Rural Credit and Income Differential in Brazil: an Unconditional Quantile Regression approach[#]

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Resumo: A produção agrícola brasileira aumentou nas últimas décadas. Apesar disso, as populações rurais ainda lidam com alta desigualdade de renda. O Brasil implementou várias políticas visando aumentar a renda rural e reduzir a desigualdade nas últimas décadas, como o Sistema Nacional de Crédito Rural. Neste artigo, estima-se a influência do crédito rural na renda familiar rural e na desigualdade de renda nas áreas rurais brasileiras. Para tanto, foi operacionalizada uma Regressão do Quantílica Incondicional e a Decomposição de Diferenciais de Renda. Os resultados indicam que a política de crédito rural levou a aumentos na renda familiar rural, mas também amplia sua desigualdade, embora o efeito do Pronaf, especificamente, seja menos desigual. A educação e o acesso à extensão rural contribuíram para aumentar o efeito do crédito na renda familiar. Esses resultados sugerem que o desenho de uma política pública conjunta sobre crédito rural, extensão rural e promoção do capital humano teria um efeito mais elevado no aumento da renda e na redução de sua desigualdade na área rural brasileira, devido à sinergia entre essas políticas.

Palavras-chave: Crédito rural; Pronaf; Desigualdade de Renda; Regressão Quantílica Incondicional

Abstract: *Brazilian agricultural production has increased in the last decades. In spite of that, rural populations still deal with high income inequality. Brazil has implemented several policies seeking to increase rural income and reduce inequality in the last decades such as rural credit availability. In this paper, we estimate the influence of rural credit on rural household income and income inequality in Brazilian rural areas. To obtain these estimates we estimate an Unconditional Quantile Regression and the Decomposition of Income Differentials. Results indicate that the rural credit policy has led to increases on rural household income, but also increases on income inequality. Education and access to rural extension have contributed to boost the credit effect on household income. These findings suggest that the design of a joint public policy on rural credit, rural extension and promotion of the human capital would have much a stronger effect on reducing income inequality in the Brazilian rural area, due to synergy among those policies.*

Keywords: *Rural credit; Pronaf; Income inequality; Unconditional Quantile Regression*

JEL: Q12; O15; C31; R58

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1. INTRODUCTION

Brazil has increased agricultural production in the last decades and has engaged in stronger participation in the international scenario. In spite of that, rural populations still deal with high income inequality. Commercial agricultural production is still concentrated in large farms with around 85% of the agricultural gross income being generated in 11.4% of the farms in Brazil (Alves et al., 2013). Barros et al. (2006) and Helfand et al. (2009) found evidence of great inequality in rural areas of Brazil using a Gini Index. For instance, in 2010 the index has shown a value of 0.483 (Brazilian Institute of Geography and Statistics – IBGE, 2017). Although income inequality has decreased over time, there is still a long road to go in order to achieve a desirable scenario where income inequality is inexistent (Gini index equals zero).

Several factors could contribute to a less unequal income distribution in rural areas such as access to rural extension and financial markets. The Brazilian government has implemented several public policies aiming to decrease income inequality. These policies were based on programs such as income transfer, pension and credit, but they have shown only a modest contribution to the decrease of income inequality in rural areas (Barros et al., 2006; Soares, 2010; Batista and Neder, 2014).

In 1965, Brazil created the National Rural Credit System (SNCR) to enhance agricultural production and improve living standards of rural households. The National Agricultural Policy created in 1991 also contributed to income generation in the rural areas of Brazil. Although these instruments sought to improve the rural income distribution they have obtained questionable outcomes. Vega (1987), Bacha, Danelon and Belson (2005), and Araújo (2011) have found that large farmers are obtaining greater benefit from the access to credit than small farmers.

To overcome the inequality on the distribution of benefits, the Brazilian government created in 1995 the Program for the Strengthening of Family Farming (Pronaf). It seeks to stimulate income generation of small farms that face low productivity and are unable to obtain inputs to modernize their farm and increase productivity (Guanziroli, 2007; Santana et al., 2014). However, Corrêa and Silva (2004) and Guanziroli (2007) also suggest that this program is not achieving its initial goal of decreasing inequality.

We have observed a consensus in the literature indicating that even thou Brazil has improved rural household access to financial markets, also represented in access to credit, income inequality in these areas are still high and that policies put in place to combat inequality have been benefiting larger farms. It is missing in the literature a research that identifies the other factors that can contribute to the reduction of rural inequality, such as rural extension, that boost the effect of credit on household income. It is also lacking in the literature an analysis that breaks down the effect of credit on income per income quantiles; e.g. access to credit might have a stronger effect on income in households with a higher income compared to household with a lower income. In this paper, we address these two limitations to estimate the effect of credit on household income in rural areas of Brazil.

To obtain the influence of credit on household income we use an income decomposition proposed by Firpo et al. (2007) and the household survey of 2014 from the IBGE (National Household Sample Survey – PNAD). Firpo's approach consists of 2 steps. First, we estimate income regressions for different unconditional quantiles of the income distribution. Second, the income differential is decomposed in *return* and *composition effects* to identify the main factors that explain the income gap across all quantiles analyzed. In addition to this decomposition, we also identify other factors that are important to the effectiveness of this policy, such as farmer schooling and access to rural extension. This analysis would be very helpful to guide the design of new public policies seeking to integrate different agricultural policies such as the Pronaf and rural extension policies.

Our results suggest that credit has led to higher household income inequality in rural areas of Brazil. We found that households within the higher income quantiles observe greater benefits from accessing credit compared to households in the lower quantiles. Households that have also had access to rural extension observe more benefits from accessing credit contracts. This combined effect of credit-extension is higher among households in the top income quantiles. These results indicate that the coordination of public policies on access to credit and rural extension simultaneously, would result in higher benefits to households in rural areas.

2. BACKGROUND

In Brazil, public policies on rural credit gained shape in 1965 with the National Rural Credit System (SNRC). The SNRC was in charge of operating the rural credit policy, seen as one of the main pillars to agricultural modernization (Santana et al., 2014). Overall, these policies aimed to create structural changes on national agriculture. Public policies in rural credit have gone through three distinct phases between 1969 and 2012 (Buainain et al., 2014). In the first phase, between 1969 and 1979, the total volume of credit granted to producers and cooperatives grew substantially in real terms, from R$ 32 billion to R$ 161 billion. In the second phase, between 1979 and 1996, the Brazilian government debt crisis, fiscal reforms and stabilization plans have led to a decrease on the supply of credit, registering in 1996 the lowest value of R$ 23 billion. In the third phase, the total credit supply increased gradually, reaching R$ 115 billion in 2012.

Rural credit has been used as one of the main instruments to incentivize agricultural production (Alves, 1993; Bacha, Danelon and Belson, 2006; Araujo, 2011; Garcias and Kassouf, 2016). However, it has generated larger benefits to larger farms mostly because these farms have also received access to other services and better production inputs. In 1995, the Program for the Strengthening of Family Farming (Pronaf), also connected to the SNRC, was created to provide credit to small farms.

Family-owned farms are predominantly small farms and play an important role on the Brazilian economy. They represent more than 70% of rural establishments and generate 38% of the total value produced in agriculture (IBGE, 2009). In order to have access to credit from Pronaf, family-owned farms must fall within certain eligibility categories which are highlighted on the DAP - Declaration of Aptitude to Pronaf. Eligibility. The DAP states the maximum and minimum annual income from agricultural activities, size of property, type of land tenure, and residency in/near to rural property (BNDES, 2015). The supply of credit using this instrument has continuously increased since its creation. In the first year, Pronaf provided 307 thousand contracts and R$ 543 million in total loans while in 2012, 1.8 million contracts were signed using this instrument, an equivalent to R$ 15.3 billion. The number of contracts almost doubled in the 2015/16 crop season (Araújo, 2011; Grisa, 2014; Bianchini, 2015).

