IRRIGATION, TECHNICAL EFFICIENCY AND FARM SIZE IN BRAZIL

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Abstract
It is recognized that irrigated agriculture is an effective tools to combat poverty and income distribution, generating employment at lower costs than those in other sectors of the economy, resulting in an increase in the supply of food at lower prices than those produced in non irrigated area, as well as the significant increase in productivity of land and labor factors. Thus, the objective of this research is to identify the effect of irrigation on the productive performance, in terms of technical efficiency, of Brazilian agricultural producers. The data used refer to the farm level data of the Agricultural Census of 2006, accessed directly in the Brazilian Institute of Geography and Statistics (IBGE). The approach used combines the stochastic production frontier (SFA), taking into account the selection bias in irrigation adoption (Heckman's approach), with the Entropy Balancing technique. The results show that irrigators are, on average, 5.3 percentage points more efficient than rain-fed farmers. The analysis by farm-size showed that, in both groups, the small producers are more efficient than the others, evidencing a U-inverted relationship between technical efficiency and farm-size. However, the greatest difference observed in efficiency scores between irrigators and rain-fed farmers was for large producers, which implies that irrigation technology has a significant effect on the efficiency gain for this group. Finally, the research brings results that can help the design of public policies directed to irrigated agriculture, with the aim of achieving greater rural development.
Keywords: *Irrigation, Entropy Balancing, Stochastic Production Frontier, Technical Efficiency.*

Resumo
É reconhecida que a agricultura irrigada é uma efetiva ferramenta de combate à pobreza e distribuição de renda, gerando empregos a custos inferiores a aqueles em outros setores da economia, resultando em aumento da oferta de alimentos a preços mais baixos daqueles produzidos nas áreas não irrigadas, bem como o aumento expressivo da produtividade dos fatores terra e trabalho. Assim, o objetivo da presente pesquisa foi identificar o efeito da irrigação sobre o desempenho produtivo, em termos de eficiência técnica, dos estabelecimentos agropecuários brasileiros. Os dados utilizados referem-se aos microdados do Censo Agropecuário de 2006, acessados diretamente na sala de sigilo do Instituto Brasileiro de Geografia e Estatística (IBGE). Para tal, foi utilizada uma abordagem que combina a estrutura de fronteira de produção estocástica, levando em conta o viés de seleção na adoção da irrigação (abordagem de Heckman), com a técnica de balanceamento por entropia. Os resultados mostram que os irrigantes são, em média, 5,3 pontos percentuais mais eficientes que os produtores de sequeiro. A análise por tamanho do estabelecimento mostrou que, em ambos os grupos, os pequenos produtores são mais eficientes do que os demais, evidenciando uma relação de U-invertido entre a eficiência técnica e o tamanho da fazenda. Entretanto, a maior diferença observada dos escores de eficiência entre irrigantes e produtores de sequeiro foi para os grandes produtores, indicando que a tecnologia de irrigação tem efeito significativo no ganho de eficiência para este grupo. Por fim, a pesquisa traz resultados que podem auxiliar o delineamento de políticas públicas direcionadas a agricultura irrigada, com o intuito de alcançar um maior desenvolvimento rural.
Palavras-chave: *Irrigação, Balanceamento por Entropia, Fronteira Estocástica de Produção, Eficiência Técnica.*

Classificação JEL: Q10, Q12, Q15

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1. Introduction

The great variability of precipitation in Brazilian regions led farmers to adopt irrigation to mitigate the adverse effects of climate change. In relation to the implementation of irrigation systems, there is the development of Brazilian agricultural sector, which is one of the main economic activities in the generation of employment and income, being able to raise the standard of living of the population regarding poverty reduction and food security.

Irrigation systems development is an important technology through which agricultural productivity rates can be increased (Dridi and Khanna, 2005); it also has potential to minimize the risks caused by climate change, which is associated with one of the main causes of agricultural production vulnerability (Kurukulasuriya *et al.,* 2006). Irrigation adoption can be used as a tool to reduce dependency on variable rainfall and water availability (Tubiello, 2005); decreasing the uncertainty surrounding crop yields and securing income and employment in the rural areas (Marra *et al.*, 2003).

Cunha *et al.* (2014) analyzed the irrigation adoption as an adaptive strategy under climate change scenarios in Brazil. They concluded that irrigation adoption is affected by climate change, and is used as a response to the reduction in precipitation. Although adoption is not uniform across Brazilian regions, irrigation technology adoption is expected to increase in the next 30 years for all regions. Since agricultural sector is said to be the sector most affected by climate change (Rosenzweig *et al.,* 2014), irrigation adoption is used as an adaptive strategy (Finger *et al.*, 2011; Van Passel *et al.*, 2017)

Irrigation systems are increasingly becoming more efficient (Evans; Sadler, 2008; Schaible; Aillery, 2012). Testing the ability of irrigation systems to alleviate water scarcity is an important research agenda that can provide useful information to policymakers (Koundouri *et al*., 2006). As argued by Njuki and Bravo-Ureta (2016), the greatest interest lies on the arid and semi-arid regions, where non-uniform precipitation constrains the natural development of crops. In addition, the competition for existing freshwater supplies requires maximizing water productivity in crop production (Pereira *et al.,* 2003; Sepaskhan *et al.*, 2006).

Despite of all benefits related to irrigation technology adoption in agriculture, there is a low percentage of farmers that use irrigation in Brazil, around 6.3% (IBGE, 2009), which generates an uncertainty regarding the effects of this practice on the farmers' productive performance. The uncertainty lies on the effects of irrigation on technical efficiency among irrigators and rain-fed farmers for different farms sizes, which might respond differently to irrigation adoption as adaptive strategy to climatic variability and regard to irrigation efficiency and effectiveness (Vanschoenwinkel; Van Passel, 2018), being small farmers and poorer populations most affected (Vanderlugt, 2011). Moreover, as farm size increases, the feasibility, implementation, operations and management of irrigation systems may become increasingly complex; this may compromise farmers' performance. However, this is a hypothesis that must be tested. The farm size has been discussed in the literature because of its influence on production, efficiency and productivity (Rada, Helfand and Magalhães, 2019).

Irrigation technology allows the farmer achieve higher yields maintaining the amount of others inputs constant, that is, the capacity to move farmers toward the best practice, known as potential production. This movement toward the efficient frontier is termed as technical efficient improvement. Technical efficiency estimates are often used to design programs for performance improvement, which involve changes to the management (e.g., education and training programs) and structure of the firm, as operating environment (O´Donnell *et al*., 2008).

Despite the fact that most of irrigation projects come from private initiatives, irrigation adoption has received governmental attention regarding the development of projects and provision of credit to rural producers (ANA, 2009). The goal is to adapt to climate variation and increase returns of production and profitability. Technical efficiency difference between irrigators and rain-fed farmers could justify an increase in investments and support by governmental policies to encourage the adoption of irrigation technology, generating economic development of rural Brazil, especially in areas of climatic and socioeconomic vulnerability.

Bravo-Ureta *et al.* (2012) argue that one of the main limitations of the approach adopted to estimate technical efficiency is not to consider the endogenous characteristics of some variables, such as irrigation adoption, since the adoption is an individual choice of the farmer, which can be affected by observable factors (e.g. farm and producer characteristics, such as income, schooling, experience, etc.) and unobservable factors (e.g. farmer managerial capacity). Villano *et al.* (2015) point out that by disregarding these characteristics, the results may be biased, which limits the analysis of the true effect of irrigation adoption on farmer's performance.

