Can rural extension reduce the income differential in rural Brazil?

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ABSTRACT

The objective of this research was to identify the effect of rural extension on income and income inequality in the rural Brazil. To reach this objective we apply an unconditional quantile regression approach and the method of decomposition of income differentials proposed by Firpo et al. (2007) to the PNAD 2014 household survey from IBGE. Our results indicates that although rural extension increases rural household income in all income quantiles, it also increases income inequality in rural Brazil. We also found that private rural extension have a greater effect in all levels of income compared to public rural extension. Our results also have shown that education and access to credit are the main factors to explain the higher income obtained by the farmers assisted by the rural extension.

Key-words: *Rural extension, income inequality, unconditional quantile regression, decomposition*

JEL codes: Q16, Q12, I38

1. Introduction

In developing countries, economic policies mainly target reduction of poverty and income concentration (CHAKRAVARTY *et al.*, 2008). Food insecurity and poverty are the main obstacles to the economic growth and the development of rural areas. Three out of four people living in poverty reside in rural areas and depend directly or indirectly on agricultural activity in these countries (World Bank, 2007). Therefore, it is essential to identify the factors that lead to income enhancement and reduction of income inequality to better design and implement publics policies toward the agricultural sector.

Brazilian agriculture have shown a great performance along domestic and international markets. However, this sector still faces a high income inequality. The Gini index of income distribution in rural areas decreased from 0.544 in 2000 to 0.483 in 2010 (Brazilian Institute of Geography and Statistics – IBGE, 2017), which shows a decrease on income inequality between 2000 and 2010. However, Alves *et al.* (2013) shows that 87% of the Brazilian agricultural gross income is generated by 11.4% of the farms in Brazil. The most desirable stage in income inequality, Gini index equal zero, is still a distant target.

Income transfer policies, pension, and other socioeconomic policies have contributed to a modest decrease on income inequality in rural areas. The labor-related income (both agricultural and non-agricultural) still account for more than 70% of rural household income (HELFAND *et al.*, 2009). To reduce income inequality in these areas, public policies have to increase the agricultural competitiveness, which would lead to an increase in income. Public policies should affect areas beyond agricultural production itself (BARROS *et al.*, 2000).

The National Policy on Technical Assistance and Rural Extension (PNATER) is a public policy that supports this sector giving farmers access to rural extension. There were several public policies on rural extension since the 1950s but it was the creation of PNATER in 2003 and the institutionalization of Law No. 12,188 on Technical Assistance and Rural Extension - ATER in 2010 that defined socioeconomic guidelines to these policies (RODRIGUES, 1997). It also included new goals, such as provision of managerial tools related to sustainable use of natural resources (Ministry of Agrarian Development – MDA, 2017). PNATER structures the Brazilian rural extension as a "National Decentralized Public Extension System" and encourages the participation of nongovernmental institutions, private companies, unions and cooperatives in addition to public entities (PEIXOTO, 2009).

Access to rural extension can increase farmer’s access to new technologies, knowledge and information (CHRISTOPOLOS, 2010). However, only 22% of farmers have had access to these services (IBGE, 2017) and most of the small-scale farmer shave not accessed these services (ALVES *et al.*, 2013; PATA; FERNANDES, 2011). This suggests that the current PNATER structure might not be achieving its goal of also reducing income inequality. To better tackle this problem, it is important to identify the effects of these services on income generation in the Brazilian agricultural sector. In this paper we focus on identifying these effects. To estimate them we use an income decomposition proposed by Firpo *et al.* (2007) and the National Household Sample Survey (Pesquisa Nacional de Amostra em Domicílios - PNAD). This method consists in the estimation of income regressions for different unconditional quantiles of income distribution in a first stage. Then the income differential for the groups considered is decomposed to identify the main factors that explain the income gap across all quantiles analyzed.

Our analysis allows to conclude whether rural extension contribute to welfare enhancements of rural families, to increases in rural income and to reductions on rural inequality. Our study contributes to the literature on income inequality in rural areas by identifying the effect of rural extension and other income determinants such as schooling and access to rural credit on different income ranges. We find that although rural extension increases rural household income in the all income distribution quantiles, it also increases income inequality. In addition, we also find that the private rural extension service has a greater effect on rural income compared to public service provision. Regarding the income differential decomposition, the results show that the difference in individual characteristics, especially the schooling and access to rural credit, explains the majority of the income differential.

2. Related Literature

There are several studies that have investigate the effect of rural extension on rural income in developing economies, where great disparities on agricultural income are observed and can be ameliorate. Rural extension can increase farm income in developing countries (ANDERSON; FEDER, 2004), where the majority of the population lives in rural areas and would observe a greater impact of these policies on population welfare (GAUTAM, 2000).

Rural extension services seek to facilitate producers' access to new technologies, knowledge and information. The extension agent also helps rural producers to develop their own management skills and technical practices aiming to increase agricultural productivity and income, and thus rural welfare (CHRISTOPOLOS, 2010). Alex, Ziip and Byerlee (2002) indicate several socioeconomic benefits from rural extension such as positive impacts on the environment and the rural families health as a result of the use of appropriate technology, reduction of poverty as a result of greater equity in access to information and greater economic development and food security generated by increases on productivity, competitiveness and sustainability of the agricultural activity.

2.1. Rural Extension in Brazil

Rural extension services have taken place in Brazil since the nineteenth century (BERGARMASCO, 1983). However, these services were mostly performed by non-governmental institutions that sought to assist with on-farm training (PETTAN, 2010). Although these services has always occurred in Brazil, the creation of PNATER in 2003 and the institutionalization of Law No. 12,188[1] on Technical Assistance and Rural Extension - ATER in 2010 established new dimensions (economic and socioeconomic) to the Brazilian rural extension services.

The PNATER also includes goals in developing the rural environment in a sustainable way, the adoption of ecologically based agriculture, ensuring sustainable food and nutritional security and the generation of new agricultural and non-agricultural job (MDA, 2017). However, large farms and farms in more developed agricultural regions continue to obtain greater access to rural extension than smaller farms (ALVES, 2013). It contradicts the new policy directions of focusing in vulnerable groups.

Farms in the North and Northeast regions of Brazil have been poorly provided with rural extension services compared to other regions (KAGEYAMA, 1990).Only 15% of the farms in the Northern region have had access to these services compared to farms in the South, which, on average, 49% of them have had access. However, 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).

Despite the increase on resources designated to rural extension provision, several PNATER's obstacles have led to great disparities on regional provision. 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).

[1]According to Law No. 12,188, of January 11, 2010, technical assistance and rural extension is the informal education service, of a continuous nature, in the rural environment, which promotes processes of management, production, processing and marketing of activities and agricultural and non-agricultural services, including agroextractivist, forestry and artisanal activities (MDA, 2017).

2.2. Income Inequality and Rural Extension

Several studies have investigated the determinants of income and income inequality in rural areas in Brazil but without explicitly considering the role of rural extension. Araújo *et al.* (2008) identify the determinants of income inequality in rural areas of the Northeast using data from the PNAD. They calculate poverty indices in addition to an income decomposition methodology proposed by Fei *et al.* (1978). Their findings suggest a reduction in poverty in the period 1995-2001 and that the individual educational level is the most relevant factor explaining income inequality. Mariano and Neder (2006) also examined income inequality in the rural Northeast area of Brazil using data from the PNAD for the period 1999-2001.They have calculated poverty indexes and their findings suggest that agricultural income have contributed to reductions on income inequality and non-agricultural income was associated with greater inequality.

Ney and Hoffman (2009) identify the determinants of rural income focusing on the role of human and physical capital of rural properties in Brazil using the Demographic Census of 2000. They have estimated income models using the weighted least squares method and find that although physical capital has been the main determinant of rural income, individual educational levels accounts for the largest share of income inequality. They also find that human capital has a larger effect on the formation of non-agricultural income compared to agricultural income.