2.1 Income Inequality and Rural Credit

Several studies have been investigating the determinants of income and income inequality in rural areas in Brazil also considering aspects related to rural credit access. Ferraz et al. (2008) used 2007 data from the Ministry of Finance and the direct comparison method. They conclude that both microcredit policies and lower interest rates correspond to an effective instrument to incentivize investments in productive activities and mitigate poverty. These instruments are effective when applied to low-income farmers. Batista and Nader (2014) also investigate the effects of Pronaf on rural poverty in Brazil during the period between 2001 and 2009. They assume that this instrument does not affect rural poverty directly but affects the variation of income and/or the variation in income inequality. They used the PNAD database and data from the Central Bank of Brazil in a dynamic panel approach. They found that Pronaf spending tends to reduce poverty indirectly by raising average income and reducing income concentration.

Souza et al. (2013) analyzed the inequality in Pronaf's credit distribution across the country using a descriptive approach and data from the Central Bank of Brazil. They found that, in the initial phase of the program, there was a strong increase in the number of contracts which continued until 2006, followed by an increase in the average size of the contracts. They also observed an increase on the participation of states with more capitalized agriculture. An analysis of the evolution of the program has shown that the distribution of credit in Brazil is unequal. On the other hand, Kageyama (2003) did not find evidence of positive effect of access to credit on household income, poverty reduction and educational advancement among family-owned farms. She used data from a field survey conducted in eight Brazilian states in 2001 and applied a multiple regression analyzes to compare Pronaf borrowers and non-borrowers. Feijó (2001) also found a similar result which indicated that farms that had access to the program had a lower productivity growth compared to the control group.

There are also studies investigating the effect of credit on income in other countries. Wan and Zhou (2005) investigated the determinants of income inequality in rural China using a regression-based decomposition framework. They conclude that geographic location has been the dominant factor on explaining inequality. They found that the most significant determinant of income inequality is the input capital. Mahjabeen (2008) examines the welfare and distributional implications of microfinance institutions in Bangladesh using a general equilibrium framework. They found that microcredit increase income and consumption levels of households, reduce income inequality and enhance welfare. Luan and Bauer (2016) examined the heterogeneity of rural credit effects in Vietnam using a dataset on 1,338 households collected from the Vietnam Access Resources Household Survey in 2012. They used Propensity Score Matching to evaluate this issue and found that access to credit have a positive effect on household income among households with higher income and access to large credit amounts.

3. EMPIRICAL STRATEGY

To estimate how access to credit affects (not in a causal way) household income we use the National Household Sample Survey (PNAD) for 2014 from the IBGE[1]. This survey also provides a supplementary questionnaire that includes questions related to access and source of credit for rural production. This survey categorizes rural credit in: i) Program for the Strengthening of Family Farming (Pronaf), and ii) other sources (i.e. other public programs and/or banking loans for rural usage). These questions are used to build dummy variables as a proxy to whether the farmer had access to rural creditor not.

Our dataset is a subsample of the PNAD, which includes only rural households. Similar to Ely et al. (2017) our sample considers of rural producers that are: 1) economically active; 2) employers or self-employed workers (these being the individuals interviewed in the questionnaire); 3) and the main activity was agricultural activity. Our sample also included a small portion of rural property managers that live in urban areas (IBGE, 2017). After dropping missing values and outliers, the final sample consists of 15,402 individuals.

Our dependent variable is the monthly household income in R$ (*Reais*–Brazilian currency). It is a proxy to farmer income. To control for other factors that also influence household income level, we also included:

a) *gender*: a dummy variable equals to 1 if the individual is male;
b) *race*: a dummy variable equals to 1 if the individual is black;
c) *schooling*: several dummy variables 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"; additionally, its used the study years;
d) *rural*: a dummy variable equals to 1 if the individual resides in the rural area;
e) *extension*: a dummy variable equals to 1 if the individual has received technical assistance and rural extension from private or governmental source;
f) *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;
g) *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).
h) *regions*: five dummy variables that represent Brazilian macro regions – North, Northeast, Southeast, South and Midwest.

Descriptive statistics are displayed in Figure 1 and Table 1, per groups of credit access. In our sample, around 13% of rural households had access to credit in 2014, which 75% of were from Pronaf. This is a similar percentage to that verified by Central Bank of Brazil, demonstrating the validity of PNAD on rural credit data (BCB, 2018).

[1] 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. In addition, it is the most up-to-date individual-level database available for Brazilian agricultural sector.

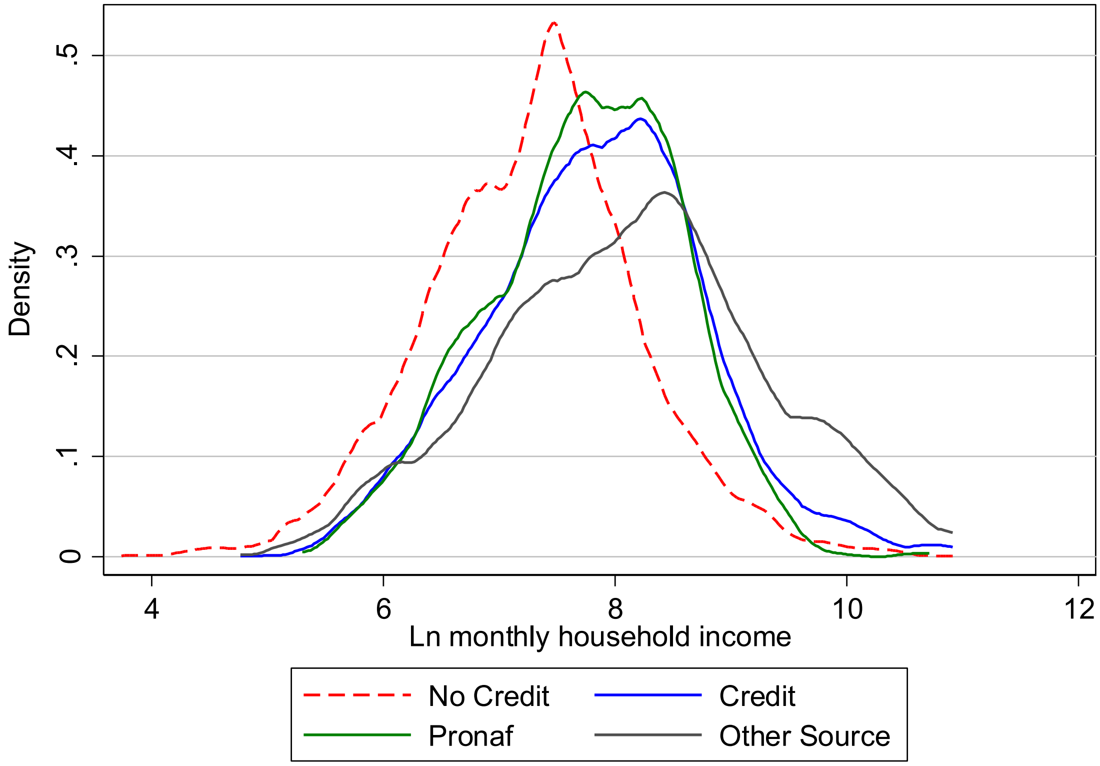

Figure 1 Monthly household income density distribution: No Credit Access – Credit Access – Pronaf – Credit from Other Sources, Brazil, 2014
Source: Own elaboration based on PNAD 2014 (IBGE, 2017).