Given the lack of studies on agricultural technical efficiency comparing irrigation adopters and non-adopters in Brazil, the objective of this research is to fill in this gap in the literature and identify the effect of irrigation on the technical efficiency of irrigators and rain-fed heterogeneous farmers differentiated by farm size due to complexity of irrigation systems management. In this context, one of the contributions of this research is to mitigate some limitations evidenced in the literature through an empirical strategy that combines the stochastic frontier approach with a method that considers the effects of endogenous sample selection. Thus, this study aims to answer three questions: *Are irrigators more efficient than rain-fed farmers in Brazil? What is the relationship between technical efficiency and farm size for both groups? And for which farm size irrigation adoption generates greater difference in technical efficiency between irrigators and rain-fed farmers?*

Our findings indicate that irrigation technology adoption increase farmers' technical efficiency, which irrigators are 5.3 percentage points more efficient than non-adopters, on average. We found an inverted U-shaped relationship between technical efficiency and farm size for both groups, where *small* farms are more efficient. However, irrigation adoption has a slightly greater effect for *large* farms in terms of technical efficiency.

This research is organized in five sections besides this introduction. In the following section we present a brief literature on technical efficiency and irrigation. The empirical model is presented in Section 3; Empirical application and data source are presented in Section 4. Results are shown in Section 5, and finally, in Section 6 we expose our finals conclusions about the research.

2. Technical Efficiency and Irrigation

Technical efficiency differences between irrigators and rain-fed farmers were assessed in several studies. Anang *et al.* (2017) compared technical efficiency of smallholder irrigated and rain-fed rice farms in Northern Ghana. On average, the irrigators were 9.2% points more efficient than the rain-fed farmers. The authors reinforce the need for investment in irrigation infrastructure as a mechanism to reach poverty reduction and food security.

Babatunde *et al.* (2017) examined the determinants of yield gap and technical efficiency between rain-fed and irrigated rice production in Nigeria. The result showed that irrigated rice producers were around 11% points more technically efficient than rain-fed farmers. Opata *et al.* (2018) also found that irrigators were 38 p.p. more technically efficient than rain-fed farmers in rice production in Nigeria. Mkanthama *et al.* (2018) found a great difference in technical efficiency in rice production in Tanzania, where technical efficiency was 96% for irrigators compared to 39% for rain-fed farmers. Low technical efficiency for rain-fed producers was also found by Makombe *et al.* (2007), where rain-fed farmers' technically efficiency was 6% and for irrigators around 24%.

On the other hand, there are studies that pointed out opposite findings, where rain-fed farmers are more technically efficient than irrigator producers. Gebrehaweria *et al.* (2012) estimated technical efficiency of irrigated and rain-fed smallholder agriculture in Ethiopia. They found that rain-fed were 82% technically efficient, while irrigators were 45%. They also found that access to credit and number of skilled household members reduces the technical inefficiency of irrigated agriculture.

Melesse and Ahmed (2015) compared the technical efficiency between irrigators and rain-fed farmers in potato production in Eastern Ethiopia. Technical efficiency score for rain-fed farmers was 75% and for irrigators 50%, while Tiruneh *et al.* (2017) found an average technical efficiency (TE) of 81% and 68%, respectively. Factors related to schooling, soil condition and seed size affected TE, while the age of the household head positively affected the TE of irrigators, indicating that experience through age matters in production.

Also for Ethiopia, Makombe *et al.* (2017) estimated and compared the levels of production and technical efficiency of different small-scale farmers. The average technical efficiency for the modern irrigated system was 71% and for rain-fed 78%. Vrachioli, Stefanou and Tzouvelekas (2018) found similar findings to Tiruneh *et al.* (2017), but for farmers that had adopted sprinkler irrigation using data covering 56 small-scale greenhouse farms from the island of Crete, Greece. Average technical efficiency to farmers who adopted sprinklers is lower than the group of non-adopters.

These findings highlight that there is no consensus whether irrigation adoption can make farmers more efficient compared to non-adopters. This outcome can be explained by the fact that after the adoption of new technologies, adopters may need more time to learn how to use the technology efficiently. For Brazilian agriculture, to the best of our knowledge, no research measured and compared technical efficiency between irrigators and rain-fed farmers; we only found studies for small specific irrigated areas[5].

3. Empiric Model

Two methodological steps are used to identify the effect of irrigation on farmers' technical efficiency. Due to the possibility of selection bias in irrigation adoption from pre-treatment observable characteristics, the technical efficiency scores comparison between irrigators and rain-fed farmers becomes impracticable.

The decision to irrigate is a farmer optimization problem influenced by their personal characteristics, economic conditions, and climatic factors, among other (Cunha *et al.*, 2015; Vanschoenwinkel; Van Passel, 2018; Watto; Mugera, 2019). Thus, comparison between irrigators and rain-fed producers would result in an overestimation of the technical efficiency due to the self-selection bias (Vrachioli, Stefanou and Tzouvelekas, 2018).

Entropy Balancing method is appropriate to find a group as similar as possible to the group of irrigators to eliminate the bias caused by such observable characteristics. Hence, the strategy consists of estimating the production function using the S*tochastic Frontier Approach (SFA)* for each group considered through the two-stage approach developed by Heckman (1979). The combination of the two approaches allows us to obtain comparable technical efficiency scores between the groups and within the groups (according to the farm size), and also free from biases from observable and unobservable characteristics (Sipiläinen; Lansink, 2005; Freitas, 2017).

Finally, the production stochastic frontier approach developed by Battese and Coelli (1995) allows us to model an equation and explain the factors that influence technical efficiency (or its variability) of the farmers. A similar approach was used by Jiang and Sharp (2015), among others.

3.1. Entropy Balancing

Hainmueller (2012) developed a multivariate method that allows us to weight a data set such that variables distributions in the reweighted observations satisfy a set of special conditions of moments, so that there is an exact equilibrium on the first, second, and larger moments of the distributions of independent variables in both treatment and control groups. In summary, this method allows the researcher to specify a desirable level of equilibrium for the covariates, using a set of conditions associated with the moments of the distribution.

To demonstrate the weighting procedure proposed by Hainmuller (2012), consider a sample with n_1 observations belonging to the treatment group and n_0 control units, which were randomly selected from a population of size N_1 and N_0, respectively ($n_1 \leq N_1$ *e* $n_0 \leq N_0$). Let $D_i \in \{1,0\}$ be a binary treatment variable, where it assume the value equal to 1 if unit i belongs to the treatment group, and 0 otherwise.

[5] For more information see Barros *et al.* (2004); Mariano and Pinheiro (2009); Sousa, Justo and Campos (2013); and Silva *et al.* (2017).

Let X be a matrix containing the observations of J pre-treatment exogenous variables; X_{ij} corresponds to the value of the j-th covariate of unit i, such that $X_i = [X_{i1}, X_{i2}, \ldots, X_{iJ}]$ refers to the characteristic vector of unit i and X_j refers to the column vector with j-th covariates.

