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COBB-DOUGLAS, TRANSLOG STOCHASTIC PRODUCTION FUNCTION AND DATA ENVELOPMENT ANALYSIS IN TOTAL FACTOR PRODUCTIVITY OF MAIN BRAZILIAN GRAIN CROPS

Estimation of Factor Employment and Inefficiencies through Time

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ABSTRACT

The objective of this paper is to apply a Cobb-Douglas, Translog Stochastic Production Function and Data Envelopment Analysis – particularly the Malmquist index - in order to estimate increases or decreases of inefficiencies over time as well as the sources of TFP changes for the main Brazilian grain crops - namely, rice, beans, maize, soybeans and wheat - throughout the most recent data available comprising the period 2001-2006. According to the Cobb Douglas model, the greatest elasticity presented is that of harvested area, followed by agricultural credit and limestone. The Translog production function presents an amelioration of aggregate productivity over time and, in a decreasing order, the Brazilian regions that have presented the greatest relative degree of efficiency are the Northeast, North, Southeast, South and Center-West regions. The results indicate that, although there have been positive changes in TFP for the sample analyzed, a decline in the use of technology has been evidenced for all the principal Brazilian grain crops between 2005/2007 – period in which we observe a remarkable downfall in the use of inputs in Brazilian agriculture.

Keywords
Total Factor Productivity, Stochastic Frontier Analysis, Data Envelopment Analysis.

JEL Code: C23, D24, Q16

1 INTRODUCTION

"Not all producers are technically efficient". As opposed to conventional microeconomic theory, such statement implies that not all producers are able to utilize the minimum quantity of required inputs in order to produce the desired quantity of output given the available technology. Similarly, not all producers are able to minimize necessary costs for the intended production of outputs.

From a theoretical point of view, producers do not always optimize their production functions. The production frontier characterizes the minimum number of necessary combinations of inputs for the production of diverse products, or the maximum output with various input combinations and a given technology. Producers operating above the production frontier are considered technically efficient, while those who operate under the production frontier are denoted technically inefficient.

The Stochastic Frontier Analysis – SFA is an analytical approach that utilizes econometric (parametric) techniques whose models of production recognize technical inefficiency and the fact that random shocks beyond producers' control may affect the product. Differently from non-parametric approaches that assume deterministic frontiers, SFA allows for deviations from the frontier, whose error can be decomposed for adequate distinction between technical efficiency and random shocks (e.g. labor or capital performance variations).

By the application of non-parametric methods as Data Envelopment Analysis – DEA, the Malmquist index is calculated by distance functions obtained by mathematical programming and allows for the absence of price information, utilizing physical quantities of multiple inputs and products instead. The main two components of the underlying index are technical change (innovation) and efficiency change ("catching up" effect towards the frontier).

The objective of this paper is to apply the Stochastic Frontier Analysis technique in order to estimate increase or decrease in inefficiencies through time, as well as the linear programming method Data Envelopment Analysis, namely the Malmquist index, for the analysis of change in TFP in main Brazilian grain crops – rice, beans, maize, soybeans and wheat – throughout the 2001-2006 period.

Among observed results, even though there have been positive changes in main Brazilian grain crops, there have been a decline in the component referring to technological innovations for all Brazilian grain crops analyzed between the 2005/2006 period in which it is observed a general downfall in input usage in agriculture.

2 THEORETICAL FRAMEWORK

2.1 Stochastic Frontier Analysis - SFA

In the presence of inefficiencies, the Stochastic Frontier Analysis – SFA emerges as a theoretical and practical framework, whose objective is to contribute for the definition and estimation of production frontiers. SFA has been developed from remote influences but the literature that directly influenced the development of SFA was the theoretical framework about production efficiency beginning in the decade of 1950 by Koopmans (1951), Debreu (1951) and Shephard (1953). Farrell (1957) was the first to measure production efficiency empirically. The use of linear programming by Farrell influenced research by Boles (1966), Bressler (1966), Seitz (1966) and Sitorus (1966) and eventually the development of Data Envelopment Analysis (DEA) by Charnes, Coopers and Rhodes (1978). The influence from Farrell is also definite for the works by Aigner and Chu (1968), Seitz (1971), Timmer (1971), Afriat (1972) and Richmond (1974) – direct collaborators for the SFA development.

This parametric method of stochastic frontier treats production frontier as a random shock. Differently from non-parametric method such as DEA that assumes a deterministic frontier, the stochastic frontier allows for deviations from the frontier to represent both inefficiency and an inevitable statistic noise which intends to be an approach closer to reality given that observations normally involve a random walk.

SFA has its origins in two papers: Aigner, Lovell and Schmidt (1977) and Meeusen e van den Broeck (1977), followed by the works by Battese and Corra (1977). These three original works represent, in the context of production frontier, the error term defined as structurally composed. Since then, the SFA has been developed by several collaborators: Schmidt and Lovell (1979), Jondrow et al. (1982), Greene (1980), Stevenson (1980), Lee (1983), Koop and Diewert (1982), Pitt and Lee (1981), Schmidt and Sickles (1984), Cornwell, Schmidt and Sickles (1990), Kumbhakar (1990), Battese and Coelli (1992), among others.

The models of stochastic production frontier treat technical efficiency and recognize the fact that random shocks beyond the control of producers may affect the product. Therefore, in these models, the impact of random shocks (as labor or capital performance) on the product can be separated from the impact of technical efficiency variation. These models were simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

This paper followed the dominant functional specification in literature, based on the work by Bettese and Coelli (1992, 1995), in which authors formalize technical inefficiency in the production function of stochastic frontier for panel data. Thus, consider the following production function of a given state i:

$$y_{it} = \exp(x_{it}\beta + v_{it} - u_{it}) = \exp(x_{it}\beta + v_{it})\exp(-u_{it})$$

or

$$\ln y_{it} = x_{it}\beta_{it} + v_{it} - \mu_{it}$$

$i = 1,2,3,...,n$ sectors and $t = 1,2,3,...,T$ years

where y_{it} is the vector representing produced quantities by the unit of production i in period t; x_{it} is the vector of inputs used by the unit of production in period t; β is the vector of coefficients to be used that define the production technology.

The terms v and u are vectors that represent distinct error components. The first term refers to the random part of error, with normal distribution, independent and identically distributed (iid), truncated in zero and variance σ_v^2 [v~iid N(0, σ_v^2)]. The second term concerns the part relating to technical inefficiency, constituting a deviation in relation to the production frontier (which can be inferred by negative sign and by restriction $u \geq 0$). They are nonnegative random variables with normal truncated distribution, that is, non-null μ mean [u ~N$^+$(μ ,σ_u^2)].

The MLS method provides a simple test for the identification of the presence of technical inefficiency in data. If $u_i = 0$, then $\varepsilon_i = 0$. Thus, the error term is symmetric and data do not evidence technical inefficiency. However, if $u_i > 0$, then the distribution of $\varepsilon_i = v_i - u_i$ is negatively symmetric and evidences of technical inefficiency in data exist. Thus, the term μ_{it} quantifies technical inefficiency or the distance in relation to the efficiency frontier. The most efficient estimate presents value 0 for μ_{it}. This suggests that the presence of technical inefficiency can be tested directly by the residuals of MLS.

