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Abstract

The determinants of technical efficiency in agriculture and cattle ranching are closely related with the debate involving the conservation-development trade-off in the Brazilian Amazon. Concerned with balancing development and environmental conservation, policy makers and academics have emphasized the importance of choosing ways of selecting areas where land use restrictions would be established. In order to understand the relationship between spatial patterns of deforestation and the associated distribution and characteristics of economic activity, issues regarding technical efficiency are clearly important. This paper aims to identify the socio-economic and environmental determinants of technical efficiency in agriculture and cattle ranching in the Brazilian Amazon emphasizing their relationship with spatial processes of deforestation and development. The study is structured in two parts. The first part is concerned with measuring technical efficiency for agriculture and cattle ranching in each geographical unit focusing on the production relationship between inputs and outputs. The second one focuses on the variation in the efficiency measure explained by exogenous factors and includes the spatial analysis. We adopt the model proposed by Battese and Coelli (1995) where the production function and the exogenous effects influencing technical efficiency are estimated simultaneously.

Keywords: stochastic frontier, technical efficiency, spatial analysis, Brazilian Amazon

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1. INTRODUCTION

The determinants of technical efficiency in agriculture and cattle ranching are closely related with the debate involving the conservation-development trade-off in the Brazilian Amazon. Concerned with balancing development and environmental conservation, policy makers and academics have emphasized the importance of choosing ways of selecting areas where land use restrictions would be established. On the one hand land zoning or tradable development rights have been proposed as forms of turning the current Forest Code more flexible (Chomitz 1999). On the other, reserves, parks or national forests have been created in order to guarantee the conservation of strategic areas (Lele et al 2000). In order to understand the relationship between spatial patterns of deforestation and the associated distribution and characteristics of economic activity, issues regarding technical efficiency are clearly important.

Firstly local economic, social and environmental factors might influence technical efficiency and explain the location of more productive farmers. Secondly, given the geographical scale together with the economic, social, and environmental heterogeneity in the Brazilian Amazon, the spatial dimension is crucial for the analysis of technical efficiency and its connections with patterns of deforestation. Market proximity, transport infrastructure, land and labour availability, and local ecological characteristics are some of the potential candidates to explain productivity variation (Nelson 2002, Mertens et al 2002, Sherlund et al). Moreover, neighbourhood effects and externalities generated by agglomerations of different kinds also provide additional elements for a spatial analysis of technical efficiency in agriculture and cattle ranching in the Amazon region (Anselin 1991, 2003). Thirdly, the connections between higher technical efficiency and deforestation rates are still to be examined. On the one hand one could argue that higher technical efficiency means better land use and, other things equal, less pressure it would be expected on land conversion of forested areas. On the other, in principle efficient producers would have better conditions to reduce costs and prices and therefore expand their individual demands which in turn would provide incentives for larger land conversion.

The investigation of the determinants of technical efficiency in agriculture and cattle ranching will contribute to the understanding of underlining spatial processes of deforestation and occupation and inform policy makers aiming to optimise economic and ecological outcomes in the selection of areas to be developed or conserved in the Amazon region. Several studies have been trying to explain land use and deforestation in the Amazon (see Andersen et al 2003 for a discussion). Some of them include spatial analysis (Pfaff 1999, Walker et al 2000, Moreira 2003, Mertens et al 2002) and others look at efficiency issues (Otsuki et al 2002). However, the research putting together a spatial analysis of technical efficiency is still very incipient (Chomitz and Thomas 2001, Moreira e Paez 2003, Helfand 2003). Otsuki et al for instance develop an efficiency analysis for the Amazon with the concern of understanding the impact of property rights. They conclude that private property does enhance efficiency and derive some policy implications. Although they control for several environmental characteristics there is no spatial analysis in their study. In addition the efficiency measure is constructed deterministically through a data envelope analysis (DEA). Also using a deterministic efficiency measure, Helfand (2003) aims to identify the determinants of efficiency in the Centre-West of Brazil. He concludes that, among other things, access to public services and size of farms matter for efficiency.

Using a different approach, Chomitz and Thomas (2001) elaborate a study on the geographical pattern of land use in the Amazon. Based on census tract information they map the different sorts of land use looking at environmental, economic and spatial characteristics. However, despite the fact that they have geographically referenced data they don’t use any explicit spatial econometric model and not relate the locations in a systematic way. They also produce some evidence about efficiency regarding cattle ranching in the Amazon. They adopt as efficiency measure the stocking ratio not establishing a more complete relation between inputs ad output.

Two issues arise when looking at these studies and motivate this research proposal. Firstly, it is desirable that the efficiency measure used to evaluate the productivity in agricultural activities encompasses a more complete and robust approach. This would be accomplished through a stochastic frontier analysis (SFA). The SFA has the advantage of combining rigorous definitions of efficiency by relating inputs and outputs through distance functions with statistical properties in the estimation (Kumbakar and Lovell 2000, Coelli et al 1998). Therefore, SFA avoids simplistic definitions of efficiency such as the stocking ratio and also provides a better way of getting the measures when compared to the DEA given that allows for the presence of random chocks disturbing the input-output relationship. The second issue concerns to the spatial analysis. Firstly, as suggested above transportation costs and proximity to markets are likely to be relevant in a large region such the Brazilian Amazon. Secondly, the lack of spatial econometric methods may produce model misspecification if points in space are co-related and spatial externalities are important (Anselin 1988 and 1991).