The entropy balancing generalizes the propensity score weighting approach by estimating the weights directly from a set of equilibrium constraints that exploit the researcher's knowledge about the sample moments. Consider w_i the weight of the entropy balancing chosen for each control unit, which were found by the following reweighting scheme that minimizes the entropy metric distance:

$$\min_{w_i} H(w) = \sum\nolimits_{\{i|D=0\}} w_i \log{(w_i/q_i)} \tag{1}$$

subject to the equilibrium and the normalization constraints

$$\sum\nolimits_{\{i|D=0\}} w_i c_{ri}(X_i) = m_r \qquad r \in 1, \ldots, R \tag{2}$$

$$\sum\nolimits_{\{i|D=0\}} w_i = 1 \tag{3}$$

$$w_i \geq 0 \; for \; all \; i, such \; that \; D = 0 \tag{4}$$

Where $q_i = 1/n_0$ is a basis weight and $c_{ri}(X_i) = m_r$ describes a set of R imposed constraints on the covariates moments in the reweighted control group. Initially, the covariates are chosen and included in the re-weighting procedure. For each covariate, a set of balancing constraints (Equation 2) is specified to match the covariate distributions moments between treatment groups and re-weighted controls. The moment constraints can be the mean (first moment), the variance (second moment), and the asymmetry (third moment). A typical balancing restriction is formulated such that m_r contains the moment of a specific covariant X_j for the treatment group. The momentum function for the control group is specified as: $c_{ri}(X_{ij}) = X_{ij}^r$ or $c_{ri}(X_{ij}) = (X_{ij} - \mu_j)^r$ with mean μ_j.

Thus, to a set of units, entropy balancing looks for weights $W = [w_i, \ldots, w_{n_0}]'$ which it minimizes Equation 1, where is the entropy distance between W and the weight base vector $Q = [q_i, \ldots, q_{n_0}]'$, subject the balance constraints in Equation 2, normalization constraint (Equation 3), and non-negativity constraint (Equation 4).

The moment restriction applied here refers to the imposition that the first moment. Thus, for all explanatory variables (chosen based on their influence on the irrigation adoption), the method calculates the means in the treatment group and seeks for a set of entropy weights such that the weighted means of the control group are similar. Such weights are used in the next steps to obtain unbiased estimates of selection bias caused by observables factor.

3.2. Sample Selection Model

The existence of sample selection bias due to the fact that there are factors influencing the irrigators and rain-fed producers' technical efficiency that are different from those influencing the probability of adopting irrigation should be verified. The methodological procedure proposed by Heckman (1979) allows us to verify the possible selection bias mentioned. The method consists in two stages, which a binary choice model is estimated in the first stage with the purpose of explaining, through the selection equation, the probability of farmers to adopt irrigation.

In the second stage, the production stochastic frontier for each group (irrigators and rain-fed farmers) is estimated. Thus, the Inverse Mills Ratio (obtained in the first step) is incorporated as a covariate with the purpose of correcting the sample selection bias. We also use the weighting scheme obtained in the

Entropy Balancing to estimate the production function. The existence of the selection bias is confirmed when the Inverse Mills Ratio is statistically significant (GREENE, 2011).

3.2.1. *Selection Equation*

The selection equation proposed by Heckman (1979) is estimated using a *Probit* model, where the likelihood of a farmer to adopt irrigation is explained. Let d_i^* be a binary variable that represents the (unobservable) selection criterion as a function of a vector of exogenous variables z_i. The Probit model can be defined as:

$$d_i = \alpha' z_i + w_i \tag{5}$$

where α is the vector of parameters to be estimated and w_i is the error term distributed as $N(0, \sigma_w^2)$. The latent variable d_i^* is observed and receives the value 1 when $\alpha' z_i + w_i > 0$, and zero otherwise:

$$d_i^* = 1[\alpha' z_i + w_i > 0], \quad w_i \sim N(0,1) \tag{6}$$

3.2.2. *Stochastic Frontier Approach (SFA)*

After weighting the sample using the Entropy Balancing and taking into account the sample selectivity bias due to the irrigation adoption decision, the production function and then technical efficiency scores is estimated by the Production Stochastic Frontier Approach (SFA).

The SFA has been widely used in studies of crop efficiency and productivity due to random factors involved in production that cannot be neglected (Battese, 1992; Coelli, 1995; Bravo-Ureta et al., 2007), as well as factors which influence the production technical efficiency.

We follow Battese and Coelli (1995) approach to specify the stochastic frontier that simultaneously models the technical inefficiency, which can be specified as:

$$Y_i = f(X_i \beta) e^{(v_i - u_i)} \tag{7}$$

where Y_i represents the production value of the *i-th* farm ($i = 1, \dots, N$); X_i is a vector $(1\ x\ k)$ of inputs and other explanatory variables associated with the production of the i-th farm; β is a vector $(k\ x\ 1)$ of unknown parameters to be estimated; v_i represents the random error term that captures shocks that are out of producer control (climate, pests and diseases, measurement errors, etc.), which is assumed to be independent and identically distributed (iid) $N(0, \sigma_v^2)$ and; u_i are non-negative random variables associated to technical inefficiency of production, i.e., it is the part that constitutes a downward deviation with respect to the production frontier (best practice), which are assumed to be independently distributed, where it is obtained by truncation (at zero) of a normal distribution with mean $z_i\delta$ and variance σ^2, such that $N(z_i\delta, \sigma_u^2)$.

Thus, the equation expressed by (7) specifies the stochastic frontier production function in terms of original production values. Following the specification of Battese and Coelli (1995), the term that explains the technical inefficiency of production, u_i, can be represented by:

$$u_i = z_i \delta + w_i \tag{8}$$

where z_i is a vector $(1\ x\ m)$ of explanatory variables associated with the technical inefficiency of the *i-th* productive unit[6]; δ is a vector $(m\ x\ 1)$ of unknown coefficients and; w_i are random errors defined by the truncation[7] of a normal distribution with mean zero and variance σ^2. We assume a half-normal distribution of the error term u_i. This equation can be modeled by specifying that inefficiency component is heterocedastic, which the variance expressed as a function of the covariates defined in z_i.

[6] This unilateral term may follow the half-normal, truncated normal, exponential and gamma distribution.
[7] The truncation point of w_i is $(-z_i\delta)$, that is, $w_i \geq -z_i$

Battese and Coelli (1995) argue that is necessary to define the functional form of the stochastic frontier. Several functional forms can be used in productive analyzes, such as the Translog and Cobb-Douglas production functions. Translog frontier is more likely to be susceptible to multicolinearity even if it is more flexible (Thiam *et al.*, 2001). The last one presents constant returns to scale, unit elasticity of substitution and its coefficients directly represent the output elasticity of inputs (Tegegne, Tadesse and Zemedu (2014). As a result of its simplicity, the Cobb-Douglas functional form is estimated in this research for irrigators and rain-fed farmers.

Once the stochastic production frontier is estimated, the technical efficiency scores are obtained following Battese and Coelli (1988) specification, which this efficiency measure is based on the conditional expectation of u_i, given the random error. The separation of the frontier deviations into their random components and inefficiency can be defined as the ratio between the observed and the potential output:

$$ET_{ij} = \frac{Y_{ij}}{Y_{ij}^*} = \frac{Y_{ij}}{f(X_{ij})} = \frac{\exp\left(X_{ij}\beta + v_{ij}\right) E[\exp\,(-u_{ij})|e]}{\exp\left(X_{ij}\beta + v_{ij}\right)} = E\left[\exp\left(-u_{ij}\right)|e\right] \tag{9}$$

where the value of ET_{ij} will be in the range [0; 1], where zero represents complete inefficiency and 1, full efficiency.