As for literature focusing on rural areas in other countries, some studies have analyzed the role of rural extension in income inequality. Deribew (2016) investigates the effect of rural extension on household income and income inequality using information on 734 rural households in the northern Ethiopia, a decomposition of the Gini index and regressions of yield function. He identifies a positive effect of rural extension on rural households income and that the rural extension policy increases agricultural income inequality and decrease non-agricultural income inequality. Akpan *et al.* (2016) identify the determinants of poverty and income inequality among 300 young rural producers selected from the state of Akwa Ibom in southern Nigeria using descriptive statistics analyzes and *Logit* regressions. They find that producers with higher levels of schooling and with access to rural extension were less likely to be below the poverty line. It implies that these factors are relevant to reduce income inequality. Akobundu *et al.* (2004) estimate income gains from participating in a rural extension program in the state of Virginia to identify the effect of rural extension on rural income. They have used a two-step procedure to identify the determinants of participation and the effect of the program on income. Results suggest that a single extension agent visit was not enough to generate significant results but income gains increases with the participation intensity.

These studies highlight the relevance of rural extension in enabling rural families development. There are several other studies that have investigated rural extension under a different perspective. A few papers have identified the impact of rural extension on farm technical efficiency (HELFAND; LEVINE, 2004, MAGALHÃES *et al.*, 2011), farm production and productivity (BALOCH; THAPA, 2016; JIN; HUFFMAN, 2016) and farm profit (HUFFMAN; EVENSON, 1989). Overall, they find that rural extension increases farm technical efficiency, productivity, production and profitability.

On the other hand, most of these studies have not focused on the effect of rural extension on these variables and have not estimated its effect on rural household income. It lacks in the literature a study that focus in this topic and uses a suitable methodology that allows to identify the effect of rural extension on different points of the income distribution, as well as to analyze the main factors that explain the difference of income between households that receive and do not receive the extension service. We seek to identify these effects using the household dataset (PNAD) made available by IBGE and the income decomposition methodology proposed by Firpo *et al.* (2007).

4. The application

We first use the unconditional quantile regression method to identify the effect of the rural extension on different income quantiles in the Brazilian rural area based on Firpo *et al.* (2007, 2009). We then identify the farmer characteristics that create generate the income difference between the groups of farms by access to rural extension. In this section we present the dataset used to identify the effect of rural extension on income and the empirical methodology used to achieve this goal.

4.1. Data

We use the National Household Sample Survey (PNAD) for 2014, being made available by the IBGE[2]. In the 2014 PNAD a supplementary questionnaire was provided to the households in which questions related to access to rural extension were included. In this article, we define

[2] According to Araújo *et al.* (2008), the National Household Survey is a unique survey, conducted annually and nationwide, raising a variety of information about the population's well-being and setting thus a major source of data on the Brazilian social environment.

rural extension as what the PNATER delineates as technical assistance and rural extension. Individuals self-declared employers or self-employed as the main activity were questioned whether they have received any technical assistance during the last year. Technical assistance was split in four categories: Technical Assistance and Rural Extension Company (Empresa de Assistência Técnica e Extensão Rural – EMATER); other government agency (federal, state or municipal); private company; or another source. We constructed dummy variables to represent access to rural extension based on these categories.

In this paper we have considered rural producers those that are: 1) economically active people; 2) employers or self-employed workers (these being the individuals interviewed in the questionnaire on productive inclusion); 3) and whose main activity of the enterprise was agricultural activity. Our sample also included a small portion of rural property managers residing in urban areas, which also appears in the microdata of the Agricultural Census of 2006 (IBGE, 2017). After dropping missing values and outliers, the final sample consists of 15,406 individuals. A descriptive statistical analysis of the data is presented in the results section.

We use monthly household income in R$ as a proxy to farmer income. In addition to a variable capturing access to rural extension, we have included the following variables:

i) Gender: a dummy variable equals to 1 if the individual is male;
ii) Race: a dummy variable equals to 1 if the individual is black;
iii) Schooling: several dummy variable split in the categories “do not read and write”, “incomplete elementary school”, “complete elementary school”, “incomplete high school”, “complete high school”, “incomplete higher education” and “complete higher education”;
iv) Rural: a dummy variable equals to 1 if the individual resides in the rural area;
v) Credit: a dummy variable equals to 1 if the individual have received credit from any credit program;
vi) Land ownership: several dummy variables seeking to identify the condition of the producer in relation to the land such as whether the producer is a partner, tenant, occupant, owner or other condition;
vii) Farm area: four dummy variables that represent the farm size split in very small (up to 10 hectares (ha)), small (10 to 100ha), medium (100 to 1000ha) and large (greater than 1000ha).

The group characteristics are presented in Table 1. Our sample is composed by 15,406 rural producers[3], in which only 14.1% have had access to rural extension in 2014 split in public extension (56% of those) and private extension (44%).

[3] Farmers were considered individuals whose main activity was agricultural, as an employer and/or self-employed.

Table 1 - Mean and standard deviation of the variables used, for total sample and by rural extension group considered.

Variables	Brazil		No Rural Extension		Rural Extension		Public Rural Extension		Private Rural Extension	
	Average	**SD**	**Average**	**SD**	**Average**	**SD**	**Average**	**SD**	**Average**	**SD**
income	2505	3473	2252	3132	4051	4797	3200	3700	5143	5734
gender	0.855	0.352	0.854	0.354	0.864	0.343	0.881	0.324	0.842	0.365
Race	0.0733	0.261	0.0778	0.268	0.0461	0.210	0.0739	0.262	0.0105	0.102
studyyears	5.588	3.988	5.314	3.909	7.262	4.059	6.433	3.914	8.326	3.995
do not read and write	0.00402	0.0633	0.00400	0.0631	0.00415	0.0643	0.00739	0.0857	0	0
incomplete elementary	0.223	0.416	0.244	0.429	0.0978	0.297	0.140	0.348	0.0432	0.203
complete elementary	0.518	0.500	0.519	0.500	0.507	0.500	0.524	0.500	0.486	0.500
incomplete high school	0.0843	0.278	0.0775	0.267	0.126	0.331	0.123	0.329	0.129	0.335
complete high school	0.0329	0.178	0.0322	0.176	0.0374	0.190	0.0320	0.176	0.0443	0.206
incomp. higher education	0.107	0.309	0.0977	0.297	0.160	0.367	0.137	0.344	0.190	0.392
comp. higher education	0.0317	0.175	0.0258	0.158	0.0678	0.252	0.0361	0.187	0.109	0.311
age25	0.0537	0.226	0.0571	0.232	0.0332	0.179	0.0255	0.158	0.0432	0.203
age26to35	0.150	0.357	0.149	0.357	0.151	0.358	0.119	0.324	0.193	0.395
age36to45	0.218	0.413	0.216	0.411	0.234	0.424	0.226	0.418	0.246	0.431
age46to55	0.261	0.439	0.256	0.436	0.295	0.456	0.291	0.455	0.300	0.459
age56to65	0.206	0.405	0.207	0.405	0.205	0.404	0.240	0.427	0.160	0.367
age65more	0.110	0.313	0.115	0.319	0.0808	0.273	0.0985	0.298	0.0580	0.234
rural	0.733	0.443	0.722	0.448	0.797	0.402	0.825	0.380	0.761	0.427
credit	0.127	0.333	0.0766	0.266	0.434	0.496	0.408	0.492	0.467	0.499
partner	0.0573	0.232	0.0581	0.234	0.0526	0.223	0.0460	0.210	0.0611	0.240
tenant	0.0531	0.224	0.0516	0.221	0.0623	0.242	0.0378	0.191	0.0938	0.292
occupant	0.0469	0.211	0.0486	0.215	0.0369	0.189	0.0427	0.202	0.0295	0.169
owner	0.754	0.430	0.746	0.435	0.805	0.396	0.824	0.381	0.780	0.415
others	0.0883	0.284	0.0956	0.294	0.0434	0.204	0.0493	0.217	0.0358	0.186
very small	0.600	0.490	0.622	0.485	0.468	0.499	0.539	0.499	0.377	0.485
small	0.262	0.440	0.242	0.428	0.386	0.487	0.346	0.476	0.437	0.496
medium	0.0704	0.256	0.0700	0.255	0.0729	0.260	0.0517	0.222	0.100	0.300
large	0.0467	0.211	0.0450	0.207	0.0572	0.232	0.0542	0.226	0.0611	0.240
#Obs	**15406**		**13239**		**2167**		**1218**		**949**	

viii) Source: Own elaboration based on PNAD data from 2014. Note: SD - Standard deviation

We observe that farmers that have had access to rural extension services (group A) had a monthly income of, on average, R$ 4,051.00, while the average income of those that have not accessed rural extension (group B), on average, was R$ 2,252.00. The large standard deviation on this variable indicates great heterogeneity or a wide income distribution. Farmers in group A have a higher education level, on average, 7.3 years compared to farmers on Group B that have, on average, 5.3 years. Farmers in Group A also have a greater access to credit, on average, 43.4% of them had access to credit while only 7.7% of the farmer in Groups B have accessed to credit.

