The effect of rural extension on farm technical efficiency in Brazil

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Abstract:

The objective of the present research was to identify the effect of rural extension on the productive performance of Brazilian agricultural establishments, using as a measure of performance the technical efficiency of farms. The data used refers to the microdata of the 2006 Agricultural Census, accessed directly from the IBGE secrecy room. For this, an approach that combines the stochastic production frontier structure, taking into account the selection bias in the adoption of the rural extension (Heckman's approach), with the entropy balancing method was used. The results show that the rural extension contributes, in fact, to increase the efficiency in the use of the productive factors, with the producers adopting, more technically efficient than the non-adopters. When considering the differences according to the size of the establishment, an even greater effect was observed for the group of large producers. In addition, in general, public rural extension generated higher technical efficiency scores than those obtained by establishments attended by the private service.

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ABSTRACT

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Key-words: *Rural Extension, Entropy balancing, Stochastic Production Frontier, Technical Efficiency*

JEL codes: Q10, Q12, Q16, C31

1. Introduction

Brazilian governmental agricultural policies have been incentivizing agricultural production throughout the generation of new economic conditions and instruments that enables the agricultural sector development. Teixeira *et al.* (2014) suggest that future performance of the Brazilian agriculture is directly related to the generation of these factors, which allows the modernization of the sector. One of these policies is the National Policy of Technical Assistance and Rural Extension (PNATER). Rodrigues (1997) suggests that this policy's goal is to provide rural extension to farms seeking to achieve rural socioeconomic enhancement by increasing agricultural production and productivity. He also adds that it also leads to higher social welfare by improving rural family health conditions, access to more nutritive food and education, and to better farm organizational structure[1].

Christoplos (2010) argues that the rural extension provision seeks to strengthen the link of new technologies discoveries with the adoption of technology in the agricultural production; i.e. it stimulates the diffusion of new technologies among farms. It also seeks to inform famers about agricultural practices and market price behavior, and provide farm management

[1]For more details about the emergence and development of extension services in Brazil, see Pettan (2010).

consultancy. This policy has changed over the decades. Formally implemented in 2003, PNATER was the first centralized policy focused on rural extension, compared to the decentralized pre-existent structure, which led to an increase on the provision of these service by non governmental entities (PETTAN, 2010). Swinner and Maertens (2007) indicate this evolution as a new direction in these service provision given that farm input suppliers are providing these services jointly with their products.

Although rural extension services have increase in the last decades, less than 30% of the 4.3 million farms analyzed in this research[2] have had access to rural extension services (Institute of Geography and Statistics – IBGE, 2017). It is also observed that medium and large farms have a greater access to these services. In 2006, the average farm size that have had access was 128.5 hectares (ha), while the average farm size of those farms that have not accessed them was 44.6 ha. Plata and Fernandes (2011) argue that this unequal outcome might occur because medium and large farms have greater volume of resources and access to information. It raises the question whether the rural extension policy has been achieving its main goal of serving the most technologically vulnerable groups of farmers and small producers, and whether it has stimulate the Brazilian agricultural sector.

A few papers have investigated indirectly the effect of rural extension in the Brazilian agricultural production and efficiency. Moura *et al.* (2000) finds that rural extension increases farm efficiency but has no effect on the use of inputs. Helfand and Levine (2004), Gonçalves *et al.* (2008) and Freitas *et al.* (2014) find that rural extension services increase farms efficiency. The latter studies focused on farm efficiency as a measure of productive performance. In this paper we seek to identify the effect of rural extension on farm technical efficiency in Brazil. Farm technical efficiency is a proxy for technical productive performance, which is a measure of how well the farm technically determine the input use to achieve the technical maximum output. In this article, we define rural extension as what the PNATER delineates as technical assistance and rural extension.

Helfand and Levine (2004), Gonçalves *et al.* (2008) and Freitas *et al.* (2014) do not considered rural extension as an endogenous decision; i.e. the choice of accessing extension services is made by the farmers. Birkheuser *et al.* (1987) indicate that results might be biased if the endogeneity issue is ignored. This choice depends on both observable factors such as experience and farm characteristics, and not observable factors such as farmer management

[2]The procedures used to treat the microdata in order to arrive at the final sample considered in the research are presented in detail in the section "Data and empirical application".

capacity. Plata and Fernandes (2011) indicate these factors as some of the reasons why greater access to rural extension is observed among medium and large farms.

To incorporate these features we estimate a stochastic production frontier considering possible selection bias from access to rural extension in addition to using a sampling matching technique, *Entropy*. Our approach allows to estimate an unbiased effect of rural extension on farm technical efficiency. This approach also permits to identify which factors affects the choice of accessing the extension services and whether there are consistent differences in the input use among groups of farms. Although Plata and Fernandes (2011) indicate a greater access of medium and large farms to these service, the effect on farm efficiency might not be higher in these groups. We test the hypothesis that rural extension has a greater effect on medium and large farms.

Our analysis contributes in three fronts. First, it provides an unbiased estimate of the effect of rural extension on farm efficiency, which is essential for policy evaluation and future policy design. Second, to obtain these estimates we use a suitable methodology that allows to incorporate the endogenous decision on accessing rural extension. Third, we use more than 4 million farm-level observations from the Agricultural Census of 2006 (IBGE, 2017). It is a unique and confidential dataset available only at the IBGE headquarters that allows us to access farm-decision level and obtain more powerful conclusions.

Results indicate that rural extension increase farm technical efficiency, it has a greater effect among large farms, and governmental provision of these services have a greater effect on technical farm efficiency opposed to nongovernmental provision. Although we do not find evidence that this policy is achieving its main goal of serving vulnerable and small farms our results suggest that, overall, farms have benefit from this policy. We do find evidence that corroborates the hypothesis derived from Plata and Fernandes (2011), which states that larger farms receive a greater benefit from this policy.