4. Empirical Application and Data Source

As discussed before, we use Entropy Balancing Method to obtain the weights for the control groups. Thus, we estimate the selection equation using a *Probit* as described in Equation (6):

$$\begin{aligned} d_i^* = {} & \alpha_0 + \alpha_1 gender + \alpha_2 age + \alpha_3 age^2 + \alpha_4 schooling + \alpha_5 experience + \alpha_6 tv \\ & + \alpha_7 phone + \alpha_8 internet + \alpha_9 energy + \alpha_{10} farm.status + \alpha_{11} urban \\ & + \alpha_{12} qualif + \alpha_{13} ag.family + \alpha_{14} priv.exten + \alpha_{15} gov.exten + \alpha_{16} coop \\ & + \alpha_{17} financ + \alpha_{18} vl.financ + \alpha_{19} vl.invest + \alpha_{20} ag.pract + \alpha_{21} chem \\ & + \alpha_{22} fert + \alpha_{23} soilph + \alpha_{24} water + \alpha_{25} deg.land + \alpha_{26} vl.land \\ & + \alpha_{27} summer.prec + \alpha_{28} winter.prec + \alpha_{29} summer.temp \\ & + \alpha_{30} winter.temp + \alpha_{31} var.temp + \alpha_{32} var.prec \\ & + \varepsilon_i \end{aligned} \tag{10}$$

All those variables specified in Equation (10) are described later. We use a Cobb-Douglas production function weighted by the vectors of weights obtained by Entropy Balancing and we included the Inverse Mills Ratio (*Mills)*. The Mills was obtained by the estimation of Equation (10). We also use some controls to estimate the production function, as dummies for each Brazilian state; climatic variables and its interactions with Brazilian macro-regions; and dummies related to farm size. Thus, the Cobb-Douglas functional form following Battese and Coelli (1995) can be specified as:

$$ln\, Y_i = \beta_0 + \sum_{k=1}^{N} \beta_k ln\, X_{ki} + \sum_{n=1}^{N} \beta_n ln\, C_{ni} + \sum_{n=1}^{N}\sum_{r=1}^{5} \beta_{nr} lnC_{ni} R_r + \rho Mills + \sum_{h=1}^{26} FS_h + \sum_{g=1}^{4} G_g + v_i - u_i \tag{11}$$

where Y_i represents the gross value of the production of farm *i*; X_{ki} is a vector of inputs *k* used in production, which are: land, labor, capital, and purchased inputs (expenses); C_n represents the climatic variables; R_r represents the dummies for the five Brazilian regions; FS_h represents dummies for federative states; and G_g represents dummies for the four farm size considered. Such dummies were included to capture fixed effects and to control spatial autocorrelation. The production function was clustered by the Brazilian municipalities. The climatic variables are considered as non-market inputs, that is, they are not found in the market, and therefore, according to Hughes *et al.* (2011), the production function can be termed as "*climate adjusted production frontier*". Finally, the selection bias hypothesis is verified by evaluating the statistical significance of parameter ρ. The error term v_i is due to random factor and u_i is due to inefficiency

The production technical inefficiency term u_i (Equation 8) specified by Battese and Coelli (1995) is modeled by a set of covariates already recurrent in the literature with the purpose to explain inefficiency variability, being specified as follows:

$$u_i = \delta_0 + \delta_1 schooling + \delta_2 experience + \delta_3 rural.extension + \delta_4 financing + w_i \qquad (11)$$

where *schooling* refers to the manager's education level and it is divided into 7 categories (higher education as base category); *experience* refers to manager's experience into four categories (over 10 years of experience as base category); *rural.extension* is a dummy variable that receives value 1 if the producer accessed any type of technical assistance; *financing* is a dummy variable that receives value 1 if the producer received any type of financing; and w_i is the random error term which it is assumed to be a half normal distribution. In the case of rural extensions services and financing, the results imply a correlation on technical efficiency scores due those services are a farmers' decision and may be endogenous.

The dataset used in the present research comes from the 2006 Agricultural Census microdata (farm level), which only can be accessed in the Brazilian Institute of Geography and Statistics (IBGE) headquarter in Rio de Janeiro, Brazil. The dataset contains information for more than 5 millions of farmers.

To adequate the dataset for this research, is necessary to perform some treatment in the dataset, such as the exclusion of farms without area declaration (255,019 observations); farms settled in the urban area (192,350 observations); and farms classified as special sectors - favelas, barracks, lodgings, boats, indigenous villages, nursing homes, etc. (117,530 observations). We also excluded farms belonging to rural settlements (139,496 observations) to avoid possible variables measurement errors.

In addition, we only have included those farms owned by an individual producer, i.e., we excluded those farmers which were considered condominium, consortium or partnership, cooperative, public limited company or by quotas of limited liability, public utility institutions, government (Federal, state or municipal) or other condition (190,838 observations). Likewise, farms which producer type is "not identified" (20,440 observations) were excluded. After the exclusion and transformations, 915,673 observations were deleted (17.7% of the original sample), and the final sample is composed of 4,259,963 farms.

The dataset were also organized into four classes according to the farm size (very small, small, medium and large). The sizes were classified by IBGE according to the fiscal module classes[8]. Furthermore, the database generation procedure was performed by the SAS® software, and the methodological procedures were performed using the STATA® software.

The treatment variable, that is, the indicative of the use of irrigation, is a dichotomous variable and represents the answer to the following question: "Did you use irrigation in the farm?". After the database treatments, 6.22% of the farmers declared to have used irrigation technology in the farm.

In addition to economic variables, we also use socioeconomics, institutions, agronomics and climatic characteristics in both entropy balancing and selection equation. All these variables were provided by 2006 Agricultural Census, except those related to climate. Variables used in the sample selection (Equation 10) are described as follow: The variable *gender* is a dummy variable equals 1 if the farm's manager is male and 0 otherwise; *age* is the manager's age; *schooling* is a categorical variable related to the farm manager's education level: do not read and write, literate, incomplete elementary school, complete elementary school, agricultural technician, high school and higher education (base); *experience* is a categorical variable that represents the years in which the manager is in the farm header activity: up to one year, between 1 and 5 years, between 5 and 10 years, over 10 years (base). We also included

[8] Fiscal module classification is defined as the minimum area required for rural properties to be considered economic viable, ranging in area from 5 to 110 hectares. Based on the fiscal module, the farms can be classified into: very small (less than 1 fiscal module); small (between 1 and 4 fiscal module); medium (between 4 and 15 fiscal module); and large (more than 15 fiscal module). (Landau *et al*., 2012).

information on some resources as *tv* (television), *phone*, *internet* and *energy*, which are dummies variables that receive value equal 1 if the farmer has the resource, and 0 otherwise.

Other characteristics as farm ownership, whether the farmer lives in urban area or not, the presence of skilled labor in the farm workforce and family farm classification may influence irrigation technology adoption. We explore the farm ownership (*farm.status*) by including a categorical variable: Owner (base), tenant, partner and occupant. *Urban* is a dummy set with value 1 if the farm's manager lives in an urban zone and zero otherwise; *qualif* is a dummy that capture the presence of skilled labor with value equal 1 and 0 otherwise; and *ag.family* is a dummy related to family farm classification[9] which is equal 1 and 0 otherwise.