We do not observe a substantial difference between groups on farmer's age. 85% of the sample is male, 73% of sample lives in rural areas and 75% of them own the farm. On average, the monthly household income reported by farmers that have accessed private rural extension (R$ 5,143) is 60% higher than the average income of farms that have had access to public service (R$ 3,200). Farmers that have accessed private rural extension services have a higher level of education and have had greater access to credit. Among farmers in group A, 54% of them have had access to public rural extension services.

4.2 The unconditional quantile regression approach

To identify the effects of rural extension on rural income and income inequality we use the unconditional quantile regression approach proposed by Firpo *et al.* (2009) and the concept of Recentered Influence Function (RIF). The influence function[4] allows to identify the relative effect (the influence) of an individual observation on a statistic of interest (SILVA; FRANÇA, 2016). That is, for a distribution statistic $\upsilon(F_y)$, the influence of each observation on $\upsilon(F_y)$ is given by the influence function $IF(y;\upsilon,F_y)$. The incorporation of the statistic $\upsilon(F_y)$ in the influence function results in the so-called Recentered Influence Function, $RIF(y;\upsilon)=\upsilon(y)+IF(y;\upsilon)$. It allows to analyze the effects of individual covariates on the statistical distribution of interest. We are interested on the distribution of the quantiles but it can also be applied to different statistical distributions such as Gini coefficient, variance, or another that can represent income inequality.

[4] The influence function method basically provides a linear approximation for a nonlinear function of a statistical distribution of interest, such as quantiles, variance or others, allowing to estimate the effect of one or more covariates on the distribution of the statistics of interest (CHI; LEE, 2008). For more details, see Chi and Lee (2008) and Firpo *et al.* (2009).

We define the *τ-th* quantile (q_τ) of the income distribution *Y* as $q_\tau = \upsilon_\tau(F_y) = \inf_q \{q : F_y(q) \geq \tau\}$, and its influence function $IF(y; q_\tau, F_y)$ as:

$$IF(y; q_\tau, F_y) = \frac{\tau - 1\{y \leq q_\tau(F_y)\}}{f_y(q_\tau(F_y))} \tag{7}$$

where $1\{y \leq q_\tau(F_y)\}$ is an indicator function, which shows whether the variable *Y* (monthly household income) is less than or equal to the quantile q_τ, and $f_y(q_\tau(F_y))$ represents the marginal density function of the distribution of *Y* evaluated in q_τ.

The recentered influence function, which will replace the dependent variable Y in the unconditional quantile analysis, is defined by the sum of the distribution statistics and their respective influence function, $RIF(y; \upsilon, F_y) = \upsilon(F_y) + IF(y; \upsilon, F_y)$. Thus, adapting the expression to the τ - *th* quantile (q_τ), the RIF for each income quantile is given by:

$$RIF(y; q_\tau, F_y) = q_\tau + \frac{\tau - 1\{y \leq q_\tau(F_y)\}}{f_y(q_\tau(F_y))} = c_{1\tau}.1\{y \leq q_\tau(F_y)\} + c_{2\tau} \tag{8}$$

where $c_{1\tau} = \dfrac{1}{f_y(q_\tau)}$ and $c_{2\tau} = q_\tau - c_{1\tau}.(1-\tau)$ and the conditional expectation is $\upsilon(F_y)$ (FIRPO *et al.*, 2009; SILVA; FRANÇA, 2016)

$$E\lfloor RIF(y; \upsilon, F_y) \rfloor = \upsilon(F_y) \tag{9}$$

We first obtain the sample quantile $\hat{q}_\tau$ (FIRPO *et al.*, 2009; KOENKER; BASSET, 1978) and then the marginal density function $\hat{f}_y\left(\hat{q}_\tau\right)$ through Kernel functions. After obtaining these estimates, they are incorporated in (8).

Assume a covariate vector *X* and the conditional expectation of the RIF as a function of *X*; i.e. $E\lfloor RIF(y; \upsilon, F_y) \mid X = x \rfloor$. Then, it can be represented as a linear regression in function of $X, RIF(y; \upsilon, F_y) = X\beta + \varepsilon$. Assuming $E[\varepsilon \mid X] = 0$ and applying the Law of Iterated Expectations, we have the unconditional quantile regression

$$\upsilon(F_y) = E_x \lfloor E \lfloor RIF(y; \upsilon, F_y) \rfloor \rfloor = E[X].\beta \tag{10}$$

where *y* represents the monthly rural household income; $RIF(y; \upsilon, F_y)$ is the recentered influence function, which replaces the observed *y* in each observation; *X* is the vector of explanatory variables; and β are the coefficients of interest, which capture the effect of changing the distribution of a variable on the unconditional quantile of *y* or the unconditional quantile partial effect (FIRPO *et al.*, 2009). These coefficients can be estimated by OLS or another linear estimator.

4.3. Decomposition of income differentials

We use an income decomposition procedure proposed by Firpo *et al.* (2007)[5] to estimate the income differentials between groups: farms that have accessed rural extension and farmers that have not. It consists of estimating the RIF regression along with a re-weighting scheme proposed by DiNardo *et al.* (1996). It is an adaptation of the Oaxaca-Blinder[6] decomposition approach which allows to expand the decomposition to other statistics of interest such as quantiles, variance and Gini coefficient.

Let's assume two groups of households: *A* (farmers that have accessed rural extension) and *B* (that have not accessed); a result variable *Y* (logarithm of household incomes); and a group of covariates that represents individuals characteristics. The decomposition seeks to identify the difference in the income distributions of the two groups based on some statistics of these distributions opposed to only analyzing the mean. It is represented as

$$\Delta^{\upsilon} = \upsilon(F_{yA}) - \upsilon(F_{yB}) \tag{11}$$

where $\upsilon(F_{yt})$ represents a statistic of the income distribution (income quantiles on this paper), for two groups $t = A, B$.

The term Δ^{υ} is then divided in two components: Composition Effect: represents the income differential explained by the differences in observable characteristics such as gender, education, age, farm size and others; and Return Effect: represents the differences in the returns of these characteristics (estimated parameters) between the two groups. To implement this decomposition, first a counterfactual distribution (F_{yc}) has to be obtained in addition to its statistics of interest $\upsilon(F_{yc})$ such as in (10). It allows to simulate an income distribution with characteristics of group *A* and the returns (coefficients) to the characteristics of group *B*. We can insert F_{yc} in (11) to obtain

$$\begin{aligned} \Delta^{\upsilon} &= \left[\upsilon(F_{yB}) - \upsilon(F_{yc})\right] + \left[\upsilon(F_{yC}) - \upsilon(F_{yA})\right] \\ \Delta^{\upsilon} &= \Delta^{\upsilon}_{R} + \Delta^{\upsilon}_{X} \end{aligned} \tag{12}$$

[5]This method has been used in other studies such as in Machado and Mata (2005).

[6] For more details on the traditional Oaxaca-Blinder decomposition approach (Blinder, 1973; Oaxaca, 1973), see Jann (2008).

where the total income differential is decomposed into two terms: Δ_R^{υ}, which represents the portion of the differential resulting from the differences in the returns (coefficients) of the characteristics (return effect); and Δ_X^{υ}, which represents the portion of the differential associated with the differences in the distributions of the characteristics (composition effect).