2. Background on rural extension

Rural extension in Brazil

In Brazil, farms have been having access to rural services since the nineteenth century (Bergamasco, 1983). However, Pettan (2010) argues that these services were mostly performed by non-governmental institutions that sought to assist with on-farm training. In 2003, rural extension provision directions were defined within the PNATER guidelines, developed by the MDA, which substituted the decentralized governmental policy introduced in the late 1940s.

Peixoto (2014) indicates that this policy sought to build a new rural extension provision structure incorporating both governmental and non-governmental institutions.

Alves (2013) suggests that large farms and farms in more developed agricultural regions continue to obtain greater access to rural extension than smaller farms. This contradicts the new policy directions, which indicates that more vulnerable groups should receive greater attention. Peixoto (2014) suggests a revision on the provision's structure of these services where it should incorporate the socioeconomic features described in the PNATER. Rivera and Alex (2004) agree with Christoplos (2010) and argue that a greater participation of non-governmental institutions within PNATER lines and a broader rural development agenda would lead to a more efficient provision of these services.

Kageyama (1990) highlights the great disparity on these services provision, farms in the North and Northeast regions of Brazil have been poorly provided. A higher proportion of farms that have had access is observed in municipalities at the South and Southeast regions of Brazil. On average, 49% of the farms in the South have had access to these services compared to the North with only 15%. Although disparities on the provision are still observed the implementation of PNATER have led to an increase in resources used on rural extension, from R$ 3 million on the 2001/02 crop season to R$ 1.1 billion on the 2015/16 crop season (Sistema Integrado de Administração Financeira do Governo Federal – SIAFI, 2016). Pettan (2010) and Peixoto (2014) also indicate an increase in non-governmental provision during this period.

Despite the increase on resources designated to rural extension provision, several PNATER's obstacles have led to great disparities on regional provision and farm size access to this services. The PNATER system still has low remuneration for extension agents and large costs to provide a rural extension to several farms within the municipality (Peixoto, 2014).

Effect of rural extension on technical efficiency

Several studies have indirectly investigated the effect of rural extension on farm technical efficiency using the stochastic frontier approach. In this approach, the error term is composed by a random standard error and an error term that measures the distance from the frontier or the inefficiency. A few of these studies incorporate heterogeneity in the inefficiency term by including variables that might affect the efficiency level; i.e. a measure of rural extension. However, these studies do not consider possible effects from selection bias and the endogenous nature of the choice to access rural extension.

Gonçalves *et al.* (2008) estimate technical efficiencies of 771 dairy farms in Minas Gerais. They divided the sample into three groups: farms with production smaller than 50 liters of milk per day; with production between 50 and 200 liters of milk per day; and with production with more than 200 liters of milk per day. To obtain the technical efficiency scores, they use a Data Envelopment Analysis (DEA) approach and then identify the efficiency determinants using a Tobit regression. They include a dummy to capture the effect of rural extension on farm technical efficiency. Results show a statistically significant effect of rural extension on farm technical efficiency but only for the farms with large production of milk (more than 200 liters per day). This conclusion adds up to the hypothesis we derived from Alves *et al.* (2013) and Plata and Fernandes (2011), which states that larger farms benefit more from rural extension.

Using a similar approach, Helfand and Levine (2004) investigate the determinants of the technical efficiency of agricultural farms in the Central West region using the 1995/96 Agricultural Census. Although their variable of interest is farm size, they include access to rural extension as a determinant of farm technical efficiency. They find a positive and significant effect of rural extension on farm technical efficiency.

Moura *et al.* (2000) investigate the effect of rural extension services on efficiency and input use of 68 small farms in the State of Ceará. They use a stochastic production function approach where the functional form is a Cobb-Douglas. They find a positive effect of rural extension on farm efficiency. Using a similar approach, Magalhães *et al.* (2011) investigate the determinants of technical and allocative inefficiency of establishments that participated in the agrarian reform program known as “Cedula da terra”. This program incorporates establishments in five states of the Northeast region of Brazil. They include a dummy variable to capture the effect of rural extension in the efficiency error term and find no effect of this variable on farm technical efficiency.

Freitas *et al.* (2014) also identify the effect of rural extension on the agricultural production and technical efficiency of Brazilian agricultural farms, combining stochastic production frontier with quantile regression methods and using the Agricultural Census of 2006 as a database. They find a positive effect of the rural extension services on technical efficiency only in farms at the lower efficiency quantiles, while for the more efficient farms, this variable had a negative effect.

These studies highlight the relevance of rural extension in enabling farm development, productivity and socioeconomics welfare enhancements, and in increasing technical efficiency. However, it lacks in the literature a study that focus in this topic and uses a suitable methodology that incorporates specific features of this issue such as the endogenous nature of accessing rural extension. We seek to identify the effect of rural extension on farm technical efficiency and the determinants of choosing to access it using a unique dataset with more than 4 million farm-level observations.

3. Methodology

To identify the effect of rural extension on farm technical efficiency we use an approach that consists of two steps. We first deal with possible selection bias in the choice of accessing rural extension caused by the observable pre-choice characteristics. This possible selection bias does not allow the direct comparison between the technical efficiency of farms that have had access to it with farms that have not had access it. We use the *Entropy* methodology to eliminate the bias caused by the observable characteristics. This method is used to obtain a control group as similar as possible to the group of farms that have had access to rural extension, which it allows us to compare the groups without any possible selection bias. In the second step we estimate a stochastic production frontier for each group, using the two-stage approach developed by Heckman (1979).

3.1. Entropy Balancing

We use the Entropy Balancing method proposed by Hainmuller (2012) to obtain a balanced "matching" sample. It allows to find a sample with the closest possible control units of the treatment units based on the vector of observable characteristics. This method consists of a non-parametric method that allows to weight a set of information (covariates) to reweight the observations in a manner that the distribution of the variables satisfy a set of special conditions of moments. The weighting scheme ensures balance and similarity between the control and treatment groups.