Consider technical inefficiency as time-variant

$$\mu_{it} = [\exp(-\eta(t-T))]\mu_i$$

When η is positive, the value inside the brackets of the exponential term will become non-negative and exp($-\eta(t-T))]\mu_i$ will not be greater than unity. This is the case in which $\mu_{it} \geq \mu_i$. In other words, technical inefficiency will have decreasing effects through time (positive effect in technical efficiency over time). In case η is negative, inefficiency will be increasing through time (also defined as persistent inefficiency).

2.2 Data Envelopment Analysis - DEA

The work by Coelli and Rao (2003) analyzes levels and tendencies in product and productivity in world agriculture utilizing the Malmquist index described in Färe et al. (1994). This approach applies Data Envelopment Analysis – DEA for the construction of a linear piece-wise production frontier for each sample year.

According to Coelli and Rao (2003), DEA is a linear programming methodology that utilizes data in relation to quantities of inputs and products of a group of countries in order to establish a piecewise-linear surface over points of sample data. The frontier surface is established by the solution of a linear programming problem sequence – one for each sample country. The degree of technical inefficiency for each country (the distance between observed data and frontier) is expressed as a subproduct of the frontier construction method.

Coelli and Rao (2003) state that DEA method can be either input-oriented or output-oriented. In the first case, DEA method defines the frontier by seeking maximum proportional reduction in the utilization of inputs, with maintained product levels for each nation. On the other hand, in the case of output orientation, DEA method aims to capture the maximum proportional increase in production, maintaining input levels constant.

Coelli and Rao (2003) analyze that both measures provide the same scores relative to technical efficiency when the technology of constant returns of scale is applied (CRS). However, punctuations become different when assuming variable returns of scale (VRS).

Research by Coelli and Rao (2003) assumes a CRS technology type, given that it concerns aggregate data of nations and not individual farm information; it is also assumed product orientation since it is believed that in agriculture industry, agents maximize products given a set of inputs (and not the contrary). Thus, data is analyzed for N countries in a determined period of time and the linear programming problem (LP) is solved for the i-th country in a DEA product-oriented model:

$$\begin{aligned} &\max_{\phi,\lambda}\phi, \\ \text{s.t.}\quad & -\phi y_i + Y\lambda \geq 0 \\ & x_i - X\lambda \geq 0, \\ & \lambda \geq 0, (1) \end{aligned}$$

where

y_i is a product vector $M \times 1$ for the i-th country;
x_i is an input vector $K \times 1$ for the i-th country;
Y is a product matrix $N \times M$ for all N countries;
X is a quantity input matrix $N \times K$ for all N countries;
λ is a weight vector $N \times 1$; and
ϕ is a scalar

Observe that ϕ will assume a value greater or equal to 1, and $\phi - 1$ is the proportional product increase that could be achieved by the i-th country with input quantities maintained constant. Observe also that $\frac{1}{\phi}$ defines a score relative to technical efficiency (TE) varying between zero and one, and this is product-oriented TE score as described in the results by Coelli and Rao (2003).

The LP above is solved N times – once for each sample country. Each LP products the vectors ϕ e λ . The ϕ parameter provides information on the punctuation of technical efficiency for the i-th country and vector λ contains information on the "peers" of the i-th (inefficient) country. Peers of the i-th country represent efficient nations that define the facet of the frontier in relation to which the i-th inefficient country is projected.

The DEA problem can be illustrated by a simple example. Following the work by Coelli and Rao (2003), consider the case where a group of five countries produce two outputs (e.g. wheat and meat). For simplicity purpose, suppose that each country has identical output vectors. These five countries are described in Figure 1. Countries A, B and C are efficient nations, since they define the frontier. Countries D and E are inefficient countries. For country D, the number of technical efficiency equals to:

(1) $TE_D = 0D / 0D'$

and their peers would be countries A and B. In the DEA output listing, this country would be a number of technical efficiency of approximately 70% and would have weights λ different than zero associated with countries A and B. For country E, the number of technical efficiency equals to

(2) $TE_E = 0E / 0E'$

and their peers would be countries B and C. In the DEA output listing, this country would have a technical efficiency of approximately 50% and would have weights λ different than zero associated with countries B and C. Observe that the DEA output listing for countries A, B and C would provide technical efficiency scores equal to 1 and each country would be computed as being its own peer.

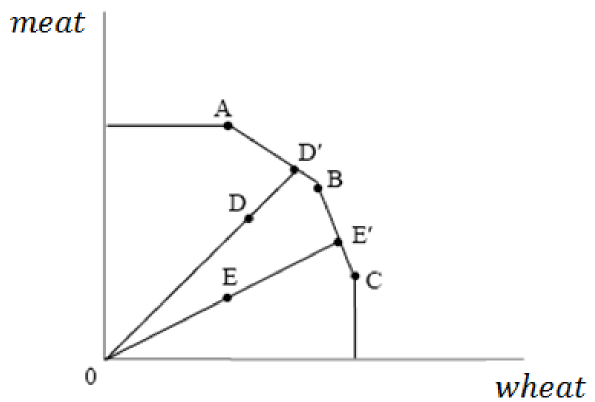

Figure 1: Product-Oriented DEA
Source: Adapted by the authors from Coelli and Rao (2003).

2.2.1 Malmquist Index

A productively efficient firm is the one not able to increase its production unless some of its inputs are also increased. By the Malmquist index, such firm achieves an efficiency score of 1. Similarly, a productively inefficient firm obtains an efficiency punctuation smaller than 1.

Introduced by Caves et al. (1982) in its empirical usage, the Malmquist index do not require costs or income, being capable of measuring increase in TFP in a scenario of multiple products.

For the Malmquist index definition, we assume that for each period of time, $t = 1, \ldots, T$ production technology S^t models the transformation of inputs $x^t \in \Re^n_+$ into products $y^t \in \Re^m_+$.

(3) $$S^t = \{(x^t, y^t): x^t \text{ produces } y^t\}$$

Färe et al. (1994) define the output distance function at time t as

(4) $$D_0^1(x^t, y^t)$$

Thus, the distance function in relation to two different periods measure the maximum proportional change required in production to turn (x^{t-1}, y^{t-1}) feasible in relation to technology in period t. Caves, Christensen e Diewert (CCD) (1982) define Malmquist productivity as

(5) $$M_{CCD}^t = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}$$

In this formulation, technology at time t is the reference technology. Alternatively, Färe et al. (1994) define a Malmquist index based on period $(t+1)$ as

(6) $$M_{CCD}^{t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}$$

In order to avoid an arbitrary benchmark, Färe et al. (1994) specify the Malmquist index for changes in productivity as the geometric mean of both CCD type Malmquist indexes:

(7) $$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right)\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)\right]^{1/2}$$

An equivalent form to express this index:

(8) $$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right)\right]^{1/2}$$

In the study concerning industrialized countries, Färe et al. (1994) observe that this decomposition allows for a measure in which one distinction exists between technical efficiency components (“catching-up”) and technology change (innovation), given that previous works did not distinguish between these two components.

The ratios inside the brackets measure changes in technology dislocations to input levels x^t and x^{t+1}, respectively. Thus, changes in technology is measured as the geometric mean of these two components. The terms out of the brackets measure technical efficiency relative to t and $t+1$, capturing changes in efficiency over time, that is, whether production becomes closer (catching up effect) or more distant from the frontier.

Observe that if $x^t = x^{t-1}$ and $y^t = y^{t-1}$ (i.e., no input and product change between periods), the productivity index do not signalize any change: $M_0(.) = 1$. Improvements in productivity result in Malmquist indexes greater than unity. Similarly, performance deterioration over time is associated with a Malmquist index smaller than unity. Besides, improvements in any of the Malmquist index components are also associated with values greater than unity of these components; and deterioration is associated with values smaller than unity.