To obtain (12) we re-estimate the RIF regressions for each of the groups and obtain the conditional expectation of the recentered functions of influence. This allows to obtain the expected value of the RIF for the observed distributions $\upsilon(F_{yt})$ and the counterfactual distribution $\upsilon(F_{yC})$ in a linear specification

$$\upsilon(F_{yt}) = E\left[RIF(y_t;\upsilon_t) \mid X, T = t\right] = X_t \beta_t \tag{13}$$

$$\upsilon(F_{yC}) = E\left[RIF(y_A;\upsilon_C) \mid X, T = B\right] = X_C \beta_C \tag{14}$$

for t = A, B. To obtain the parameters of interest β, Firpo *et al.* (2007) uses a reweighting technique based on the study of DiNardo *et al.* (1996). The reweighting factors for each group are

$$\hat{\omega}_A(T) = \frac{T}{\hat{\rho}},$$

$$\hat{\omega}_B(T) = \frac{1-T}{1-\hat{\rho}}, \text{ and} \tag{15}$$

$$\hat{\omega}_C(T;X) = \left[\frac{\hat{\rho}(X)}{1-\hat{\rho}(X)}\right] . \left[\frac{1-T}{\hat{\rho}}\right]$$

where T is either 1 or 0 and indicates whether the individual participates in group A (value 1) or B (value 0); and $\hat{\rho}$ is an estimator of the probability that a farmer have accessed rural extension (group A, or T = 1) given the characteristics vector X and may be estimated using a probability model such as *Logit* or *Probit* (CHI; LI, 2008).

After obtaining the reweighting factors the RIF regressions for each group can be estimated by OLS

$$\hat{\beta}_t = \left(\sum_{i\in t} \hat{\omega}_t . X_i . X_i^{'}\right)^{-1} . \sum_{i\in t} \hat{\omega}_t . \hat{RIF}(y_{ti};\upsilon_t) X_i \tag{16}$$

for t = A, B and for the counterfactual the RIF is estimated as

$$\hat{\beta}_C = \left(\sum_{i\in A} \hat{\omega}_C (X_i) .. X_i . X_i^{'}\right)^{-1} . \sum_{i\in A} \hat{\omega}_C (X_i) . \hat{RIF}(y_{Ai};\upsilon_C) X_i \tag{17}$$

where the decomposition presented in (11) can be obtained as

$$\hat{\Delta}^{\upsilon} = \left[\overline{X}_B . \hat{\beta}_B - \overline{X}_C . \hat{\beta}_C \right] + \left[\overline{X}_C . \hat{\beta}_C - \overline{X}_A . \hat{\beta}_A \right]$$
$$\hat{\Delta}^{\upsilon} = \hat{\Delta}^{\upsilon}_R + \hat{\Delta}^{\upsilon}_X \tag{18}$$

We can also identify the contribution of each covariate X_k, where $k = 1, ..., K$, on each of the effects obtained in (18) as in

$$\hat{\Delta}^{\upsilon}_X = \sum_{k=1}^{K} \left(\overline{X}_{ck} - \overline{X}_{Ak} \right) \hat{\beta}_A \tag{19}$$

$$\hat{\Delta}^{\upsilon}_R = \left(\hat{\beta}_{B1} - \hat{\beta}_{C1} \right) + \sum_{k=2}^{K} \overline{X}_{Bk} \left(\hat{\beta}_{BK} - \hat{\beta}_{CK} \right) \tag{20}$$

where in (20) the first term (difference in the returns of the covariate $k = 1$) represents the difference in the intercepts of the regressions of groups A and B, and the second term represents the contribution of the return of each covariate in the total return effect.

Fortin *et al.* (2011) argue that one of the main shortcomings of this method is that the feedback effect is sensitive to the choice of the base group. However, they indicate that there is no other method that corrects this limitation. On the other hand, this method presents is path independent which means that the order in which the different elements of the detailed decomposition are calculated does not affect the results of the decomposition (OLIVEIRA; SILVEIRA NETO, 2015).

5. Results and discussion

We first present the results of the unconditional quantile regression and then the results of the income decomposition to our sample of 15,406 rural producers.

5.1. Effect of rural extension in rural income

In this section we present the results of the RIF regressions for the unconditional income distribution quantiles of the logarithm of monthly household income and of the ordinary least squares (OLS). The estimated coefficients have shown some variations along the income distribution quantiles with respect to the estimated coefficients obtained for the mean. This result re-enforces the need to use the unconditional quantile regression approach. Results are displayed in Table 2.

Table 2 – Estimates of unconditional quantile regression – Brazil (2014).

Ln(Yi)	MQO	q10	q20	q30	q40	q50	q60	q70	q80	q90
Rural Extension	0.426***	0.285***	0.339***	0.394***	0.469***	0.361***	0.411***	0.523***	0.581***	0.601***
	(0.0208)	(0.0301)	(0.0264)	(0.0273)	(0.0292)	(0.0240)	(0.0249)	(0.0318)	(0.0411)	(0.0583)
Gender	-0.0339*	-0.0492 NS	-0.132***	-0.156***	-0.0605**	-0.00654 NS	-0.0286 NS	-0.0115 NS	0.0312 NS	0.0481 NS
	(0.0189)	(0.0434)	(0.0314)	(0.0298)	(0.0301)	(0.0233)	(0.0221)	(0.0249)	(0.0279)	(0.0359)
Race	-0.168***	-0.0135 NS	-0.0808*	-0.171***	-0.212***	-0.232***	-0.192***	-0.247***	-0.253***	-0.192***
	(0.0270)	(0.0629)	(0.0464)	(0.0438)	(0.0415)	(0.0307)	(0.0283)	(0.0298)	(0.0292)	(0.0361)
Incomplete Elementary	0.0311 NS	0.482 NS	0.585**	0.115 NS	-0.288 NS	-0.223 NS	-0.310**	-0.191 NS	-0.385**	0.0378 NS
	(0.120)	(0.343)	(0.228)	(0.195)	(0.183)	(0.143)	(0.132)	(0.141)	(0.159)	(0.0650)
Complete Elementary	0.287**	0.674**	0.791***	0.318 NS	-0.0140 NS	0.00729 NS	-0.0501 NS	0.114 NS	-0.0539 NS	0.356***
	(0.119)	(0.342)	(0.228)	(0.194)	(0.182)	(0.143)	(0.131)	(0.140)	(0.159)	(0.0643)
Incomplete High School	0.480***	0.893***	0.971***	0.470**	0.187 NS	0.183 NS	0.0833 NS	0.344**	0.188 NS	0.600***
	(0.121)	(0.344)	(0.230)	(0.197)	(0.185)	(0.145)	(0.134)	(0.144)	(0.164)	(0.0828)
Comp. High School	0.504***	0.850**	0.959***	0.599***	0.156 NS	0.172 NS	0.0951 NS	0.323**	0.323*	0.777***
	(0.125)	(0.352)	(0.236)	(0.203)	(0.191)	(0.149)	(0.138)	(0.149)	(0.171)	(0.112)
Incomp. Higher education	0.691***	0.890***	1.154***	0.718***	0.448**	0.388***	0.350***	0.578***	0.416**	0.894***
	(0.121)	(0.344)	(0.229)	(0.196)	(0.184)	(0.144)	(0.133)	(0.144)	(0.163)	(0.0834)
Comp. Higher education	1.289***	1.035***	1.223***	0.826***	0.631***	0.629***	0.633***	1.077***	1.384***	2.306***
	(0.126)	(0.343)	(0.229)	(0.198)	(0.186)	(0.146)	(0.136)	(0.149)	(0.174)	(0.145)
Age26_35	-0.0312 NS	-0.0106	-0.0970 NS	-0.180***	-0.156***	-0.114***	-0.0471 NS	-0.0748*	-0.0989**	0.0409 NS
	(0.0340)	(0.0922)	(0.0664)	(0.0599)	(0.0568)	(0.0420)	(0.0363)	(0.0413)	(0.0479)	(0.0616)
Age36_45	0.138***	0.252***	0.197***	0.0910 NS	0.0782 NS	0.0160 NS	0.102***	0.0530 NS	-0.00802 NS	0.133**
	(0.0329)	(0.0867)	(0.0629)	(0.0576)	(0.0552)	(0.0410)	(0.0357)	(0.0408)	(0.0473)	(0.0609)
Age46_55	0.197***	0.153*	0.245***	0.186***	0.157***	0.105**	0.208***	0.165***	0.0838*	0.193***
	(0.0328)	(0.0874)	(0.0624)	(0.0574)	(0.0552)	(0.0411)	(0.0360)	(0.0413)	(0.0480)	(0.0625)
Age56_65	0.476***	0.513***	0.677***	0.638***	0.590***	0.405***	0.411***	0.329***	0.234***	0.337***
	(0.0341)	(0.0871)	(0.0627)	(0.0586)	(0.0572)	(0.0430)	(0.0381)	(0.0433)	(0.0500)	(0.0649)
Age65m	0.786***	0.845***	1.053***	1.062***	1.165***	0.844***	0.644***	0.509***	0.364***	0.466***
	(0.0372)	(0.0862)	(0.0616)	(0.0585)	(0.0578)	(0.0455)	(0.0424)	(0.0489)	(0.0563)	(0.0724)
Rural	-0.246***	-0.178***	-0.209***	-0.210***	-0.232***	-0.201***	-0.225***	-0.304***	-0.283***	-0.312***

