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Irrigation, Technical Efficiency, and Farm Size: The Case of Brazil

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Abstract: In developing countries, irrigation can help to decrease poverty in rural areas through increased employment in the agricultural sector. Evidence shows that irrigation may increase farm productivity and technical efficiency. In this paper, we estimate the effect of irrigation on farm technical efficiency in Brazil using the 2006 Agricultural Census dataset on more than 4 million farms. We estimate a stochastic production frontier at farm level, considering potential selection bias in irrigation adoption. We find that farms using irrigation are on average 2.51% more technically efficient compared to rain-fed farms. Our findings also suggest that while small farms are more efficient than medium and large farms, the largest difference in technical efficiency between rain-fed and irrigated farms is among large farms. Our results indicate that policies that seek to support expansion of irrigation adoption has also the potential to achieve greater rural development given the estimated effects estimated in this paper among very small and small farms, which are more than 70% of the farms in Brazil.

Keywords: irrigation; entropy balancing; stochastic production frontier; technical efficiency

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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 [1]. The implementation of irrigation systems by farms in Brazil can potentially raise the standard of living of rural population by reducing poverty and increasing food security.

The adoption of irrigation systems is an important technology that can lead to increases in agricultural productivity [2]. 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 [3]. Irrigation adoption can be used as a tool to reduce dependency on variable rainfall and water availability [4], decreasing the uncertainty surrounding crop yields and securing income and employment in the rural areas [5].

Several studies analyzed the irrigation adoption as an adaptive strategy under climate change scenarios in Brazil and find that adoption is also driven by climate change and used as a response to the precipitation reduction [1,6]. Although the use of irrigation is not uniform across Brazilian regions, it is expected to increase in the next 30 years given that irrigation is used as an adaptive strategy [7,8] and the agricultural sector is the sector most affected by climate change [9].

Irrigation systems are increasingly becoming more efficient in relation to water usage [10,11]. The actual debate about water scarcity supports studies that are testing the ability of irrigation systems to alleviate water scarcity, which can also provide useful information to policymakers [12]. As argued by [13], 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 [14,15].

Irrigation can generate higher yields holding other inputs constant. Adoption of irrigation has also the potential to improve technical efficiency, the movement toward the efficient frontier. Estimates of technical efficiency 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 the operating environment [16]. Technical inefficiency indicates how far a farm is from the efficient frontier. In other words, it indicates the level of output that could be achieved using the same level of inputs [17,18]. There are a few studies that focus in the estimation of water efficiency such as [13]. It is important to state that the concept of technical efficiency is quite different from the concept of irrigation efficiency, which is termed as the ratio between the amounts of water actually used by the crop and the total amount applied [13,19,20].

Increases in technical efficiency are achieved with the appropriate combination of inputs used in the production process, reducing unnecessary amounts of resources to achieve the same level of production. This is in line with the 2th UN Sustainable Development Goal, which conceptualizes the end of hunger, the achievement of food security and improved nutrition, and the promotion of sustainable agriculture by 2030 [21]. It also indicates that by 2030, agricultural productivity may double, as well as the incomes of small scale-food producers, in particular family farmers and other vulnerable people in rural areas. Resilient agricultural practices that increase productivity and production, that strengthen capacity for adaptation to climate change, extreme weather, droughts, among others, are part of this Goal [21]. Their agenda also highlight the importance of rural infrastructure, agricultural research, extension services, and technology development to enhance agricultural productive capacity in developing countries [21]. The adoption of irrigation can also contribute to the achievement of these goals by reducing poverty and ensuring food production in areas of climatic vulnerability. In this paper, despite all the benefits listed above, only 6.3% of the farmers use irrigation in Brazil in 2006 [22]. However, there has been considerable growth in the use of this technology. Aggregate data from the 2017 Agricultural Census indicates that the number of farms that used irrigation increased by 52.6% compared to the 2006 Agricultural Census, while t area irrigated grew approximately 47.6% [23]. In 2017, more than 500,000 farmers used irrigation in 6.7 million hectares [23]. In 2006, most of the agricultural areas in Brazil were irrigated using conventional sprinkler (35%), followed by flooding (24%) and central pivot (19%) [22]. Additionally, localized irrigation (drip and micro-sprinkler) accounted for only 8% of the area irrigated. In comparison, in2017 conventional sprinkler remained the most widespread method (27.21%), followed by flooding (21.02%) and central pivot (20.78%) [23]. The 2017 Ag. Census provide disaggregated information on localized irrigation - drip and micro-sprinkler irrigation represented 15.04% and 8.95% of the areas irrigated respectively [23]. The remaining were irrigated by furrows (1.3%) and other methods (5.25%) [23]. Trifonov et al. [24] argue that drip and micro-sprinkler irrigation exert less pressure on water resources and achieve greater irrigation efficiency compared to other methods, providing an ideal amount of water and fertilizer in the root zone of the plant. Brazilian farmers have been increasingly adopting the most efficient irrigation methods, aiming at the rational use of water. However, there is still room for improvement moving away from flooding to more efficient irrigation methods, i.e., “on-demand”, such as drip irrigation.

Despite the growth in adoption rates and area irrigated in Brazil during the period 2006–2017, the still low adoption rate generates doubts about its effect on the productive performance among farmers. The effect of irrigation on technical efficiency among irrigators and rain-fed farmers might be different, even across different farms sizes. These farmers deal with climatic variability differently, having different adoption behavior [25]. 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. There is a vast literature that discuss the relationship between farm size and production, efficiency, and productivity such as [26], paper discussed in the Section 3.2.