Finally, Färe et al. (1994) highlight that, while the product of the components of efficiency change and technical change must, by definition, equal the Malmquist index, these components may be moving in opposite directions. For instance, a Malmquist index greater than unity, say 1.25 (which signalizes productivity gain), could have a component of efficiency change smaller than 1 (e.g. 0.5) and a change in technology component greater than unity (e.g., 2,5).

Alternatively, Alam (2001) expresses the Malmquist index in terms of distances throughout the y-axis, based on Figure 2:

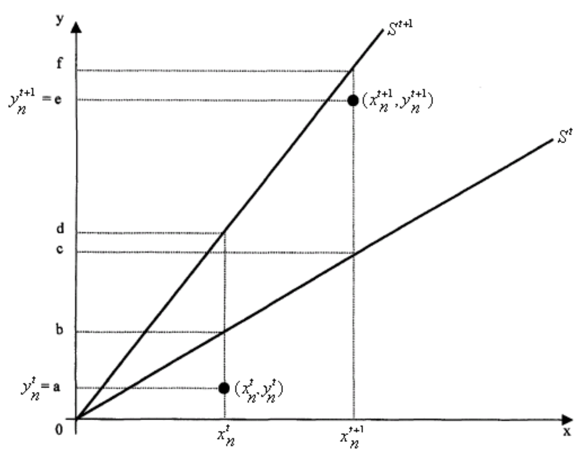

Figure 2: Malmquist Index

Source: Adapted by the authors from Alam (2001).

$$\text{Malmquist index} = \frac{\left(Oe/Of\right)}{\left(Oa/Ob\right)} * \left[\frac{\left(Oc/Od\right)}{\left(\frac{Oe}{Of}\right)}\frac{\left(Oa/Ob\right)}{\left(\frac{Oa}{Od}\right)}\right]^{\frac{1}{2}}$$

$$= \left(\frac{Oe}{Of}\right)\left(\frac{Ob}{Oa}\right) * \left[\left(\frac{Of}{Oc}\right)\left(\frac{Od}{Ob}\right)\right]^{1/2} = E_{t+1} * A_{t+1} \quad (9)$$

Consider the case of a firm n in period t represented by (x_n^t, y_n^t). Given that it is located under S_t, this firm is not efficient and its productive inefficiency is measured by the ratio $\frac{Oa}{Ob}$. Similarly, the same firm in *t+1*, denoted by (x_n^{t+1}, y_n^{t+1}) is efficient in relation to the frontier S^{t+1} and its inefficiency measure is given by $\frac{Oe}{Of}$.

Given that this index captures the productivity dynamics by the incorporation of data from two different adjacent periods, E_{t+1} reflects change in relative efficiency, while A_{t+1} reflects changes in technology between periods t and $t+1$. As for the index and its components, values smaller than 1 indicate a decline in productivity (regression), while values greater than 1 indicate growth (progress). For the firm n in the example, both components exceed 1. In terms of technical efficiency, the firm moved to a point closer to the contemporary relevant frontier, indicating that the production for this firm is converging to the frontier. In terms of technological change, the frontier, measured at levels x of inputs x^t and x^{t+1}, moved between periods t and $t+1$ $(A_1(t+1) > 1)$ (ALAM, 2001).

2.3 Theoretical Relationship between Total Factor Productivity and Mark-Up

A substantial body of literature has been devoted to the empirical identification of market power (e.g. Schmalensee, 1989; Bresnahan, 1989), focusing on the identification of monopoly pricing. In theory, it is possible to define the degree of monopoly power of a given producer as the mark-up of product price (P) over marginal cost (MC). This indicador, the *Lerner index*, can be defined as $\frac{P - MC}{P}$. In perfect competition, price equals marginal cost and the index will equal to zero. When prices exceed marginal cost, the Lerner index becomes positive and varies between zero and unity. The greater the index, the greater the degree of monopoly power, thus reflecting the actual conduct and not the potential for monopolistic behavior.

However, as Martins, Scarpetta and Pilat (1996) analyze, empirical measure of the Lerner index and related measures is quite difficult and at an aggregated level, the theoretical and empirical economic literature has provided few suggestions on how to establish appropriate measures. This occurs mainly due to the fact that, while prices can be measured, marginal costs are not directly observable and therefore indirect measures need to be developed.

In microeconomic terms, Sumanth (1985) refers that a company with better productivity than the average of the sector is provided to have larger mark-up. In addition, if the productivity of a certain company grows with larger velocity than the one of the competitors, the margins tend to grow still more. One explanation for the positive correlation is that changes in labor input and wage costs coincide, and that these have strong influences on TFP growth and the mark-up, respectively. An alternative explanation is that increasing foreign competition leads to lower sales for domestic firms. If the domestic firms are slow to adjust but stay in the market productivity might decline. This would also imply a positive correlation between mark-up and productivity.

Considering an open market economy, Bellone, Musso e Nesta (2008) state that the optimal price and output levels of a domestic firm of cost efficiency *c*, can be expressed as:

$$\begin{cases} p(c) = \frac{1}{2}(c_D + c), & q(c) = \frac{L}{2\iota(c_D - c)} \\ p^*(c) = \frac{\tau^*}{2}(c_X^* + c), & q^*(c) = \frac{L}{2\iota}\tau^*(c_x - c) \end{cases}$$

respectively in the domestic market and in the foreign ones. τ and τ^* are barriers to imports for the domestic and the foreign economy, respectively, whereas c and c_D denote the upper bound exclusive of trade costs respectively for domestic firms selling at home and for domestic firms selling abroad. The set of equations above yield the following maximizing operating profit levels:

$$\begin{cases} p(c) = \frac{1}{2}(c_D + c), & q(c) = \frac{L}{2\iota(c_D - c)} \\ p^*(c) = \frac{\tau^*}{2}(c_X^* + c), & q^*(c) = \frac{L}{2\iota}\tau^*(c_x - c) \end{cases}$$

with markups

$$\begin{cases} \mu(c) = p(c) - c = \dfrac{1}{2(c_D - c)} \\ \mu^*(c) = p^*(c) - c = \dfrac{\tau^*}{2}(c_X) - \left(1 - \dfrac{\tau^*}{2}\right)c \end{cases}$$

The last equation provides three straightforward implications about the determinants of firm markups.

1) *Firm mark-ups are positively related to firm productivity*. Ceteris paribus, firms with lower costs are able to set higher mark-ups as they do not pass all of the cost differential to consumers in the form of lower prices.

2) *Firm mark*-ups are negatively related to domestic market size as a larger domestic market size lowers the cost cutoff on the home market c_D. Such implication arises because in the presence of trade costs, the domestic size of an open economy still exerts an important role in determining the firm performance measure (including mark-up).

All else equal, firms charge higher mark-ups on foreign markets than on domestic markets because of the presence of trade costs. Indeed, it can easily be shown that, for equal competition toughness and production technology in the domestic and foreign economies, the last equation with positive trade costs, $\tau^* > 1$, implies $\mu^*(c) > \mu(c)$

3 METHODOLOGY

From LSPA (Systematic Survey of Agricultural Production) of January 2007 by the Brazilian Institute of Geography and Statistics (IBGE), data was gathered for the main Brazilian grain crops – rice, beans, maize and wheat. Thus, obtained productions have been analyzed for each culture (outputs), as well as harvested area in acres for each crop (inputs) annually.