Following Hainmuller (2012), consider a random sample with n_1 observations from the treatment group and n_0 from the control group, selected from a total population $N = N_1 + N_2$, where $n_1 \leq N_1 e n_0 \leq N_0$. Let $D_i \in \{1,0\}$ be a binary treatment variable such as access to rural extension, which assume a value equal to 1 if unit *i* is exposed to the treatment, and 0 if not. Also consider **X** an matrix containing observations of the *J-th* exogenous pre-treatment variables; X_{ij} correspond to the value of the *j-th* covariates of unit i, such that, $X_i = \left[X_{i1}, X_{i2}, \dots, X_{iJ}\right]$ refers to the vector of observable characteristics of the unit *i* e X_j refers to the column vector with *j-th* covariates.

This method looks for a set of weights $\boldsymbol{W} = [w_i, \dots, w_{n_0}]'$ minimizing the entropy distance between **W** and the weight vector $\boldsymbol{Q} = [q_i, \dots, q_{n_0}]'$, Equation (1), subject to the balancing constraint, Equation (2), the normalization constraint, Equation (3), and a non-negativity constraint, Equation (4).

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} w_i \log(w_i/q_i) \qquad (1)$$

subject to the equilibrium and the normalization constraints

$$\sum_{\{i|D\,=\,0\}} w_i c_{ri}(X_i) = m_r\,, \qquad r \in 1,\dots,R \qquad (2)$$

$$\sum_{\{i|D\,=\,0\}} w_i = 1 \qquad (3)$$

$$w_i \geq 0 \quad for\ all\ i, such\ that\ D = 0 \qquad (4)$$

where $q_i = 1/n_0$ is a basis weight and $c_{ri}(X_i) = m_r$ describes a set of R constraints imposed on the moments (m_r) of the covariates in the reweighted control group. First, we choose the covariates that will be included in the re-weighting scheme. For each covariate, a set of balancing restrictions (Equation (1)) is specified to match the moments of the covariates distribution between treatment groups and reweighted controls. There are three possible moment constraints: mean (first moment), variance (second moment), and asymmetry (third moment). A typical balancing restriction is formulated such that $m_r$contains the moment of a specific covariate X_j for the treatment group. The moment function for the control group is then specified as: $c_{ri}\left(X_{ij}\right) = X_{ij}^r$ or $c_{ri}\left(X_{ij}\right) = (X_{ij} - \mu_j)^r$, where X_{ij}^r is the covariate vector and μ_j is the mean.

We set the moment restriction to the first moment of the covariates. After selecting the covariates, the method calculates the means in the treatment group and searches for a set of entropy weights such that the weighted averages of the control group are similar. Such weights are used in the following steps in order to obtain unbiased estimates of selection bias caused by observable characteristics.

3.2. Sample Selection Model

We use the procedure proposed by Heckman (1979) to test for possible sample selection bias; i.e. factors that affect farm technical efficiency might be different from the factors that determine the likelihood of accessing rural extension services. First, we estimate a binary choice model (selection equation) to find out which factors increase the likelihood of accessing (choosing) rural extension, the treatment variable. Second, we estimate a stochastic production frontier (interest equation) for each group incorporating the Inverse Mills Ratio[3], obtained at the selection equation. We performed this two-step procedure to three different treatment variables: rural extension overall; public rural extension; and private rural extension.

Selection Equation

First, as proposed by Heckman procedure (1979) we estimate the likelihood the treatment occur using a Probit model; i.e. the likelihood a farm have accessed rural extension. Assume that$d_i^*$is a binary variable that represents the (unobservable) selection criterion and that is a function of a vector of exogenous variables(z_i)

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

where α is a 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 of 1 when $\alpha' z_i + w_i > 0$ and zero otherwise:

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

Stochastic Production Frontier

Second, we estimate a stochastic production frontier model correcting for sample bias and the matching sample weighting scheme. It means that we include the inverse Mills ratio and estimate considering a weight vector obtained using the *Entropy* method. The Stochastic Frontier approach[4] has been widely used to obtain efficiency measures. It consists in estimating a production function that represents the relation between agricultural input and output (Helfand and Levine, 2004; Rada; Valdez, 2012; Helfand *et al.* 2015). Aigner, Lovell and Schmit (1977) and Coelli and Battese (1996) specify the model as follows:

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

where Y_i is the value of production of *i-th* farm; $X_i$is the vector of expenses with inputs of the *i-th* farm ; and β is a vector of the parameters to be estimated, which define the production technology. The error terms v_i and u_i are vector that represent distinct components of the error: v_i, the random error component, has a normal distribution, independent and identically

[3]Variable generated from the Probit model and included in the stochastic production frontier to correct the sample selection bias. The existence of the selection bias is confirmed when the inverse mills ratio is statistically significant (GREENE, 2011).

[4]According to Agner *et al.* (1977) and Chambers (1988), the objective of the model is to estimate a production function in which it is expected to obtain the maximum product from the combination of inputs, considering a certain technological level. However, there is no guarantee that an efficient combination of inputs will be used to maximize production, since there may be technical inefficiencies in the use of these inputs. This implies that the unit may be producing below the maximum production frontier.

distributed (iid), with variance $\sigma_v^2 [v \sim iidN(0, \sigma_v)]$and captures the stochastic effects beyond the control of the productive unit, such as measurement errors and climate, for example; and $u_i$is responsible for capturing the technical inefficiency of the i-th farm, that is, the distance from the production frontier, and are non-negative random variables. This unilateral (non-negative) term can follow half-normal, truncated normal, exponential or gamma distributions with mean $\mu > 0$ and variance σ_u^2 (Aigner *et al.*, 1977; Greene, 1980). We have assumed a exponential distribution to the inefficiency error term $[u \sim iidN^+(0, \sigma_u)]$.