In Brazil, even though most of irrigation projects are financed by private initiatives, the government has indirectly covered irrigation projects through the provision of credit to rural producers [27]. One of the goals is to adapt to climate variation and increase production and profitability. The measurement of the difference on technical efficiency between irrigators and rain-fed farmers could also provide support for an increase in investments and support by governmental policies to encourage the adoption of irrigation technology.

There is a vast literature on farm technical efficiency estimation [28–31]. Simple comparison of technical efficiency estimates from two set of samples, for example, irrigators and rain-fed farmers, can lead to bias results because of the potential endogeneity issue associated with the characteristics determining irrigation adoption [28]. The adoption is a choice made by the farmer and is 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. [31] 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. The objective of this paper is two-fold: fill the gap in the literature on technical efficiency estimation for Brazilian farms considering irrigation as a key variable; and identify the effect of irrigation on the technical efficiency of irrigators and rain-fed heterogeneous farmers by farm size. To do so we use a simple approach that consider the effect of observable and unobservable when estimating the effect of irrigation on farm technical efficiency. We use farm level data from 2006 Agricultural Census, a database with almost 5 million farms in Brazil.

This paper is organized in four sections besides this introduction. In the following subsection, we present a brief literature on technical efficiency and irrigation. The materials and methods are presented in Section 2; Results are shown in Section 3, and, finally, in Section 4, we present our final conclusions about the research.

Background

The difference in technical efficiency between irrigators and rain-fed farmers has been widely studied. In this section we will review some of these papers. Anang et al. [32] compared technical efficiency of irrigated and rain-fed rice farms in Northern Ghana and found that, on average, farms using irrigation were 9.2% more efficient than the rain-fed farms. They reinforce the need for investment in irrigation infrastructure as a mechanism to reach poverty reduction and food security. Babatunde et al. [33] examined the determinants of yield gap and technical efficiency between rain-fed and irrigated rice production in Nigeria, and found that irrigated rice producers were 11% more technically efficient than rain-fed farmers. Opata et al. [34] also found that irrigators were 38% more technically efficient than rain-fed farmers in rice production in Nigeria. Mkanthama et al. [35] 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. Lower technical efficiency for rain-fed producers was also found by Makombe et al. [36], where rain-fed farmers' technically efficiency was 6% and for irrigators around 24%.

On the other hand, there are studies that found an opposite effect, where rain-fed farmers are more technically efficient than irrigators producers [36–39]. Cobrehaweria et al. [37] estimated technical efficiency of irrigated and rain-fed smallholder agriculture in Ethiopia and 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 [38] compared the technical efficiency between irrigators and rain-fed farmers in potato production in Eastern Ethiopia and found that rain-fed farmers were 75% technically efficient while irrigators were 50% [39] found an average technical efficiency (TE) of 81% and 68% when examining the same product in the same country.

They found that schooling, soil condition, and seed size affected positively TE. They also found that 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. [40] found that the average technical efficiency for the small-scale irrigated farmers was 71% and for rain-fed farmers was 78%. Vrachioli et al. [41] found for 56 small-scale greenhouse farms from the island of Crete, Greece an average technical efficiency lower for farmers that adopted sprinklers compared to non-irrigators.

Also relevant to our analysis is the literature that investigate the determinants of technical efficiency such as the factors that affect the technical efficiency level of irrigators and rain-fed farmers. Adhikari et al. [42] found that variety type and irrigation have a positive effect on the technical efficiency of potato production, where irrigators are 10% more efficient than rain-fed producers in Nepal. The authors reinforce that farmers could increase the technical efficiency level with better use of available resources, the use of improved varieties, and irrigation as well.

Adelodun et al. [43] compared farm level of four major crop production systems under the irrigation scheme in Nigeria. The estimated technical efficiency was up 40%. A similar study for smallholders in Ghana was carried out [44], which found an average technical efficiency of 78.1%. The latter studies investigated the determinants of technical efficiency and found that education, experience, credit accessibility, off-farm income, extension services, among other factors, positively affect the technical efficiency level.

Yusuf.et al. [45] estimated technical efficiency in rain-fed rice production for Nigeria and found that farmers' average technical efficiency was 74.2%. They find that farming experience; efforts to acquire more knowledge and skills; adequate extension services, and governmental support in training youths in the agriculture field would improve the technical efficiency of the farmers.

These papers indicate that there is no consensus whether irrigation can lead to more technically efficient farmers compared to non-irrigators. To the best of our knowledge, it is lacking in the literature a paper that performs a study in large scale of Brazilian farms that estimate and compared technical efficiency between irrigators and rain-fed farmers. There are a few studies that have investigated only small and specific irrigated areas [46–48].

2. Materials and Methods

Two methodological approaches 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, a simple comparison of the technical efficiency scores between irrigators and rain-fed farmers may be biased. The decision to irrigate is a farmer optimization problem influenced by their personal characteristics, economic conditions, and climatic factors, among others [6,25,49]. Thus, comparison between irrigators and rain-fed producers would result in an overestimation of the technical efficiency due to the self-selection bias [41].

The 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 Stochastic Frontier Approach (SFA) for each group considered through the two-stage approach developed by Heckman et al. [50]. 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 controls the biases from observable and unobservable characteristics [29,51].

Finally, the production stochastic frontier approach described by Battese and Coelli [52] allows us to model an equation to explain the factors that influence technical efficiency (or its variability) of the farmers, which has been widely used to explain efficiencies' determinants [33,37,39,42,53].

