), bee keeping, poultry (chicken, egg etc.), cattle (beef, milk and mix purposes), buffalo (keeping, fattening and milk production), goats, rabbits, horses, sheep, fishery, pig, pastures (beef and dairy cattle), vaccines, mineral salts and medicaments.

Agricultural investments include several items. The establishment of perennial crops, the renovation of plantations, the improvement of agricultural enterprises, rural electricity, storage building, machinery and implements are among the items covered by credit for investment. As examples of investments for agriculture can be mentioned the establishment of perennial crops, like pineapples, acacia, bananas, cashew, sugar cane, tea, flowers, forestry (with local and introduced species), several fruits, guaraná, oranges, lemons, apples, cassava, passion fruit, peaches, tangerines, grapes etc. In livestock production, the official credit for investment covers the acquisition of production animals (domestically or imported).

For agriculture, the investment credit also covers soil correction and fertilization, soil protection (includes recovery measures), hand craft related to agricultural and livestock activities, small on-farm processing plants, tourism and rural recreation activities related to agriculture and livestock, rural housing, storing capacity, greenhouses, land clearing, rural electricity, irrigation systems. For livestock production, it includes the building of housing and equipment for poultry production, equipment for fisheries and pork production. Regarding machinery, the credit for investments covers the acquisition of combine harvesters, tractors, equipment, drying facilities and power tillers, among others. Also transportation vehicles and animals as power source.

Tables 1 and 2 show the production data used in our analysis, being Table 1 for year 1995/96 and Table 2 for year 2006.

States	Land (10^6 ha)	Labor (10^6)	Other Inputs (10^6 R$)	Capital (10^6 R$)	Total Value of Production (10^6 R$)	GDP *per capita* (10^3 R$/inhab)
Acre	0.690	0.094	1.312	4.489	107.200	3.307
Alagoas	1.710	0.432	14.606	24.235	654.670	2.275
Amazonas	0.265	0.017	0.268	4.036	68.871	7.170
Amapá	0.764	0.350	6.494	14.496	366.495	5.731
Bahia	18.380	2.509	93.183	153.698	2,102.241	3.203
Ceará	4.001	1.171	31.895	35.758	919.170	2.816
Distrito Federal	0.163	0.014	12.081	13.097	135.344	11.521
Espírito Santo	2.650	0.351	36.687	27.680	1,082.501	6.982
Goiás	21.580	0.472	291.608	100.683	2,582.846	4.171
Maranhão	6.132	1.332	20.779	41.540	698.162	1.465
Minas Gerais	24.404	0.327	234.444	121.701	1,984.847	5.773
Mato Grosso do Sul	23.194	0.203	181.533	86.722	2,181.819	5.533
Mato Grosso	29.521	2.000	403.333	155.734	6,409.086	4.258
Pará	8.264	0.884	28.226	104.842	1,026.712	3.355
Paraíba	2.493	0.480	16.711	11.257	468.348	2.412
Pernambuco	11.778	1.288	643.016	104.215	5,562.875	3.549
Piauí	3.364	0.975	41.908	33.023	1,229.492	1.766

Paraná	3.075	0.666	17.738	20.910	342.258	6.664
Rio de Janeiro	1.882	0.174	34.871	5.277	630.441	8.468
Rio Grande do Norte	1.835	0.333	13.774	14.324	355.930	2.770
Rondônia	17.316	1.377	708.364	76.728	6,169.907	3.343
Roraima	3.354	0.305	7.151	31.832	334.211	2.709
Rio Grande do Sul	1.676	0.034	1.508	7.707	62.085	8.476
Santa Catarina	3.909	0.719	365.726	24.093	3,270.470	7.375
Sergipe	1.433	0.313	26.945	20.698	273.526	3.330
São Paulo	14.318	0.915	771.109	117.098	8,412.369	10.291
Tocantins	11.345	0.194	40.642	49.526	356.366	1.842

Table 1 - Data of independent and dependent variables, Year = 1995/1996.