The literature using stochastic frontier to analyse the determinants of technical efficiency is now well established and studies applying alternative methods have been done looking at different regions of the world (for examples see Sherlund et al 2002, van der Vlist and Folmer 2004, Pascual 2005). This paper aims to identify the socio-economic and environmental determinants of technical efficiency in agriculture and cattle ranching in the Brazilian Amazon emphasizing their relationship with spatial processes of deforestation and development. The study will be structured in two parts. The first one is concerned with measuring technical efficiency for agriculture and cattle ranching in each geographical unit focusing on the production relationship between inputs and outputs. The second part focuses on the variation in the efficiency measure explained by exogenous factors and includes the spatial analysis. This research therefore relates to the general applied literature on stochastic frontier and on land use and deforestation in the Amazon (see Andersen et al 2003), extending the scope and methodology of Chomitz and Thomas (2001), Otsuki et al (2002), and Helfand (2003). The remainder of the paper proceeds as follows. Section 2 presents the stochastic frontier model and discusses the spatial analysis of exogenous influences. Sections 3, 4 and 5 describe the data and the empirical methodology respectively. Section 6 describes the results referring to the relevant literature. Section 7 concludes.

2. TECHNICAL EFFICIENCY AND EXOGENOUS INFLUENCES

Considering that producers use multiple inputs *x* to produce a single output y, a production function can be written to represent a particular technology as $y_i = f(x_i)$. Where $f(x_i)$ is called a production frontier if produces the maximum output for a given set of inputs or requires the minimum set of inputs to produce a given level of output[1]. Standard microeconomic theory usually assumes that there is no inefficiency in the economy implying that all individual production functions are optimal and all firms produce at the frontier.

However, the literature, which focuses on market imperfections has been exploring the theoretical foundations for the existence of inefficiency providing the background for empirical research that mounted from the 1970s (see Kumbhakar and Lovell 2000 for a discussion). An inefficient producer would produce beneath the production frontier. If only a single output is

[1] For a formal discussion on production frontiers, see Coelli et al (1998).

produced, departing from Debreu-Farrell measures (see Kumbhakar and Lovell 2000), an output-oriented measure of technical efficiency is given by the function

$$TE_i(x, y) = \left[\max\{\phi : \phi y \leq f(x)\}\right]^{-1} \quad [1]$$

which measures the reciprocal of the maximum output expansion ϕ feasible with a given set of inputs. Chart 1 in the appendix provides a graphical illustration of this measure. Following the notation provided by Kumbhakar and Lovell (2000) this output-oriented technical efficiency measure can be applied into an empirical model as

$$y_i = f(x_i; \beta).TE_i \quad [2]$$

where y_i is the scalar output of producer i, $i = 1,...,I$, x_i is a vector of N inputs used by producer i, $f(x_i; \beta)$ is the production frontier and β is a vector of technology parameters to be estimated. Then a measure of technical efficiency TE_i can be calculated as the ratio of observed output to the maximum feasible output

$$TE_i = \frac{y_i}{f(x_i; \beta)} \quad [3]$$

If $TE_i = 1$ then producer i is efficient. Otherwise TE_i will be less than one providing a measure of inefficiency. A stochastic frontier incorporates random shocks that cannot be attributed to the relationship between inputs and outputs. To arrive to a stochastic production frontier it is possible to write the above equations as

$$y_i = f(x_i; \beta).\exp\{v_i\}.TE_i \quad \text{and} \quad TE_i = \frac{y_i}{f(x_i; \beta).\exp\{v_i\}} \quad [4]$$

where v_i represents a random shock experienced by producer i.

The stochastic frontier model presented above focuses exclusively on the relationship between outputs produced and inputs used in production, namely choice variables for the producers. However, the literature on productivity has emphasized that a second set of factors should be included in the analysis, which are neither outputs nor inputs but also influences the producer performance ((Huang and Liu 1994, Kumbhakar et al 1991, Reifschneider and Stevenson 1991, Battese and Coelli 1995, 1997, and Sherlund et al 2003). These factors are exogenous to the producer choice and normally characterize the economic environment in which the production is embedded. Including exogenous factors in the analysis allows the association of variation in the producer performance with variables that are out of the control of the technological domain and shed light onto public policies concerned with technical efficiency and resource allocation as briefly outlined above, formally

$$TE_i = g(z_i) \qquad [5]$$

where z_i is a vector of exogenous influences on efficiency.

In this study we assume that the productive unit is a municipality and not a firm as usual. This opens up the room for investigating variables that assume relevance and varies spatially. Many factors have been listed as usual candidates for exogenous influences in the literature of productivity in agriculture (Battese 1992, Bravo-Ureta and Pinheiro 1993, Coelli 1995, and Sherlund 2002). In the remaining of this section we discuss some of them that will be used later in our empirical analysis.

The first group of exogenous influences suggested by studies of agricultural and environmental economics is formed by the agro climatic conditions where the production takes place. Environmental characteristics such as vegetation, soil quality, rivers, rain, to list just a few are recognized as key elements for technical performance in agriculture.

Secondly, it is important to consider the externalities generated by public infrastructure. As in rural areas of developing countries there is severe shortage of such public facilities it is possible to imagine that availability of running water, electricity and sewage would impact the general conditions of production and the resulting technical performance.

A third element is concerned to human capital. Although producers have some control over skills taking part in production by trying to hire labour efficiently, the availability of high skilled labour might vary across different regions and firms are constrained in their choices.

Fourthly, there are the geographical characteristics of the locations where production take place. Here proximity to markets and transport infrastructure are the key variables (Anderesen et al 2003, Reis and Weinhold 2004). Also, the size of agglomeration of firms or population might contribute to technical efficiency if it is assumed that they generate external economies. As suggested by the so-called New Economic Geography (Fujita et al 1999, Baldwin et al 2003), the combination of agglomerations with low transportation costs might positively impact the emergence of innovations and the rate of technical progress of a particular area.