2.1. Entropy Balancing

Hainmueller [54] developed a multivariate method that allows us to weight a data set such that variables' distributions in the reweighted sample satisfies a set of special conditions of moments, so that there is an exact equilibrium on the first (mean), second (variance), and third (asymmetry) moments of the distributions of covariates 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, 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 assumes a value equal to 1 if unit i belongs to the treatment group, and 0, otherwise. 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

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

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

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

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. 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 of the first moment. Thus, for all covariates (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 the observables factor.

2.2. 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 [50] allows us to verify the possible selection bias mentioned. The method consists of two stages, in 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 [55].

2.2.1. Selection Equation

The selection equation proposed by [50] 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:

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

2.2.2. 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 [56,57], as well as factors which influence the production technical efficiency.

We follow the approach in [52] 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 output of the *i-th* farm $(i = 1, \ldots, N)$; 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 with technical inefficiency of production, i.e., it is the part that constitutes a downward deviation with respect to the production frontier (best practice), which is assumed to be independently distributed with a half normal distribution with mean zero and variance σ^2, such that $N(0, \sigma_u^2)$.

Thus, the equation expressed by (7) specifies the stochastic frontier production function in terms of original production values. Following the specification described in [58], the term that explains the technical inefficiency of production, u_i, can be represented by:

$$u_i = \exp(z'_i\delta)e_i, \tag{8}$$

where z_i is a vector $(1\ x\ m)$ of explanatory variables associated with the technical inefficiency of the *i-th* productive unit. δ is a vector $(m\ x\ 1)$ of unknown coefficients and; e_i are random errors defined by the half normal distribution with mean zero and variance σ^2.

This equation can be modeled by specifying that inefficiency component is heterocedastic, which the variance is expressed as a function of the covariates defined in z_i.

Moreover, it is necessary to define the functional form of the stochastic frontier [52]. Several functional forms can be used in productive analyses, 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 [59]. The last one presents constant returns to scale, unit elasticity of substitution, and its coefficients directly represent the output elasticity of inputs [60]. The Likelihood Ratio Test (LR Test) may be conducted to test the model specification of the stochastic production frontier. The null hypothesis of the LR Test is that all the interactions and second order terms regarding Translog specification equal zero [52].

Once the stochastic production frontier is estimated, the technical efficiency scores are obtained following [61] specification, and 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:

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

where values of ET_{ij} equal to zero represents complete inefficiency, and 1 represents full efficiency [61].

2.3. 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):

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

All of the variables specified in Equation (10) are described later. We use a production function weighted by the vectors of weights obtained by Entropy Balancing, and we included the Inverse Mills Ratio (Mills), which was obtained by the estimation of Equation (10). We also use some controls to estimate the production function: indicators variables for each Brazilian Federative Units (States); climatic variables and its interactions with Brazilian macro-regions indicators; and variables related to farm size. A Cobb–Douglas functional form can be specified as:

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

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 variables for the five Brazilian regions; FS_h represents indicators variables for Federative Units (States); and G_g represents variables for the four farm sizes considered. Such variables were included to capture fixed effects and to control spatial autocorrelation; and standard errors were clustered at the municipality level. The climatic variables are considered as non-market inputs, i.e., they are not found in the market, and therefore, the production function can be termed as "climate adjusted production frontier" [62]. 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 technical inefficiency

The production technical inefficiency term u_i (Equation (8)) specified [57] is modeled by a set of covariates already recurrent in the literature with the purpose to explain the inefficiency variability, being specified as follows:

$$u_i = \delta_0 + \delta_1 \text{schooling} + \ \delta_2 \text{experience} + \ \delta_3 \text{rural.extension} + \delta_4 \text{financing} + w_i \qquad (12)$$

where schooling refers to the manager's education level, and it is divided into seven 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 variable that receives value 1 if the producer accessed any type of technical assistance; financing is a variable that receives value 1 if the producer received any type of financing; and w_i is the random error term, which 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 to those services being a farmers' decision and possibly being endogenous.

The dataset used in the present research comes from the 2006 Agricultural and Livestock Census at farm level, which only can be accessed in the Brazilian Institute of Geography and Statistics (IBGE) headquarters in Rio de Janeiro, Brazil. Even though the most recent Agricultural Census was released in 2017, the data at the farm level is classified and have not yet made available to researchers in time to update this research, and will not be available until the Covid-19 pandemic stops. For this reason, we use the 2006 Agricultural Census in this paper. The dataset contains information on more than 5 million farmers. The aggregation of the production value across crops is driven mainly by the fact that we do not have farm-level data on the hectares irrigated by crops, while we do have data on total hectares irrigated for all crops. In addition, the Brazilian Agricultural Census does not provide data on production value or quantity produced disaggregated by irrigation systems used by the producers, which makes it impossible to analyze technical efficiency by irrigation method. Therefore, our analysis is restricted to information on whether the farmer use irrigation technology in the production process or not.

To obtain the dataset used in the estimation we dropped farms that have not report any area (255,019 observations); that are in urban areas (192,350 observations); and 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 variable measurement errors.

In addition, we only have included those farms owned by an individual producer, i.e., we excluded those farmers that 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 (190,911 observations). Likewise, farms whose producer type is "not identified" (20,440 observations) were excluded. After the exclusion and transformations, 915,746 observations were deleted (17.7% of the original sample), and the final sample is composed of 4,259,865 farms.

The dataset was also organized into four classes according to the farm size (very small, small, medium, and large). The sizes were classified by the IBGE according to the fiscal module classes. 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, farms are classified as 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) [63]. The data manipulation was performed using SAS® software, and the methodological procedures were performed using 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?" In our sample, 6.22% of the farmers reported using irrigation in the farm.