States	Land (10^6 ha)	Labor (10^6)	Other Inputs (10^6 R$)	Capital (10^6 R$)	Total Value of Production (10^6 R$)	GDP *per capita* (10^3 R$/inhab)
Acre	1.210	0.099	25.739	24.506	394.760	4.180
Alagoas	1.854	0.435	101.342	178.331	1,323.943	3.066
Amazonas	0.516	0.013	3.305	5.277	85.673	7.022
Amapá	4.214	0.271	11.682	34.165	633.880	5.072
Bahia	18.911	2.322	726.110	628.802	8,410.289	4.109
Ceará	5.097	1.143	85.886	306.171	2233.491	3.346
Distrito Federal	0.274	0.022	50.736	19.141	315.983	22.322
Espírito Santo	2.243	0.300	499.683	176.734	3,363.061	9.045
Goiás	19.115	0.402	1,616.190	786.750	9,484.811	5.914
Maranhão	10.240	0.994	230.962	426.373	2,075.573	2.747
Minas Gerais	29.675	0.363	1,042.836	1,065.720	12,295.853	6.547
Mato Grosso do Sul	20.639	0.201	1,065.068	379.267	6,108.961	6.292
Mato Grosso	27.466	1.861	3,708.628	970.629	19,346.268	7.332
Pará	16.382	0.798	191.547	481.974	4,220.543	3.705
Paraíba	2.703	0.489	37.397	168.754	1,044.622	3.269
Pernambuco	13.826	1.097	4,130.842	882.181	18,071.808	3.875
Piauí	7.116	0.955	101.796	289.577	2,977.304	2.501
Paraná	4.426	0.831	110.279	201.707	844.954	7.812
Rio de Janeiro	2.210	0.157	77.211	14.203	1,153.630	10.505
Rio Grande do Norte	2.448	0.247	65.647	156.299	1,067.118	4.009
Rondônia	16.194	1.220	3,911.969	1,102.965	17,626.219	4.981
Roraima	5.578	0.277	149.261	92.194	2,097.253	5.387
Rio Grande do Sul	1.035	0.030	7.866	29.416	169.936	8.495
Santa Catarina	6.439	0.568	2,076.046	525.304	8,784.919	9.283
Sergipe	2.069	0.270	52.008	152.157	794.796	4.488
São Paulo	16.049	0.873	4,061.247	875.024	27,815.883	11.605
Tocantins	11.103	0.175	225.278	157.719	1,539.653	4.280

Table 2 - Data of independent and dependent variables, Year = 2006 (Data in states alphabetic order).

3. Results and Discussion

Table 3 shows the statistical results of maximum likelihood estimation of the stochastic frontier model using Stata 10.1 software (STATA, 2007).

	Coefficient	Standard error	z	P>|z|	[95% Confidence interval]	
Production (y)						
Labor (l)	0.3238	0.0442	7.33	0.000	0.2373	0.4103
Capital (k)	0.1413	0.0529	2.67	0.008	0.0376	0.2449
Land (t)	0.2672	0.0286	9.34	0.000	0.2111	0.3232
Other Inputs (c)	0.2633	0.0470	5.60	0.000	0.1712	0.3554
Constant	-0.9182	0.4623	-1.99	0.047	-1.8243	-0.0120
Technical effect						
l(GDP pc)	-0.7699	0.1114	-6.91	0.000	-0.9881	-0.5516
Constant	1.8278	0.2726	6.71	0.000	1.2935	2.3620
sigma_S2	0.0604				0.0396	0.0921
gamma	0.4627				0.0319	0.9574

Table 3 - Stochastic frontier estimation.

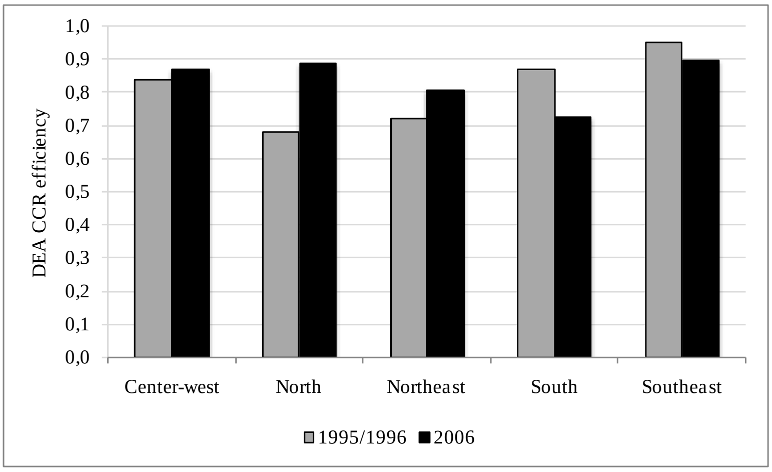
Table 4 shows statistics computed as a function of model parameters estimates. These are per capita income elasticities, deterministic (DEA) under constant returns to scale and stochastic efficiency estimates. We see that the Pearson correlation between the last two measures is only 57%, indicating strong differences between the two approaches.