We consider that the access to services and financing play an important role on the likelihood of irrigation adoption. In this sense, we capture access to services by including dummies set with values equal 1 if the farmer had received private extension services (*priv.exten*), governmental extension services (*gov.exten*), and if they were co-ops membership (*coops*). *Financ* is a dummy that represents the access to any type of financial resource (rural credit); *vl.financ* is the total amount supplied by the financial institution and; *vl.invest* is the total amount invested in the farm.

We added some variables to capture agronomic characteristic and natural resources endowment on the likelihood of irrigation adoption: *Ag.pract* is a dummy equals 1 that indicates if the farmer uses any agricultural practice[10], and 0 otherwise; *chem, fert* and *soilph* are dummies that inform if the farmer used chemicals, fertilizers and/or have corrected the soil pH, respectively. These dummies received values 1 in an affirmative case, and zero otherwise. To capture natural resources endowment we set a dummy equal 1 if the farm has any water resource[11] (*water*), and zero otherwise. Furthermore, we also included the amount of total land degraded (*deg.land*) in hectares and the value of the land (*vl.land*) in R$ of 2006.

Climatic variables are summer precipitation (*summer.prec*) and winter precipitation (*winter.prec*) in millimeters; and summer temperature (*summer.temp*) and winter temperature (*winter.temp*) in Celsius degree. These variables were averaged by municipality for 2006[12]. We also have included the variance of both temperature (*var.temp*) and precipitation (*var.prec*). Data was obtained from the Terrestrial Hydrology Research Group (Civil and Environmental Engineering Department of Princeton University)[13].

We use in the production function the gross value of production in 2006 (GVP) as a proxy to the output (dependent variable). As inputs, we use land, labor, expenses and capital. *Land* is the sum of the farm area designed to crops and pastures (in hectares), except irrigated land; *Labor* is the sum of both family and hired labor; *Expenses* are the sum of purchased inputs (R$ of 2006) as energy, soil correctives, fertilizers, agrochemicals, animal medicines, transportation, packages, seeds and seedlings, and feed/salt; *Capital* is the sum of buildings, land and vehicles (R$ of 2006).

5. Results

5.1. Descriptive Analysis and Entropy Balancing

The descriptive statistics of the variables used are displayed in Table 1, which also shows the result of the Entropy Balancing. Table 2 in Appendix A shows the remaining descriptive statistics of the variables

[9] Classified according to Law 11.326 of 07/24/2006.

[10] Refers to practices such as: planting in a level curve; terraces; crop rotation; use of crops for pasture recovery; fallow or rest of the soil; burned; and protection of slopes

[11] Refers to resources such as: rivers or streams; natural lakes or dams; and wells/cisterns.

[12] To use climatic variables at the farm level, it would be necessary to obtain the longitude and latitude of the farm, which violates the confidentiality of the dataset provided by IBGE. In this sense, the assumption adopted in this research is that the climatic variables at the municipal level fit a good approximation for those that would be observed within the farm.

[13] Available on: http://hydrology.princeton.edu/data/pgf/1.0deg/monthly/ . Data are measured in "pixels" and were transformed in "averages" by Agricultural Engineering Department at Federal University of Viçosa, Brazil.

used in the selection equation. In general, farmers that use irrigation have higher levels of schooling, reaching 4.5% on higher education when compared to rain-fed farmers, 2.5%.

As can be observed in Table 1, irrigators have a higher share of electricity and the workforce with skilled labor. Regarding the age, experience and farm ownership, there are no disparities on averages between the groups.

Although the large proportion of irrigators with water resources in the farm, around 87%, we also can observe a large proportion of farmers that have water resources into the farm and do not use irrigation technology (74.2%). This result may be related to the low proportion of rain-fed farmers that received rural extension (mainly governmental extension) and accessed financial resources when compared to irrigators (Table 2 – Appendix A). However, we should consider that irrigation is not needed when farmers are facing some regularity in precipitation as observed in some regions of Brazil[14].

We also can observe in Table 2 (Appendix A) significant differences in the proportion of irrigators that performed some agricultural practice (e.g. crop rotation) and irrigators that used agrochemicals, fertilizers and soil pH correctives, which imply that these farmers had used irrigation technology with some soil management seeking to ensure crops' yield. Thus, the value of the land (asset) of the irrigators is greater than rain-fed farmers due the technology embodiment (Schoengold and Ziberman, 2007) and this result also can be observed in Table 2.

The great difference between the groups can be observed in the gross value of production obtained in 2006 by the irrigators' farmers, which is almost two times higher when compared to rain-fed producers. This result shows the importance of irrigation in national agricultural production in terms of value produced and, therefore, productivity gains from irrigation, which demonstrates the advantages of this technology. The value of land, buildings and vehicles (*proxy* for capital), expenses in purchased inputs and labor have a higher average for irrigators when compared to the rain-fed. On the other hand, there are no significant differences in the amount of land employed in crops and pastures, which reinforce productivity gains due to irrigation.

Table 1 – Mean of the variables used in the Entropy Balancing, Selection Equation and Stochastic Production Frontier

	Non Balanced Sample		Balanced Sample	
Variables	**Rain-Fed (Control)**	**Irrigators**	**Rain-Fed (Control)**	**Irrigators**
Gender	0.876	0.912***	0.912	0.912ns
Age	50.36	49.32***	49.32	49.32ns
Total Area	62.91	60.50***	60.50	60.50ns
Read and write	0.096	0.084***	0.084	0.084ns
Do not read and write	0.252	0.151***	0.151	0.151ns
Literate	0.054	0.038***	0.038	0.038ns
Incomplete elementary	0.424	0.458***	0.458	0.458ns
Complete Elementary	0.081	0.112***	0.112	0.112 ns
Agric. Technician	0.012	0.022***	0.022	0.022 ns
High School	0.057	0.090***	0.090	0.090 ns
Higher Education	0.025	0.045***	0.045	0.045 ns
Exp_1	0.026	0.019***	-	-
Exp_1to5	0.166	0.162***	0.162	0.162 ns
Exp_5to10	0.169	0.165***	0.165	0.165 ns
Exp_10	0.639	0.654***	0.654	0.654 ns
Energy	0.684	0.876***	0.876	0.876 ns
Qualif.	0.037	0.075***	0.075	0.075 ns

[14] Table 1 show that rain-fed farmers had faced a slightly average precipitation higher than irrigators in both winter and summer seasons.

Water Resource	0.742	0.868***	0.868	0.868 ns
Owner	0.838	0.852***	0.852	0.852 ns
Tenant	0.046	0.053***	0.053	0.053 ns
Partner	0.028	0.027***	-	-
Occupant	0.087	0.067***	0.067	0.067 ns
Summer precipitation	4.418	4.099***	4.099	4.099 ns
Summer temperature	25.77	25.62***	25.62	25.62 ns
Winter precipitation	1.574	1.271***	1.271	1.271 ns
Winter temperature	22.06	21.63***	21.63	21.63 ns
Precipitation variance	2.645	2.470***	2.470	2.470 ns
Temperature variance	1.880	1.918***	1.918	1.918 ns
GVP	23,436.65	67,133.37	-	-
Labor	2.65	3.55	-	-
Land	42.21	42.60	-	-
Capital	185,815.50	269,614.00	-	-
Purchased Inputs	7,802.84	18,751.76	-	-
N° Obs.	3,994,735	265,228	3,994,735	265,228

Source: Research results
Norte: ***Means are statistically different from the control group (rain-fed) at 1%; NS – Means are statistically the same as in the control group at 1%

The result of the Entropy Balancing, which is based on the mean of the covariates (first moment of the sample), can be observed in the column "Balanced sample" in Table 1. Before the Entropy Balancing the means of the variables between irrigators and rain-fed farmers were statistically different. After the Entropy Balancing, we did not find any statistically significant difference between these groups. This balance is confirmed by the non-significance of null hypothesis of the test of equality of means (Table 1). It implies that, for each treatment group there is a similar control, differing only for irrigation adoption.