In addition to economic variables, we also use socioeconomics, institutions, agronomics, and climatic characteristics in both entropy balancing and selection equations. All of these variables were provided by the 2006 Agricultural and Livestock Census, except those related to climate. Variables used in the sample selection (Equation (10)) are described as follows: The variable gender is a variable that 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 information on some resources as tv (television), phone, internet, and energy, which are variables that receive a value equal to 1 if the farmer has the resource, and 0 otherwise.

Other characteristics such 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 variable set with value 1 if the farm's manager lives in an urban zone and zero otherwise; qualify is a dummy that captures the presence of skilled labor with value equal to 1 and 0 otherwise; and ag.family is a variable indicating if the farm is a family farm based on the classification reported in the Law 11.326 of 07/24/2006.

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 variables with values equal to 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).

We added some variables to capture agronomic characteristic and natural resources endowment on the likelihood of irrigation adoption: Ag.pract is a variable equal to 1 that indicates if the farmer uses any agricultural practice (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 and 0 otherwise; chem, fert, and soilph are variables that inform if the farmer used chemicals, fertilizers and/or have corrected the soil pH, respectively. These variables received a value of 1 in an affirmative case, and zero otherwise. To capture natural resources endowment, we set a variable equal to 1 if the farm has any water resource (rivers or streams; natural lakes or dams; and wells/cisterns), and zero otherwise. Furthermore, we also included the value of the land (vl.land) in US$ from 2006.

Climatic variables are cumulative precipitation (in millimeters) segregated by summer (summer.prec) and winter (winter.prec); and summer temperature (summer.temp) and winter temperature (winter.temp) in degrees Celsius for the period of 2003–2006, which were averaged by municipality. 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. We also have included both temperature and precipitation standard deviation by season as a proxy to intra-annual climatic anomaly. Climatic Dataset was obtained from the Climate Research Unit—CRU/University of East Anglia [64]. As our analysis in this research uses a cross-sectional dataset in the production function, we assume that the climatic dataset for three years before (2003–2005) the production process and, for the current year (2006), is sufficient enough to help farmers decide to use irrigation or not.

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); Labor is the sum of both family and hired labor; Expenses are the sum of purchased inputs (US$ 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 (US$ of 2006).

3. Results and Discussion

3.1. 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. In general, farmers that use irrigation have higher levels of schooling, (4.5% with higher education compared to 2.5% among rain-fed farmers). As can be observed, 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.

Despite the large proportion of irrigators with water resources in the farm, around 87%, we also observe a large proportion of farmers that have water resources in 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 1). However, irrigation may not be needed when farmers are facing regularity in precipitation as observed in some regions of Brazil.

We also can observe 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 may imply that these farmers had used irrigation technology with some soil management seeking to ensure crops' yield. This might also explain why the value of the land (asset) of the irrigators is greater than rain-fed farmers, in other words, due the technology embodiment [65].

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. However, this result can also be explained in part by the effect of scale economies that irrigation could provide, mainly for large farms, given that they have more resources to access the latest technology, they are more educated, and they have facilities to access the credit market and rural services extension. Economies of scale are achieved when the increase in production results in a decrease in the product average cost. However, our results do not provide any information about scale efficiency. However, rural development policies should not take into account the effects of economies of scale to invest and provide adequate support to expand irrigation, otherwise it could benefit only large producers, which would break, with the UN Sustainable Development Goals.

Finally, 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.

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.

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	0.912 ns
Age	50.36	49.32 ***	49.32	49.32 ns
Read and write	0.096	0.084 ***	0.084	0.084 ns
Do not read and write	0.252	0.151 ***	0.151	0.151 ns
Literate	0.054	0.038 ***	0.038	0.038 ns
Incomplete elementary	0.424	0.458 ***	0.458	0.458 ns
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 ***	0.09	0.090 ns
Higher Education	0.025	0.045 ***	-	-
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
Private Extension	0.123	0.185 ***	0.185	0.185 ns
Governmental Extension	0.084	0.170 ***	0.170	0.170 ns
Co-op Membership	0.409	0.443 ***	0.443	0.443 ns
Television	0.198	0.240 ***	0.240	0.240 ns
Telephone	0.230	0.401 ***	0.401	0.401 ns
Internet	0.011	0.030 ***	0.030	0.030 ns
Energy	0.684	0.876***	0.876	0.876 ns
Financing	0.181	0.230 ***	0.230	0.230 ns
Qualification	0.037	0.075***	0.075	0.075 ns
Urban	0.133	0.146 ***	0.146	0.146 ns
Agr. Practice	0.581	0.699 ***	0.699	0.699 ns
Water Resource	0.742	0.868 ***	0.868	0.868 ns
Agrochemicals	0.259	0.573 ***	0.573	0.573 ns
Soil pH	0.068	0.237 ***	0.237	0.237 ns
Fertilizers	0.314	0.745 ***	0.745	0.745 ns
Value of Land	71,784.18	91,683.00 ***	91,683.00	91,683.00 ns
Agr. Family	0.852	0.779 ***	0.778	0.778 ns
Owner	0.838	0.852 ***	0.852	0.852 ns
Tenant	0.046	0.534 ***	-	-
Partner	0.028	0.278 ***	0.278	0.278 ns
Occupant	0.087	0.665 ***	0.665	0.665 ns
Summer precipitation	161.01	162.69 ***	162.69	162.69 ns
Winter precipitation	53.07	43.02 ***	43.02	43.02 ns
Summer temperature	25.7	25.43 ***	25.43	25.43 ns
Winter temperature	21.87	21.38 ***	21.38	21.38 ns
Summer Prec. S. Dev.	81.23	82.96 ***	82.96	82.96 ns
Winter Prec. S. Dev.	30.37	25.14 ***	25.14	25.14 ns
Summer Temp. S. Dev.	0.718	0.812 ***	0.812	0.812 ns
Winter Temp. S. Dev.	0.790	0.797 ***	0.797	0.797 ns
GVP	10,900.92	31,225.24	-	-
Labor	2.65	3.55	-	-
Land	42.21	42.6	-	-
Capital	86,426.93	125,403.53	-	-
Purchased Inputs	3629.29	8721.85	-	-
N° Obs.	3,994,641	265,224	3,994,641	265,224

Source: Research results. Note: ***: 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%.