Additionally, from PAM (Municipal Agriculture Production) and the statistics available at the Ministry of Agriculture, data has been gathered related to total produced quantity (in ton.), harvested area (acres), agricultural credit (in Brazilian Real) and agricultural limestone (in ton.) for the period 2001 to 2006 for the 26 States of the Federation and the Federal District, allowing for the creation of regional *dummies* for the comparative analysis of total factor productivity.

Initially, data has been analyzed based on the stochastic frontier theory in order to verify gains or losses in efficiencies over time, expressed by the component η and the estimated parameters of variables that explain technical inefficiency. Considering technical inefficiency $\mu_{it} = [\exp(-\eta(t-T))]\mu_i$ as varying through time, if η is positive, the value inside the brackets of the exponential term will become nonnegative and $\exp(-\eta(t-T))$ will not be greater than 1. This is the case in which $\mu_{it} \geq \mu_i$. In other words, technical inefficiency will be decreasing over time (positive effect of technical efficiency through time). If η is negative, inefficiency will be increasing. In case η is null, it is observed technical inefficiency that does not vary over time (also referred as persistent inefficiency).

The Cobb-Douglas function can exhibit any degree of returns to scale, depending on the values of *a* and *b* in the formula $q = f(k, l) = ak^a l^b$. Suppose all inputs were increased by a factor of *t*. Then, $f(tk, tl) = A(tk)^a(tl)^b = at^{a+b}k^a l^b = t^{a+b}f(k, l)$. Hence, if $a + b = 1$, the Cobb-Douglas function exhibits constant returns to scale, since output also increases by a factor of *t*. If $a + b > 1$, the function exhibits increasing returns to scale, whereas $a + b < 1$ corresponds to decreasing returns-to-scale case. It is also known that the elasticity of substitution is 1 for the Cobb-Douglas function. This function has also proved to be quite useful in many applications because it is linear in logarithms $lnq = lnA + alnk + blnL$. The constant *a* is then elasticity of output with respect to capital input, and *b* is the elasticity of output with respect to labor input. These constants can sometimes be estimated from actual data, and such estimates may be used to measure returns to scale (by examining *a*+*b*) and for other purposes (NICHOLSON, 2005).

Once empirical economists would prefer to let the data show what the actual substitution possibilities among inputs are, they have tried to find more flexible functional forms. One especially popular form is the translog production function, which can be expressed as

$$lnq = \beta_0 + \sum_{i=1}^{n} \beta_i lnx_i + 0.5 \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} lnx_i lnx_j ,$$

$\beta_{ij} = \beta_{ji}$. Note that the Cobb-Douglas function is a special case of this function where $\beta_0 = \beta_{ij} = 0$ for all i, j (NICHOLSON, 2005).

In relation to Data Envelopment Analysis and the Malmquist index, Färe et al. (1994) discuss the usage of the VRS approach in the Malmquist index calculation. By calculating "change in efficiency" in relation to the VRS frontier, it is obtained the denominated "change in efficiency" and measured changes in production scale by the ratio between "change in efficiency" and "change in pure efficiency". Thus, the component change in efficiency (or technical efficiency) calculated in relation to technology with CRS can thus be decomposed in a component of change in pure efficiency (PEC, calculated in relation to the technology with VRS) and, in a component of change of scale efficiency (SEC), which represents changes in deviations between the CRS and VRS technologies.

Thus,

$$M_0(y_{t+1}, x_{t+1}, y_t, x_t) = Technical\ Change\ (TECH) * Change\ in\ Pure\ Efficiency\ (PEC) * Change\ in\ Scale\ (SEC)$$

where

$$Efficiency\ Change\ (EFCH) = Change\ in\ Pure\ Efficiency\ (PEC) * Change\ in\ Scale\ (SEC)$$

which can be re-written in the following form:

$$Growth\ in\ TFP = Efficiency\ Change\ (EFCH) * Technical\ Change\ (TECH)$$

The decomposition of Malmquist index assists in the determination of efficiency or inefficiency sources in a firm. $TECH > 1$ indicates technical progress. $EFCH > 1$ means the firm is approximating towards optimal scale in $t + 1$.

4 RESULTS AND DISCUSSION

4.1 Stochastic Frontier Analysis for Brazilian Agriculture: Cobb-Douglas Production Function

The results related to the estimation of the stochastic frontier analysis according to a Cobb-Douglas production function is presented in Table 1. In the case of a Cobb-Douglas model, the significant variables were harvested area, agriculture credit and limestone – all assuming expected signs. The LR (Likelihood Ratio) statistic, which is a chi-square ($\chi^2 2)$ distribution under the null hypothesis that there has not been effects of technical efficiency, presents significant value to the 1% level, indicating effects of technical inefficiency in the model.

The greatest elasticity observed is that of harvested area. This indicates the intense relation that exists between production and harvested area, independently of the utilization of other factors that, *ceteris paribus*, would contribute for productivity. The credit variable reveals the second major elasticity, confirming the importance of agriculture credit to cover costs and particularly, to execute investments which responds for the greatest share of the data analyzed. As expected, assuming positive and inferior elasticity in relation to the other relevant factors, limestone contributes for productivity by correcting sole acidity, which assumes a maximizing role for the potential of productivity already established by the other factors.

The estimate of parameter γ, which measures the variability of the two sources of error (white noise disturbance and unilateral error), reached the level of 0.9469. This result means that about 95% of total variance of composed error of the production function is explained by the variance of the term of technical inefficiency. This represents the importance of incorporating technical inefficiency in production function.

The term relative to technical inefficiency assumes a temporal pattern of behavior represented by the η sign. In case this term is positive (negative), technical inefficiency will be decreasing (increasing) in time. If it assumes a null value, it is considered that technical inefficiency does not vary in time - also called persistent inefficiency. In the analysis, the term assumes negative value, which indicates that technical inefficiency in Brazilian agriculture, though not predominant, is increasing in time from 2000 to 2005.

Thus, the punctual reduction of inefficiency, which includes the concession of credit of costs for income maintenance against fluctuations in prices and exchange rates, as well as investment credit for capital acquisition such as tractors and harvesters will certainly avoid the persistence of increasing inefficiency path in Brazilian agricultural productivity.

Table 1 – Cobb-Douglas Production Function

Log-Likelihood Function	15.419691		Prob > χ^2 = 0,0000
	Coefficients	z-Stat	P>z
β_0	-1.2327	-1.76	*
$\beta_A(\ln[harvestedarea])$	1.0665	19.87	***
$\beta_C(lncredit)$	0.8882	2.25	***
$\beta_D(defensives)$	0.0154	0.51	
$\beta_R(limestone)$	0.0721	4.18	***
μ	1.3621		
η	-0.0123		
γ	0.9469		
σ_u^2	0.4073		
σ_v^2	0.0228		

Source: Research results obtained from gathered PAM and Ministry of Agriculture data for the proposed stochastic frontier model.
Note: *** significant to the 1% level; ** significant to the 5% level; * significant to the 10% level.

4.2 Stochastic Frontier Analysis for Brazilian Agriculture: Translog Production Function

Assuming a logarithmic transcendental (translog) technology, the parameters estimates of the production frontier and the technical inefficiency component are presented in Table 2. The statistically significant parameters at the level of 5% are essentially related to harvested area and agricultural credit, as well as the measures of regional technical inefficiency expressed by dummy variables. The LR (Likelihood Ratio) statistic presents significant value at 1% level, indicating effects of technical inefficiency in the model.