	(0.0158)	(0.0317)	(0.0244)	(0.0242)	(0.0245)	(0.0190)	(0.0186)	(0.0221)	(0.0256)	(0.0344)
Rural Credit	0.257***	0.204***	0.166***	0.251***	0.241***	0.235***	0.259***	0.318***	0.407***	0.303***
	(0.0215)	(0.0316)	(0.0285)	(0.0286)	(0.0309)	(0.0249)	(0.0258)	(0.0326)	(0.0421)	(0.0579)
Partner	-0.0374 NS	0.0368 NS	0.0414 NS	-0.0171 NS	-0.0765 NS	-0.128***	-0.0644**	-0.0898**	-0.120***	-0.0880*
	(0.0290)	(0.0666)	(0.0519)	(0.0485)	(0.0466)	(0.0347)	(0.0327)	(0.0365)	(0.0414)	(0.0525)
Tenant	0.000632 NS	-0.0608 NS	-0.0159 NS	0.0151 NS	0.0567 NS	0.0331 NS	0.0368 NS	0.0177 NS	-0.0741 NS	0.00342 NS
	(0.0287)	(0.0673)	(0.0501)	(0.0467)	(0.0462)	(0.0355)	(0.0356)	(0.0411)	(0.0458)	(0.0627)
Ocupant	-0.0989***	0.0409 NS	-0.0637 NS	-0.130**	-0.211***	-0.129***	-0.100***	-0.157***	-0.125***	-0.143***
	(0.0356)	(0.0820)	(0.0650)	(0.0609)	(0.0572)	(0.0411)	(0.0368)	(0.0355)	(0.0357)	(0.0346)
Other_condition	-0.261***	-0.450***	-0.235***	-0.258***	-0.260***	-0.225***	-0.268***	-0.296***	-0.265***	-0.138***
	(0.0242)	(0.0694)	(0.0468)	(0.0422)	(0.0399)	(0.0292)	(0.0252)	(0.0265)	(0.0272)	(0.0362)
Small	0.257***	0.268***	0.266***	0.219***	0.240***	0.202***	0.224***	0.276***	0.346***	0.296***
	(0.0164)	(0.0302)	(0.0239)	(0.0243)	(0.0249)	(0.0197)	(0.0195)	(0.0231)	(0.0279)	(0.0360)
Medium	0.370***	0.183***	0.186***	0.158***	0.167***	0.196***	0.305***	0.445***	0.541***	0.881***
	(0.0291)	(0.0479)	(0.0387)	(0.0389)	(0.0401)	(0.0315)	(0.0317)	(0.0386)	(0.0492)	(0.0771)
Large	0.334***	0.339***	0.320***	0.329***	0.375***	0.247***	0.252***	0.266***	0.331***	0.427***
	(0.0335)	(0.0529)	(0.0452)	(0.0468)	(0.0485)	(0.0406)	(0.0396)	(0.0474)	(0.0576)	(0.0824)
Intercept	6.811***	5.218***	5.525***	6.392***	6.928***	7.207***	7.449***	7.556***	7.964***	7.832***
	(0.124)	(0.353)	(0.235)	(0.202)	(0.190)	(0.149)	(0.137)	(0.148)	(0.169)	(0.0916)
Observations	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406
F	233.93	42.84	107.09	129.21	169	189.47	205.42	198.2	147.52	64.51
R-squared	0.259	0.058	0.118	0.143	0.168	0.183	0.190	0.204	0.201	0.157

Source: Own elaboration.

Note: RE – Rural Extension; *** significant at 1%, **significant at 5%, * significant at 10%, NS - non significant; Standard errors in parentheses.

Our results suggest a positive effect of rural extension services on rural income and it increases as we evaluate higher quantiles of the income distribution. For instance, the coefficients for the first two income quantiles, q10 and q20, suggest that farmers in group A are associate with an income 28.5% and 33.9% higher than those in group B. The distance between the two immediate quantiles decreases as we evaluate higher quantiles; i.e. for q80 and q90, they were 58.1% and 60.1%, respectively. These results show two effects of rural extension: these services raise monthly household income; and, on the other hand, it increases income inequality in rural Brazil by having a stronger effect in higher income quantiles.

Alves *et al.* (2013) state that one of the main objectives of rural extension services is to increase rural income throughout the dissemination of new technologies and reduction of the negative effects caused by market imperfections. However, a higher access to these services by large and more profitable farms contributes to the maintenance of the income inequality. Deribew (2016) find a similar result for farmers in Ethiopia in which results suggest a positive effect of rural extension on the rural income and an increase on income inequality in the agricultural activity.

Gender and *race* variables do not show a great discriminatory effect in the income quantiles analyzed. Woman shows a higher income compared to man only at the bottom of the income distribution. We also find that black individuals face lower wages compared to non-black individuals but there is no clear pattern along the income distribution. Overall, a higher level of education such as "complete elementary school", "high school" and "higher education" is related to greater income compared to the base variable, "people who cannot read or write". Oliveira and Silveira Neto (2015), and Reis *et al.* (2017) have also identified positive effects of investments in human capital on income. Our results show that education can decrease income inequality; i.e. great income returns to "high school" level in the first quantiles of income distribution. On the other hand, focusing on "higher education" increases the inequality even thou only 3.2% of the sample has a high education level. These results show the relevant role of human capital on explaining rural income inequalities (NEY; HOFFMAN, 2009).

Experience (the age variable) has a stronger effect at the bottom of income distribution; i.e. older individuals are related to higher income level compared to those younger than 25 years old (base category). It implies a significant contribution of experience on reducing rural income inequality. Overall, access to rural credit is also associated with higher income in all quantiles of the distribution. It allows improvements on farm productive capacity through acquisition of inputs and new technologies. Along the top quantiles of the income distribution, q70, q80 and q90, farmers that had access to rural credit obtained an income 31.8%, 40.7% and 30.3% higher than the others, respectively.

Farmers that are partners, occupant and other classifications face lower income compared to farm owners (base category) in all quantiles of the income distribution. Farm owners have a greater incentive to invest in innovations and in other long-term technology, which contribute to increase rural income. These properties also have greater access to credit and other services given that the land can be used as a tangible guarantee for the fulfillment of the financial obligations. Farmers that reside in rural areas are associated with lower income in all quantiles of the income distribution. Living in an urban area might lead to a greater access to information about market, banking institutions and other services. The farm size dummies suggest that all categories other than "very small" are associated with greater income compared to "very small" farms.

We are also interested in identifying whether the source of the rural extension provision have a different effect on income distribution. To obtain these effects we estimate RIF equations for each income quantile and different source of rural extension service provision. These results are displayed in Table 3 and Figure 1 shows the effect of rural extension, both aggregate and disaggregate by source, on income. It is important to note that the same control variables were considered as the estimation for aggregate rural extension. However, there were no significant changes in the coefficients of such variables[7].

[7] The control variables in Table 3 are omitted due the words limit, but can be available upon request.

Table 3– Estimates of unconditional quantile regression– Public and Private Rural Extension, Brazil (2014).