3.2. Production Elasticities

We estimated the stochastic production frontier for the total sample and for both irrigators and rain-fed farmers. The parameters of the production function were obtained by the Maximum Likelihood. The null hypothesis of the LR Test is not rejected at a high level of statistical significance for three production functions (Pooled, Irrigators, and Rain-Fed), which means that Cobb–Douglas specification presents more adequacy to represent the production technology than Translog specification. Results are shown in Table 2. Therefore, the coefficients estimated represent the production elasticities, except for climatic variables. For a better visualization, we omitted the parameters of climatic variables and its interactions with the indicator variables of Brazilian regions; parameters of the Federative Units (states); and parameters of farm size dummy variables.

Table 2. Functional form specification test—LR test.

	Cobb–Douglas	Translog	X^2 Statistic	X^2 0.99 Value	Decision	Choice
Pooled	-8.613×10^6	-8.521×10^6	-0.02147	67.357 (*df* = 36)	Acept H_0	CD
Irrigators	-5.308×10^5	-5.250×10^5	-0.02197		Acept H_0	CD
Rain-Fed	-8.055×10^6	-7.981×10^6	-0.01845		Acept H_0	CD

Source: Research results. Note: CD is Cobb–Douglas production function assuming half normal distribution for the inefficiency effects.

The results for the production function are displayed in Table 3. 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 increase the likelihood of irrigation adoption, since the decision to irrigate is correlated to the availability of this resource in the farm. Results of the selection equation using Probit are shown in Table A1—Appendix A. In addition, the use of agrochemicals, soil pH correction, and soil fertilization contributed positively to the probability of irrigation technology adoption.

The estimated model for the Brazilian agriculture (pooled) indicates that purchased inputs and labor have the highest elasticities, indicating that a 10% increase in the amount of these factors used would lead to an increase, on average, of 3.85% and 2.84% in gross value of production (GVP), respectively. Similar results were found in [26,29].

Our results indicate that the production elasticities are different for irrigators and rain-fed farmers. For the irrigators, we observed the same pattern found for the *pooled* model, since the purchased inputs and labor have the highest values. On the other hand, purchased inputs and land are the factors with the highest production elasticities for rain-fed farmers. This result may be explained in part by the lack of knowledge of the irrigation benefits and productive techniques, or constraints in the credit market, which make the adoption of new technology more difficult. Thus, the only alternative for these farmers to increase their production is through increments of expenses and workforce. However, Ullah and Perret [66] point 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) [52], 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 unity indicates that most of the deviations are due to inefficiency. Thus, for the pooled model, we can infer that 73.4% of the deviations from the efficient frontier come from technical inefficiency sources; for irrigators, 71.3%, and for rain-fed farmers, 75.4%. This result may be an indicator that irrigators are more efficient than rain-fed farmers.

Table 3. 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)	0.215 ***	0.221 ***	0.278 ***
	(0.00999)	(0.0154)	(0.00694)
lx2 (Labor)	0.284 ***	0.264 ***	0.268 ***
	(0.00738)	(0.0111)	(0.00657)
lx3 (Purchased Inputs)	0.385 ***	0.335 ***	0.333 ***
	(0.00639)	(0.00899)	(0.00530)
lx4 (Capital)	0.0575 ***	0.0291 *	0.0722 ***
	(0.0115)	(0.0171)	(0.00472)
Mills Irrigators	-	2.548 ***	-
	-	(0.2016)	-
Mills Rain-Fed	-	-	1.149 ***
	-	-	(0.0605)
Constant	3.915	16.29	−8.469
	(7.6080)	(12.1063)	(8.6966)
Inefficiency (Usigma)			
Read and write	−0.625 ***	−0.543 ***	−0.742 ***
	(0.0281)	(0.0483)	(0.0261)
Do not read and write	−0.609 ***	−0.516 ***	−0.785 ***
	(0.0281)	(0.0487)	(0.0250)
Literate	−0.313 ***	−0.218 ***	−0.442 ***
	(0.0409)	(0.0740)	(0.0340)
Incomplete Elementary	−0.681 ***	−0.638 ***	−0.746 ***
	(0.0232)	(0.0407)	(0.0224)
Complete Elementary	−0.522 ***	−0.514 ***	−0.529 ***
	(0.0236)	(0.0413)	(0.0242)
Agricultural Technician	−0.155 ***	−0.200 ***	−0.124 ***
	(0.0297)	(0.0490)	(0.0345)
High School	−0.327 ***	−0.328 ***	−0.317 ***
	(0.0213)	(0.0379)	(0.0230)
exp_1	1.008 ***	1.046 ***	0.990 ***
	(0.0249)	(0.0433)	(0.0238)
exp_1to5	0.453 ***	0.456 ***	0.460 ***
	(0.0149)	(0.0267)	(0.0141)
exp_5to10	0.238 ***	0.242 ***	0.237 ***
	(0.0146)	(0.0285)	(0.0124)
Technical Assistance	−0.261 ***	−0.170 ***	−0.282 ***
	(0.0222)	(0.0417)	(0.0167)
Financing	−0.591 ***	−0.557 ***	−0.639 ***
	(0.0153)	(0.0253)	(0.0152)
Constant	2.606 ***	2.419 ***	2.753 ***
	(0.0245)	(0.0422)	(0.0237)
Vsigma	0.00500	0.0680 **	−0.148 ***
	(0.0250)	(0.0347)	(0.0192)
E(Sigma_u)	2.775	2.5696	2.8501
Sigma_v	1.0025 ***	1.0346 ***	0.9284 ***
	(0.0125)	(0.0179)	(0.0088)
Lambda (λ)	0.734	0.713	0.754
Log-Likelihood	-8.613×10^6	−530,808	-8.055×10^6
Wald Test	42,683.85	22,400.31	64,020.64
Chi2	42,684 ***	22,400 ***	64,021 ***
N° Obs.	4,259,865	265,224	3,994,641