Farm size and property rights are also potentially relevant for associating technical efficiency with spatial patterns of economic activity and deforestation (Helfand 2003, Otsuki et al 2002). Land use in the Amazon is marked by two important characteristics. On the one hand, it is well known that land is extremely concentrated in the region with 1% of properties concentrating around 50% of the agricultural land. It is not clear whether small establishments with less than 20 hectares have similar production systems, choose same location or pursue equal economic objectives of large farms with over 10,000 hectares. On the other, producers have different conditions regarding land ownership. Owners, renters, sharecroppers and squatters carry out agricultural activities in the region. They have different property rights and pay different prices for land use.

Another element that must be added to the exogenous influences to local technical efficiency is related to inputs local availability. For instance, labour or suitable land for agriculture and cattle ranching might vary spatially as well as their respective prices, reflecting not only the variation of environmental conditions but also differences in the degree of competition or local development levels.

Finally, it is important to include the role of spatial externalities in diffusing technical progress. As discussed by the new developments of spatial economics and regional and urban economics, proximity is crucial for generating externalities and a number of neighbourhood effects are expected. To capture spatial externalities the model outlined above includes variables that could serve as proxies for proximity between agents within between the municipality. We also expand it to correlate the technical efficiency in one area with the exogenous influences present in neighbouring areas. A formulation for a spatial model involving local spillovers can be expressed in a mixed regressive, spatial cross-regressive model (Florax and Folmer 1992 and Anselin 2003). Formally we have

$$y_i = x_i \beta + W x_i \rho + u_i \qquad [6]$$

Where x_i is a vector of explanatory variables (including social, economic, geographical, and environmental information), W is a spatial weights matrix connecting points in space, u is a spherical disturbance, and β and ρ are vectors of parameters to be estimated. Combining equation 4 and a spatial version of equation 5 we arrive to the empirical model used in our subsequent analysis.

3. DATA

The empirical exercise covers the Brazilian Legal Amazon (AML), which is an administrative area in the northern part of Brazil including 10 states and around 5million of km^2 (about 60% of the Brazilian national territory). The data used is part of a database (Desmat) managed by IPEA/DIMAC (The Directorate of Macroeconomic Studies of the Institute of Applied Economic Research, Brazil). IPEA/DIMAC assembled a data panel for all the municipalities of Brazilian Legal Amazon (AML) including thousands of variables on major economic, demographic and geo-ecological aspects**.** The unit of observation is the municipality (*município***),** which compromises between the spatially detailed geo-ecological information available in GIS and the systematic and relatively long time-consistent series available in socio-economic sources, in particular Demographic and Economic Census data observed in 5-year periods from 1970 to 2000.

To illustrate the relevance of this database for statistical analysis, it suffices to say that Legal Amazonia had 763 municipalities in 1997 (which were 508 in 1991). Another important aspect of the database is to take account of changes in the number and areas of municipalities between Census years, thus providing information for a panel of comparable geographic areas from 1970 to 1997. For the period 1970-1997 as a whole, the size of the panel is 257 comparable areas. In our analysis we use this 257 comparable areas as geographical units using the Census of 1996 as the main source of information (for a detailed presentation of this database see Andersen et al 2003).

The variables entering in the estimation of the production function are for the year 1995.

The dependent variable accounting for the level of output is a measure of total production. In order to eliminate the impact of local price variation we first multiply the amount of each product by its average price in the Amazon and then sum across products to get the overall value. Formally we have

$$V^j = \sum_i^n x_i^j \bar{p}_i$$

Where

V^j is the aggregate production value in the municipality j

x_i^j is the amount of product i produced in the municipality j

$$\bar{p}_i = \frac{\sum_i^n p_i}{n}$$

There are 4 inputs used in the analysis: labour used in agriculture and cattle ranching, herd as proxy for capital, and land allocated to two different uses (agricultural land and planted pasture). As exogenous factors influencing technical efficiency we follow the literature reviewed above and include proxies for the main groups as follows:

- Environmental conditions: soil qualities, classes of vegetation, rain precipitation, temperature, altitude, and existence of rivers and forests;
- Agglomeration and size effects: municipality area, population, and the area under agricultural establishments;
- Geography: roads, distance to Sao Paulo, distance to the nearest state capital, distance to the federal capital;
- Public infrastructure: running water, electricity, and sewage;
- Human capital: educational attendance;
- Farm size: shares of different farm size classes in the municipality;
- Property rights: shares of farms under private ownership.

In order to be able to test the impact of spatially lagged variables on the technical efficiency we construct a so-called Spatial Weight Matrix (W matrix henceforth), which is a square matrix of dimension 257. The values in W reflect an *ad-hoc* hypothesis of spatial interaction between the municipalities. The diagonal contains zeros, and the off-diagonal elements reflect the spatial proximity between the municipalities. We follow fairly standard practice in assuming that interaction is a diminishing function of distance. For each municipality we set the distance decay for the 5 nearest neighbours and zero for the remaining ones. A further step in the construction of the W matrix is to standardise it so that each row sums to 1. Hence

$$W_{ij}^{*} = \frac{1}{d_{ij}}$$
$$W_{ij} = \frac{W_{ij}^{*}}{\sum_{j} W_{ij}^{*}} \qquad [7]$$

Standardising helps with interpretation, since the value for area *j* of the spatial lag, defined as the *j*'th cell of *Wx*, is then the weighted average of the values of the variable *x* in the areas that are 'neighbours' to J, and so its estimated coefficient can be compared directly to the coefficient for *x*. Also, using the standardised *W* matrix usefully identifies a parameter value below 1 as being consistent with a 'non-exploding' process while 1 and above leads to complex and little understood consequences for inference and estimation (the mathematical background to this and implications of spatial unit roots consistent with a parameter equal to 1 are discussed in Fingleton, 1999).