Ln(Yi)	**MQO**	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
Public RE	0.268***	0.205***	0.216***	0.264***	0.324***	0.246***	0.249***	0.346***	0.417***	0.355***
	(0.0263)	(0.0421)	(0.0362)	(0.0364)	(0.0377)	(0.0306)	(0.0319)	(0.0403)	(0.0512)	(0.0696)
Private RE	0.610***	0.378***	0.481***	0.545***	0.637***	0.495***	0.599***	0.729***	0.771***	0.887***
	(0.0280)	(0.0311)	(0.0279)	(0.0316)	(0.0358)	(0.0308)	(0.0315)	(0.0422)	(0.0577)	(0.0879)
Intercept	6.828***	5.227***	5.539***	6.407***	6.944***	7.220***	7.467***	7.575***	7.982***	7.860***
	(0.124)	(0.350)	(0.233)	(0.200)	(0.187)	(0.148)	(0.136)	(0.148)	(0.169)	(0.0890)
Controls Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406	15,406
F	229.54	41.86	103.7	125.8	163.17	183.73	207.31	197.13	143.85	62.81
R-squared	0.264	0.058	0.119	0.144	0.170	0.185	0.195	0.208	0.204	0.160

Source: Own elaboration.

Note: RE – Rural Extension; *** significant at 1%, **significant at 5%, * significant at 10%, NS - non significant; Standard errors in parentheses.

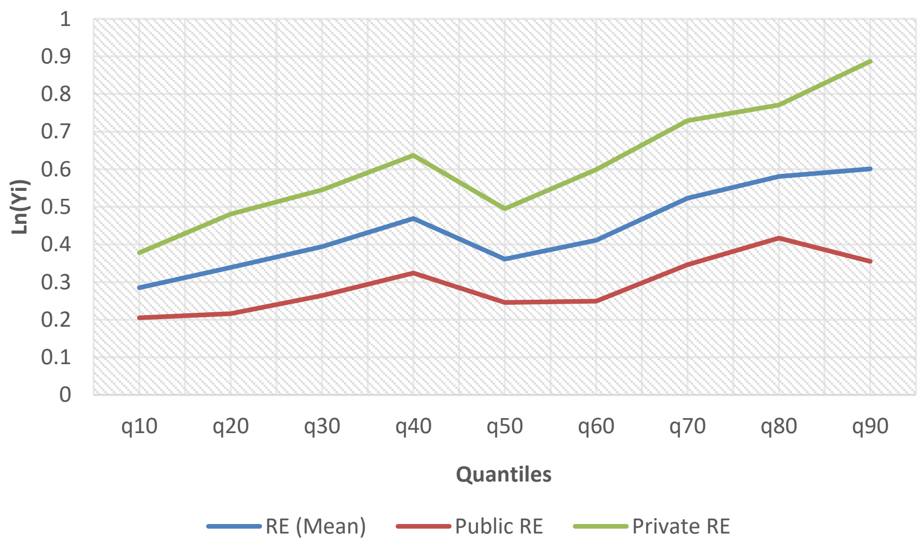

Figure 1 - Effects of rural extension on the distribution of income in the Brazil rural.

Note: RE: Rural Extension.

Source: Own elaboration.

Our results show that the private rural extension service have a greater effect on rural income. For instance, these private services have a twice larger effect on income on the top part of the income distribution (q90) compared to the public services. For this quantile, private services increase rural income in 88.7% compared to non-adopters while the public services increase in 35.5%. A higher effect of private services compared to public service might be explained by the restriction on resources that small and poor farmers face, which limits the effect of public policy on rural extension. On the other hand, large farmers have easier access to a more specialized private extension service, which explains the increasing income gap between the source of extension as higher income quantiles are considered.

5.2. Decomposition of income differentials

The analysis of the data indicate differences in the characteristics of farms in group A and B. The results presented in the previous subsection also indicate differences in the return to rural extension on income. Although it increases rural income it also increases income inequality. In this section we identify which factors explain this difference in income between these farm groups. The income decomposition method is used along the RIF regressions to evaluate how much of the income differences between the farm groups is attributed to the *composition effect* and to the *return effect*. The former effect represents the differences in the distribution of the individuals characteristics and the latter effect represents the differences in the returns of the characteristics. It allows to identify the contribution of each explanatory variable on each of the estimated effects. The outcome of this methodology is presented in Tables A1 and A2 and are summarized in Figures 3, 4 and 5.

The decomposition of the income differential between groups A and B in the *composition effect* and *return effect* is displayed in Figure 3. Farmers that have access to rural extension obtain a higher level of income in all the quantiles considered compare to farmers that have not accessed these services. Overall, the *return effect* predominates which means that the majority of the income differential between groups is explained by the high returns of the explanatory variables. On the other hand, the *composition effect* impact on income increases along the quantiles; i.e. the differences in the individual characteristics such as schooling and access to rural credit explain almost the entire income gap between such groups in the top part of the income distribution, q90.

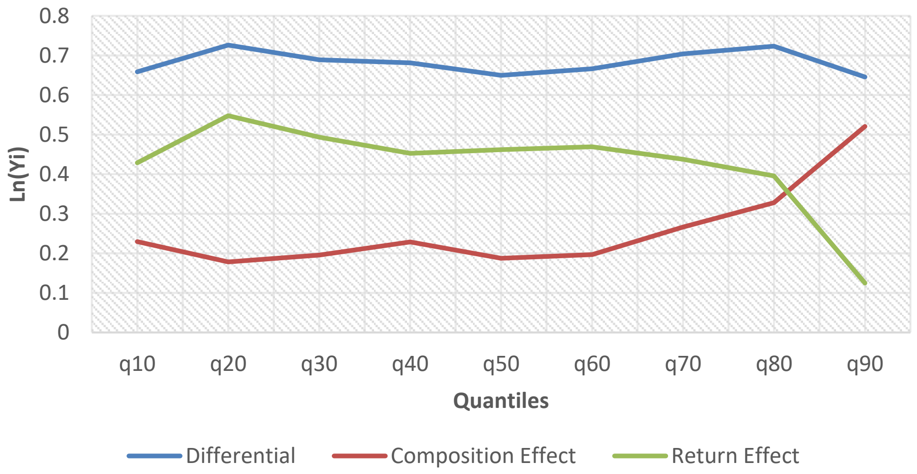

Figure 2 - Decomposition of the income differential between groups A and B.

Source: Own elaboration.

The detailing decomposition of the *composition effect* for each individual characteristic is displayed in Figure 4. Schooling and access to rural credit are the main factors explaining higher level of income for farmers that have accessed to rural extension (group A) compared to farmers in group B. This result indicates that might be occurring a selection bias on the provision of rural extension services, as also suggested by Plata and Fernandes (2011). The negative effect of age and other characteristics such as gender and race indicate that these variables contribute to the reduction of the income differential between the two groups.

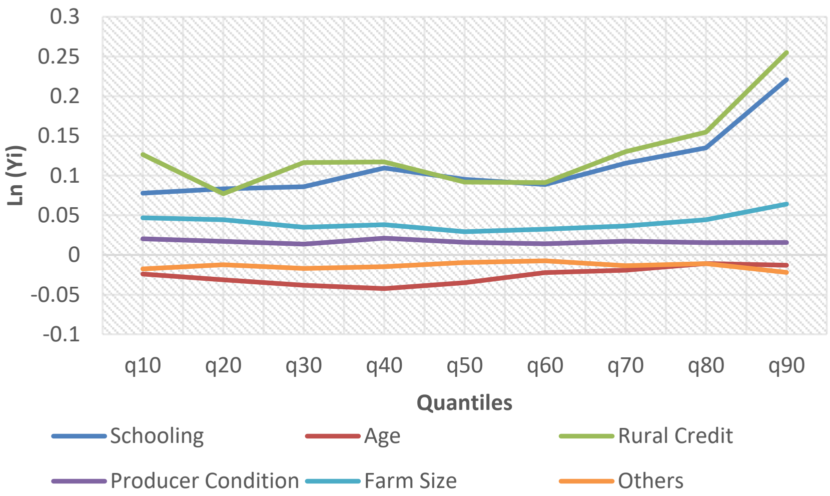

Figure 3 - Detailed decomposition of the *composition effect* of the income differential.
Source: Own elaboration.

Our findings suggest that the outcome of an extension agent might be limited among the poorest farmers due to their lack of education and access to credit. Higher education levels facilitates their interaction with the extension agents allowing them to absorb information and implement the technical recommendations more precisely. Alves *et al.* (2013) also indicate that these farmers have greater access to rural credit and allow them to invest in modern inputs and adopt more productive technologies. Therefore, the current structure of the national rural extension policy is reinforcing social inequalities.