5.2. Production Elasticities

We estimated the stochastic production frontier for the total sample and for both irrigators and rain-fed farmers. The parameters of the Cobb-Douglas function were obtained by the Maximum Likelihood. Therefore, the estimated coefficients represents itself the production elasticities[15]. Results are shown in Table 4.

Wald statistic indicates a good fit of the model, rejecting the null hypothesis of joint insignificance of the variables for the three estimated models at 1%. The hypothesis of sample selection bias related to irrigation adoption was statistically confirmed by the significance of the estimated coefficients for the Inverse Mills Ratio for both irrigators and rain-fed farmers, which imply that there are unobservable factors that influence the irrigation adoption decision.

In summary, we found that water resources endowment in the farm are capable of increasing the likelihood of irrigation adoption, since the decision to irrigate is straightforward related to the availability of this resource in the farm. The use of agrochemicals, soil pH correction and soil fertilization contributed positively to the probability of irrigation technology adoption. Nonetheless, these inputs were the ones that most influenced the probability of adopting irrigation, including the electricity endowment.

The estimated model for the Brazilian agriculture (pooled) indicates that *purchased inputs* and the *labor* most contributed to the formation of the gross value of production (GVP) in 2006, indicating that an increase in 10% in the amount used of these factors would lead to an increase, on average, of 3.72% and 3.55% in GVP, respectively. Similar results were found in Freitas (2017) and Rada *et al.* (2019). On the

[15] For a better visualization, we omitted the parameters of the climatic variables and its interactions with dummies of region; and also the parameters of the Federative states dummies and farm size dummies.

other hand, *land* and *capital* were the factors that contributed less to the GVP, since an increase in 10% in these inputs would lead to an increase, on average, in 2.06% and 0.6% in GVP, respectively.

Regarding the production elasticities related to irrigators and rain-fed farmers, there were significant differences in the contribution of each input to the GVP formation. For the irrigators, we observed the same pattern found for the *pooled* model, since the *purchased inputs* and *labor* were the inputs that most contributed, on average, to GVP formation.

Table 4 – Estimation of Stochastic Production Frontier for the total sample, irrigators and rain-fed farmers, 2006.

Ly(GVP)	**Total Sample (Pooled)**	**Irrigators**	**Rain-Fed**
lx1 (Land)	0.206***	0.225***	0.285***
	(0.010)	(0.015)	(0.006)
lx2 (Labor)	0.355***	0.265***	0.358***
	(0.008)	(0.011)	(0.007)
lx3 (Purchased Inputs)	0.372***	0.326***	0.250***
	(0.005)	(0.008)	(0.004)
lx4 (Capital)	0.0621***	0.0277*	0.0773***
	(0.011)	(0.016)	(0.004)
Mills Irrigators	-	2.936***	-
	-	(0.193)	-
Mills Rain-Fed	-	-	2.481***
	-	-	(0.050)
Constant	-6.640	6.609	1.367
	(9.467)	(15.19)	(9.451)
Inefficiency (Usigma)			
Read and write	-0.741***	-0.545***	-0.846***
	(0.0239)	(0.0482)	(0.0177)
Do not read and write	-0.753***	-0.527***	-0.926***
	(0.0248)	(0.0495)	(0.0175)
Literate	-0.438***	-0.218***	-0.567***
	(0.0336)	(0.0739)	(0.0220)
Incomplete Elementary	-0.738***	-0.635***	-0.784***
	(0.0192)	(0.0409)	(0.0133)
Complete Elementary	-0.541***	-0.510***	-0.532***
	(0.0189)	(0.0421)	(0.0136)
Agricultural Technician	-0.0879***	-0.201***	-0.0711***
	(0.0233)	(0.0491)	(0.0186)
High School	-0.327***	-0.326***	-0.302***
	(0.0165)	(0.0383)	(0.0119)
exp_1	0.876***	1.049***	0.823***
	(0.0207)	(0.0433)	(0.0131)
exp_1to5	0.355***	0.461***	0.326***
	(0.0128)	(0.0267)	(0.00894)
exp_5to10	0.210***	0.245***	0.203***
	(0.0115)	(0.0287)	(0.00722)
Technical Assistance	-0.398***	-0.161***	-0.371***
	(0.0222)	(0.0417)	(0.0138)
Financing	-0.710***	-0.556***	-0.811***
	(0.0148)	(0.0253)	(0.0111)
Constant	2.997***	2.412***	3.240***
	(0.0202)	(0.0421)	(0.0144)
Vsigma	0.0725***	0.0655*	0.00655

	(0.0232)	(0.0342)	(0.0147)
E(Sigma_u)	3.1365	2.5668	3.3891
Sigma_v	1.0369***	1.0332***	1.0032***
	(0.0120)	(0.0176)	(0.0073)
Lambda (λ)	0.751	0.713	0.771
Log Likelihood	-9.047e+06	-530508	-8.732e+06
Wald Test	46782.45	21973.13	95822.59
Chi^2	46782***	21973***	95823***
N° Obs.	4,259,963	265,228	3,994,734

Source: Research results.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1

On the other hand, *labor* and *land* are the factors that most contributed to an increase of GVP for rain-fed farmers. This result can be explained in part by the lack of knowledge of the irrigation benefits and productive techniques, or constrains in the credit market, which become the new technologies adoption more difficult. Thus, the only alternative for these farmers increase their production is through increments of productive land and workforce. However, Ullah and Perret (2014) points out that labor-intensive farming system can be a source of employment for rural populations.

The variance of the model was re-parameterized according to Battese and Coelli (1995), such that $\sigma_s^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u^2/\sigma_s^2$. The value of λ is between zero and the unity. If λ is close to zero, it implies that deviations from production frontier are entirely due to random noise, while a value around the unity indicates that most of the deviations are due to inefficiency. Thus, for the *pooled* model, we can inferred that 75.1% of the deviations to the efficient frontier come from technical inefficiency sources; for irrigators, 71.3%, and for rain-fed farmers is 77.1%. This result may be a signal that irrigators are more efficient than rain-fed farmers. This result also indicates that the Stochastic Production Frontier approach is suitable, since λ were equal to zero, the production function could be estimated by Ordinary Least Squares (OLS).

Table 4 also shows the result for inefficiency equation. We modeled this equation which the error term (inefficiency) variance is a function of a covariates vector. If a variable tends to decrease the inefficiency variance, it implies that the observations are close to the efficiency average level. For all models, we can infer that farmers' schooling levels in the lower bound decrease the variance when compared to farmers that have higher education (base). On the other hand, low levels of experience are associated with an increase in the inefficiency variance when compared to those who have more than 10 years of farm's management. This result implies that higher education is not enough to increase efficiency, but it can be observed once farmer has high level of experience. Tiruneh *et al.* (2017) found that experience through age matters in production.