To obtain farm technical efficiency we follow Jondrow *et al.* (1982). Farm technical efficiency is defined as the ratio between the observed product and the potential product of the sample:

$$ET_{ij} = \frac{Y_{ij}}{Y^*_{ij}} = \frac{Y_{ij}}{f(X_{ij})} = \frac{\exp(X_{ij}\beta + v_{ij})\exp(-u_{ij})}{\exp(X_{ij}\beta + v_{ij})} = \exp(-u_{ij}) \qquad (8)$$

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

3.3. Data and Empirical application

We use a rich farm level dataset only available at the secrecy room at the IBGE, the micro-data of the 2006 Census of Agriculture. We first clean the dataset, excluding farms without area declaration (255,019 observations), farms located in the urban area (192,350 observations), farms in special sectors such as favelas, barracks, indigenous villages, nursing homes, etc. (117,530 observations), and farms in settlements[5](139,496 observations).We also excluded observations in which the producer type was not identified (20,440 observations) and observations where the farm is not owned by an individual producer (190,838 observations)[6].Around 17% of the original data was dropped. We use a dataset composed by 4,259,963 farms. In the following section (Table 1) we present a descriptive statistics analysis of our sample.

The three treatment variables –rural extension, public rural extension and private rural extension –are binary variables. They are constructed based on the farmer's answer to the following questions: "The establishment received technical guidance?" And "what is the origin of the guidance?". In our sample, 27.7% of the farmers have received technical guidance,

[5]Kageyama *et al.* (2013) suggest that the inclusion of these observations might lead to possible variable measurement error given that the agricultural production is performed collectively.

[6] We exclude farms categorized as condominium, consortium or partnership, cooperative , corporation or limited liability shares, public utility, government (Federal, state, or municipal) or other condition.

11.4% from public institutions and 16.3% from private institution. We also divided our sample in four size classes according to the IBGE classification. We categorized the farms in very small, small, medium and large based on the concept of fiscal module classes[7].

The Agricultural Census of 2006 also presents farm socioeconomic characteristic. In addition to economic variables, we use these characteristics in the selection equation. We obtain information on farmer gender, age, schooling level and experience. The variable *gender* is a dummy variable equals 1 if it is male and 0 otherwise. Farmer's age is the manager's age. The variable schooling is a categorical variable for the farm manager's education level (from 0 to 7) in the following order: do not read and write, read and write, literate, incomplete elementary school, complete elementary school, agricultural technician, high school and higher education. We capture experience using a categorical variable of the years in which the farmer is in charge of the activity, being divided in: up to 1 year, between 1 and 5 years, between 5 and 10 years, over 10 years.

Farm ownership, the presence of skilled labor in the farm workforce, family farm classification and whether the farm's manager lives in urban area also play an important role on the likelihood of accessing rural extension. We capture farm ownership by including a categorical variable: Owner (base), tenant, partner and occupant. Skilled labor is capture with a dummy variable equals 1 if there is presence of skilled labor in the farm and zero otherwise. Family farm classification is capture in a similar manner. To capture whether the farm's manager lives in a urban area or not we construct a dummy variable that equals 1 if the head of the farm lived in the urban area and zero otherwise.

We use the gross value of production in 2006 (GVP) in R$ as a proxy to the output variable, Y_i. We obtain information on 4 inputs. We use the sum of the farm area (in hectares) designated to agriculture, livestock and agroforestry to capture the land input. The total value in R$ of the assets in the agricultural establishment is used as a proxy to capital. As a proxy to labor, we use the sum of the family member and hired labor. As in Helfand *et al.* (2015) we include a variable to capture purchased inputs (other): the sum of expenses with soil correctives, fertilizers, pesticides, animal medicines, seeds and seedlings, salt/feed, fuel and energy.

[7]Fiscal module is defined as the minimum area required for rural properties to be considered economically viable, ranging in area from 5 to 110 hectares, depending on the municipality. Based on the concept of fiscal module, the agricultural 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).

Estimation

After obtaining the weights for the control groups using the Entropy balancing method we estimate the selection equation using a *Probit* as in Equation (6):

$$d_i^* = \alpha_0 + \sum_{e=1}^{7} \alpha_e Z_e + \sum_{0=1}^{3} \alpha_o Exp_o + \sum_{k=1}^{7} \alpha_k School_k + \sum_{r=1}^{4} \alpha_r FarmStatus_r + \varepsilon_i \qquad (9)$$

where Z_e is a vector of explanatory variables that includes gender, total farm area (*totalarea*), age, age square, skllied labor (*Qualif*) in the workforce, family farm classification (*Family*) and if the farm's manager lives in a urban area (*Urban*); *Exp* represents experience and it is divided into three categories, *School* represents schooling and it is divided into 7 categories, and farm ownership (*FarmStatus*) into 4 categories. We include the square of the variable farm manager's age seeking to capture a nonlinear effect. From this estimation we obtain the inverse mills ratio (*Mills*). Then, we include it in the stochastic production frontier.

We use a *Translog* production function to represent the technology given that it presents some desirable properties such as flexibility, linearity in parameters, regularity and parsimony (Mariano *et al.*, 2010). In addition to the inverse mills ratio we also include in the stochastic production dummy variables for each state and farm size group seeking to capture non-observable factors that are fixed across these groups. As in Coelli *et al.* (2003) the technology can be represented as

$$\ln y_i = \beta_0 + \sum_{k=1}^{N} \beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{N}\sum_{h=1}^{N} \ln x_{ki} \ln x_{hi} + \rho Mills_i + \sum_{h=1}^{26} FS_h + \sum_{g=1}^{4} G_g + v_i - u_i \qquad (10)$$

where y_i represents the gross value of production of *i-th* farm; x_{ki} represents inputs *k*, which are: productive area, labor, capital stock and expenses with purchased inputs; FS_h represents dummies for federative states; and G_g represents dummies for the four farm sizes groups considered. We test whether we face selection bias by analyzing the statistical significance of the parameter ρ.We have assumed a exponential distribution to the inefficiency error term$[u \sim iidN^+(0, \sigma_u)]$.We use the STATA® 2014 software to estimate all steps of this approach.