The *return effect* for each group of farmer is displayed in Figure 4. Although we observe a decreasing effect of schooling on rural income this variable contributes considerably to income in the first two income quantiles (q10 and q20). This result might be associated to the lower presence of farmers with high schooling levels in these quantiles, which leads to a higher return of this variable (marginal effect). Most of the variables have a similar effect on income differentials.

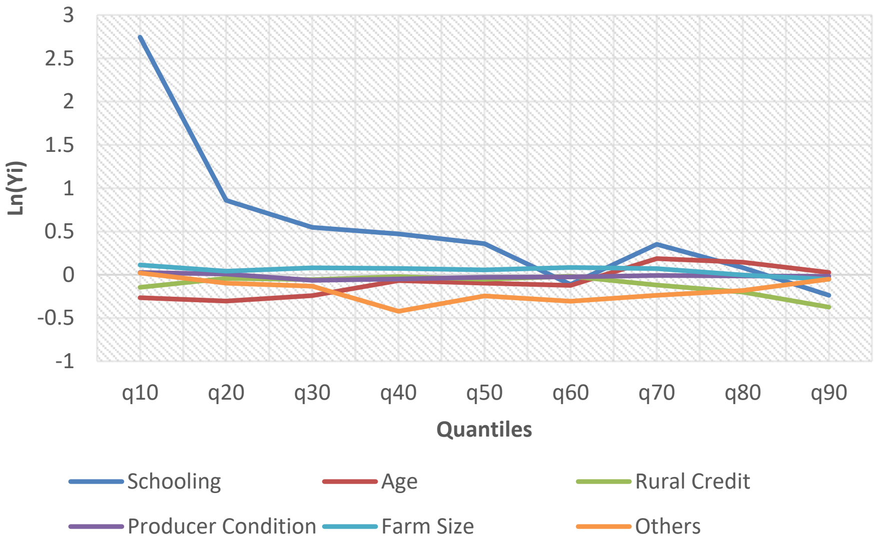

Figure 4 - Detailed decomposition of the return effect of the income differential.

Source: Own elaboration.

Our findings of the unconditional quantile regression presented in previous subsection also show a different effect of rural extension by source of provision. Then, we decompose these income differential by source of provision in the two *effect*. This results are displayed in Figure 5.The total income differential between the groups of farmers that have access to private and public rural extension services has a U-shape format. Although both effects are positive, the *return effect* explains the majority of the income differential. It implies that the observed higher income obtained by farmers that had access to private rural extension is mainly due to the greater returns to the individuals characteristics such as schooling and access to rural credit.

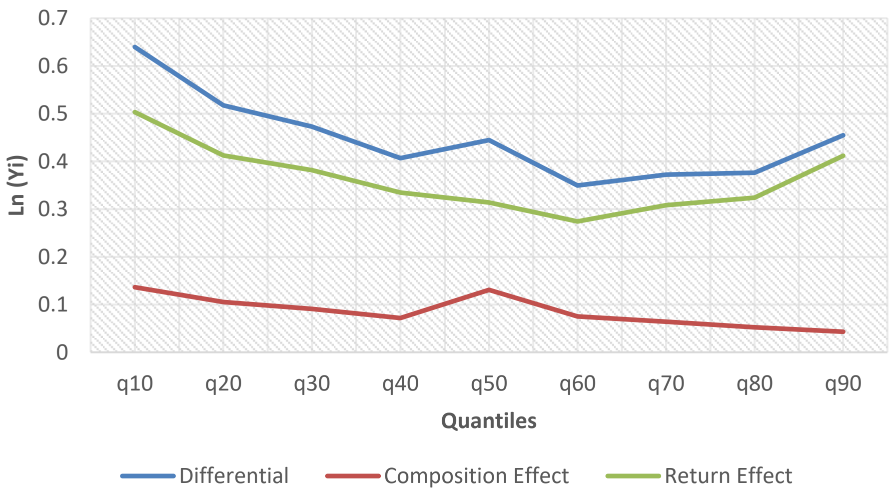

Figure 5 - Decomposition of the income differential between producers assisted by private rural extension and assisted by the public rural extension.

Source: Own elaboration.

6. Conclusions

In this paper we identify the effect of rural extension on income levels and income inequality in the Brazilian rural area using unconditional quantile regression along with an income differential decomposition approach. To obtain these effects, we use the household survey made available by the IBGE for 2014.

Our results indicates that although rural extension increases rural household income in the all income distribution quantiles, it also increases income inequality. We also find that the private rural extension service has a greater effect on rural income compared to public service provision. The results of the income differential decomposition show that the difference in individual characteristics explains great part of the income differential. We find that higher level of schooling and access to rural credit augment the effect of rural extension on rural income but also contribute to the aggravation of the income inequality. Thus, access to rural extension alone it is not enough to raise social welfare of the poorest farmers. These farmers are constrained by limited access to credit and schooling. The design of a joint public policy toward rural extension, rural credit and promotion of the human capital is needed to achieve the goal of reducing income inequality.

7. References

AKOBUNDU, E. *et al.* Does extension works? Impacts of a program to assist limited-resources farmers in Virginia. **Review of Agricultural Economics**, v.26, n.3, p. 361-372, 2004.

AKPAN, S. B.; PATRICK, I. V.; AMAMA, A. Level of income inequality and determinants of poverty incidence among youth farmers in Akwa Ibom State, Nigeria. **Journal of Sustainable Development**, v.9, n.5, 2016.

ALEX, G.; ZIJP, W.; BYERLEE, D. **Rural extension and advisory services: New directions.** Rural Development Strategy Background, paper 9. World Bank, Agriculture and Rural Department, Washington, D.C., 2002.

ALVES, E.; SOUZA, G. S.; ROCHA, D. P. Desigualdade nos campos na ótica do Censo Agropecuário 2006. **Revista de Política Agrícola**, v. 22, n. 2, p. 67-75, 2013.

ANDERSON, J. R.; FEDER, G. Agricultural Extension: Good Intentions and Hard Realities. **The World Bank Research Observer**, v. 19, n. 1, p. 41-60, 2004.

ARAÚJO, J. A.; FEITOSA, D. G.; BARRETO, F. A. D. F. Determinantes da desigualdade de renda em áreas rurais do Nordeste. **Revista de Política Agrícola**, v. 17, n. 4, p. 65-82, 2008.

BALOCH, M. Ali; THAPA, G. B.. The effect of agricultural extension services: Date farmers' case in Balochistan, Pakistan. **Journal of the Saudi Society of Agricultural Sciences**, n.6, 2016.

BARROS, R. P.; HENRIQUES, R.; MENDONÇA, R. Desigualdade e pobreza no Brasil: retrato de uma estabilidade inaceitável. **Revista Brasileira de ciências sociais**, v. 15, n. 42, 2000.

BLINDER, A. Wage Discrimination: Reduced Form and Structural Estimates. **Journal of Human Resources**, v.8, n.4, p. 436-455, 1973.

CHAKRAVARTY, S.R.; DEUTSCH, R.; SILBER, J. On the watts multidimensional poverty index and its decomposition. **World Development**, V.36, n.6, p. 1067-1077, 2008.

CHI, W.; LI, B. Glass Ceiling or Sticky Floor? Examining the Gender earnings differencial across the earnings distribution in urban China, 1987-2004. **Journal of comparative economics**, n.36, p. 243-263, 2008.

CHRISTOPLOS, I. **Mobilizing the potential of rural and agricultural extension.** In: The Global Forum for Rural Advisory Services. Food and Agriculture Organization of the United Nations, 2010.

DERIBEW, H. N. Effects of agricultural extension packages on income inequality: Case from northern Ethiopia. **International Journal of Current Research**, v.8, n.7, p. 34421-34433, 2016.

DINARDO, J; FORTIN, N. M.; LEMIEUX, T. Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. **Econometrica,** v. 64, n.5, p. 1001-1044, 1996.

FEI, J. C. H., RANIS, G., KUO, S. W. Y. Growth and The Family Distribution of Income by Factor Components. **Quarterly Journal of Economics**, XCII, p.17−53, 1978.

FIRPO, S.; FORTIN, N.; LEMIEUX, T. **Decomposing wage distributions using recentered influence function regressions**. University of British Columbia (June), 2007.