Rural households that had access to credit have a higher monthly household income on average, R$ 4,019.00, compared to households that did not have access, on average, R$ 2,286.00. We observe a large heterogeneity on household income, as could be seen in standard deviation. Household that had access to credit have shown a higher education level and access to rural extension. More than 80% of the sample is male, 73% lives in rural areas and 75% own the property.

Households that had access to credit from other sources have shown a 50% higher income compare to households that had access to credit from Pronaf. These households also have shown a higher level of education and greater access to extension services. The South of Brazil has the majority of households that had access to credit (35%), followed by the Northeast (24%). A similar pattern is observed when analyzing credit from Pronaf, south of Brazil accounts for 39.7% of households followed by the northeast with 22.6%. Around 37% of households in our sample is in the northeast.

We used this dataset to obtain the effect of rural extension on household income. First, we use the unconditional quantile regression method to identify the effect of the rural credit on different income quantiles in the Brazilian rural area based on Firpo et al. (2007, 2009). Second, we identify household characteristics that might generate income disparity in the access to rural credit outcome.

Table 1 Mean and standard deviation of the variables used, for total sample and by rural credit group, Brazil, 2014

Variables	Brazil		No Rural Credit		Rural Credit		Pronaf		Other sources	
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
Monthly Household Income	2505	3473	2286	3043	4019	5360	3190	3123	6548	8846
Gender	0.855	0.352	0.848	0.359	0.905	0.293	0.903	0.296	0.913	0.282
Race	0.0733	0.261	0.0778	0.268	0.0425	0.202	0.0476	0.213	0.0270	0.162
Study years	5.588	3.988	5.410	3.951	6.817	4.034	6.452	3.775	7.929	4.563
Don't read and write	0.00402	0.0633	0.00439	0.0661	0.00154	0.0392	0.00204	0.0451	0	0
Incomplete elementary	0.223	0.416	0.239	0.427	0.112	0.316	0.116	0.320	0.102	0.303
Complete elementary	0.518	0.500	0.515	0.500	0.536	0.499	0.570	0.495	0.434	0.496
Incomplete high school	0.0843	0.278	0.0806	0.272	0.110	0.313	0.116	0.321	0.0892	0.285
Complete high school	0.0329	0.178	0.0318	0.176	0.0405	0.197	0.0381	0.191	0.0477	0.213
Incomp. higher education	0.107	0.309	0.101	0.302	0.143	0.350	0.122	0.328	0.205	0.404
Comp. higher education	0.0317	0.175	0.0280	0.165	0.0569	0.232	0.0354	0.185	0.122	0.328
Age25	0.0537	0.226	0.0564	0.231	0.0359	0.186	0.0395	0.195	0.0249	0.156
Age26to35	0.150	0.357	0.149	0.356	0.156	0.363	0.144	0.351	0.191	0.393
Age36to45	0.218	0.413	0.219	0.414	0.214	0.410	0.214	0.410	0.212	0.409
Age46to55	0.261	0.439	0.256	0.436	0.299	0.458	0.301	0.459	0.295	0.456
Age56to65	0.206	0.405	0.205	0.404	0.213	0.410	0.231	0.422	0.158	0.365
Age65more	0.110	0.313	0.114	0.318	0.0825	0.275	0.0701	0.255	0.120	0.326
Rural	0.733	0.443	0.727	0.445	0.769	0.422	0.813	0.390	0.635	0.482
Extension	0.141	0.348	0.0912	0.288	0.482	0.500	0.502	0.500	0.419	0.494
Partner	0.0573	0.232	0.0606	0.239	0.0348	0.183	0.0381	0.191	0.0249	0.156
Tenant	0.0531	0.224	0.0527	0.223	0.0558	0.230	0.0537	0.226	0.0622	0.242
Occupant	0.0469	0.211	0.0514	0.221	0.0164	0.127	0.0156	0.124	0.0187	0.136
Owner	0.754	0.430	0.742	0.438	0.842	0.365	0.835	0.372	0.863	0.344
Other condition	0.0883	0.284	0.0935	0.291	0.0512	0.221	0.0578	0.233	0.0311	0.174
Very small	0.600	0.490	0.628	0.483	0.405	0.491	0.424	0.494	0.346	0.476
Small	0.262	0.440	0.239	0.426	0.421	0.494	0.465	0.499	0.288	0.453
Medium	0.0704	0.256	0.0657	0.248	0.103	0.305	0.0483	0.214	0.272	0.445
Large	0.0467	0.211	0.0466	0.211	0.0476	0.213	0.0381	0.191	0.0768	0.266
North	0.269	0.443	0.284	0.451	0.166	0.372	0.154	0.361	0.201	0.401
Northeast	0.378	0.485	0.397	0.489	0.241	0.428	0.226	0.418	0.288	0.453
Southeast	0.114	0.317	0.111	0.314	0.131	0.337	0.121	0.326	0.160	0.367
South	0.158	0.365	0.130	0.336	0.354	0.478	0.397	0.489	0.224	0.417
Midwest	0.0657	0.248	0.0626	0.242	0.0871	0.282	0.0878	0.283	0.0851	0.279
#Obs	**15402**		**13450**		**1952**		**1470**		**482**	

Source: Own elaboration based on PNAD 2014.

Note: SD - Standard deviation.

3.1 The unconditional quantile regression approach

To identify the effects (not causally) of rural credit 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[2] allows identifying the relative effect (the influence) of an individual observation on a statistic of interest (Silva and França, 2017). 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[3].

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:

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

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:

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

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 and França, 2017). It implies that:

$$E\lfloor RIF(y;\upsilon,F_y)\rfloor=\upsilon(F_y) \tag{3}$$

[2] The influence function method provides a linear approximation for a nonlinear function of a statistical distribution of interest, such as quantiles, variance or others, allow estimating the effect of one or more covariates on the distribution of the statistics of interest (Chi and Li, 2008).

[3] For an average, e.g. $\mu(F_y)$, the influence function - IF, would be given by $IF(y;\mu(F_y))=y-\mu(F_y)$, with the RIF specified as: $RIF(y;\mu)=IF(y;\mu)+\mu$. Firpo et al. (2007) present the RIF regressions for the case of the variance and Gini coefficient.

We first obtain the sample quantile $\hat{q}_\tau$ (Firpo et al., 2009; Koenker and Basset, 1978) and then the marginal density function $\hat{f}_y\left(\hat{q}_\tau\right)$ through Kernel functions[4]. After obtaining these estimates, they are incorporated in (2).

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

$$\upsilon(F_y) = E_x\left[E\left[RIF(y;\upsilon,F_y)\right]\right] = E\left[X\right].\beta \tag{4}$$

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, described in the previous section; 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[5].

The conditional quantile regression approach proposed by Koenker and Basset (1978) is different from the unconditional quantile regression proposed by Firpo et al. (2007, 2009), which is used in this paper. The former approach only allows to estimate the "within-group"[6] effect (Firpo et al., 2009). The unconditional quantile regression allows to estimate both “within-group" effect and the "between-group" effect. The latter effect represents the influence of a given variable throughout the entire distribution.