4. SPECIFICATION AND ESTIMATION PROCEDURES

There are two standard functional forms used in the literature, namely Cobb-Douglas and Translog functions (Coelli et al 1998). In principle a Translog specification would be preferable given our lack of knowledge regarding the precise technological relationship relating inputs and outputs. However, the Cobb-Douglas function adjusted better to our data and is chosen for our estimations. We start writing equation 4 as

$$y_i = f(x_i;\beta).\exp\{v_i\}.\exp\{-u_i\} \qquad [8]$$

where $TEi = \exp\{-u_i\}$. Since $TE_i \leq 1$ is required, we have $u_i \geq 0$. Then, assuming that $f(x_i;\beta)$ takes the log-linear Cobb-Douglas form the stochastic production frontier model can be written as

$$\ln y_i = \beta_o + \sum_n \beta_{ni} x_i + v_i - u_i \qquad [9]$$

where v_i is the two-sided 'noise' component ($v_i \sim iid \quad N(0,\sigma_v^2)$), and u_i is the nonnegative technical inefficiency component of the error term. In studies that don't include exogenous influences (error component model) u_i might assume different positive distributions. The standard ones are the half normal ($u_i \sim iid \quad N^+(0,\sigma_v^2)$), truncated normal ($u_i \sim iid \quad N^+(\mu,\sigma_v^2)$, or exponential. A third assumption, normally made, states that v_i and u_i are independently distributed of each other, and of the regressors.

This error component model produces measures of technical efficiency and these measures could enter as dependent variable in a second stage to test the impact of exogenous influences on the variation of technical efficiency by estimating an empirical spatial version of equation 5. Although a two-stage estimation could be conceived as conceptually valid (measuring efficiency first and explaining it latter) and has been done in the past (Mester 1993, 1997) there are econometric problems suggesting that simultaneous estimation would be preferable. Kumbhakar and Lovell (2000) point out that there are potentially two main problems in the two-stage estimation.

First, if *x* and *z* are correlated the estimates will be biased due to the omission of z in the first-stage estimation, and consequently they will be biased in the second-stage as well. Therefore, unless one has very good reasons to believe that inputs and the exogenous variables are uncorrelated this is a serious shortcoming. Second, there is an intrinsic problem regarding the distribution of TE_i. In the first stage it is normally assumed that the inefficiencies are identically distributed. However, this assumption is contradicted in the second stage when it is assumed a functional relationship with *z*.

The recent literature on exogenous effects influencing technical efficiency presents different models for estimating equations 9 and 5 simultaneously (Huang and Liu 1994, Kumbhakar et al 1991, Reifschneider and Stevenson 1991, Battese and Coelli 1995, 1997). They vary with regards to assumptions on the functional form of the production function, distribution and restriction of error components, and neutrality of exogenous influences on technical efficiency. Here we adopt the model proposed by Battese and Coelli (1995)[2]. In the Battese and Coelli model specification

$u_i \sim iid \quad N^+(\mu_i, \sigma_u^2)$ and $\mu_i = z_i\delta$

Where z_i is the vector of variables (including spatially lagged variables), which may influence efficiency and δ is a vector of parameters to be estimated. Battese and Coelli adopt the parametrisation proposed by Battese and Corra (1977), replacing σ_v^2 and σ_u^2 with $\sigma^2=\sigma_v^2+\sigma_u^2$ and $\gamma=\sigma_u^2/(\sigma_v^2+\sigma_u^2)$ to arrive to a likelihood function feasible to be estimated by maximum likelihood. The log-likelihood function of this model is presented in the appendix of Battese and Coelli (1993). The efficiency measure is calculated as $\exp(-u_i)$. Therefore positive coefficients for the exogenous variables are interpreted as negative impacts on the efficiency mean.

5. RESULTS

We have estimated a log-linear Cobb-Douglas production function with and without exogenous influences. Table 1 provides descriptive statistics for the variables included in the final models and Table 2 shows the estimates and respective standard errors of the two models. In both models labour, capital and land have positive and significant coefficients[3], providing evidence that the technological relationship is appropriately represented by the variables. Moreover, the sums of input estimates in both models are close to one (1.16 in the error correction model and .95 in the model with exogenous influences) suggesting constant returns to scale.

The error correction model has a lower likelihood providing evidence that including exogenous influences is desirable for estimating and explaining inefficiencies. Individual significance and the global likelihood of several alternative combinations oriented the selection of exogenous variables for the final model. Table 3 shows the estimates and respective standard errors of the exogenous influences. The results provide evidence that allow us to discuss some of hypothesis suggested by the literature reviewed above.

Firstly, as suggested by Sherlund et al (2002) some environmental variables have significant coefficients in the final model. The presence of forests and rivers are negatively and significantly

[2] The estimations were done using the software Frontier 4.1 developed by Prof Tim Coelli. For details see *A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation*, CEPA Working Paper 96/07.

[3] Pasture is only marginally significant in the model including exogenous influences

correlated with efficiency. Temperature and share of 'good' soil are positively correlated but not significant. Precipitation and altitude are negatively correlated and not significant.

Secondly, the estimate for transport costs to Sao Paulo shows that proximity to national markets matters for efficiency in line with the spatial economics theory. However, transport costs to the state capital have the opposite result. This is a surprising result and deserves careful additional investigation, which goes beyond the scope of this paper. In addition, controlling for transport costs the length of roads in the municipalities is not significantly correlated to efficiency.

Thirdly, population size has positive and significant estimates. This result can be interpreted as evidence of the role of local markets and also the presence of agglomeration external economies, again in line with the arguments provided by spatial economics. This is reinforced by the results regarding output and past growth, which are both positively and significantly correlated with efficiency. In addition, we also find similar results with respect to shares of classes of farm sizes. There we see evidence of internal increasing returns to scale in terms of gains in efficiency. The three smallest size classes are negatively and significantly correlated with efficiency and the estimates reduce with size. These results together with the input estimates in the production function provide an interesting contrast between internal constant returns to scale in production and external increasing returns to scale impacting technical efficiency.