4. Results

We first present the descriptive statistics of the variables used, displayed in Table 1. This table also shows the result of the Entropy method. On average, farms that have had access to rural extension have a greater agricultural area and a manager with higher levels of schooling (a higher *share*). They also have shown a greater gross value of the production in 2006, on average, R$77.3 thousand opposed to farms that have not accessed these service, on average, R$12.0 thousand. These farms have also a greater input expenditure (fertilizers, agrochemicals, electricity, transportation, and others). These disparity is not observed in the averages of age, experience and farm ownership status.

[TABLE 1]

The analysis of Table 1 corroborates Plata and Fernandes (2011) argument, that medium and large farms have greater volume of resources and access to information. Farms that have had access to private rural extension have a larger agricultural area, higher schooling and a higher share of the workforce with skilled labor opposed to farms that have not accessed these services. These farms also obtained, on average, a three times larger income in 2006, compared to the farms that have accessed public rural extension. The same behavior is observed in the value of land, buildings and other facilities.

The columns in the "Balanced sample" part of Table 1 show the result of the balancing method using the first moment of the sample (average of the variables). Before using this method, we observe statistically significant difference between the treatment and control groups. However, after using the entropy method, we did not find any statistically significant difference between these groups (test of equality of means). It implies that, we are able to obtain a very similar control for each treatment group. The only difference between these two groups is the access to rural extension services.

Sample Selection

We present in Table 2 the determinants of the likelihood to access rural extension services using a *Probit* model. We rejected the null hypothesis of joint insignificance of the variables (χ^2) at 1% in all models considered. We found that larger farms face greater likelihood of accessing rural extension services. This confirms the hypothesis that larger farms have higher access to rural extension. Being male is associated with a greater probability of accessing these services, compared to being female. We also find that farm with managers that have more experience have higher probability to access these services.

[TABLE 2]

Our results suggested that farms with managers with a high level of education have greater probability to access rural extension services. Lapple and Hennessy (2014) investigate the participation of dairy farms in extension programs in the United States, and they also find that higher education increases the adoption of these services. These authors highlight the importance of investments in rural education to facilitate access to rural extension because: the farmer inherent motivation to obtain information and knowledge; and/or the extension services are often promoted by agricultural education. Farms classified as "family agriculture" and farm's manager that lives in urban areas lead to lower probability of accessing rural extension services. Genius *et al.* (2006) also find similar results. We also find that hiring skilled labor increases the probability of accessing these services.

For the treatment variables private rural extension and public rural extension, also in Table 2, we did not observe any difference on the effects of gender, age, skilled labor and experience. However, we observed that a higher education of the farm's manager have a stronger effect on the probability of accessing private extension compared to public services. Where farm's manager lives also has a different impact, positive on the probability to access private rural extension and negative on accessing public services. Swinnen and Maertens (2007) indicate that part of the private extension services is carried out by input suppliers and/or food processing and distribution companies. A higher interaction between farm managers and these companies is expected when farm managers live in urban areas.

Stochastic Production Frontier

We estimated the stochastic production frontier function for the entire sample and for each group of the rural extension services. In addition to the inputs, the Inverse *Mills* Ratio - IMR, estimated in the previous step, was included in the production function to correct for possible selection bias caused by unobservable factors. We estimated the *Translog* production function using the weighting scheme from the *Entropy* method. The Wald statistic indicates that the model has a good fit, rejecting at 1% the null hypothesis of joint insignificance of the variables. Results are shown in Table 3.

[TABLE 3]

Our results suggest that unobservable factors influence the producer's decision to access rural extension services. It confirms the hypothesis of sampling selection bias, demonstrated in the statistically significance of the coefficients for the IMR. The negative coefficient found in all three models suggests that these factors are associated with the selection of producers at the lower level of gross value of production. Our results also suggest that most of the error is due to inefficiency, given that the value of the Lambda parameter found is above the unit in all the estimated models.

We estimated the production elasticities for *land*, *labor*, *capital* and *purchased inputs*, displayed in Table 4. The sum of these elasticities gives us a measure of returns to scale. We found it to be close to one in all models, which suggests that the technology used is under constant returns to scale. Alves *et al.* (2012) find a similar result using the same data. For the pooled model, we found that *other* and *labor* were the inputs with the greatest production elasticities. An increase of 10% in these inputs would lead to an increase, on average, of 4.4% and 3.2% in the production, respectively. Helfand *et al.* (2015) also find that these inputs have the greatest elasticities for Brazilian agricultural[8].

[TABLE 4]

We found significant differences in the production elasticities in the models of the treatment and control groups. For both groups, *purchased inputs* still has the greatest production elasticity. For the treatment group, there is a greater contribution of *capital* and *labor* compared to the control group, as expected. One of the main goals of rural extension is to facilitate the access to new technologies and knowledge, which leads to greater investments and capital use generating higher agricultural income. *Land* production elasticity is greater for the control group. This group is composed mostly by small farmers that often increases production by expanding the productive area. This occurs because of lack of knowledge on more productive techniques or existence of constrained access to financial resources.

The production elasticities of *purchased inputs* and *labor* were the greatest in the two models related to the type of rural extension: public and private. The *capital* production elasticity is around 6 percentage points higher for farmers that have accessed private rural

[8]The elasticities found by Helfand *et al.* (2015) for purchased inputs and labor were, respectively, 0.62 and 0.21. Although they also use the 2006 Agricultural Census, the authors use a more aggregated database, with information grouped in representative farms.

extension compared to farmers that have accessed public services. Farms that have access to private rural extension usually have greater financial resources available. It allows them to have greater investment in capital goods, which also facilitates the extension agent action.

Analysis of technical efficiency scores

We obtained unbiased farm technical efficiency scores for the five models estimated, and we present the mean and the standard deviation in Table 5[9].We observed that the average technical efficiency of the farms that have had access to rural extension was of 32.1% opposed to 31.4% from the farms that have not accessed. It suggests that farms that have had access to these services are technically more efficient than the others. The value of the estimated standard deviation for both groups (0.22 and 0.19, respectively) shows the dispersion of the data, which reflects the very heterogeneous sample we have.