3.2 Decomposition of income differentials

We use an income decomposition procedure proposed by Firpo et al. (2007)[7] to estimate the income differentials between groups: farms that have accessed to rural credit and farmers that did 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[8] 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 credit) 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

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[4] According to Koenker and Basset (1978), the τ - *th* quantile estimator of the marginal distribution of Y ($\hat{q}_\tau$) can be defined as: $\hat{q}_\tau = \arg\min_q \sum_{i=1}^{N} (\tau - 1\{Yi - q \le 0\}).(Yi - q)$. The density function of Y is obtained by estimating the kernel density: $\hat{f}_y\left(\hat{q}_\tau\right) = \frac{1}{N.b}.\sum_{i=1}^{N} K_y\left(\frac{Y_i - \hat{q}_\tau}{b}\right)$, where $K_y(z)$ is a kernel function and b is a positive scalar bandwidth. For more details see Firpo et al. (2009).

[5] Firpo et al. (2009) present three possibilities of estimators: OLS, logistic estimator, and a non-parametric estimator, all with very close results.

[6] The result for each quantile depends on the X characteristics of the individuals in that group and cannot be extrapolated to the other quantiles. It does not allow to analyze the effect of a given variable on the entire Y distribution.

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

[8] For more details, see Jann (2008).

the two groups based on some statistics of these distributions opposed to only analyzing the mean. It is represented as

$$\Delta^{\upsilon} = \upsilon(F_{yA}) - \upsilon(F_{yB}) \tag{5}$$

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: difference in the observable individual characteristics (*composition effect*); and difference in coefficients between the two groups (*return effect*). 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 (4). 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 (5) to obtain

$$\begin{aligned} \Delta^{\upsilon} &= \left[\upsilon(F_{yB}) - \upsilon(F_{yc})\right] + \left[\upsilon(F_{yC}) - \upsilon(F_{yA})\right] \\ \Delta^{\upsilon} &= \Delta^{\upsilon}_{R} + \Delta^{\upsilon}_{X} \end{aligned} \tag{6}$$

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

To obtain (6) we re-estimate the RIF regressions for each of the groups and obtain the conditional expectation of the recentered functions of influence. This allows us 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

$$\upsilon(F_{yt}) = E\left[RIF(y_t;\upsilon_t) \mid X, T = t\right] = X_t \beta_t \tag{7}$$

$$\upsilon(F_{yC}) = E\left[RIF(y_A;\upsilon_C) \mid X, T = B\right] = X_C \beta_C \tag{8}$$

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

$$\begin{aligned} &\hat{\omega}_A(T) = \frac{T}{\hat{\rho}}, \\ &\hat{\omega}_B(T) = \frac{1-T}{1-\hat{\rho}}, \text{ and} \\ &\hat{\omega}_C(T;X) = \left[\frac{\hat{\rho}(X)}{1-\hat{\rho}(X)}\right]\cdot\left[\frac{1-T}{\hat{\rho}}\right] \end{aligned} \tag{9}$$

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

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

$$\hat{\beta}_t = \left(\sum_{i \in t} \hat{\omega}_t . X_i . X_i^{'}\right)^{-1} . \sum_{i \in t} \hat{\omega}_t . \hat{RIF}(y_{ti};\upsilon_t) X_i \tag{10}$$

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

$$\hat{\beta}_C = \left(\sum_{i \in A} \hat{\omega}_C(X_i)..X_i.X_i^{'}\right)^{-1} . \sum_{i \in A} \hat{\omega}_C(X_i).\hat{RIF}(y_{Ai};\upsilon_C) X_i \tag{11}$$

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

$$\hat{\Delta}^{\upsilon} = \left[\overline{X}_B . \hat{\beta}_B - \overline{X}_C . \hat{\beta}_C \right] + \left[\overline{X}_C . \hat{\beta}_C - \overline{X}_A . \hat{\beta}_A \right]$$
$$\hat{\Delta}^{\upsilon} = \hat{\Delta}^{\upsilon}_R + \hat{\Delta}^{\upsilon}_X \tag{12}$$

We can also identify the contribution of each covariate X_k, where $k = 1,..., K$, on each of the effects obtained in (12) as in

$$\hat{\Delta}^{\upsilon}_X = \sum_{k=1}^{K} \left(\overline{X}_{ck} - \overline{X}_{Ak} \right) \hat{\beta}_A \tag{13}$$

$$\hat{\Delta}^{\upsilon}_R = \left(\hat{\beta}_{B1} - \hat{\beta}_{C1} \right) + \sum_{k=2}^{K} \overline{X}_{Bk} \left(\hat{\beta}_{BK} - \hat{\beta}_{CK} \right) \tag{14}$$

where in (14) 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*. We used the following codes *rifreg* e *oaxaca8* in Stata 12®. In the next section, we present the results obtained with the two methods.

4. RESULTS

In this section, we first present the results of the unconditional quantile regression and then the results of the income decomposition. Finally, we have a brief regionally analysis of the Decomposition of the Income Differential.

4.1 Influence of rural credit 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. Table 2 displays that the results of the RIF regressions for the unconditional income distribution quantiles of the logarithm of monthly household income. Our results suggest a positive influence of rural credit on household income in Brazil, which increases as we evaluate it at higher income quantiles. For instance, households in the bottom two quantiles, q10 and q25, that had access to credit are associate with an income 18.9% (i.e. R$ 94.5, on average) and 17.2% (i.e. R$ 145.68 avg.) higher than those who did not. This effect is higher on the top two quantiles, q75 and q90, around 28,3% (i.e. R$ 805.98 avg.) and 24,6% (i.e. R$ 1,230.00 avg.) respectively (see also Figure 2).

Table 2 Estimates of unconditional quantile regression, Brazil, 2014

Ln(Yi)	MQO	q10	q25	q50	q75	q90
Rural Credit	0.224***	0.189***	0.172***	0.191***	0.283***	0.246***
	(0.0206)	(0.0311)	(0.0282)	(0.0240)	(0.0346)	(0.0578)
Extension	0.263***	0.122***	0.200***	0.202***	0.337***	0.447***
	(0.0206)	(0.0306)	(0.0274)	(0.0240)	(0.0354)	(0.0589)
Gender	-0.0611***	-0.108**	-0.193***	-0.0333 NS	-0.0220 NS	0.0517 NS
	(0.0181)	(0.0431)	(0.0297)	(0.0224)	(0.0247)	(0.0357)
Race	-0.0948***	0.0450 NS	-0.0378 NS	-0.153***	-0.122***	-0.106***
	(0.0259)	(0.0634)	(0.0448)	(0.0309)	(0.0298)	(0.0359)
Incomplete Elementary	-0.274***	0.546 NS	0.382*	-0.206 NS	-0.223*	0.0125 NS
	(0.0151)	(0.338)	(0.197)	(0.133)	(0.125)	(0.0599)
Complete Elementary	0.0548NS	0.580*	0.440**	-0.120 NS	-0.0591 NS	0.214***
	(0.114)	(0.337)	(0.196)	(0.133)	(0.125)	(0.0588)
Incomplete High School	0.166NS	0.754**	0.552***	0.00850 NS	0.112 NS	0.405***
	(0.114)	(0.338)	(0.199)	(0.135)	(0.129)	(0.0782)