Genius *et al.* (2014) suggest that the high levels of experience linked to a technology transmission channel, such as technical assistance services and social network, may be more important in new technologies adoption in irrigation than education levels. Although this study did not consider technical efficiency, they argued that technical assistance and social learning through experience could help them in this task. In addition, Speelman *et al.* (2008) found that education did not significantly affect technical efficiency, while Watto and Mugera (2019) argued that in relation to education effects on technical efficiency, researchers should consider the relevance of a farmer's education to his farming business.

We also found that any type of access to technical assistance and financing (credit) influences farmers to reach the efficiency average level since this factors decrease inefficiency variance. The findings of Karagiannis *et al.* (2003), Haji (2007), Freitas (2017) and Watto and Mugera (2019) also confirm the positive effect of financial resources and extension services in improving farmer's technical efficiency.

Notwithstanding, our result can be evaluated through descriptive statistics in Table 1, which only 2.5% of rain-fed and 4.5% of irrigators has higher education level, while 67.6% (rain-fed) and 60.9% (irrigators) do not read and write or did not complete elementary school. On the other hand, 63.8% (rain-fed) and 65.3% (irrigators) have more than 10 years of experience in farm management. Moreover, Table

2 (Appendix A) shows that 12.3% and 8.4% of rain-fed farmers had access to private and governmental technical assistance, respectively. Better result can be observed to irrigators, where 18.5% and 17% of them had access to private and public assistance respectively, which corroborate with Foster and Rosenzweig (1995; 2010) and Genius *et al.* (2014) on the role of social learning, learning-by-doing and extension services (mainly governmental assistance) in irrigation technology adoption and efficiency improvements.

5.3. Technical Efficiency Scores

The unbiased technical efficiency scores (TE) were obtained for all models estimated and classified by farm size. Table 6 shows the result. We found that average technical efficiency of the irrigators was 29.68%, whereas for those who are rain-fed were 24.38%, which imply that irrigators are technically more efficient than rain-fed at 5.3 percentage points. These results imply that irrigation technology adoption is capable to move farms to the best practice, that is, the potential production. However, there is a lot of room for both irrigators and rain-fed farmers to increase production maintaining the same amount of inputs.

Table 6 – Mean of technical efficiency scores by farm size, 2006.

Balanced Sample	Mean	Very Small	Small	Medium	Large
	0.2321	**0.2271**	**0.2512**	**0.2451**	**0.2363**
Total Sample (Pooled)	(0.1777)	(0.1784)	(0.1722)	(0.1786)	(0.1834)
	[4,259,963]	[3,283,982]	[694,133]	[208,886]	[72,962]
	0.2968	**0.2914**	**0.3156**	**0.3064**	**0.3018**
Irrigators	(0.1701)	(0.1743)	(0.1539)	(0.1609)	(0.1656)
	[265,228]	[196,082]	[47,999]	[15,337]	[5,810]
	0.2438	**0.2426**	**0.2513**	**0.2423**	**0.2370**
Rain-Fed	(0.1831)	(0.1843)	(0.1770)	(0.1827)	(0.1898)
	[3,994,734]	[3,087,900]	[646,134]	[193,549]	[67,151]

Source: Research results.
Note: Standard deviations in ( ); Number of observations in [ ]

The values of the standard deviations for both irrigators and rain-fed (0.1701 and 0.1831, respectively) suggest that, in relation to the mean, there is a great dispersion of the data, i.e., there is a great heterogeneity in terms of technical efficiency, which leads to a low average of TE. To confirm this result, TE distributions are shown in Figure 3 - Appendix A for both groups. We also observed a great number of farmers that had non-positive value of production, but they had used some amount of inputs, which may be explained in part for losses in production due to climate anomaly or diseases involved in the production process, which decrease TE scores. Estimates of technical efficiency scores for those farmers only with positive production make the TE scores double.

We found for all models estimated that technical efficiency (TE) scores by farm size, on average, increase from the *very small* to *small* farmers. Then, we observed that average TE scores decrease as the farm size increases. Therefore, we conclude that *small* farmers are the most technically efficient, which imply they are those that transform productive factors into gross production value more efficiently and corroborates with Schutz (1965), who argued that small farmers are poor but efficient.

A test of equality of means (t-test) between both groups irrigators and rain-fed farmers and within each group taking into account the farm size was performed to verify if the technical efficiency mean scores were different from each other or were statistically the same. Table 7 shows the result, which indicated that all the means of technical efficiency between and within the groups were statistically different, except for the *very small* and *medium* rain-fed farmers. Between irrigators and rain-fed, the difference is -0.0530 and t-test is equal to $-1.4e^{+02}$, which imply the rejection of the null hypothesis of equality of means.

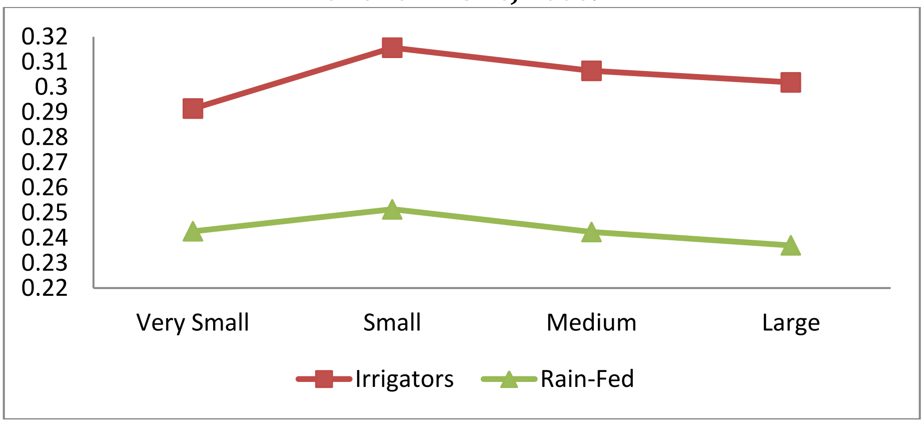
Table 7 – Test of equality of means (t-test) of the technical efficiency scores, 2006

	Total Sample		Irrigators		Rain-Fed	
	Diff.	t-test	Diff.	t-test	Diff.	t-test
Very Small x Small	-0.0240^{***} (0.0002)	$-1.00e^{+02}$	-0.0242^{***} (0.0008)	-27.9396	-0.0087^{***} (0.0002)	-34.8358
Very Small x Medium	-0.0179^{***} (0.0004)	-44.6916	-0.0150^{***} (0.0014)	-10.3639	0.0003 (0.0004)	0.7666
Very Small x Large	-0.0092^{***} (0.0006)	-13.7773	-0.0104^{***} (0.0023)	-4.4997	0.0055^{***} (0.0007)	7.7009
Small x Medium	0.0060^{***} (0.0004)	14.0369	0.0091^{***} (0.0014)	6.3671	0.0090^{***} (0.0004)	19.5948
Small x Large	0.0148^{***} (0.0006)	22.0482	0.0138^{***} (0.0021)	6.414	0.0142^{***} (0.0007)	19.7338
Medium x Large	0.0087^{***} (0.0007)	11.3608	0.0046^{*} (0.0024)	1.8562	0.0052^{***} (0.0008)	6.3029

Source: Research results. Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1; Standard Deviations in ( ); Diff means the difference of technical efficiency average.