FIRPO, S.; FORTIN, N. M.; LEMIEUX, T. Unconditional quantile regressions. **Econometrica**, v. 77, n. 3, p. 953-973, 2009.

FORTIN, N.; LEMIEUX, T.; FIRPO, S. Decomposition methods in economics. **Handbook of labor economics**, v. 4, p. 1-102, 2011.

HELFAND, S.M., LEVINE, E.S. Farm Size and the Determinants of Productive Efficiency in the Brazilian Center-West. **Agricultural Economics**, v. 31, p. 241-49, 2004.

HELFAND, S.; ROCHA, R.; VINHAIS, H. Pobreza e desigualdade de renda no Brasil rural: uma análise da queda recente. **Pesquisa e Planejamento Econômico,** v. 39, n.1, p. 59–80, 2009.

HUFFMAN, W. E., EVENSON, R. E. Supply and demand functions for multiproduct U.S. cash grain farms: Biases caused by research and other policies. **American Journal of Agricultural Economics**, v. 71, n.3, p. 761-773, 1989.

IBGE – Instituto Brasileiro de Geografia e Estatística. **Microdados da Pesquisa Nacional por Amostra de Domicílios (PNAD).** Disponível em: <http://www.ibge.gov.br//> Acesso em janeiro de 2017.

JAN, B. **A Stata implementation of the Blinder-Oaxaca decomposition**. ETH Zurich Sociology, Working paper n.5, 2008.

JIN, Y., HUFFMAN, W. E. Measuring public agricultural research and extension and estimating their impacts on agricultural productivity: New insights from U.S. evidence. **Agricultural Economics**, v.47, n.1, p. 15-31, 2016.

KOENKER, R.; BASSETT, G. Regression Quantiles. **Econometrica**, v. 46, n.1, p.33-50, 1978.

MACHADO, J. F.; MATA, J. Counterfactual decomposition of changes in wage distributions using quantile regressions. **Journal of Applied Econometrics**, v. 20, n.4, p. 445-465, 2005.

MAGALHÃES, M. M.;SOUZA FILHO, H.M.; SOUZA, M. R.; SILVEIRA, J. M. F. J.; BUAINAIN, A. M. Land reform in NE Brazil: a stochastic frontier production efficiency evaluation. **Revista de economia e sociologia rural**, v. 49, n.1, p9-30, 2011.

MARIANO, J. L.; NEDER, H. D. Desigualdade de renda e pobreza entre famílias no meio rural do nordeste. **Economia e Desenvolvimento**, v.5, n.2, p.221-242, 2006.

MDA – Ministério do Desenvolvimento Agrário. Disponível em :<www.mda.gov.br>. Acessoemjulho de 2017.

NEY, M. G.; HOFFMANN, R. Educação, concentração fundiária e desigualdade de rendimentos no meio rural brasileiro. **Revista de Economia e Sociologia Rural**, v. 47, n. 1, p. 147-181, 2009.

OAXACA, R. L. Male-Female Wage Diferentials in Urban Labor Markets.**International Economic Review**, n. 14, v.3, p. 693-709, 1973.

OLIVEIRA, R. C.; SILVEIRA NETO, R. M. **Afinal, Quão importantes são as desigualdades de escolaridade para explicar as disparidades regionais de renda no Brasil?** In: 43º Encontro Nacional de Economia - ANPEC, Anais, Florianópolis – SC, 2015.

PEIXOTO, M. **A extensão privada e a privatização da extensão: uma análise da indústria de defensivos agrícolas.** Tese (Doutorado em Ciências Sociais) – Programa de Pós-graduação de Ciências Sociais em Desenvolvimento, Agricultura, Sociedade. Universidade Federal do Rio de Janeiro. 331 p., 2009.

PEIXOTO, M. **Mudanças e desafios da extensão rural no Brasil**. In: O mundo rural no Brasil do século 21. Brasília, 2014.

PLATA, L. E. A.; FERNANDES, R. L. **A nova assistência técnica e extensão rural brasileira.** In: VI Workshop de Pós-Graduação e Pesquisa do Centro Paula Souza. Unidade de Ensino de Pós-Graduação, Extensão e Pesquisa, 2011.

REIS, C. V. S.; MOREIRA, T. B. S.; CUNHA, G. H. M. O efeito marginal do capital humano na agricultura familiar. **Revista Espacios**, v.38, n.23, 2017.

RODRIGUES, C. M. Conceito de seletividade de políticas públicas e sua aplicação no contexto da política de extensão rural no Brasil. **Cadernos de Ciência & Tecnologia**, Brasília, n.1, v. 14, p. 113-154, 1997.

SCHNEIDER, S.. A pluriatividade como estratégia de reprodução social da agricultura familiar no Sul do Brasil. **Estudos sociedade e agricultura**, v.16, n.1, p. 164-184, 2001.

SILVA, V. H. M. C.; FRANÇA, J. M. S. Decompondo o diferencial regional de salários entre Sudeste e Nordeste: uma aplicação da abordagem da quantílica incondicional. **Revista Econômica do Nordeste**, v.47, n.3, p.109-129, 2016.

SINGH, I., SQUIRE, L.; STRAUSS, J. **Agricultural Household Models: Extensions, Applications, and Policy.** Baltimore: Johns Hopkins University Press, 1986.

WORLD BANK. **Agricultural for development**. World bank report 2008, 386p., 2007.

Appendix

Table A1 – Decomposition of the income differentials: With Rural Extension – Without Rural Extension (2014).

	q10	q20	q30	q40	q50	q60	q70	q80	q90
Differential (LnYi)	0.65838	0.72606	0.68896	0.68119	0.64949	0.66605	0.70397	0.7232	0.64546
Composition Effect	0.22971	0.17838	0.19562	0.22875	0.18752	0.19684	0.26651	0.32788	0.52055
Return Effect	0.42867	0.54768	0.49333	0.45244	0.46197	0.46922	0.43746	0.39532	0.12491
Composition Effect Detailed									
Schooling	0.07781	0.08334	0.0859	0.10951	0.09517	0.0888	0.11548	0.13494	0.22071
Age	-0.0241	-0.0312	-0.0382	-0.0424	-0.035	-0.0223	-0.0193	-0.0108	-0.013
Rural Credit	0.12649	0.07709	0.11634	0.11724	0.09168	0.09108	0.13014	0.15469	0.25497
Producer Condition	0.02033	0.01712	0.01365	0.02111	0.01599	0.01415	0.01735	0.01556	0.01576
Farm Size	0.04675	0.04433	0.03494	0.03802	0.02927	0.0325	0.03644	0.04444	0.06406
Others	-0.0176	-0.0123	-0.017	-0.0147	-0.0096	-0.0074	-0.0136	-0.0109	-0.022
Return Effect Detailed									
Schooling	2.74381	0.85986	0.54795	0.47161	0.35943	-0.1123	0.35136	0.0825	-0.2374
Age	-0.2661	-0.3043	-0.2422	-0.0683	-0.0983	-0.1226	0.18654	0.14499	0.02634
Rural Credit	-0.1449	-0.0422	-0.0564	-0.0212	-0.0523	-0.018	-0.1203	-0.2001	-0.3743
Producer Condition	0.02589	0.0086	-0.0648	-0.0501	-0.0283	-0.026	-0.009	-0.0145	-0.0172
Farm Size	0.11253	0.04192	0.08047	0.07246	0.05576	0.08304	0.07112	-0.0041	-0.0532
Others	0.02019	-0.0966	-0.1317	-0.4223	-0.2448	-0.3058	-0.2381	-0.1825	-0.0506

Source: Own elaboration.

Table A2 – Decomposition of the income differential: Private Rural Extension – Public Rural Extension (2014).

	q10	q20	q30	q40	q50	q60	q70	q80	q90
Differential (LnYi)	0.63968	0.51764	0.47284	0.40674	0.44489	0.34952	0.37236	0.37637	0.45494
Composition Effect	0.13639	0.10524	0.09107	0.07197	0.13094	0.0753	0.06423	0.05223	0.04312
Return Effect	0.50329	0.4124	0.38177	0.33477	0.31394	0.27423	0.30813	0.32414	0.41182

Fonte: Own elaboration.