Analyzing the sample on the basis of stochastic frontier theory for the verification of gains or losses of efficiencies through time, it is observed that the η component assumes negative sign and is significant at 5% level. Thus, technical inefficiency is increasing over time for the analyzed sample. It is important to emphasize that η is unique for the analyzed sample. Thus, this component does not reveal productivity specificities for each State.

The coefficient for the mean of the error component relative to inefficiency, μ, is not statistically significant, indicating that the semi-normal distribution is more appropriate in relation to the normal truncated distribution ($\mu = 0$).

The positive sign of parameter β_t indicates that the occurrence of technical progress. The indicator of technical inefficiency, γ, presents approximated value of 0,90. This result indicates that 90% of total composed error variance of the production function is explained by the variance of the technical inefficiency term. This reveals the importance to incorporate technical inefficiency in the production function.

In relation to the dummy variables parameters, they are all statistically significant to the 5% level. By having the Northeast region as reference for presenting a larger number of observations, it is verified that all the other regions are technically less efficient in relation to the reference region. Thus, by classifying according to the degree of increasing inefficiency, North region is followed by Southeast region, South and Center-West, respectively.

The coefficients β_t and β_{tt} indicate that the neutral part of technical progress has a positive effect over production. The signs of the coefficients β_{At}, β_{Ct}, β_{Dt} and β_{Rt} indicate, respectively, that the non neutral part of technical progress moves inversely with area, credit, defensives and accordingly with limestone. However, these parameters are not significant at the 5% level. That is, technical progress tends to diminish the usage of harvested area, agricultural credit, defensives and, on the other hand, is associated with the increase of limestone utilization.

Table 2 – Time-varying Inefficiency Model (B&C, 1992)

Num. of obs = 162					Obs. by State: min = 6	
Num. of States = 27					Avg: 6	
					Max: 6	
					Wald $\chi^2_{(24)}$ = 3638,03	
Log likelihood = 46,578465					Prob > χ^2 = 0,0000	
lny	Coef.	Std. Error	z	P>z	95% Conf. Interval	
					lower limit	upper limit
$\beta_t(t)$	0,5324	0,2963	1,80	*	-0,0483	1,1131
$\beta_{tt}(1/2)t^2$	0,0094	0,0175	0,53		-0,0250	0,0437
$\beta_A(\ln harvesteda\ rea)$	1,9117	1,8004	2,39	***	0,3428	3,4805
$\beta_C(\ln credit)$	-2,6287	0,6895	-3,81	***	-3,9801	-1,2771
$\beta_D(\ln defensives)$	0,0022	0,4079	0,01		-0,7974	0,8018
$\beta_R(\ln \lim estone)$	1,1503	0,7372	1,56		-0,2945	2,5952
$\beta_{AA}((1/2)\beta_A\beta_A)$	-0,3438	0,0810	-4,24	***	-0,5025	-0,1849
$\beta_{CC}((1/2)\beta_C\beta_C)$	0,1024	0,0583	1,76	**	-0,0118	0,2167
$\beta_{DD}((1/2)\beta_D\beta_D)$	-0,0006	0,0323	-0,39		-0,0759	0,0507
$\beta_{RR}((1/2)\beta_R\beta_R)$	-0,0658	0,0693	-0,95		-0,2017	0,0702
$\beta_{At}(t\beta_A)$	-0,0149	0,0231	-0,64		-0,0602	0,0304
$\beta_{Ct}(t\beta_C)$	-0,0193	0,0200	-0,97		-0,0585	0,0198
$\beta_{Dt}(t\beta_D)$	-0,0006	0,0097	-0,06		-0,0196	0,0185
$\beta_{Rt}(t\beta_R)$	0,0189	0,0193	0,98		-0,0190	0,0568
β_{AC}	0,1267	0,0577	2,19	***	0,0134	0,2399
β_{AD}	0,0180	0,0425	0,42		-0,0652	0,1013
β_{AR}	0,1189	0,0516	3,66	***	0,0879	0,2903
β_{CD}	-0,0029	0,0239	-0,12		-0,0498	0,0440
β_{CR}	-0,1518	0,0425	-3,56	***	-0,2352	-0,0682
β_{DR}	-0,0351	0,0413	-0,85		-0,1161	0,0458
δ_1 *(dummy North region)*	0,8565	0,1539	5,56	***	0,5546	1,1582
δ_2 *(dummy Southeast region)*	1,0735	0,2525	4,25	***	0,5785	1,5684
δ_3 *(dummy South region)*	1,1111	0,2599	4,27	***	0,6016	1,6206
δ_4 *(dummy Center-West region)*	1,2213	0,1893	6,45	***	0,8503	1,5923
β_0	15,1157	5,8720	2,57	***	3,6067	26,6246
μ	0,9707	0,6959	1,39		-0,3932	2,3346
η	-0,1290	0,0395	-3,26	***	-0,2066	-0,0514
$\ln\sigma^2$	-1,7685	0,4409	-4,01	***	-2,6327	-0,9043
ilgt γ	2,1697	0,5366	4,04	***	1,1179	3,2215
σ^2	0,1705	0,0752			0,0718	0,4048
γ	0,8974	0,0493			0,7536	0,9616
σ_u^2	0,1530	0,0756			0,0048	0,3013
σ_v^2	0,0174	0,0023			0,0129	0,0220

Source: Research results obtained from gathered PAM and Ministry of Agriculture data for the proposed stochastic frontier model.
Note: *** significant to the 1% level; ** significant to the 5% level; * significant to the 10% level.

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In Table 3 are presented some statistical tests constructed in order to verify the consistency of specific hypothesis related to the production function frontier adopted in the empirical model.

Table 3 – Log likelihood test of stochastic production frontier parameters

Test	Null Hypothesis	Value of λ	Prob> χ^2	Decision (5% level)
1	$H_0 : \beta_{tt} = \beta_{AA} = ... = \beta_{RR} = \beta_{AC} = ... = \beta_{DR} = 0$	40.71	0.0000	Reject H_0
2	$H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4$	50.67	0.0000	Reject H_0
3	$H_0 : t = t^2 = t\beta_A = t\beta_C = t\beta_D = t\beta_R = 0$	6.23	0.3984	Accept H_0

Source: Research results obtained from gathered PAM and Ministry of Agriculture data for the proposed stochastic frontier model.

The first null hypothesis relates to the adequacy test of Cobb-Douglas model relative to the less restrictive functional form expressed by the translog. Thus, it is tested the hypothesis that all the second order coefficients and the cross products are equal to zero. The value of the log likelihood ratio, 40.71, is greater than the critical value of the statistic $\chi^2_{(11)}$ with 5% significance level to the right.

Duffy and Papageorgiou (2000) reject the Cobb-Douglas specification utilizing a data panel for 82 countries in a period of 28 years. Additionally, by examining the impact of production technology over technical efficiency, Kneller and Stevens (2003) reject the specification of the aggregate production function over the efficiency measures. Thus, translog production function constitutes a more flexible firm and is an approximation for any production frontier. The result of this test is presented on Table 2 rejects the specification in the form of a Cobb-Douglas function in favor of the translog specified model.

The second analysis refers to the joint significance tests of the parameters of the variables that explain technical inefficiency. The result rejects the hypothesis that the parameters are simultaneously equal to zero.

The last test examines the stability of the production frontier in relation to the time variable, that constitutes the presence or not of technology progress in the analyzed period. Thus, the result of the test accepts the null hypothesis that there have not been any of the known forms for the sample and the analyzed period.