The use of a very heterogenous and large sample leads to low average technical efficiency. Alves *et al.* (2012) also use microdata from the 2006 Census of Agriculture and find that around 66% of the farms produces around 3% of the gross value of production. They also argue that around 64% of these farms were not been able to pay for their inputs. It is very likely that these farms are located in the lower part of the technical efficiency distribution, which pulls down the average efficiency.

Studies using more aggregate data usually find higher average technical efficiency because these farms are geographically dispersed. Magalhães *et al.* (2011) use a more homogenous sample and find an average technical efficiency of 47%. Almeida (2012) uses a more aggregate sample and finds an average technical efficiency of 92%. On the other hand, Freitas *et al.* (2014) uses the Agricultural Census of 2006 and finds an average technical efficiency of 62%. Although we are finding low averages, we are interested in the difference between groups. We believe that the magnitude of these differences is not affected by the level of the efficiency.

[TABLE 5]

We find that farms that have accessed public rural extension have a technical efficiency average 2 p.p. higher than the technical efficiency average of farms that have accessed private

[9]It should be emphasized that, among the rules for the use of the secrecy room in the IBGE, it is not allowed to extract any maximum and minimum values, in order to prevent any producer from being identified through such information.

rural extension. Farms that have accessed public rural extension are associated with relatively low use of inputs (*land*, *labor*, *capital* and *purchased inputs*). Then the role of extension agents is to transfer knowledge, teach alternative agricultural practices and assist farmers to manage scarce resources more efficiently. Peixoto (2014) states that the acquisition of large input quantities and the adoption of more advanced technologies is limited because of their budget and credit constraints.

In Figure 1 we display technical efficiency averages per farm size and group considered in this paper. "Small" farms have shown the highest technical efficiency averages. As the farm size increases the average score decreases. Our results corroborate what have been found in the literature, that a U-inverted relation between farm size and technical efficiency exists in which small farms have the highest efficiency scores (Helfand and Levine, 2004; Helfand *et al.*,2015).We found that access to rural extension has a stronger effect on technical efficiency in the medium and large farms. For large farms the difference in technical efficiency due to these service is approximately 4 p.p..

[FIGURE 1]

5. Conclusions

In this paper we seek to estimate the unbiased effect of rural extension on the Brazilian farm technical efficiency using a stochastic frontier approach that considers sample selection bias and endogeneity of the treatment variable.

We have found that a more educated farm manager, more skilled labor in the workforce and the farm ownership status increase the likelihood of accessing rural extension services. The production elasticities results indicated that farms that have not accessed rural extension services rely more on *land* input opposed to farms that have accessed these services. We also find that the private access to these services increase the *capital* production elasticity, which indicates that these services are *capital-intensive*. Our estimates of technical efficiency suggest that public provision of these services increase farm technical efficiency, compared to non-access and private-access. An even greater effect was observed among large farms, an increase of 4p.p..

Our findings suggest that an increase on public investments in rural extension would result in greater development of rural areas given its effect on agricultural technical efficiency.

Although small farms are the main focus of these services, large farms are benefiting more from them. In other words, a more organized strategy such as greater access to rural credit is needed to obtain a more effective rural extension effect among small producers. It will increase the likelihood of accessing these services and the access to new knowledge and technology, which is already being used by large farms.

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TABLES AND FIGURES

Table 1 - Mean of the variables used in the selection equation and in the Stochastic Production Frontier

	Non Balanced Sample				Balanced Sample					
Variables	**Without RE (Controle)**	**RE**	**Public RE**	**Private RE**	**Without RE (Control)**	**RE**	**Control**	**Public RE**	**Control**	**Private RE**
Gender	0.863	0.933***	0.921***	0.940***	0.933	0.933 ns	0.921	0.922 ns	0.940	0.940 ns
Total Area	44.56	128.5***	66.00***	172.5***	128.5	128.500 ns	65.99	66.000 ns	172.4	172.500 ns
Age	50.5	49.56***	50.61***	48.82***	49.56	49.560 ns	50.61	50.610 ns	48.82	48.820 ns
Read and write	0.108	0.0462***	0.0666***	0.0319***	-	-	-	-	-	-
Do not read and write	0.295	0.0685***	0.116***	0.0352***	0.069	0.068 ns	0.116	0.116 ns	0.036	0.035 ns
Literate	0.0577	0.0341***	0.0467***	0.0252***	0.034	0.034 ns	0.047	0.047 ns	0.025	0.025 ns
Incomplete elementary	0.404	0.506***	0.526***	0.491***	0.506	0.506 ns	0.526	0.526 ns	0.491	0.491 ns
Complete elementary	0.072	0.121***	0.113***	0.127***	0.121	0.121 ns	0.113	0.113 ns	0.127	0.127 ns
Agricultural Technician	0	0.0607 ns	0.0178***	0.0909***	0	0	0.018	0.018 ns	0.091	0.091 ns
High School	0.0482	0.0966***	0.0803***	0.108***	0.097	0.097 ns	0.080	0.080 ns	0.108	0.108 ns
Higher Education	0.0155	0.0669***	0.0339***	0.0900***	0.067	0.067 ns	0.034	0.034 ns	0.090	0.090 ns
exp1	0.0281	0.0190***	0.0168***	0.0205***	0.019	0.019 ns	0.017	0.017 ns	0.021	0.021 ns
exp2	0.169	0.152***	0.140***	0.161***	0.153	0.153 ns	0.140	0.140 ns	0.161	0.161 ns
exp3	0.168	0.173***	0.172***	0.174***	0.173	0.173 ns	0.172	0.172 ns	0.174	0.174 ns
exp4	0.635	0.656***	0.671***	0.645***	-	-	-	-	-	-
Qualif	0.0236	0.0964***	0.0621***	0.121***	0.096	0.096 ns	0.062	0.062 ns	0.121	0.121 ns
Family	0.876	0.745***	0.821***	0.692***	0.745	0.745 ns	0.821	0.821 ns	0.692	0.692 ns
Urban	0.118	0.194***	0.136***	0.234***	0.194	0.194 ns	0.136	0.136 ns	0.234	0.235 ns
Owner	0.824	0.894***	0.905***	0.887***	0.894	0.894 ns	0.905	0.905 ns	0.887	0.887 ns
Tenant	0.0451	0.0530***	0.0354***	0.0653***	0.053	0.053 ns	0.035	0.035 ns	0.065	0.065 ns
Partner	0.0316	0.0172***	0.0173***	0.0170***	0.017	0.017 ns	0.017	0.017 ns	0.017	0.017 ns
Ocupant	0.0997	0.0355***	0.0424***	0.0307***	-	-	-	-	-	-
GVP	12009	77292	35761	106488	-	-	-	-	-	-
Labor	2.559	3.272	2.953	3.497	-	-	-	-	-	-
Area	28.53	91.81	45.71	124.2	-	-	-	-	-	-
Capital	101960	524921	236827	727447	-	-	-	-	-	-
Purchased Inputs	1995	31938	9117	47981	-	-	-	-	-	-
Nº Obs.	3,336,328	923,228	381,104	542,124	3,336,328	923,228		381,104		542,124