Complete High School	0.308***	0.778**	0.695***	0.0708 NS	0.248*	0.655***
	(0.116)	(0.346)	(0.205)	(0.139)	(0.136)	(0.107)
Incomplete Higher educ.	0.407***	0.721**	0.738***	0.202 NS	0.310**	0.700***
	(0.119)	(0.338)	(0.198)	(0.135)	(0.129)	(0.0797)
Complete Higher education	0.509***	0.825**	0.731***	0.392***	0.971***	2.062***
	(0.115)	(0.337)	(0.200)	(0.136)	(0.136)	(0.143)
Age26to35	1.055***	-0.0319 NS	-0.0983 NS	-0.133***	-0.0696*	0.0183 NS
	(0.120)	(0.0902)	(0.0610)	(0.0407)	(0.0397)	(0.0606)
Age36to45	-0.0514NS	0.177**	0.118**	-0.0579 NS	-0.0135 NS	0.0632 NS
	(0.0323)	(0.0850)	(0.0583)	(0.0397)	(0.0390)	(0.0602)
Age46to55	0.0671**	0.0564 NS	0.157***	0.00441 NS	0.0409 NS	0.0892 NS
	(0.0314)	(0.0859)	(0.0582)	(0.0400)	(0.0399)	(0.0625)
Age56to65	0.0961***	0.380***	0.613***	0.273***	0.164***	0.209***
	(0.0314)	(0.0855)	(0.0589)	(0.0423)	(0.0421)	(0.0656)
Age65m	0.351***	0.731***	1.003***	0.710***	0.309***	0.322***
	(0.0327)	(0.0847)	(0.0585)	(0.0451)	(0.0482)	(0.0731)
Rural	0.664***	-0.218***	-0.288***	-0.229***	-0.303***	-0.333***
	(0.0357)	(0.0316)	(0.0239)	(0.0186)	(0.0222)	(0.0342)
Partner	-0.0926***	-0.0319 NS	-0.00350 NS	-0.185***	-0.141***	-0.113**
	(0.0278)	(0.0652)	(0.0493)	(0.0341)	(0.0370)	(0.0528)
Tenant	-0.0230NS	-0.0586 NS	0.0253 NS	0.00830 NS	-0.0332 NS	-0.0435 NS
	(0.0274)	(0.0657)	(0.0456)	(0.0336)	(0.0413)	(0.0621)
Occupant	-0.0579*	0.0485 NS	-0.0409 NS	-0.0801*	-0.0573*	-0.0932***
	(0.0339)	(0.0835)	(0.0639)	(0.0415)	(0.0347)	(0.0349)
Other condition	-0.176***	-0.341***	-0.0957**	-0.152***	-0.178***	-0.0994***
	(0.0231)	(0.0681)	(0.0438)	(0.0291)	(0.0264)	(0.0360)
Small	0.222***	0.234***	0.216***	0.175***	0.270***	0.266***
	(0.0157)	(0.0299)	(0.0237)	(0.0191)	(0.0238)	(0.0357)
Medium	0.357***	0.146***	0.156***	0.195***	0.516***	0.900***
	(0.0278)	(0.0480)	(0.0384)	(0.0307)	(0.0412)	(0.0773)
Large	0.239***	0.197***	0.208***	0.164***	0.208***	0.398***
	(0.0322)	(0.0519)	(0.0469)	(0.0405)	(0.0514)	(0.0832)
North	0.238***	0.505***	0.362***	0.200***	0.176***	-0.0597**
	(0.0197)	(0.0379)	(0.0293)	(0.0207)	(0.0210)	(0.0252)
Southeast	0.472***	0.578***	0.540***	0.489***	0.484***	0.259***
	(0.0199)	(0.0411)	(0.0324)	(0.0265)	(0.0335)	(0.0493)
South	0.584***	0.599***	0.600***	0.574***	0.689***	0.523***
	(0.0199)	(0.0381)	(0.0310)	(0.0254)	(0.0326)	(0.0500)
Midwest	0.590***	0.596***	0.483***	0.516***	0.574***	0.613***
	(0.0306)	(0.0398)	(0.0381)	(0.0321)	(0.0419)	(0.0720)
Intercept	6.828***	5.184***	5.930***	7.237***	7.713***	7.931***
	(0.118)	(0.347)	(0.204)	(0.139)	(0.133)	(0.0879)
Observations			15,402			
R-squared	0.079	0.161	0.227	0.242	0.172	0.079
F-statistic	42.14	111.5	210.8	188.2	60.78	42.14

Source: Own elaboration.

Notes: ***significant at 1%, **significant at 5%, *significant at 10%, NS non-significant; Standard-errors in parentheses.

These results imply that access to credit increases monthly household income and increases income inequality in rural areas in Brazil. It means that access to credit is not achieving one of its goal. In Brazil, Public policies on rural credit availability also pursue to raise rural income by given the opportunity to rural households to acquire more inputs, access new technologies and reduce market imperfections effects (Alves et al., 2013; Leite, 2013; Hartarska et al., 2015; Garcias and Kassouf, 2016).

Variables capturing the effect of gender and race did not show different effect on household income quantiles. We only observe a difference at the bottom of the income distribution, where woman have a higher income compared to man. Our results also suggest that household headed by black individuals observe lower income compared to other individuals. Experience, here represented by the age of the individual, has a stronger effect at the bottom of income distribution.

We found that variables related to higher level of education ("complete elementary school", "high school" and "higher education") increases household income compared to the base variable ("people who cannot read or write"). Costa et al. (2016), Oliveira and Silveira Neto (2015) and Reis et al. (2017) have also identified positive effects of investments in human capital on income. We found that education can decrease income inequality; i.e. great income returns to "high school" level in the bottom quantiles of the income distribution. Although "higher education" increases the inequality, only 3.2% of the sample has a high education level.

Another public policy associated to agricultural production also observed in this sample, rural extension seeks to generate improvements on farm production and income by helping farmers to access new technologies and knowledge. It is traditionally associated with rural credit in Brazil. Our results suggest that access to rural extension also generate higher income in all quantiles of the distribution. Along the top quantiles of the income distribution, q75 and q90, farmers that had access to rural credit obtained an income 34% and 45.5% higher than the others, respectively.

We found that farm ownership and living in urban areas lead to greater household income. Farm owners have greater incentive to invest in innovations and long-term technologies, which contribute to increase rural income. These farmers 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 (Besley, 1995). Living in urban areas might lead to greater access to information about market input and output, banking institutions and other services.

Our results also suggest that greater the farm greater the income and that households in the South, Midwest and Southeast (base) regions are better off compared to households in the North and Northeast. These household differences are also identified in the literature (Assunção and Chein, 2007; Souza, Ney and Ponciano, 2013; Oliveira and Silveira Neto, 2015; Costa et al., 2016).

Access to credit might affect household income differently by source, Pronaf or others. To test whether they differ from an aggregate analysis we also estimated these equations disaggregating the variable credit in these two sources. Results are displayed in Table 3 and Figure 2 (which includes the average household income per quantiles).

Table 3 Estimates of unconditional quantile regression – Pronaf and Credit from Other Sources, Brazil, 2014