According to the data of the analyzed period, it is observed that an amelioration of aggregate productivity exists over time. In a decreasing order, the Brazilian regions that represent greater relative degree of efficiency were the Northeast, North, Southeast, South and Center-West regions. This result points to the new Brazilian agriculture frontiers where the production of grain crops advances rapidly, followed by livestock activity.

Additionally, the most significant inputs that have contributed to Brazilian agriculture productivity were the land factor, as well as the agriculture credit. On the other hand, the inputs related to agricultural defensives and limestone were not significant to explain Brazilian agriculture productivity throughout the analyzed period.

According to the Economic Bulletin by IPEA (Brazilian Institute of Applied Economic Research), considering the agriculture years 2000/2001 to 2004/2005, the sector has increased its debt in R$ 41,8 billion solely due to investment credit, constituting half of the total agriculture credit. The investment credit differs for not having annual cycle as credit destined for covering costs destined to cover normal expenses of production cycles. It is cumulative and exerts significant importance in the analysis of behavior in the agriculture sector.

For illustration purposes, considering only the agriculture years 2003/2004 and 2004/2005, the sector has contracted *additional* debt of R$20,9 billion, only on investment rubric - almost the same value of credit for costs which was, in average, R$ 22 billion (B. CONJ. IPEA, 2005). Thus, agriculture credit inserted in the model is an adequate and relevant proxy for the representation of machinery in the contribution of productivity in Brazilian agriculture.

4.3 Stochastic Frontier Analysis for Main Brazilian Grain Crops

It is estimated the following model f unique input and output:

$$\ln Y_{it} = \beta_0 + \beta_L \ln L_{it} + v_{it} - \mu_{it}$$

in which Y_{it} is the production obtained for the i-th grain crop at period t and L_{it} is the harvested area for the i-th grain crop at period t .

Analyzing the wheat culture, it is observed that the component η assumes a negative coefficient, but is not significant to the 5% level, which indicates a decreasing inefficiency over time. The LR statistic indicates a relevance of the presence of technical inefficiency in the model. This LR test is a chi-square distribution under the null hypothesis indicating technical inefficiency effects. For the wheat culture, this test is significant at the 1% level.

For the maize crop, it is verified that the component η assumes a positive coefficient. Thus, $\mu_{it} \geq \mu_i$ and technical inefficiency will increase at decreasing rates, which presents a positive effect of technology efficiency (movement towards the frontier). In addition, the LR test confirms such absence of technical inefficiency effects, whose value is not significant at the 5% level.

Observing the results for the rice crop, we verify that the component η assumes a negative coefficient, but not significant at the 5% level. Thus, technical inefficiency will be decreasing over time, in which the LR test indicates no effects of technical inefficiency.

In relation to beans and soybeans, though non-convergence of maximum likelihood estimation (MLE) has been achieved, it is observed that η assumes a positive coefficient, which indicates a positive effect in technical efficiency over time, even though it is not significant at the 5% level in both analyzed cultures.

The results obtained were not entirely satisfactory to interpret efficiency or inefficiency for individual crops through time, given that μ does not present itself as a statistically important component (at the 5% level) in order to conclude that inefficiency is an important component for each one of the Brazilian grain crops individually. Table 4 presents the principal obtained results.

Table 4 – SFA Results, Inefficiency Time-Varying Model, Grain Crops, Brazil (2001-2006)

Crop	μ	P>z	η	P>z	Prob> χ^2
Rice	0.0969	0.123	-18.9413	0.999	0.0000
Beans*	1.7772	0.832	0.0153	0.826	0.0000
Maize	0.0817	0.585	0.4466	0.072	0.2713
Soybeans*	2.17e-06	0.002	-	-	0.0000
Wheat	0.0712	0.716	-2.3633	0.913	0.0001

Source: Research results obtained from gathered LSPA/IBGE.
Note: * indicates non-convergence of MLE.

4.4 Data Envelopment Analysis (DEA): Malmquist Index

Utilizing data from LSPA/IBGE for the main grain crops in Brazilian agriculture – rice, beans, maize, soybeans and wheat – the following results have been obtained according to Table 5.

Table 5 – Total Factor Productivity Means and its Components, Grain Crops, Brazil (2001-2006)

Crop	Malmquist Index	Technical change (TECH)	Efficiency change (EFCH)	Change in Pure Efficiency (PEC)	Change in Scale (SEC)
Rice	1.152	1.270	0.907	0.930	0.975
Beans	1.303	1.270	1.027	1.013	1.013
Maize	1.300	1.270	1.024	1.020	1.004
Soy	1.262	1.270	0.994	0.970	1.024
Wheat	1.218	1.270	0.959	1.001	0.958
Mean	**1.246**	**1.270**	**0.981**	**0.986**	**0.995**

Source: Research results.

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In the period from 2001 to 2006, PTF in main Brazilian grain crops increased 24.6% according to calculation of Malmquist indexes. The component of this growth was the technical change index, which increased 27%. On the other hand, the component referring to efficiency change declined 1.9% during the period. Thus, it is considered that the effect of technology innovation during the period in study has been more expressive than effect in efficiency change for the analyzed crops.

Among analyzed crops, beans were the culture that experimented the greatest increase in TFP (+0.30%) during the observed period. In addition, it 5% is analyzed that the principal component of such TFP increase was technical change (+27), since growth in efficiency responded for only 2.7% of TFP elevation. Decomposing the EFCH index, it is verified that the indexes of pure efficiency change and scale change have responded for 50% of the underlying index increase, given the 1.3% growth for both.

Maize culture was the crop that obtained the second largest rise in TFP during the analyzed period. It is observed that its increase of 30% in the Malmquist index is predominantly due to technical change, which incurred an increase of 27%, similarly to global mean of data in study. However, the component of technical efficiency did not suffer a regress, but a 2.4% increase. Among its subcomponents, the elevation of the EFCH index occurred mainly due to change in pure efficiency, which progressed 2%, while the change in scale component suffered a 0.4% increase.

It is also observed that the soybeans culture suffered the third major increase in TFP (+26,2%), in which index of technical change was predominant over change in efficiency. However, in contrast to the soybeans culture, there has been a regress in change in efficiency (-0.6%). It is verified that such decline in this component occurs due to the regression of change in scale, which presented a 3% decline, and not because of alterations in the component referring to scale change, which obtained a 2.4% growth during the study period.

Additionally, the wheat crop obtained the 4th major elevation in TFP (+21.8) throughout the observed period, in which effects occurred exclusively by effects in technical change, in which technology innovation is implicit, which in turn obtained a 27% progress, corresponding to the mean of crops in study. However, there has been efficiency change for this culture throughout the analyzed period (-4.1%). Among its components, the regression in this item occurred due to changes in scale, which suffered a decline of 4.2% during the years from 2001 to 2006. In different circumstances, an amelioration or stability in this index would have been verified, since the component referring to change in pure efficiency for the wheat crop obtained a 0.01% progress.

It is observed that, among main Brazilian grain crops, the rice culture suffered the smallest growth in TFP between 2001 and 2006 (+15.2%). Similarly to other crops, a progress in technical change (+27%) is observed. However, the regress in the index related with change in efficiency was the most expressive between the analyzed grains (-9.3%), being the unique culture to suffer a decrease in pure efficiency (-7%) and change in scale (2.5%).