Source: Own elaboration.

Note: RE = Rural extension; ***Means are statistically different from the control group (no extension) at 1%; NS – means are statistically the same as the control group at 1%.

Table 2 – Estimation of the selection equation (*Probit*) for participation in rural extension services, after balancing the sample.

Variables	Rural Extension (1)	Public Rural Extension (2)	Private Rural Extension (3)
Gender	0.393***	0.237***	0.389***
	(0.00258)	(0.00302)	(0.00322)
Total Area	7.68e-05***	-3.96e-05***	9.24e-05***
	(1.64e-06)	(2.53e-06)	(1.59e-06)
Age	0.0340***	0.0268***	0.0257***
	(0.000324)	(0.000388)	(0.000384)
Age2	-0.000302***	-0.000229***	-0.000239***
	(3.08e-06)	(3.67e-06)	(3.68e-06)
Read and write	-1.115***	-0.327***	-1.231***
	(0.00497)	(0.00621)	(0.00557)
Do not read and write	-1.386***	-0.507***	-1.574***
	(0.00468)	(0.00587)	(0.00527)
Literate	-0.946***	-0.206***	-1.063***
	(0.00535)	(0.00663)	(0.00604)
Incomplete Elementary	-0.515***	-0.00855	-0.570***
	(0.00426)	(0.00546)	(0.00438)
Complete Elementary	-0.334***	0.0842***	-0.401***
	(0.00463)	(0.00589)	(0.00480)
Agricultural Technician	-	0.0700***	1.579***
	-	(0.00853)	(0.00799)
High School	-0.259***	0.108***	-0.325***
	(0.00473)	(0.00603)	(0.00489)
Exp1	-0.344***	-0.213***	-0.305***
	(0.00513)	(0.00636)	(0.00593)
Exp2	-0.162***	-0.0808***	-0.157***
	(0.00223)	(0.00268)	(0.00258)
Exp3	-0.0919***	-0.0128***	-0.121***
	(0.00209)	(0.00248)	(0.00244)
Qualif.	0.484***	0.157***	0.445***
	(0.00346)	(0.00410)	(0.00357)
Family	-0.274***	-0.0323***	-0.336***
	(0.00201)	(0.00251)	(0.00221)
Urban	-0.0575***	-0.138***	0.0264***
	(0.00224)	(0.00275)	(0.00247)
Tenant	0.137***	-0.135***	0.282***
	(0.00348)	(0.00455)	(0.00383)
Partner	-0.178***	-0.194***	-0.0998***

	(0.00500)	(0.00614)	(0.00598)
Ocupant	-0.418***	-0.298***	-0.391***
	(0.00330)	(0.00389)	(0.00417)
Constant	-1.086***	-2.069***	-1.159***
	(0.00972)	(0.0119)	(0.0112)
Log likelihood	-1.894e+06	-1.238e+06	-1.330e+06
chi2	492307***	90057***	587009***

Source: Own elaboration.
Note: ***significat at 1%; Standard erros in parentheses.

Table 3 - Estimation of Stochastic Production Frontier for the total sample and for the different treatment groups considered.