Fourthly, education is negatively and significantly correlated with efficiency. Again this is a counterintuitive result as human capital is expected to produce positive impacts. One possible explanation has to do with the industrial composition of municipalities. One could imagine that municipalities with better educated populations would start shifting from agricultural to manufacturing and services and their remaining agricultural sector would only provide for local markets not facing strong competition from other production areas. Moreover, one could argue that technical skills in agricultural activities, especially in developing countries, are more influenced by 'hands on' training than school attendance.

Finally, the estimates for spatially lagged variables do not present strong evidence of spatial spillovers between municipalities. In the final model we include spatial lags for roads and education and although their estimates have the expected signs (given the sign of estimates for education in the municipality), only the spatial lag for education is marginally significant. A possible reason for this result is related to the large area of many of the municipalities preventing a more systematic relationship between them.

The mean efficiency in the region is 0.38 showing that in general agriculture and cattle ranching in the Amazon region is subject to a consider degree of inefficiency. Table 4 provides descriptive statistics for the estimated efficiency measures. Technical efficiency varies considerably in the region, both across states and locally. Map 1 shows the spatial distribution of the estimated efficiency measures across the region and Table 5 provides descriptive statistics for the aggregated efficiency measures for the states.

The state of Maranhao has 17 of the top 20 most efficient municipalities. These are concentrated in three micro-regions (Alto Mearim e Grajau, Medio Mearim, and Pindare). Table 6 lists the top 20 municipalities with highest estimated efficiency measures. Excluding Maranhao, shows the states of Mato Grosso and Tocantins with more municipalities with higher efficiency (see table 7). Looking at the top municipality in each state we see that half of them are within the metropolitan areas of the state capital (see table 8).

6. DISCUSSIONS AND CONCLUSION

The spatial analysis of the determinants of technical efficiency in agriculture and cattle ranching in the Brazilian Amazon is relevant for the understanding of underlying processes of development in one of the richest regions in biodiversity in the world. In this paper we developed an econometric analysis by estimating a stochastic production frontier model, including exogenous factors that contribute to the spatial variation of technical efficiency in the region.

The empirical results suggest that technical efficiency is influenced by a number of factors that are not related to the technological choices made by the producers. Environmental conditions, location, transportation network, farm size distribution, and the size of local economies are the main elements explaining technical efficiency variation. The role of most of these factors have been present in previous studies for other regions and the results are consistent with the literature, in particular to recent developments of economic geography, which emphasize the importance of external economies of scale, transportation costs and proximity to markets. However, our result related to transport costs to the state capital goes to the opposite direction and provides motivation for additional analysis.

Given that the overall efficiency level is considerably low, the mapping of efficient locations and the understanding of their respective determinants is crucial for informing policy makers aiming to set up selection mechanisms for constraining land use and promoting environmental conservation, with minimum impact in terms of foregone economic opportunities.

The analysis presented in this paper therefore contributes for the discussion concerned with the spatial balance of the conservation-development trade-off in the Amazon. However, the development processes in the region have been evolving considerably in recent years, assuming very diverse local characteristics. Thus, a more comprehensive analysis must include a dynamic perspective and look at less aggregated geographical levels. This provides material for further research.

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REFERENCES

Andersen, L. et al (2003) *The Dynamics of Deforestation and Economic Growth in the Brazilian Amazon*, Cambridge: Cambridge University Press.

Anselin, L. (1988) *Spatial Econometrics: methods and models*. The Netherlands: Kluwer Academics Publishers.

Anselin, L. (1991) “Spatial Effects in Econometric Practice in Environmental and Resource Economics”, paper presented at Allied Social Science Association Annual Convention, New Orleans, 5-7 January 2001.

Anselin, L. (2003) ‘Spatial Externalities, Spatial Multipliers, and Spatial Econometrics’, *International Regional Science Review*, vol. 26 (2): 153-166.

Arima, E. (1997) “Subsidies, efficiency, and inequality: the ranching sector in the Brazilian Amazon”. MSc thesis, Dept. of Agricultural Economics and Rural Sociology. The Pennsylvania State University, 110p.

Baldwin, R. et al (2003) *Economic Geography and Public Policy*, New Jersey: Princeton University Press.

Battese, G.E (1992) Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. Agricultural Economics 7, 185– 208.

Battese, G.E. and Coelli, T.J. (1993) A Stochastic Frontier Production Function Incorporating a Model for Technical Inefficiency Effects, Working Paper No. 69, Department of Econometrics, University of New England.

Battese, G.E., Coelli, T.J., (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325– 332.

Battese, G. E. and Coelli, T. J. (Eds.) (1997) “Efficiency and Productivity Measurement”, Journal of Productivity Analysis, vol. 8(4).

Bravo-Ureta, B.E., Pinheiro, A.E. (1993) ‘Efficiency analysis of developing country agriculture: a review of the frontier function literature’. *Agricultural and Resource Economics Review*, vol. 22: 88– 101.

Coelli, T.J. (1995) ‘Recent developments in frontier modelling and efficiency measurement’, *Australian Journal of Agricultural Economics*, vol. 39: 219– 245.

Coelli, T. J. (1996) ‘A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation’, CEPA Working Paper 96/07.

Coelli, T. J. et al (1998) *An Introduction to Efficiency and Productivity Analysis*, The Netherlands: Kluwer Academics Publishers.

Chomitz, K. (1999). 'Transferable Development Rights and Forest Protection: An Exploratory Analysis', paper presented at *Workshop on Market-Based Instruments for Environmental Protection*, 18-20 July 1999, John F. Kennedy School of Government, Harvard University.