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

Table 3 also shows the result for inefficiency equation. A negative sign indicates that the variable decreases the inefficiency variance. For all models, we can infer that farmers' schooling levels has this effect 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 a farmer has a high level of experience. Tiruneh et al. [39] found that experience through age matters in production.

High levels of experience linked to a technology transmission channel, such as technical assistance services and social network, may be more important in new technology adoption in irrigation than education levels [67]. Although this study [67] 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. [68] found that education did not significantly affect technical efficiency, while Watto and Mugera [49] 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) affect the farm technical efficiency. The findings of [29,49,69,70] also confirm the positive effect of financial resources and extension services in improving the farmer's technical efficiency.

Notwithstanding, our result can be evaluated through descriptive statistics in Table 1, in which only 2.5% of rain-fed and 4.5% of irrigators have a 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, 12.3% and 8.4% of rain-fed farmers had access to private and governmental technical assistance, respectively. Among irrigators, 18.5% and 17% of them had access to private and public assistance, respectively, which corroborate with [67,71,72] on the role of social learning, learning-by-doing, and extension services (mainly governmental assistance) in irrigation technology adoption and efficiency improvements.

3.3. Technical Efficiency

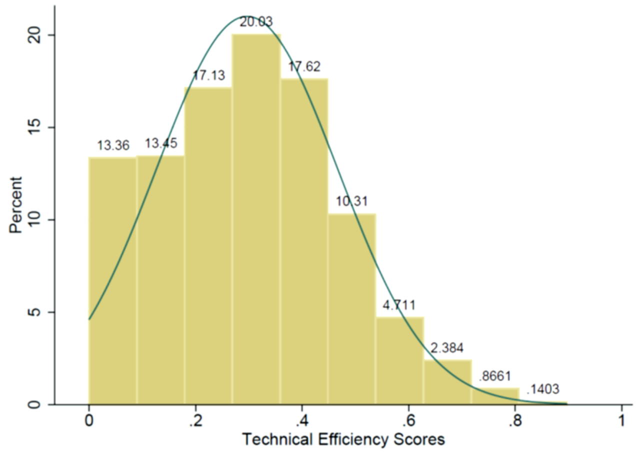
The technical efficiency scores (TE) were obtained for all models estimated and classified by farm size. Table 4 shows the results. We found that average technical efficiency of the irrigators was 29.65%, whereas for those who are rain-fed were 27.14%. These results imply that irrigation has the potential of increasing technical efficiency. However, there is room for both irrigators and rain-fed farmers to increase production while maintaining the same amount of inputs.

Table 4. Mean of technical efficiency scores by farm size, 2006.

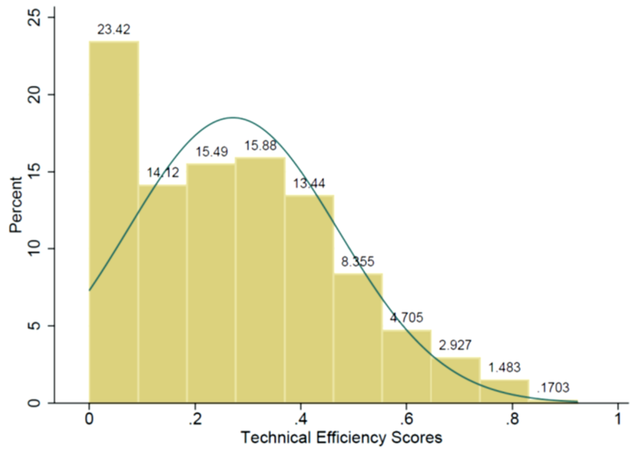
Balanced Sample	Mean	Very Small	Small	Medium	Large
Total Sample (Pooled)	**0.2730** (0.1974) {4,259,865}	**0.2439** (0.1865) {3,283,910}	**0.2629** (0.1776) {694,116}	**0.2528** (0.1825) {208,881}	**0.2408** (0.1862) {72,959}
Irrigators	**0.2965** (0.1702) {265,224}	**0.2909** (0.1744) {196,078}	**0.3155** (0.1540) {47,999}	**0.3063** (0.1609) {15,337}	**0.3019** (0.1655) {5810}
Rain-Fed	**0.2714** (0.1990) {3,994,642}	**0.2721** (0.2014) {3,087,832}	**0.2740** (0.1891) {646,117}	**0.2602** (0.1935) {193,544}	**0.2474** (0.1976) {67,149}

Source: Research results. Note: Standard deviations in (); Number of observations in {}.

The values of the standard deviations for both irrigators and rain-fed (0.1702 and 0.1990, respectively) suggest that, in relation to the mean, there is a great dispersion of the data, i.e., a great heterogeneity in terms of technical efficiency, which leads to a low average of TE. As argued by [73], using the same data, 66% of Brazilian farms produce about 3% of the production value, of which the majority operate with net income. Such farms are likely to be located at the low part of the distribution of efficiency scores. This pattern is hardly observed when we use more aggregated data (e.g., at the municipality level), since such farms are geographically dispersed. To confirm this result, TE distributions are shown in Figure 1 for both groups.