Thus, all main Brazilian grain crops incurred in progress by the index referring to technical change. In other words, it is observed the dislocation of the technology frontier, once detected that, on average, the product of a crop at $t+1$ is greater than the potential maximum product that could have been obtained at t in relation of production factors of $t+1$.

The component that negatively influenced in the Malmquist index performance verified in the cultures of rice, soybeans and wheat relates to change in efficiency. Given that this component of “change in efficiency”, calculated in relation to CRS technology, can be decomposed in changes in “pure efficiency” and “changes in efficiency”, it is observed that all crops experience regress either in “pure efficiency” only – change in efficiency in relation to the VRE frontier, as is the case of soybeans - or solely the regress in “scale change” – ratio between change in efficiency and change in pure efficiency, representing alterations in deviations between technologies CRS and VRE – as occurred with the wheat culture. However, exception is verified for rice culture in which both types of regress related to changes in efficiency occurred.

From Tables 6, 7 and 8, we verify the annual TFP evolution and its principal components – efficiency change (approximation to the frontier) and technical efficiency (innovation) – for each crop, analyzing changes particularly among the last studied periods (2005/2006).

Table 6 – Total Factor Productivity, Grain Crops, Brazil (2001-2006)

Year	Rice	Beans	Maize	Soy	Wheat
2002	0.719	1.113	1.327	1.310	1.297
2003	1.538	1.194	4.057	2.720	3.498
2004	2.407	1.802	0.644	1.235	0.987
2005	1.445	1.504	1.153	0.878	0.757
2006	0.526	1.045	0.929	0.830	0.790

Source: Research results.

Table 7 – Efficiency Change, Grain Crops, Brazil (2001-2006)

Year	Rice	Beans	Maize	Soy	Wheat
2002	0.649	1.005	1.198	1.182	1.171
2003	0.414	0.321	1.091	0.731	0.941
2004	2.666	1.996	0.714	1.367	1.093
2005	1.397	1.454	1.115	0.849	0.732
2006	0.614	1.218	1.084	0.967	0.921

Source: Research results.

Table 8 – Technical Change, Grain Crops, Brazil (2001-2006)

Year	Rice	Beans	Maize	Soy	Wheat
2002	1.108	1.108	1.108	1.108	1.108
2003	3.719	3.719	3.719	3.719	3.719
2004	0.903	0.903	0.903	0.903	0.903
2005	1.034	1.034	1.034	1.034	1.034
2006	0.858	0.858	0.858	0.858	0.858

Source: Research results.

From the presented tables, it is observed that only the culture of beans increased in its TFP from 2005 to 2006. We analyze that efficiency changes surpassed the negative performance of the component related do innovation. On the other hand, maize culture was the sole crop besides beans that obtained an increase in the component related to change in efficiency. However, this progress did not compensate the decline suffered by the technical change index.

Thus, taking into account the hypothesis that firms mark-ups are positively related to productivity, the crops of rice, wheat, soy and beans incurred in the largest declines in mark-up in 2006 - mainly due to technological issues but also significantly affected by efficiency. For the last two periods, the largest and only mark-up increase is observed for beans. Following Sumanth (1985), since the productivity has grown at a larger velocity (in this case, due to efficiency change) than other crops, mark-up increase for beans has been favored due to lower costs that are not entirely transmitted to consumers.

A general decline in technological change certainly affected mark-ups negatively for all grain crops in Brazilian agriculture. Therefore, the manner in which farmers could maintain and increase their mark-ups has been either by exports, since higher mark-ups can be charged due to the presence of trade costs, or increase in efficiency that affects mark-ups to all markets. Assuming that commodity producers are essentially price takers, total factor productivity is the ultimate form of cost decrease and opportunity for greater mark-ups both domestically and abroad. However, in 2006 in particular, technology has not been able to function as a tool for cost decrease and mark-up increase in the agriculture of grain crops in Brazil.

Common evidence to all analyzed cultures is the decline in technology component in 2006 as consequence of agriculture crisis and its indebtedness which affected mainly grain crops, thus interfering in the acquisition of inputs such as machinery and fertilizers that would represent technology innovation captured by this component in Malmquist index for increase in productivity.

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According to IPEA, the increase in indebtedness occurred because of two conditions satisfied: excessively optimistic expectations in relation to the future and a generous supply of credit given the underlying business risk. The optimistic expectations were on the basis of increase in commodities prices that coincided with exchange rate devaluation, seen as a permanent phenomenon with the end of anchor currency in 1999 and Chinese economic growth. On the other hand, the expansion of agricultural frontier especially in the Center-West for the grain crops was covered by credit from private and public banking institutions, as well as by product supplier firms. The crop expansion was associated with a high indebtedness of producers in the short and long term, inducing the financial system to restrict industry's access to new borrowings, interfering in maintenance of the current level of activities and, therefore, reflecting on acquisition of new technologies for productivity increase (B. CONJ. IPEA., 2005, 2006, 2006a, 2007).

Nonetheless, even with government intervention by renegotiation of farmers' debts in 2006, accumulated debts continue to slow a new expansionary leap in activity that would be verified by positive technological indexes, depressing the potential capacity for growth and making new investments unfeasible both for the incorporation of new areas and for capital seeking productivity increase. Thus, the negative performance in 2006 in technology change for all cultures is evidenced by downfall in agriculture inputs usage such as fertilizers and limestone (B. CONJ. IPEA., 2005, 2006, 2006a, 2007).

5 CONCLUSION

In this paper, the technique of Stochastic Frontier Analysis has been applied for the estimation in increase or decrease in inefficiencies through time, as well as the linear programming method Data Envelopment Analysis and Malmquist index for the analysis of TFP sources for the Brazilian crops of beans, maize, soybeans, wheat and rice – considered as the main grain crops in Brazil – throughout the period that comprehends the years from 2001 to 2006.

According to the Cobb Douglas model, we verify that the greatest elasticity observed is that of harvested area, followed by credit variable, confirming the importance of agriculture credit to cover costs and particularly, to execute investments which responds for the greatest share of the data analyzed. As expected, assuming positive and inferior elasticity in relation to the other relevant factors, limestone contributes for productivity by correcting sole acidity, which assumes a maximizing role for the potential of productivity already established by the other factors.

In the stochastic frontier analysis for the Brazilian agriculture, assuming a Translog technology, it is observed no increase in aggregate productivity throughout the analyzed period. In a decreasing order, the Brazilian regions presenting the highest relative degree of efficiency were the Northeast, North, Southeast and Center-West. This results points to the new Brazilian agricultural frontiers where grain crop production advances rapidly, followed by livestock activity.

Additionally, most significant inputs that contributed for the Brazilian agriculture productivity were the land factor, as well as the agriculture credit – the latter being an adequate and relevant proxy for the representation of machinery in the contribution for Brazilian agriculture productivity. On the other hand, the inputs related to agricultural defensives and limestone were not significant to explain Brazilian agriculture productivity throughout the observed period.

Applying SFA for main Brazilian grain cultures independently, the results obtained were not entirely satisfactory for clear interpretation of efficiency or inefficiency for individual crops through time, generating results that, in short, did not admit efficiency loss but simultaneously did not offer a reasonable statistic level in order to infer conclusive statements in relation to efficiency or inefficiency for each Brazilian grain crop. On the other hand, the Malmquist indexes revealed clarifying results. In relation to the means throughout the study period, it is observed that major TFP changes occurred, in a decreasing order, for the cultures of beans, maize, soybeans, wheat and rice. Although the mean variations have indicated positive TFP changes, when analyzing changes between the years of 2005 and 2006, it is verified a decline in the component representing technology innovations for all the principal Brazilian grain crops, jointly with the loss of productive efficiency for all cultures, excepting beans and maize. However, only the beans crop assumed positive variation in its TFP, since it was the only culture among principal Brazilian grain crops in which efficiency gain surpassed the negative effect of technology use. The generalized decline in the technology component can be explained by the indebtedness crisis in agriculture that affected particularly grain crops in 2005/2006, generating downfall in the use of agriculture inputs and interfering negatively in the maintenance of current level of agriculture activities in Brazil and, especially, the principal grain cultures analyzed.