Chomitz, K. and Thomas, T. (2001). Geographic Patterns of Land Use and Land Intensity in the Brazilian Amazon, Development Research Group, The World Bank, Washington.

Faminow, M. D. (1998) *Cattle, Deforestation and Development in the Amazon: An Economic, Agronomic and Environmental Perspective*, Oxon and New York: CAB International.

Florax, R. and Folmer, H. (1992) 'Specification and Estimation of Spatial Linear Regression Models: Monte Carlo Evaluation of Pre-Test Estimators', *Regional Science and Urban Economics*, vol. 22: 405-32.

Fingleton, B (1999) "Spurious Spatial Regression: some Monte-Carlo Results with a Spatial Unit Root and Spatial Cointegration", *Journal of Regional Science*, 39, 1–19.

Fujita, M. et al (1999). *The Spatial Economy: Cities, Regions and International Trade*, Cambridge MA: MIT Press.

Helfand, S. (2003) 'Os Determinantes da Eficiencia Tecnica no Centro-Oeste Brasileiro', S. Helfand and G. Castro de Rezende (eds.) *Regiao e Espaco no Desenvolvimento Agricola Brasileiro*, Rio de Janeiro: IPEA/NEMESIS.

Huang, C. J. and Liu, J-T. (1994) "Estimation of a Non-Neutral Production Stochastic Frontier Production Function", Journal of Productivity Analysis, vol. 5(2): 171-180.

Kumbhakar, S. C. and Lovell A. C. (2000) Stochastic Frontier Analysis, Cambridge: Cambridge University Press.

Kumbhakar, S. C. et al (1991) "A Generalized Production Frontier Approach for Estimating Determinants of Inneficiency in US Diary Farms", Journal of Business and Economic Statistics, vol. 9 (3): 279-286.

Lele, U. et al (2000) Brazil, Forests in the Balance: Challenges of Conservation and Development, Evaluation Country Case Studies, The World Bank.

Margulis, S. (2003) 'Causes of Deforestation of the Brazilian Amazon', *World Bank working paper n. 22*.

Mertens, B. et al (2002) “Crossing Spatial Analysis and Livestock Economics to Understand Deforestation Processes in the Brazilian Amazon: the Case of Sao Felix do Xingu”, Agricultural Economics, vol.27:269-294.

Mester, J. L. (1993) “Efficiency in the Savings and Loan Industry”, *Journal of Banking and Finance*, vol. 17(2/3):267-86.

Mester, J. L. (1997) “Measuring Efficiency at US Banks: Accounting for Heterogeneity is Important”, *European Journal of Operational Research*, vol. 98(2):230-42.

Moreira, A. (2003) “The Determinants of Amazon Forest: a Spatial VAR Model”, paper presented at the *IX Seminario de Acompanhamento NEMESIS*, 10-11 February 2003, Rio de Janeiro, Brazil.

Moreira, A. and Paez M. (2003) ‘Medindo a Produtividade Agricola Regional com Efeito Vizinhanca’, in S. Helfand and G. Castro de Rezende (eds.) *Regiao e Espaco no Desenvolvimento Agricola Brasileiro,* Rio de Janeiro: IPEA/NEMESIS.

Nelson, G. (2002) ‘Introduction to the Special Issueon Spatial Analysis for Agricultural Economists’, *Agricultural Economics*, vol. 27:197-200.

Otsuki,T. et al (2002) “The Implications of Property Rights for Joint Agriculture-Timber Productivity in the Brazilian Amazon”, *Environment and Development Economics*, vol. 7: 299-323.

Pascual, U. (2005) ‘Land-use Intensification Potential in Slash-and-Burn Farming through Improvements in Technical Efficiency’. *Ecological Economics, v*ol. 52:497-511.

Pfaff, A. (1999). “What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic” Data, *Journal of Environmental Econommics and Management*, vol. 37(1):26-43.

Reifschneider, D. and Stevenson, R. (1991) “Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency”, *International Economic Review*, vol. 32(3): 715-23.

Reis, E. and Weinhold, D. (2004) ‘Land Use and Transportation Costs in the Brazilian Amazon’, *Staff Papers Series n. 467,* Department of Agricultural and Applied Economics, University of Wisconsin-Madison.

Sherlund, S. et al (2002) ‘Smallholder Technical Efficiency Controlling for Environmental Production Conditions’, *Journal of Development Economics*, vol. 69:85-101.

Van der Vlist, A. J. and Folmer, H. (2004) ‘Testing Porter's Hypothesis: a Stochastic Frontier Panel Data Analysis of Dutch Horticulture’, paper presented at the European Association of Environmental and Resource Economists Annual Conference, Budapest.

Walker, R. et al (2000) “Deforestation and Cattle Ranching in the Brazilian Amazon: External Capital and Household Processes”, *World Development*, vol. 28 (4): 683-699.