Ln(Yi)	q10	q25	q50	q75	q90
Pronaf	0.207***	0.163***	0.195***	0.197***	0.0379 NS
	(0.0332)	(0.0318)	(0.0272)	(0.0392)	(0.0619)
Other sources	0.133**	0.198***	0.177***	0.544***	0.875***
	(0.0604)	(0.0469)	(0.0389)	(0.0580)	(0.120)
Extension	0.121***	0.200***	0.202***	0.340***	0.455***
	(0.0305)	(0.0274)	(0.0240)	(0.0353)	(0.0587)
Gender	-0.108**	-0.193***	-0.0333 NS	-0.0217 NS	0.0524 NS
	(0.0431)	(0.0297)	(0.0224)	(0.0248)	(0.0356)
Race	0.0442 NS	-0.0374 NS	-0.153***	-0.118***	-0.0965***
	(0.0634)	(0.0448)	(0.0309)	(0.0298)	(0.0360)
Incomplete Elementary	0.547 NS	0.381*	-0.206 NS	-0.229*	-0.00332 NS
	(0.338)	(0.197)	(0.133)	(0.123)	(0.0545)
Complete Elementary	0.582*	0.439**	-0.119 NS	-0.0656 NS	0.199***
	(0.336)	(0.196)	(0.133)	(0.123)	(0.0533)
Incomplete High School	0.756**	0.551***	0.00894 NS	0.104 NS	0.385***
	(0.338)	(0.199)	(0.135)	(0.128)	(0.0730)
Complete High School	0.781**	0.694***	0.0715 NS	0.235*	0.624***
	(0.346)	(0.205)	(0.139)	(0.134)	(0.104)
Incomplete Higher educ.	0.724**	0.737***	0.203 NS	0.295**	0.664***
	(0.338)	(0.198)	(0.135)	(0.127)	(0.0755)
Complete Higher education	0.831**	0.728***	0.394***	0.942***	1.990***
	(0.337)	(0.200)	(0.136)	(0.135)	(0.141)
Age26to35	-0.0308 NS	-0.0988 NS	-0.133***	-0.0747*	0.00594 NS
	(0.0902)	(0.0610)	(0.0408)	(0.0397)	(0.0609)
Age36to45	0.178**	0.118**	-0.0577 NS	-0.0165 NS	0.0560 NS
	(0.0850)	(0.0583)	(0.0397)	(0.0391)	(0.0603)

Age46to55	0.0573 NS	0.157***	0.00464 NS	0.0365 NS	0.0787 NS
	(0.0859)	(0.0582)	(0.0400)	(0.0400)	(0.0625)
Age56to65	0.380***	0.612***	0.274***	0.163***	0.207***
	(0.0855)	(0.0589)	(0.0423)	(0.0422)	(0.0658)
Age65m	0.733***	1.002***	0.711***	0.301***	0.300***
	(0.0848)	(0.0586)	(0.0451)	(0.0482)	(0.0731)
Rural	-0.219***	-0.288***	-0.229***	-0.300***	-0.325***
	(0.0316)	(0.0239)	(0.0186)	(0.0222)	(0.0341)
Partner	-0.0326 NS	-0.00320 NS	-0.186***	-0.138***	-0.106**
	(0.0652)	(0.0494)	(0.0341)	(0.0370)	(0.0529)
Tenant	-0.0582 NS	0.0252 NS	0.00839 NS	-0.0350 NS	-0.0479 NS
	(0.0657)	(0.0456)	(0.0336)	(0.0413)	(0.0621)
Occupant	0.0483 NS	-0.0409 NS	-0.0801*	-0.0564 NS	-0.0910***
	(0.0835)	(0.0639)	(0.0415)	(0.0347)	(0.0350)
Other condition	-0.341***	-0.0953**	-0.152***	-0.174***	-0.0909**
	(0.0681)	(0.0438)	(0.0291)	(0.0265)	(0.0363)
Small	0.233***	0.216***	0.175***	0.273***	0.274***
	(0.0299)	(0.0237)	(0.0191)	(0.0238)	(0.0356)
Medium	0.151***	0.153***	0.197***	0.492***	0.840***
	(0.0485)	(0.0388)	(0.0310)	(0.0413)	(0.0769)
Large	0.199***	0.207***	0.164***	0.202***	0.383***
	(0.0519)	(0.0469)	(0.0406)	(0.0512)	(0.0834)
North	0.505***	0.362***	0.200***	0.177***	-0.0568**
	(0.0379)	(0.0293)	(0.0207)	(0.0210)	(0.0250)
Southeast	0.578***	0.540***	0.489***	0.483***	0.258***
	(0.0411)	(0.0324)	(0.0265)	(0.0334)	(0.0490)
South	0.596***	0.601***	0.574***	0.700***	0.549***
	(0.0382)	(0.0311)	(0.0256)	(0.0327)	(0.0496)
Midwest	0.594***	0.484***	0.516***	0.580***	0.628***
	(0.0399)	(0.0381)	(0.0321)	(0.0418)	(0.0716)
Intercept	5.182***	5.931***	7.237***	7.720***	7.948***
	(0.347)	(0.204)	(0.139)	(0.132)	(0.0844)
Observations			15,402		
R-squared	0.079	0.161	0.227	0.244	0.178
F-statistic	40.76	107.5	203.7	186.7	60.80

Source: Own elaboration.
Notes: ***significant at 1%, **significant at 5%, *significant at 10%, NS non-significant; Standard-errors in parentheses.

These results have shown that credit from other sources have a greater effect on the top income quantiles; e.g. credit from other sources increase rural income in 54.4% (i.e. R$ 1,549.31 on average) compared to farms that did not had access for the monthly household income quantile q75. A higher effect of other sources compared to Pronaf might be explained by the restriction on resources that small and low-income farmers face. Pronaf's guidelines suggest that this line of credit is designed to low-income families. Access to this line credit has a steady influence on household income (Figure 2) around 0.2 and a non-significant effect on the top income quantile (due to the lower number of Pronaf borrowers).

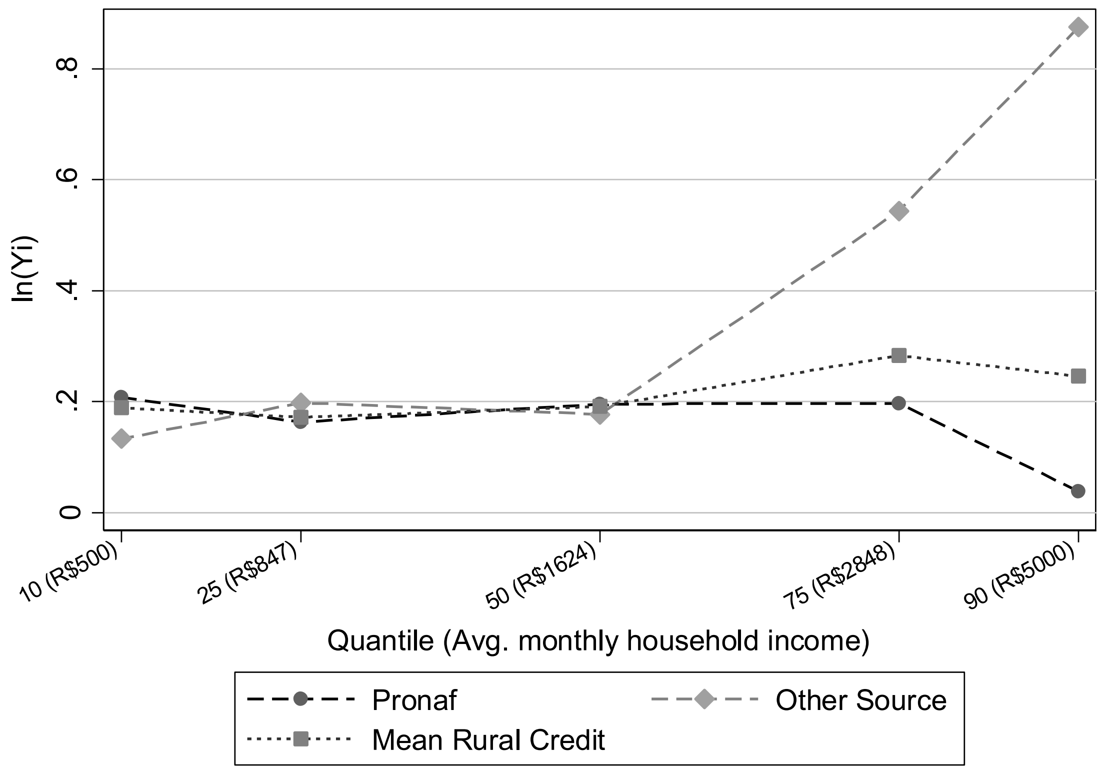

Figure 2 Effects of rural credit on the distribution of income in the rural Brazil, 2014
Source: Own elaboration.