REFERENCES

AFRIAT, S. N. Efficiency Estimation of Production Functions. **International Economic Review**, XI11, 568-98, 1972.

AIGNER, D.J.; CHU, S. F. Estimating the Industry Production Function. **American Economic Review**, 58, 826-39, 1968.

AIGNER, D.; LOVELL, C. A. K.; SCHMIDT, P. Formulation and Estimation of Stochastic Frontier Production Function Models. **Journal of Econometrics**, 6, 21–37, 1977.

ALAM, I. M. S. A Non-Parametric Approach for Assessing Productivity Dynamics of Large Banks. **Journal of Money, Credit and Banking**, 33, 121 – 139, 2001.

BATTESE, G.; COELLI, T. Frontier production functions, technical efficiency and panel data with application to paddy farmers in India. **Journal of Productivity Analysis**, v. 3, pp. 153-169, 1992.

BATTESE, G.; COELLI, T. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. **Empirical Economics**, v. 20, pp. 325-332, 1995.

BOLES, J. N. Efficiency Squared-Efficient Computation of Efficiency Indexes. Proc. Thirty-ninth Ann. Meeting, **Western Farm Econ**. **Assoc**., 1966.

BRESSLER, R. G. "The Measurement of Productive Efficiency. Proc. Thirty-ninth Ann. Meeting, **Western Farm Econ. Assoc.**, 1966.

CAVES, D. W.; CHRISTENSEN, L. R.; DIEWERT, W. E. The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity, **Econometrica** 50: 1393-1414, 1982.

CHARNES, A.; COOPER, W. W.; RHODES, E. Measuring the efficiency of decision making units. **European Journal of Operational Research**, v. 2, n. 6, p. 429-444, 1978.

COELLI, T. J.; RAO, D. S. P. Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980-2000. Working Paper no. 02/2003, **Centre for Efficiency and Productivity Analysis**, School of Economics, The University of Queensland, 2003

CORNWELL, C.; SCHMIDT, P. SICKLES, R. Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels. **Journal of Econometrics** 46, 185–200, 1990.

DEBREU, G. The coefficient of resource utilization. **Econometrica**, 19, p. 273-292, 1951.

DUFFY , J.; PAPAGEORGIOU, C. A cross-country empirical investigation of the aggregate production function specification. **Journal of Economic Growth**, 5, p. 87-120, 2000.

FARE, R.; GROSSKOPF, S.; NORRIS, M; ZHANG, Z. Productivity Growth, Technical Progress and Efficiency Changes in Industrialized Countries. **American Economic Review**, 84, 66-83, 1994.

FARRELL, M. J. The measurement of productive efficiency. **Journal of the Royal Statistical Society**, Series A, Part 3, p. 253-290, 1957.

GREENE, W. H. Maximum Likelihood Estimation of Econometric Frontier Functions. **Journal of Econometrics**, XI11, 27-56, 1980.

IBGE (Instituto Brasileiro de Geografia e Estatística). **Levantamento Sistemático da Produção Agrícola**. Rio de Janeiro, v.18, n.01, p.1-76, jan.2007.

IPEA (Instituto de Pesquisa Econômica Aplicada). **Boletim de Conjuntura**, n. 71, dez. 2005.

IPEA (Instituto de Pesquisa Econômica Aplicada). **Boletim de Conjuntura**, n. 73, jun. 2006.

IPEA (Instituto de Pesquisa Econômica Aplicada). **Boletim de Conjuntura**, n. 74, set. 2006a.

IPEA (Instituto de Pesquisa Econômica Aplicada). **Boletim de Conjuntura**, n. 76, mar. 2007.

JONDROW, J.; LOVELL, C. A. K; SCHMIDT, P. On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Model." **Journal of Econometrics** 19, 233–238, 1982.

KOOPMANS, T. C. An analysis of production as an efficient combination of activities. In: Koopmans, T. C. (Ed.). **Activity analysis of production and allocation**. Wiley, New York: Cowles Commission for Research in Economics, Monograph, n. 13, 1951.

KNELLER, R.; STEVENS, P. A. The specification of the aggregate production function in the presence of inefficiency. **Economic Letters**, 81, p. 223-226, 2003.

KOOP, R. J.; DIEWERT, W. E. The decomposition of frontier cost function deviations into measures of technical and allocative efficiency. **Journal of Econometrics**, v. 19, p. 319 – 331, 1982.

KUMBHAKAR, S. C. Production Frontiers, Panel Data and Time-Varying Technical Inefficiency." **Journal of Econometrics** 46, 201–211, 1990.

LEE, L. F. A test for Distributional Assumptions for the Stochastic Frontier Functions. **Journal of Econometrics**. 22:245-268, 1983.

MEEUSEN, W.; BROECK, J. Efficiency Estimation from Cobb–Douglas Production Functions with Composed Error." **International Economic Review** 18, 435–444, 1997.

NICHOLSON, W. **Microeconomic Theory**: Basic Principles and Extensions. Canada: Thomson South-Western. Ninth Edition, 2006.

OLIVEIRA-MARTINS, J.; PILAT, D.; SCARPETTA, S. Mark-up ratios in manufacturing industries: Estimates for 14 OECD countries", **OECD Economics Department Working Papers**, No. 162.

PITT, M. M.; LEE, L. F. Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry." **Journal of Development Economics** 9, 43–64, 1981.

RICHMIND, J. Estimating the Efficiency of Production", **International Economic Review**, XV (June), 515-21, 1974.

SCHMIDT, P.; LOVELL, C. A. K. Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers. **Journal of Econometrics**, vol. 9, pp. 343-366. North-Holland, 1979.

SCHMIDT, P.; SICKLES, R. Production Frontiers and Panel Data." **Journal of Business & Economic Statistics** 2(4), 367–74, 1984.

SEITZ, W. D. Efficiency Measures for Steam-Electric Generating Plants. Proc. Thirty-ninth Ann. Meeting, **Western Farm Econ. Assoc**, 1966.

SEITZ, W. D. Productive Efficiency in the Steam-Electric Generating Industry," **Journal of Political Economy**, LXXIX, 878-86, 1971.

SITORUS, B. L. Productive Efficiency and Redundant Factors of Production in Traditional Agriculture of Underdeveloped Countries. Proc. Thirty-ninth Ann. Meeting, **Western Farm Econ. Assoc**., 1966.

SUMANTH, D. Productivity, **Engineering and Management**, New York, McGraw-Hill, 1985.

SHEPARD, R. W. **Cost and Production Functions**, Princeton University Press, 1953.

STEVENSON, R. E. Likelihood Functions for Generalized Stochastic Frontier Estimation. **Journal of Econometrics**, vol. 13, pp. 57-66. North-Holland, 1980.

TIMMER, C. P. Using a Probabilistic Frontier Production Function to Measure Technical Efficiency, **Journal of Political Economy**, LXXIX, 776-94, 1971.