APPENDIX

Chart 1 Output Oriented Efficiency Measure

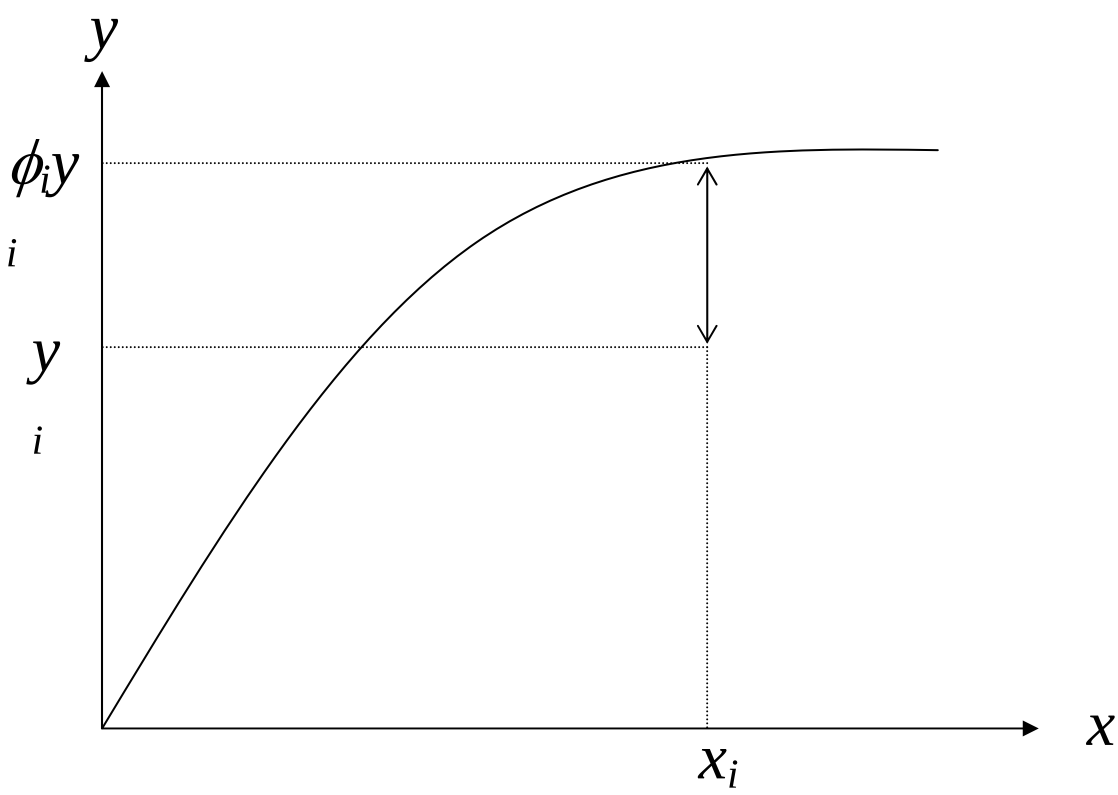

Table 1 Descriptive Statistics

Variables	Mean	median	Max	min	stdev	skew
IE96	2.37135	2.297876	5.184494	0.554289	0.811212	0.563305
EMPAG95	12729.72	6229	304523	216	26287.28	7.286956
LANDPR85	993.1363	602.1684	32038.13	34.62181	2221.865	11.3555
WAGE95	165.6116	54.80724	1976.438	0	267.7466	2.985577
LAPER95	3664.873	538.263	254334.5	0	17801.02	11.60205
LATEM95	18155.42	3636.555	1475531	0	102495.8	12.3752
PASNAT95	70543.18	10440.23	2374793	0	211037.2	7.380614
PASPLA95	130655.7	15722.56	5073642	0	500393.7	7.975517
FLONAT95	193313.8	24335.78	7703771	1.716	792465.7	7.014679
FLOPLA95	1345.811	4.08	75937	0	7473.875	7.680762
HERD95	140252.4	25714	4857335	0	493703.4	7.335426
PAV91	52.01554	0	1412.881	0	153.5837	5.978845
NPAV91	117.055	0	4965.491	0	442.7198	7.52083
DISESP95	3379.75	2951.628	10511.92	1270.5	1647.131	2.413455
DISECE95	960.3245	758.3411	5949.007	0	960.9146	3.285705
<10	0.140036	0.051119	1	0	0.217334	2.22769
>10 <100	0.24041	0.177981	0.969295	0	0.205877	0.982604
>100 <1000	0.321212	0.32668	0.871583	0	0.17147	0.040784
> 1000 <5000	0.183503	0.155679	0.735732	-2E-10	0.168845	0.648973
5000 and 10000	0.053844	0	0.971314	0	0.105965	4.464795
10000 and 100000	0.052468	0	0.789241	0	0.114048	2.935514
>100000	0.008527	0	0.927263	0	0.070538	10.99526
owners	0.855715	0.944503	1	0.055917	0.206364	-2.22641
renters	0.01697	0.002729	0.365738	0	0.037743	4.933829
sharecrop	0.006375	0.00065	0.138452	0	0.017647	4.971965
squatters	0.120941	0.039697	0.917279	0	0.198672	2.537895
RIVER	54.92181	0	2282.74	0	181.1975	8.163904
rain	610.1942	593.1081	1016.577	0	181.0546	-0.87523
SHSOL1T	8.191311	0	100	0	21.12025	3.151817
TEMP_JUN	24.70908	25.78907	27.36026	0	4.703386	-4.60976
TEMP_SET	26.49776	27.27986	29.33887	0	4.911684	-4.93647
TEMP_DEZ	26.0486	26.98737	29.38339	0	4.840366	-4.89093
VD_FO	21.44011	0	97.73401	0	32.29024	1.085811
VD_FA	7.258437	0	97.221	0	15.05019	3.021361
VD_FS	1.529493	0	60.22536	0	7.061423	5.788492
VD_FB	31.35127	15.99879	100	0	34.57505	0.855985
VD_AA	25.83873	6.437682	100	0	33.29367	1.031956
VD_CA	7.067533	0.1478	91.84601	0	14.88388	2.906489
AREA97	19748.85	3542.4	361329	104.8	49952.01	4.622097
ALTM	129.6919	60	1186	0	153.9432	2.448508
VNAGP95	22.20858	7.245671	932.04	0.207216	73.15438	9.331964