4.2 Decomposition of income differentials

The analysis of the data indicates differences in the characteristics of farms with and without access to rural credit. The results presented in the previous subsection also indicate differences in the return to rural credit on income. Although it increases rural income it also increases income inequality. In this section, we identify which factors explain this difference in income due to access to credit. 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 *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 these 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 Table 4 and are summarized in Figure 3, Figure 4 and Figure 5.

Table 4 Decomposition of the income differentials: With Rural Credit – Without Rural Credit, Brazil, 2014

	q10	q25	q50	q75	q90
Income Differential (*LnYi*)	0.5292	0.5900	0.5956	0.6302	0.5099
Composition Effect	0.3037	0.2554	0.2701	0.4586	0.7094
Return Effect	0.2255	0.3346	0.3255	0.1717	-0.1994
Detailed *Composition Effect*					
Schooling	0.0353	0.0358	0.0404	0.0747	0.1338
Age	-0.0220	-0.0229	-0.0232	-0.0083	-0.0076
Extension	0.0887	0.0873	0.0742	0.1502	0.2753
Farmer condition	0.0077	0.0078	0.0171	0.0169	0.0189
Farm size	0.0652	0.0437	0.0317	0.0606	0.1047
Region	0.1478	0.1242	0.1391	0.1748	0.1917

Others	-0.0191	-0.0205	-0.0092	-0.0102	-0.0075
Detailed *Return Effect*					
Schooling	-1.9569	-1.8952	1.0102	0.5400	0.2875
Age	0.2065	0.0033	-0.0931	0.3049	0.1860
Extension	-0.0049	-0.0094	-0.0242	-0.1267	-0.3386
Farmer condition	0.0160	-0.0241	-0.0260	0.0025	0.0074
Farm size	0.0502	0.0870	0.0805	-0.0349	-0.0902
Region	0.2529	0.3910	0.1812	-0.1969	-0.2270
Others	-0.2619	-0.1446	-0.0878	0.1462	0.1281

Source: Own Elaboration.

Rural households (farms) that had access to rural credit obtain a positive income gain in all the quantiles considered compare to farmers that have not accessed these services (Figure 3). Overall, the *composition effect* governs the income differential in the income quantiles q10 and from q50. It implies that the differences in the individual characteristics such as schooling and access to rural extension explain almost the entire income gap in these quantiles, especially from q75 (see Figure 4).

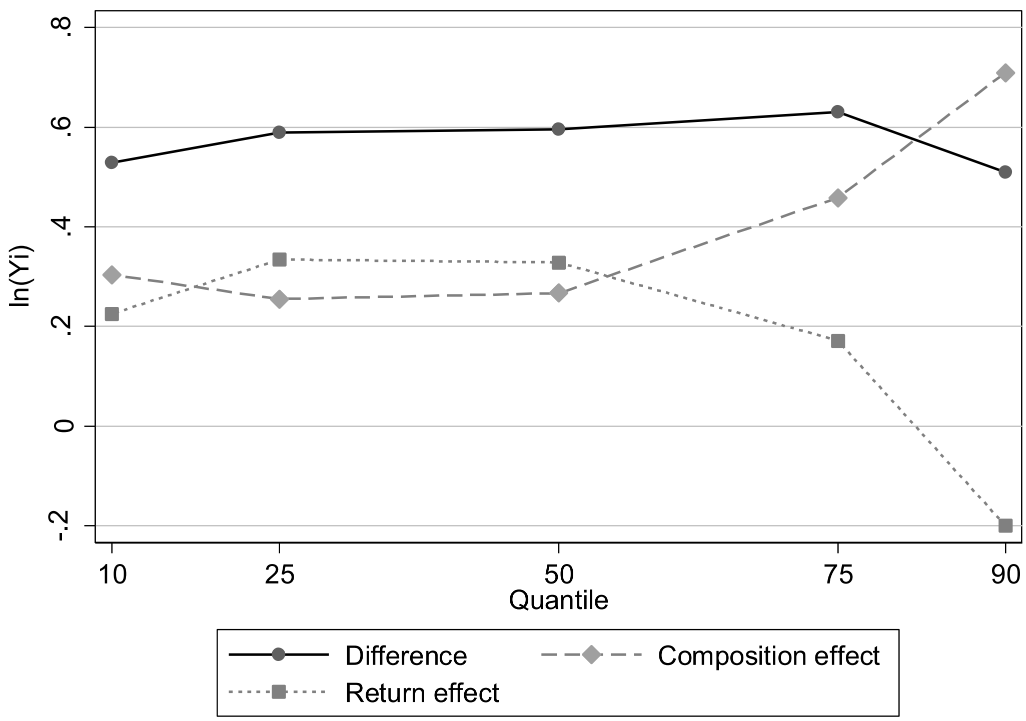

Figure 3 Decomposition of the income differential: With Rural Credit – Without Rural Credit, Brazil, 2014
Source: Own elaboration.

The *return effect* is steady over the distribution except along the top quantiles. It means that, for the top quantiles, the income differential is not explained by the difference on the return (effect on income) of household characteristics between those that had access to credit and those that did not have access to credit; e.g. for income quantiles lower than q75, the return effect is positive, which implies that households that had access to credit have obtained a higher return to household/individual characteristics on their income such as education.

Figure 4 (and Table 4) breaks down the *composition effect*. We found that access to rural extension, education, and location of residence are the main factors explaining the higher level of income for farmers that had access to rural credit compared to farmers that did not. It suggests that might be occurring a selection bias on the provision of rural credit, including Pronaf, as also suggested by Aquino and Schneider (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 farmers that had access to credit and those that did not. These results indicate that the effect of credit might be constrained for the low-income farms given the lack of education and access to rural extension. Higher education level also helps farmers to absorb information and implement the technical recommendations more precisely (Freitas, 2017).

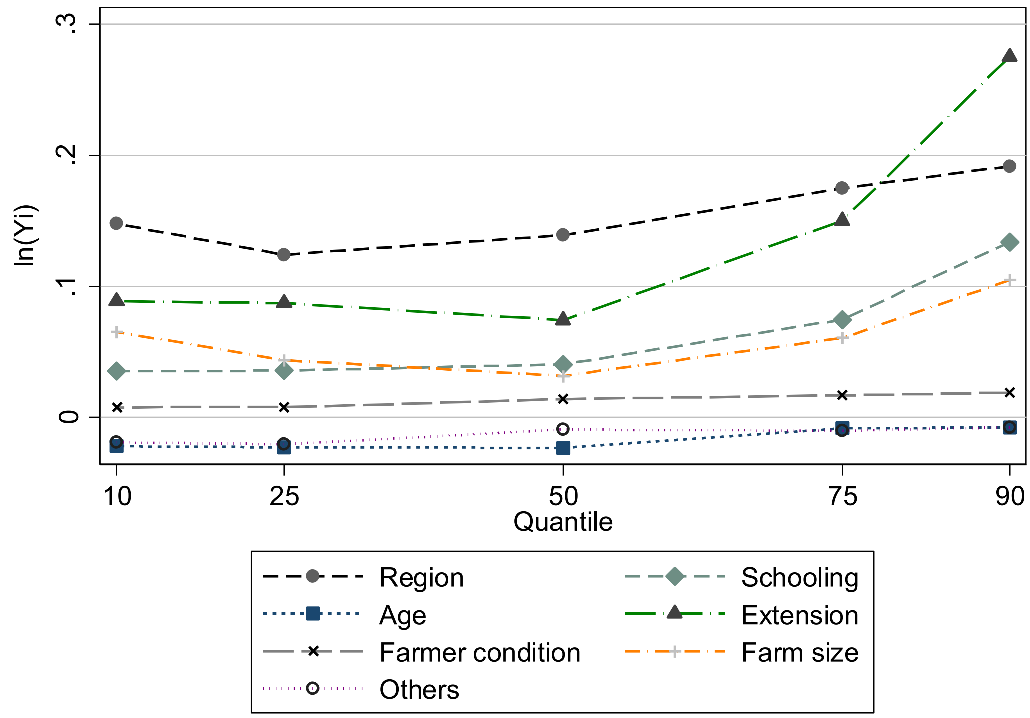

Figure 4 Detailed decomposition of the *composition effect* of the income differential, Brazil, 2014
Source: Own elaboration.