(**a**)



(**b**)

Figure 1. Distribution of estimated technical efficiency. (**a**) Irrigators; (**b**) Rain-fed. Source: Research results.

We found for all models estimated that technical efficiency (TE) scores by farm size, on average, increase between very small and small farms. Then, the average TE scores decrease as farm size increases. Therefore, small farmers are the more technically efficient, which corroborate [74] argument that small farmers are poor but efficient.

A simple test of equality of means (Student *t*-test) between both group irrigators and rain-fed farmers and within each group taking into account that the farm size was performed to verify if the technical efficiency mean scores were different from each other or were statistically the same. Table 5 shows the result. We found that the all differences of all the technical efficiency means between and within the groups were statistically significant. Between irrigators and rain-fed, the difference is 0.02509, and the Student *t*-test is equal to −63.3885, which implies the rejection of the null hypothesis of equality of means.

We display the behavior of technical efficiency and farm size in Figure 2. The greatest difference in terms of average TE between irrigators and rain-fed is for large farms, following by the group of mediums. We found a difference between irrigators and rain-fed farms of 5.45% for the former and of 4.61% for the latter. It implies that, although small farmers are, on average, more efficient than the others, irrigation has a stronger effect on TE for among large farms. The smallest difference in TE due to irrigation adoption was found for the very small farms, around 1.88%. This last result may be partly explained by the lack of knowledge on how to operate the technology, difficulties faced in the credit market, and/or the lack of extension services. [30] pointed out that large farms can have easier access to institutions and services that help reduce inefficiency such as rural electricity, technical assistance, and market access; and more intensive in the use of technologies and inputs that increase productivity, for instance, irrigation technology.

Table 5. Test of equality of means (Student *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	−0.0190 *** (0.0002)	−77.7469	−0.0245 *** (0.0008)	−28.2470	−0.0019 *** (0.0002)	−7.1581
Very Small x Medium	−0.0088 *** (0.0004)	−21.1575	−0.0154 *** (0.0014)	−10.5884	0.0118 *** (0.0004)	25.1434
Very Small x Large	0.0030 *** (0.0006)	4.3718	−0.0109 *** (0.0023)	−4.7174	0.0246 *** (0.0007)	31.4414
Small x Medium	0.0101 *** (0.0004)	22.6568	0.0091 *** (0.0014)	6.3279	0.0137 *** (0.0004)	27.9911
Small x Large	0.0220 *** (0.0006)	31.7548	0.0136 *** (0.0021)	6.3062	0.0266 *** (0.0007)	34.5956
Medium x Large	0.0119 *** (0.0007)	15.1403	0.0044 * (0.0024)	1.7862	0.0128 *** (0.0008)	14.7484

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

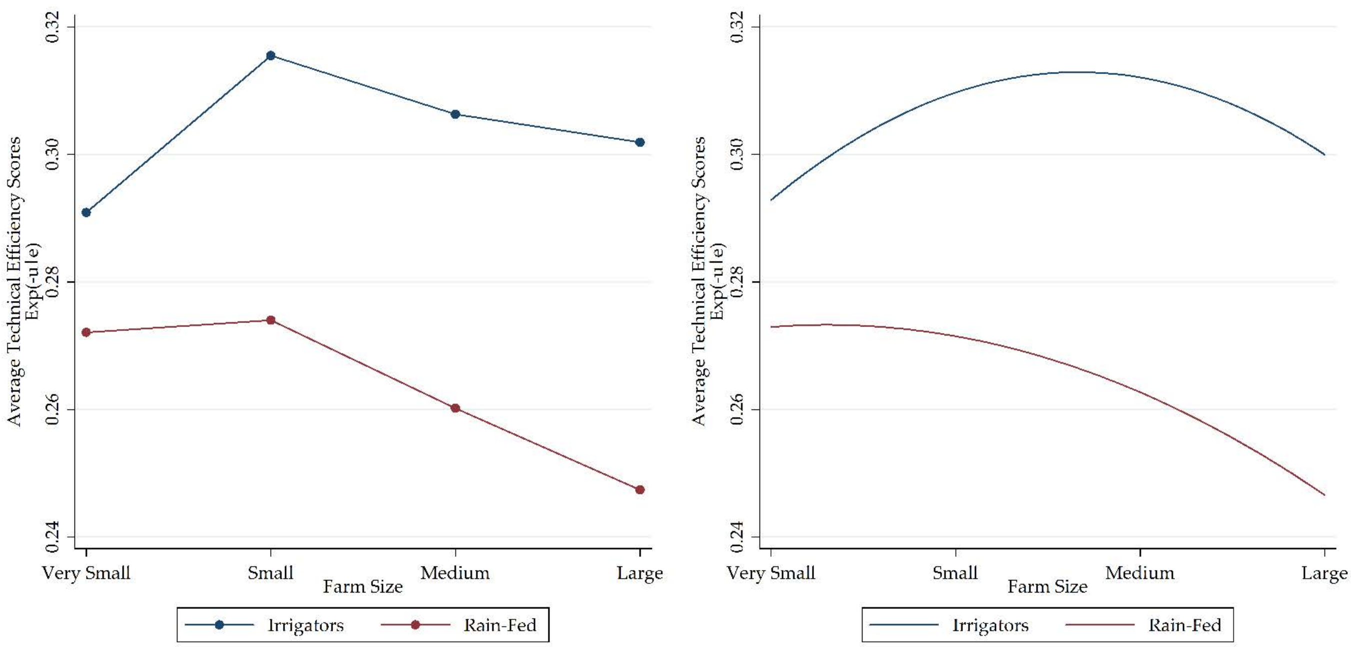


Figure 2. Average technical efficiency scores by irrigation adoption and farm size, 2006. Source: Research results.