Table 2 Stocastic Frontier Model - Estimates for Inputs

Parameter	Estimates without exogenous variables (s.e)	Estimates with exogenous variables (s.e)
Constant	10.3235 (0.5275)**	11.49198 (0.4638)***
Labour	0.2983 (0.0813)***	0.3109 (0.0763)***
Agricultural Land	0.6894 (0.06567)***	0.4792 (0.0573)***
Planted Pasture	0.0641 (0.0227)***	0.0467 (0.0255)*
Capital (herd)	0.1109 (0.0502)***	0.1171 (0.0414)***
Sigma-squared	1.9922 (0.4312) ***	0.5212 (0.0682)***
Gamma	0.9694 (0.0278)***	0.7685 (0.0727)***
Mu	1.0474 (0.3563)***	
Log-likelihood	- 366.2732	- 239.7501

*** significant at 99% confidence level

** significant at 95% confidence level

* significant at 90% confidence level

(s.e) standard errors

Table 3 Stocastic Frontier Model - Estimates for Exogenous Influences

Parameter	Estimates (s.e)
Education ***	0.4653 (0.1347)***
Rain	0.0020 (0.0020)
good soil	-0.0088 (0.0073)
Forest***	0.2133 (0.0630)***
Temperature	-0.0021 (0.0163)
altitude ***	0.0015 (0.0007)***
Roads	-0.0009 (0.0007)
Rivers ***	0.0012 (0.0005)**
dist SP ***	0.0004 (0.0001)***
dist state ***	-0.0007 (0.0002)***
Population (1000) ***	-0.0019 (0.0007)***
Owners (%)	-0.0345 (0.4174)
<10 ***	3.0450 (0.6614)***
>10 <100 **	1.2374 (0.5305)**
>100 <1000 **	1.0881 (0.5542)**
>5000 <10,000	0.2179 (0.76299)
>10,000 <100,000	0.3417 (0.7693)
>100,000	0.2360 (0.9470)
output ***	-0.2762(0.0452)***
Growth	-0.2186 (0.1046)**
Conversion	0.8241 (0.1134)
spat roads	0.0005 (0.0004)
spat educ	0.3203 (0.1709)*

*** significant at 99% confidence level

** significant at 95% confidence level

* significant at 90% confidence level

(s.e) standard errors

Additional control variables not reported: state dummies

Ommited farm size: >1000 and <5000 ha

Table 4 Efficiency Measures – Descriptive Statistics

Statistic	Value
Mean	0.38070
Median	0.31050
Standard Deviation	0.28626
Maximum	0.92344
Minimum	0.01309

Table 5 Efficiency in the States – Descriptive Statistics

State	Mean	Standard Deviation	Maximum	Minimum
Rondonia	0.49696			
Mato Grosso	0.31228	0.26297	0.91439	0.02346
Goias	0.30126	0.15659	0. 40335	0.12097
Amapa	0.08545	0.02057	0.11275	0.06349
Amazonas	0.21036	0.16565	0.65819	0.03438
Para	0.17498	0.18346	0.70276	0.01309
Roraima	0.79415			
Acre	0.31742	0.06690	0.41683	0.27139
Tocantins	0.46025	0.18797	0.92344	0.11563
Maranhao	0.60142	0.26513	0.90120	0.02568

Table 6 Top 20 Efficient Municipalities

Municipalities	Micro Region	State
Palmas	Porto Nacional	Tocantins
Chapada dos Guimaraes	Cuiaba	Mato Grosso
Joselandia	Alto Mearim e Grajau	Maranhao
Bom Jardim	Pindare	Maranhao
Grajau	Alto Mearim e Grajau	Maranhao
Esperantinopolis	Medio Mearim	Maranhao
Paulo Ramos	Pindare	Maranhao
Benedito Leite	Chapada das Mangabeiras	Maranhao
Altamira do Maranhao	Pindare	Maranhao
Lago da Pedra	Pindare	Maranhao
Barra do Corda	Alto Mearim e Grajau	Maranhao
Governador Eugenio Barros	Presidente Dutra	Maranhao
Pocao das Pedras	Medio Mearim	Maranhao
Bacabal	Medio Mearim	Maranhao
Presidente Dutra	Presidente Dutra	Maranhao
Great Cuiaba	Cuiaba	Mato Grosso
Tuntun	Alto Mearim e Grajau	Maranhao
Colinas	Chapadas do Alto Itapecuru	Maranhao
Alto Parnaiba	Geral das Balsas	Maranhao
Amarante do Maranhao	Imperatriz	Maranhao

Table 7 Top 20 Efficient Municipalities (without Maranhao)

Municipalities	Region	State
Palmas	Porto Nacional	Tocantins
Chapada dos Guimaraes	Cuiaba	Mato Grosso
Great Cuiaba	Cuiaba	Mato Grosso
Roraima		
Araguacema	Miracema do Tocantins	Tocantins
Pium	Rio Formoso	Tocantins
Aripuana	Aripuana	Mato Grosso
Augusto Correa	Bragantina	Para
Santana do Araguaia	Conceicao do Araguaia	Para
Pedro Afonso	Porto Nacional	Tocantins
Araguatins	Bico do Papagaio	Tocantins
Altamira	Altamira	Para
Itaituba	Itaituba	Para
Maraa	Japura	Amazonas
Alvorada	Gurupi	Tocantins
Axixa do Tocantins	Bico do Papagaio	Tocantins
Sao Joao do Araguaia	Maraba	Para
Lizarda	Jalapao	Tocantins
Nortelandia	Alto Paraguai	Mato Grosso
Maraba	Maraba	Para

Table 8 Top Efficient Municipalities in Each State

Municipalities	Region	State
Great Rio Branco	Rio Branco	Acre
Maraa	Japura	Amazonas
Macapa	Macapa	Amapa
Sao Miguel do Araguaia	Sao Miguel do Araguaia	Goias
Joselandia	Alto Mearim e Grajau	Maranhao
Chapada dos Guimaraes	Cuiaba	Mato Grosso
Augusto Correa	Bragantina	Para
Palmas	Porto Nacional	Tocantins

Map 1 Spatial Distribution of Efficiency