We display the behavior of technical efficiency and farm size in Figure 1. The greatest difference in terms of average TE between both irrigators and rain-fed was for *large* farmers, which irrigators in this size are 6.48 p.p. more efficient than non-adopters, which imply that, although *small* farmers are, on average, more efficient than the others, the irrigation technology adoption has a stronger effect on TE for the *large* farmers. The smallest difference in TE due to irrigation adoption was found for the *very small* farms, around 4.9 p.p.. Helfand and Levine (2004) pointed out that large farms can have preferential access to institutions and services that help reduce inefficiency such as rural electricity, technical assistance, and market access; and more intensive use of technologies and inputs that increase productivity, for instance, irrigation technology.

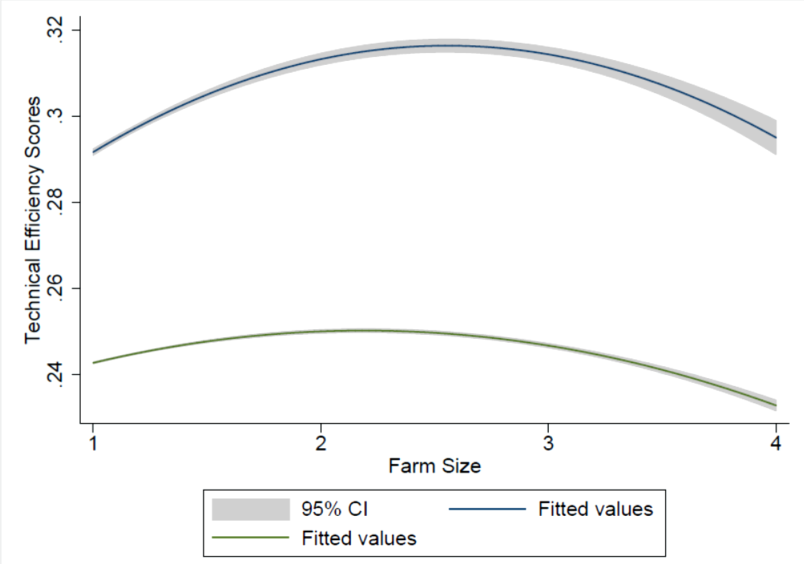
Figure 1 – Average technical efficiency scores by irrigation adoption and farm size, 2006.



Source: Research results

Figure 2 shows the behavior between technical efficiency scores and farm size as a smoothed shape of this relationship. The blue line is related to irrigators and green line is related to rain-fed farmers. We found a U-inverted relationship between farm size and technical efficiency. Similar behavior between technical efficiency (or technical efficiency change) and farm size were found in Helfand and Levine (2004), and Freitas (2017) and Rada *et al.* (2019). They also found the highest efficiency for small farms.

Figure 2 – Smoothed shape of average technical efficiency scores and farm size, 2006.



Source: Research results

6. Conclusions

Irrigated agriculture in Brazil is an effective tool to alleviate poverty and improve income distribution, generating employment at lower costs than those in other sectors of the economy, which increase food supply at lower prices than those produced in non-irrigated areas and significant increase in productivity of land and labor factors.

In this sense, the present research aimed to identify the effect of irrigation technology adoption on the productive performance of farmers, in terms of technical efficiency. The analysis also extended to different farm sizes. Dataset at farm level of 2006 Agricultural Census were accessed in the Restricted Access Room (SAR) of the Brazilian Institute of Geography and Statistics - IBGE.

Regarding the technical efficiency, both irrigators and rain-fed had a low level of technical efficiency, where irrigators are more efficient than rain-fed farmers in 5.3 percentage points, on average. The analysis by farm size showed that, in both groups, the small farmers are more efficient than the others. However, the greatest difference observed in efficiency scores between irrigators and non-adopters was for large farms, which imply that irrigation technology has a significant effect on the efficiency gain for this group.

The outline of public policies to encourage irrigation adoption can be led, initially, to the effective provision of rural extension services and the increase in skilled workforce in the farm, and projects that promote rural electrification and the existence of water resources, since these factors contributed to the increase of irrigation technology adoption. Nevertheless, electricity and water resources are, in general, prerequisites for the implementation of irrigation systems. The role of public policies also relies on rural technical assistance provision and credit market access due the importance of these factors to increasing efficiency.

Irrigation revealed itself capable of making farmers more efficient, which shows the effectiveness of the technology. However, greater investments in public policy on irrigated agriculture are suggested with special attention to very small producers, 77% of the total, which irrigation adoption had less impact in technical efficiency, which is related to farmers' managerial skills. To achieve improvements in rural development, better management of governmental credit and investment programs are also essential in those tasks.

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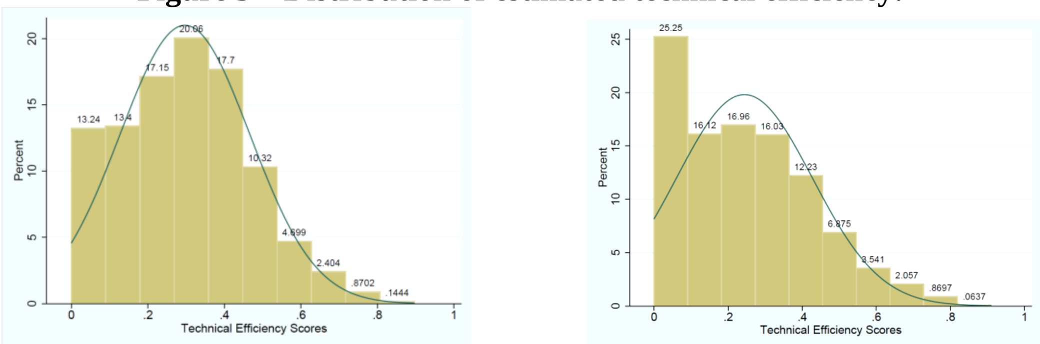
APPENDIX A

Table 2 – Mean and standard deviation of the remaining variables used in the Selection Equation

	Rain-Fed		Irrigators	
Variables	**Mean**	**S.D**	**Mean**	**S.D**
Private Extension	0.123	0.3289	0.185	0.3883
Governmental Extension	0.084	0.2775	0.169	0.3753
Co-op membership	0.408	0.4915	0.443	0.4967
Financing	0.180	0.3848	0.229	0.4205
Financing Value	2,461.06	97,390.58	7029.5	214215.2
Total Investment	3,040.83	151,273.4	7035.85	254216.1
Urban	0.133	0.34	0.146	0.3531
Agr. Practice	0.58	0.4934	0.699	0.4586
Agrochemicals	0.259	0.4381	0.573	0.4945
Soil pH	0.068	0.252	0.236	0.425
Fertilizers	0.313	0.464	0.745	0.4357
Degraded Land	0.146	9.1689	0.229	17.1221
Value of Land	154,337	1,495,851	197,115	1,887,837
Agr. Family	0.852	0.3547	0.778	0.415
N° Obs.	3,994,735		265,228	

Source: Research results

Figure 3 – Distribution of estimated technical efficiency:



(a) Irrigators (b) Rain-fed

Source: Research results