State	Region	Efficiency				Income elasticity	
		DEA CCR-O		Stochastic			
		1995/1996	2006	1995/1996	2006	1995/1996	2006
Acre	North	1.0000	0.8074	0.4538	0.4929	0.7699	0.7698
Alagoas	Northeast	0.9855	1.0000	0.4261	0.4408	0.7699	0.7699
Amazonas	North	1.0000	1.0000	0.6814	0.6004	0.6615	0.6763
Amapá	North	1.0000	1.0000	0.8142	0.5454	0.7563	0.7672
Bahia	Northeast	0.4877	0.7884	0.3412	0.4869	0.7699	0.7698
Ceará	Northeast	0.7875	1.0000	0.3743	0.4373	0.7699	0.7699
Distrito Federal	Center-west	1.0000	0.8439	0.8898	0.9529	0.2302	0.0463
Espírito Santo	Southeast	1.0000	0.9504	0.7387	0.8571	0.6802	0.4376
Goiás	Center-west	0.6810	0.7188	0.4716	0.6632	0.7698	0.7504
Maranhão	Northeast	0.6231	0.4597	0.2441	0.3098	0.7699	0.7699
Minas Gerais	Southeast	0.7916	0.6522	0.5947	0.6720	0.7551	0.7166
Mato Grosso do Sul	Center-west	1.0000	0.9278	0.5900	0.6599	0.7610	0.7329
Mato Grosso	Center-west	0.6611	1.0000	0.4445	0.7937	0.7697	0.6441
Pará	North	0.4651	1.0000	0.3821	0.4732	0.7699	0.7698
Paraíba	Northeast	0.9923	0.9484	0.3634	0.4282	0.7699	0.7699
Pernambuco	Northeast	0.9723	1.0000	0.4811	0.5075	0.7699	0.7698
Piauí	Northeast	0.5085	0.3906	0.2443	0.2619	0.7699	0.7699
Paraná	South	0.7746	0.7541	0.6857	0.8113	0.7078	0.5880
Rio de Janeiro	Southeast	1.0000	1.0000	0.8018	0.8773	0.5064	0.2975
Rio Grande do Norte	Northeast	0.7352	0.9020	0.3748	0.4877	0.7699	0.7698
Roraima	North	0.5082	0.9301	0.3804	0.5953	0.7699	0.7678
Rondônia	North	0.4318	0.8930	0.3206	0.5021	0.7699	0.7636
Rio Grande do Sul	South	0.8218	0.6501	0.7538	0.7971	0.5055	0.5031
Santa Catarina	South	1.0000	0.7872	0.8125	0.8426	0.6394	0.4111
Sergipe	Northeast	0.4116	0.7921	0.3351	0.4661	0.7699	0.7695
São Paulo	Southeast	1.0000	1.0000	0.9040	0.9467	0.3146	0.2256
Tocantins	North	0.3350	0.5691	0.2215	0.4247	0.7699	0.7697

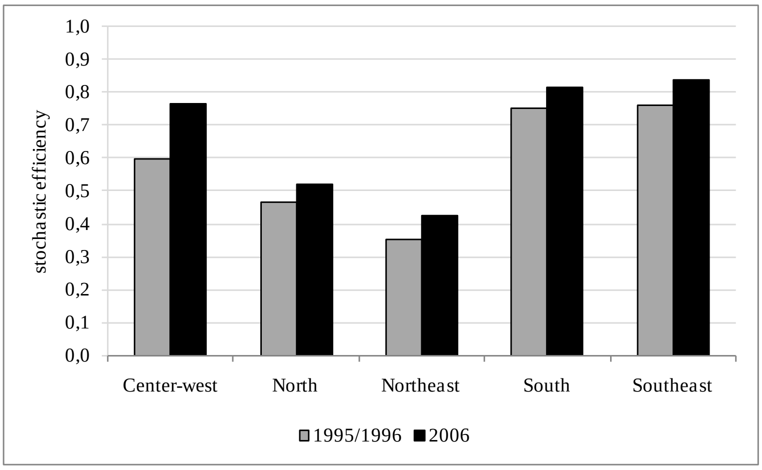
Table 4 - Technical efficiencies (DEA, Stochastic) and Income elasticities.

Figure 1 show these differences. Figure 1(a) represents the DEA efficiencies averages under constant returns to scale (output oriented). This model did not fit well our data: the regions look very similar, against expectations. Figure 1(b) represents the results of the stochastic frontier model. In this figure we see suggestions of regional differences: the Southeast and South are more efficient, followed by the Center-west region. For all, technical efficiencies change from 1995/96 to 2006. However, the highest gain in regions efficiency can be observed in the Center-west region.

For the analysis all variables are measured in log form. The actual model used, stochastic frontier, postulates a linear relationship between the log agricultural production y and the log inputs l, k, t, and c denoting labor, capital, land and fertilizers, respectively. The Pearson correlation between observed and predicted values is about 99%, indicating a good fit for the frontier model. The 95% confidence interval for the parameter γ suggests a technical components model.



(a)



(b)

Figure 1 - Average efficiencies: DEA CCR (a) and stochastic frontier (b) models.