Figure 2 also shows the behavior between technical efficiency scores and farm size as a smoothed shape of this relationship (quadratic prediction). We found a U-inverted relationship between farm size and technical efficiency level. Similar behavior between technical efficiency (or technical efficiency change) and farm size were found in [26,29,30]. They also found the highest efficiency for small farms. These results indicate that the greatest gain in technical efficiency is observe among large farms. Expansion or modification of public policies in place such as those associated with provision of rural extension could provide greater support to farms to adopt irrigation leading to a higher technical efficiency, as shown in Figure 2. A focus in very small and small farms, the majority of the farms in Brazil, would also contribute to socio-economic development through a decrease in inefficiency.

4. Conclusions

There is evidence that indicate that irrigation in Brazil may be an effective tool deal with climate vulnerability [1,6] and to reduce poverty through increase in productivity, profit and technical efficiency. In this paper we estimate the effect of irrigation on technical efficiency of farms of different sizes in Brazil using a rich dataset on almost 5 million farms. To do so, we used a simple approach that accounts for observed and unobserved characteristics [50,54]. It is a step forward correctly accounting for the effect of these characteristics in the estimation of unbiased technical efficiency.

Our results indicate that farms with irrigation had higher average technical efficiency compared to non-irrigators. The analysis by farm size showed that, in among both groups, small farms are more efficient than the others. However, the greatest difference observed in the average technical efficiency was observed for medium and large farms, which implies that irrigation technology has a significant effect on the efficiency gain for those groups.

These results and the literature discussed indicate that several factors that could also improve technical efficiency such as the provision of rural extension, could also increase the adoption of irrigation systems, having a two-fold effect on farm technical efficiency. Another key public policy that might increase adoption of irrigation systems is the provision of rural credit, which decrease the financial burden of adoption.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are not available on request from the corresponding author. The data are not publicly available due to confidentiality. A requirement has to be submitted to Brazilian Institute of Geographic and Statistics (IBGE) to use the dataset, which only can be accessed at IBGE headquarter in Rio de Janeiro, Brazil.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Sample Selection

Table A1. Estimation of the selection equation (Probit) for irrigation adoption, after balancing the sample.

Variable	Marginal Effect (dy/dx)	Standard-Error	Estat. Z	*p*-Value
Gender	0.00206	0.0003690	5.58	0.0001
Age	0.00077	0.0000480	15.97	0.0001
Age2	-7.43×10^{-6}	0.0000005	−16.37	0.0001
Read and write	−0.01132	0.0007554	−14.99	0.0001
Do not read and write	−0.02243	0.0007223	−31.06	0.0001
Literate	−0.01635	0.0008422	−19.41	0.0001
Incomplete elementary	−0.00668	0.0006614	−10.1	0.0001
Complete Elementary	0.00315	0.0007123	4.43	0.0001
Agric. Technician	0.00956	0.0010204	9.37	0.0001
High School	0.00586	0.0007204	8.14	0.0001
Exp_1	0.00519	0.0007868	6.6	0.0001
Exp_1to5	0.00661	0.0003350	19.73	0.0001
Exp_5to10	0.00277	0.0003199	8.67	0.0001
Private Extension	−0.00856	0.0003608	−23.72	0.0001
Governmental Extension	0.01973	0.0003453	57.14	0.0001
Co-op Membership	−0.00795	0.0002336	−34.05	0.0001
Television	0.00561	0.0002690	20.84	0.0001
Telephone	0.01805	0.0002662	67.81	0.0001
Internet	0.01820	0.0007853	23.17	0.0001
Energy	0.03873	0.0003172	122.12	0.0001
Financing	−0.00883	0.0002826	−31.23	0.0001
Qualif.	0.01529	0.0004906	31.17	0.0001
Urban	−0.00293	0.0003558	−8.25	0.0001
Agr. Practice	0.00186	0.0002423	7.67	0.0001
Water Resource	0.03337	0.0003220	103.63	0.0001
Agrochemicals	0.04416	0.0002558	172.61	0.0001
Soil pH	0.02455	0.0003287	74.68	0.0001
Fertilizers	0.09043	0.0002928	308.81	0.0001
Value of Land	-1.42×10^{-9}	0.0000000	−16.66	0.0001
Agr. Family	−0.00713	0.0003031	−23.51	0.0001
Owner	−0.00319	0.0004382	−7.28	0.0001
Tenant	0.00736	0.0006383	11.53	0.0001
Partner	−0.00113	0.0007716	−1.46	0.145
Summer precipitation	−0.00024	0.0000031	−78.41	0.0001
Winter precipitation	−0.00038	0.0000056	−68.87	0.0001
Summer temperature	−0.00560	0.0001974	−28.39	0.0001
Winter temperature	0.00473	0.0001185	39.91	0.0001
Summer Prec. Stand. Dev.	0.00022	0.0000062	35.91	0.0001
Winter Prec. Stand. Dev.	−0.00045	0.0000101	−43.91	0.0001
Summer Temp. Stand. Dev.	0.01652	0.0004981	33.16	0.0001
Winter Temp. Stand. Dev.	−0.06200	0.0006704	−92.48	0.0001
N° Obs.	4,259,865			
Log Likelihood	−798,547.93			
Chi^2	389230.58			0.0001
Pseudo R^2	0.196			

Source: Research results.

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