Ly(GVP)	**Total Sample (Pooled) (1)**	**RE (2)**	**Without Rural Extension (3)**	**Public Rural Extension (4)**	**Private Rural Extension (5)**
lx1 (Area)	0.454***	0.437***	0.423***	0.332***	0.486***
	(0.0029)	(0.0076)	(0.0033)	(0.0108)	(0.0103)
lx2 (Labor)	0.204***	0.294***	0.193***	0.223***	0.516***
	(0.0078)	(0.0175)	(0.0095)	(0.0268)	(0.0238)
lx3 (Purchased Inputs)	-0.116***	0.0859***	-0.0953***	-0.0547***	0.161***
	(0.0019)	(0.0056)	(0.0024)	(0.0082)	(0.0077)
lx4 (Capital)	-0.288***	-0.233***	-0.262***	-0.221***	-0.233***
	(0.0029)	(0.0069)	(0.0036)	(0.0095)	(0.0098)
lx12	-0.0031***	0.0491***	-0.0006 NS	0.00112	0.0768***
	(0.0005)	(0.0013)	(0.0006)	(0.0020)	(0.0017)
lx22	-0.0065**	0.103***	0.0008 NS	0.0719***	0.149***
	(0.0032)	(0.0048)	(0.0038)	(0.0091)	(0.0056)
lx32	0.0978***	0.0973***	0.102***	0.103***	0.0916***
	(0.0003)	(0.0005)	(0.0003)	(0.0008)	(0.0007)
lx42	0.0349***	0.0508***	0.0317***	0.0363***	0.0576***
	(0.0004)	(0.0008)	(0.0004)	(0.0012)	(0.0011)
lx1x2	-0.0243***	-0.0281***	-0.0234***	-0.0105***	-0.0343***
	(0.0010)	(0.0019)	(0.0011)	(0.0032)	(0.0023)
lx1x3	-0.0174***	-0.0275***	-0.0209***	-0.0195***	-0.0284***
	(0.0003)	(0.0007)	(0.0003)	(0.0010)	(0.0009)
lx1x4	-0.0097***	-0.0196***	-0.0046***	-0.0043***	-0.0296***
	(0.0003)	(0.0008)	(0.0004)	(0.0011)	(0.0010)
lx2x3	-0.0608***	-0.0492***	-0.0694***	-0.0504***	-0.0619***
	(0.0006)	(0.0015)	(0.0007)	(0.0022)	(0.0019)
lx2x4	0.0514***	0.0303***	0.0567***	0.0321***	0.0224***
	(0.0009)	(0.0020)	(0.0011)	(0.0030)	(0.0025)
lx3x4	0.0031***	-0.0209***	-0.00125***	-0.0092***	-0.0251***
	(0.0002)	(0.0007)	(0.0003)	(0.00095)	(0.0008)
Mills	-	-0.0151***	-0.0446***	-	-
		(0.0020)	(0.0011)		
Millspub	-	-	-	-0.0119***	-
				(0.0046)	
Millspriv	-	-	-	-	-0.0120***
					(0.0033)
Constant	7.897***	7.314***	8.039***	7.790***	6.945***
	(0.0186)	(0.0434)	(0.0214)	(0.0632)	(0.0637)
Usigma	1.571***	1.101***	1.822***	1.165***	1.194***
	(0.00128)	(0.00278)	(0.0014)	(0.0043)	(0.0034)
Vsigma	0.0814***	-0.385***	0.0458***	-0.224***	-0.497***
	(0.00134)	(0.00274)	(0.0016)	(0.0042)	(0.0036)
Lambda	19.299	2.859	39.782	5.201	2.402
Wald-Test	3.016e+06	738658	1.783e+06	229269	476631
Prob>chi2	0.000	0.000	0.000	0.000	0.000
Observations	4,259,963	867,145	3,336,328	381,104	542,124

Source: Own elaboration.

Note: *** significant at 1%, ** significant at 5%, * significant at 10%; Standard erros (bootstrap)in parentheses.

Table 4 - Elasticities of the inputs for the total sample and for the differents treatment groups considered.

	Area	Labor	Purchased Inputs	Capital	Sum
Total Sample (Pooled)	0.2316	0.3183	0.4372	0.1023	1.0894
	(0.0018)	(0.0035)	(0.0013)	(0.0016)	
Rural Extension	0.1469	0.3421	0.3700	0.1436	1.0025
	(0.0036)	(0.0066)	(0.0024)	(0.0030)	
Without Rural Extension	0.2367	0.3171	0.4313	0.0843	1.0694
	(0.0017)	(0.0038)	(0.0013)	(0.0015)	
Public Rural Extension	0.1696	0.2900	0.3994	0.1071	0.9662
	(0.0053)	(0.0105)	(0.0038)	(0.0044)	
Private Rural Extension	0.1353	0.4369	0.3675	0.1634	1.1030
	(0.0047)	(0.0086)	(0.0031)	(0.0040)	

Source: Own elaboration.
Note: All elasticities were statistically significant at 1%. Standard error in parentheses.

Table 5 - Mean and standard deviation of the technical efficiency scores for rural extension group considered.

Balanced Sample	**Nº OBS**	**Mean**	**Standard Deviation**
Rural Extension	923228	0.3209	0.2245
Without Rural Extension	3336328	0.3137	0.1998
Type of Extension			
Public Rural Extension	381104	0.3285	0.2178
Private Rural Extension	542124	0.3077	0.2274

Source: Own elaboration.

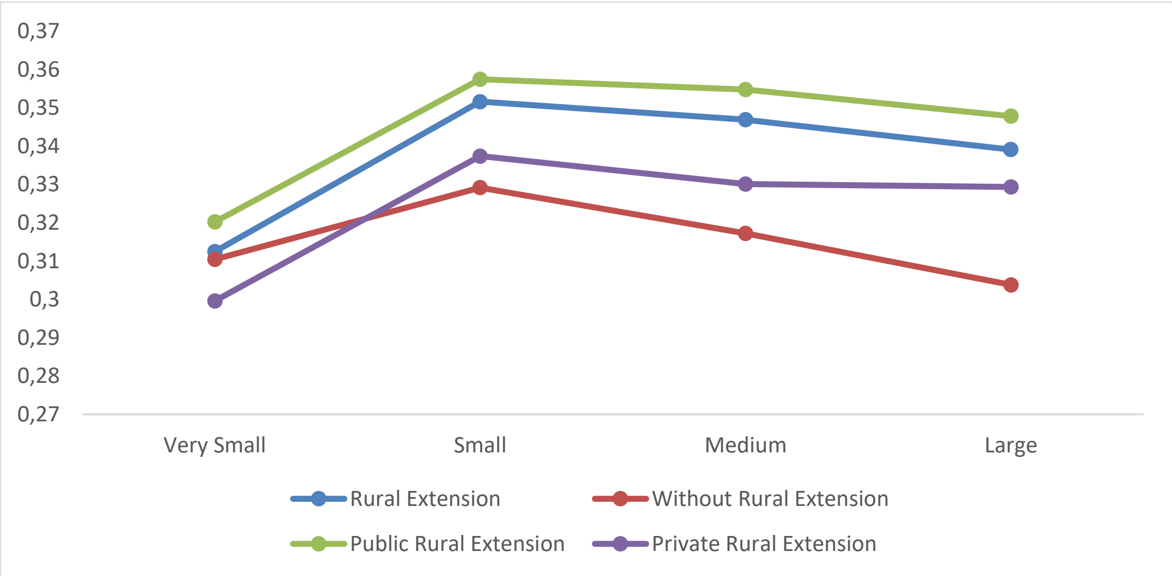

Figure 1 - Averages of the technical efficiency scores by farm size.