The likelihood ratio test statistic for the joint hypothesis implying the presence of IDH, time, and regional effects has a value of 7.15, with a p-value of about 31%. For this reason we dropped log IDH and all the other categorical variables and use the more parsimonious model presented in Table 3, although Figure 1(b) suggests regional differences. The chi-square test for constant returns to scale ($l+k+t+c=1$) has a p-value of 90%, non significant.

Although the confidence intervals for all input variables do intercept, the pair wise Wald tests of equality indicate that the labor (l) elasticity is stronger than the capital (k) elasticity (p-value 0.02) and the capital elasticity is weaker then the land elasticity (t) (p-value 0.03). The difference between labor and land elasticities is marginal (p-value 0.10). No other pair wise comparison is significant.

Average income per capita elasticity over all states and years is 0.67 with a standard error of 0.17. The minimum per capita income elasticity is 0.05 and the maximum 0.77. States highly efficient have smaller income elasticities. This means, that a 1% increase in per capita income will increase the agricultural production in wealthier states like Distrito Federal by only 0.14%, but can achieve up to 0.77% in those states with lower technical efficiency.

The mean technical efficiencies for each state and by region are shown in Tables 5 and 6. The most efficient state is São Paulo (0.93) and the least efficient is Piauí (0.25). The Southeast dominates, followed by South, Center-west, North and Northeast. The dominance of the Southeast and South over the other regions is strong. These results are somewhat expected and serves the purpose to further validation of our model

States	Average elasticity
Distrito Federal	0.1383
São Paulo	0.2701
Rio de Janeiro	0.4020
Rio Grande do Sul	0.5043
Santa Catarina	0.5253
Espírito Santo	0.5589
Paraná	0.6479
Amazonas	0.6689
Mato Grosso	0.7069
Minas Gerais	0.7359
Mato Grosso do Sul	0.7470
Goiás	0.7601
Amapá	0.7618
Roraima	0.7668
Rondônia	0.7689
Sergipe	0.7697
Tocantins	0.7698
Acre	0.7699
Alagoas	0.7699
Bahia	0.7699
Ceará	0.7699
Maranhão	0.7699
Pará	0.7699
Paraíba	0.7699
Pernambuco	0.7699
Piauí	0.7699
Rio Grande do Norte	0.7699

Table 5 - Average income per capita elasticities by state, in ascending order.

Region	Frequency	Average elasticity
Southeast	8	0.4917
South	6	0.5592
Center-west	8	0.5881
North	14	0.7537
Northeast	18	0.7699

Table 6 - Average income per capita elasticities per region, in ascending order.

Distrito Federal was the most efficient state in 2006 and second most efficient in 1995/96. The state was created with the foundation of Brasilia as federal capital. The state is small, if compared to other states, but with a strong market-oriented agriculture producing mainly cotton, soybeans, common beans and poultry production. Additionally, its population is small, since an important part lives outside Brasilia, belonging to Goiás state and the high per capita GDP is strongly related to the higher salaries of federal government staff.

With the study we confirmed the strong presence of agriculture and livestock production in the states of South, Southeast and Center-west regions. These states have export-oriented agriculture. Whereas, the states with lower efficiency represent dryer regions, like in the Northeast, with rainfall between 200 and 600 mm per year, high temperatures, with limited infrastructure for irrigation and processing of agricultural production. In the North region, the lower efficiency is explained by large areas and a more subsistence oriented agriculture, exploring mostly native species like hevea, brazil nuts and timber extraction. Those activities represent the main vocation of the North region and could be further explored in a study focusing only on the states of the Amazon region.

4. Summary and Conclusions

We fit a DEA Model (CCR-O) and a stochastic frontier model to state agricultural production data in Brazil. The second fit was very good as measured by a correlation of about 99% between observed and predicted values. The technology seems to show constant returns to scale.

The model also includes a statistically significant contextual inefficiency effect defined by per capita income. The average per capita income elasticity is 0.67, with a standard error of 0.17. The income variable is used as a proxy for infra structure and technology assessment. We find stronger elasticities results for labor, other inputs (running costs) and land.

Southeast and South states are significantly more efficient than other states on average. São Paulo, Distrito Federal, Rio de Janeiro, Santa Catarina, Espírito Santo, Rio Grande do Sul and Paraná are the most efficient states with product oriented technical efficiencies, over 70% well above the other states.

These empirical results suggest important findings. There are significant possibilities to increase efficiency levels in Brazil agriculture production, especially in the Northeast and North Region. The results indicate the diversity of the scores of efficiency among regions. This suggests that the considerable variability of regions in climate, natural resources, irrigation, infrastructure, agro industries etc., can have different impacts on efficiency in Brazil agricultural production in different regions.

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