We also break down the *return effect* to better understand how the return to the characteristics affects the household income. These results are displayed in Table 4. Although we observe an erratic effect of schooling on rural income this variable contributes considerably to income in the last two income quantiles (q75 to q90). 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). The exact opposite is true for the lowest quantiles (q10 to q50). In general, most of the variables have a similar influence on income differentials.

4.3 Regional analysis

Regional disparities are still a strong factor in Brazilian rural areas, as pointed out by Azzoni (2001), Alves (2013) and Costa et al. (2016). In Figure 5 we show the regional differences on the income gap focusing on the *return effect*, the most prominent effect in the comparison between the regions. The models were re-estimated for selected pairs of Brazilian regions. It suggests that a household in the Northeast region would obtain a much greater income effect from access to credit if they had the same characteristics as the households in the Southeast, but not necessary with reduction on income inequality. A similar trend occurs in the comparison between Northeast and South regions: if Northeastern farmers had the same Southern characteristics, they would obtain a greater income, but now with an important effect in decreasing income inequality in Northeastern rural area.

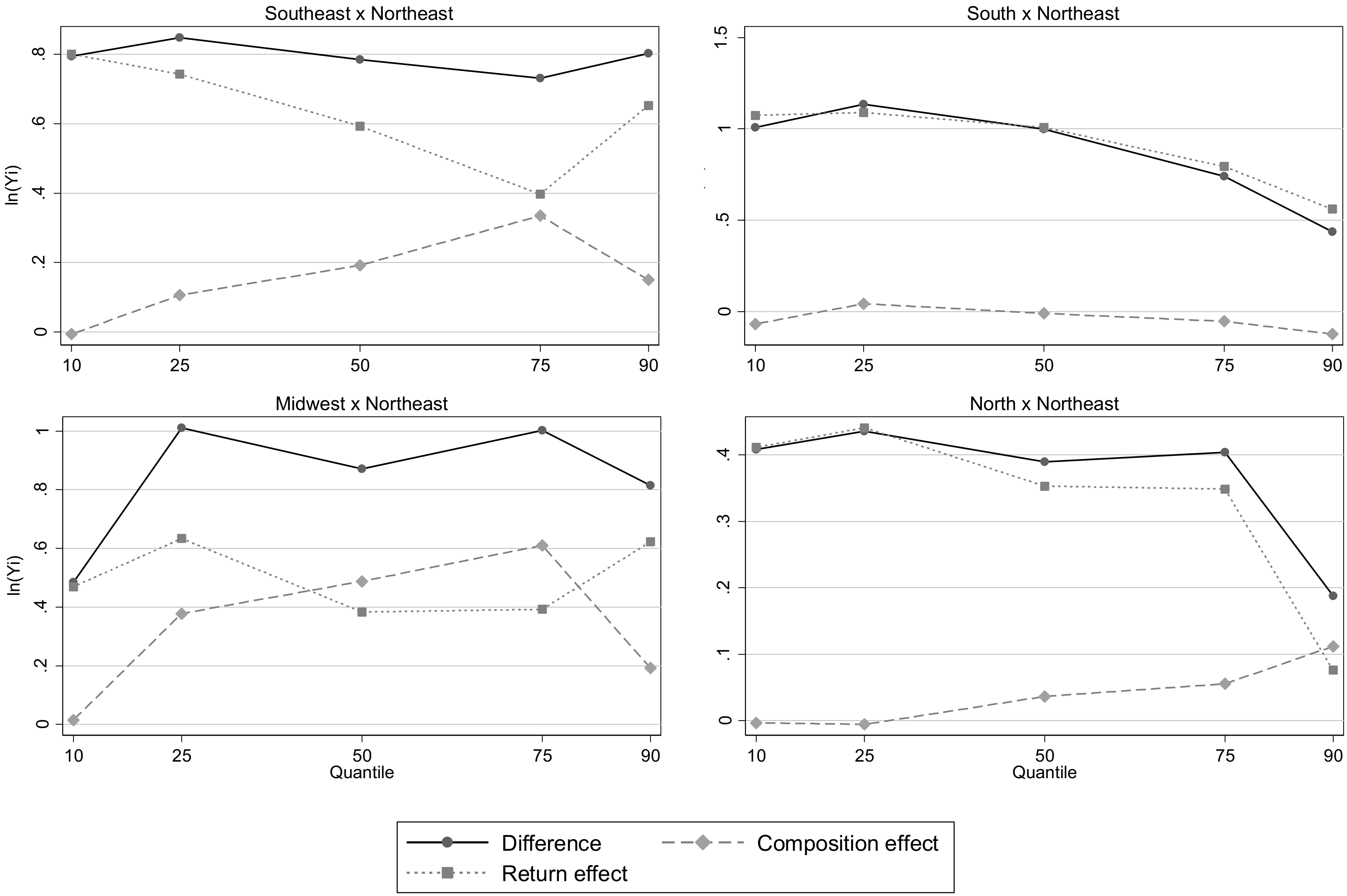

Figure 5 Decomposition of the income differential: With Rural Credit – Without Rural Credit, selected regions, Brazil, 2014
Source: Own elaboration.

5. CONCLUSIONS

Brazilian agriculture has been growing exponentially in the last decades, also expanding its participation on international markets. However, it still faces a high level of rural inequality. In this paper, we seek to identify whether access to credit deepens or reduces the rural household inequality in Brazil. To obtain the effect of credit on household income we use an income decomposition proposed by Firpo et al. (2007) and the household survey of 2014 from the IBGE (National Household Sample Survey-PNAD).

Our results indicated that Brazilian rural credit policy was capable to increases rural household income in all income quantiles, but it has also increased income inequality. However, we observed a smaller effect of Pronaf on increasing inequality compared to rural credit from other sources. Additionally, we found that the rural credit from other sources has a greater effect on rural income in the top income quantiles compared to Pronaf. The income differential decomposition has shown that the difference in individual characteristics explains the majority of the income differential in top part of the income distribution.

Results indicate that higher level of education and access to rural extension increase the effect of rural credit on household income. It implies that access to rural credit alone cannot raise social welfare of the low-income farmers. Our findings suggest that the design of a joint public policy on rural credit, rural extension and promotion of the human capital would have much a stronger effect on reducing income inequality in the Brazilian rural area, evidencing, in this case, the existence of synergy between public policies and public services linked to rural credit.

Additionally, it is important to note that the Northeast region of Brazil should be focused on receiving services and policies. This would allow its farmers to act similarly to farmers in the South and Southeast regions, which would boost the result of rural credit in this region.

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