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ARTICLE

Heterogeneous regional effects of rural credit on agricultural production in Brazil

Efeitos regionais heterogêneos do crédito rural sobre a produção agropecuária no Brasil

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Abstract: Access to rural credit has been persistently heterogeneous across Brazilian regions over time. This work aimed to estimate the regional effects of rural credit on agricultural production due to the heterogeneity observed in access to credit. Based on data from the 2017 Agricultural Census and climate variables, the effect of rural credit was estimated by standard regressions, combined with the entropy balancing technique. The results show positive and significant effects of rural credit on Brazilian agricultural production, even after controlling for observed covariates. This result was consistent even after balancing the covariates with regard to entropy. The effect of rural credit proved to be heterogeneous across Brazilian regions, being positive and significant for regions with greater access to rural credit and statistically null in less credit-intensive regions. Furthermore, estimates show that technical assistance is an important transmission mechanism of the rural credit effect.

Keywords: rural credit, technical assistance, agricultural production, Brazil.

Resumo: O acesso ao crédito rural tem sido persistentemente heterogêneo entre as regiões brasileiras ao longo do tempo. Este estudo teve como objetivo estimar os efeitos regionais do crédito rural sobre a produção agropecuária devido à heterogeneidade observada no acesso ao crédito. Com base em dados do Censo Agropecuário 2017 e variáveis climáticas, o efeito do crédito rural foi estimado por meio de regressões padrão, combinadas com a técnica de balanceamento de entropia. Os resultados mostram efeitos positivos e significativos do crédito rural na produção agrícola brasileira, mesmo após o controle das covariáveis observadas. Esse resultado foi consistente mesmo após o balanceamento das covariáveis em relação à entropia. O efeito do crédito rural mostrou-se heterogêneo entre as regiões brasileiras, sendo positivo e significativo para as regiões com maior acesso ao crédito rural e estatisticamente nulo nas regiões menos intensivas em crédito. Além disso, as estimativas mostram que a assistência técnica é um importante mecanismo de transmissão do efeito do crédito rural.

Palavras-chave: crédito rural, assistência técnica, produção agropecuária, Brasil.

1. Introduction

Productivity increases and agricultural production growth have placed Brazil in a prominent position in the international scenario in recent decades with agricultural production reaching around 4.5% of GDP between 1996 and 2020 (Universidade de São Paulo, 2022).[1] This may be the result of various public policies and technological advances that have contributed to maintaining the competitiveness of this sector. In Brazil, several rural credit policies have been implemented[2] which have allowed small producers in regions with less modernized

[1] In 2020, agricultural production accounted for 7% of Brazilian GDP, which is the largest share recorded between 1996 and 2020.

[2] For example, the National Support Program for Medium Rural Producers (PRONAMP) and the Program for the Strengthening of Family Farming (PRONAF), among others.

production systems[3], low technical efficiency, and which are more susceptible to climatic variations to have access to financial support, thus reducing market failures. However, the most recent Agricultural Census, conducted in 2017, revealed a subtle reduction in the share of agricultural establishments that had access to rural credit.[4] Furthermore, access to credit has been persistently lower in the North and Northeast regions of the country over time. Belik (2014, 2015) highlights that, in 2006, rural credit granted to family farming was concentrated in the South region, representing more than 60% of the credit. On the other hand, the Northeast region, which had 50.8% of family farming establishments, received only 26% of the credit and, ten years earlier, this region received only 6.6% of the total.

The effect of rural credit has been widely discussed in previous studies, especially in developing economies. These works suggest that rural credit had positive effects on different economic and environmental variables in the agricultural sector.[5] In terms of agricultural production and/or productivity in Brazil, these results have not been different (Araújo & Vieira Filho, 2018; Assunção & Souza, 2019; Costa & Vieira Filho, 2018; Freitas et al., 2020; Gasques et al., 2017). However, usually these works assume that the effects of rural credit are homogenous.

In addition to the fact that the Brazilian territory is extensive, there are significant differences in the natural and climatic conditions, and particularities of rural producers, as access to rural credit tends to be more restricted in some regions. These differences allow us to expect that rural credit produces heterogeneous effects on agricultural production across regions. However, there is little evidence in this regard (e.g., Eusébio et al., 2020; Garcias & Kassouf, 2016; Maia et al., 2019).

This work aims to estimate the regional effects of rural credit on agricultural production due to observed heterogeneous access to credit in Brazil. Based on data from the Agricultural Census (Instituto Brasileiro de Geografia e Estatística, 2023b) and climate variables, the effect of rural credit was estimated using standard regressions, combined with entropy balancing. By expanding the debate on the causal effects of rural credit across Brazilian regions, we provide at least two contributions to the literature. First, in contrast to studies based on propensity scores, our estimates take into account an exact balance of covariates between the treated and control groups, without loss of valuable information in the preprocessed data. Second, we provide evidence on potential transmission mechanisms through which rural credit can influence agricultural production.

In order to estimate the effect of rural credit, data were needed for the characteristics of rural producers and agricultural activity, which allowed identifying those with and without access to rural credit. The only database that met these conditions was the Agricultural Census. However, two important limitations should be mentioned. First, it was not possible to obtain a data panel of rural producers which limited the use of more robust techniques to estimate the treatment effect. Furthermore, since access to microdata requires authorization from the Brazilian Institute of Geography and Statisticis - IBGE (*Instituto Brasileiro de Geografia e Estatística*), for restricted use in a confidential room in Rio de Janeiro, we used the census data which is publicly available at the municipal level. Thus, we adopted the concept of representative farms, used in previous works (Freitas et al., 2020; Helfand et al., 2015).

[3] Silva & Vian (2021) classified Brazilian municipalities according to the standard of agricultural modernization, identifying a concentration of municipalities with a low standard in North and Northeast regions.

[4] The proportion of rural establishments that received some funding decreased from 17.76% in 2006 to 15.46% in 2017 (Instituto Brasileiro de Geografia e Estatística, 2022).

[5] Positive effects on agricultural income and participation in agricultural activities (Ely et al., 2019; Khandker & Koolwal, 2016; Luan & Bauer, 2016; Neves et al., 2020; Chen et al., 2021); on farmland rental market participation of rural households (Li et al., 2020); on GDP (Borges & Parré, 2022); on land use, agricultural practices and deforestation (Assunção et al., 2020; Assunção & Souza, 2019; Carrer et al., 2020; Porgo et al., 2018).

As for the treatment variable, we created a dummy variable that received the value of 1 if the municipality had a proportion of rural establishments that obtained funding in 2017 above the average, plus one standard deviation in each region. Thus, the treatment condition in this work indicated greater intensity in rural credit access.

We expect that in regions where access to rural credit is less restricted, the increase in agricultural production will be greater in relation to the gain in regions where access to rural credit is more restrictive. With this, we hope to provide evidence on which regions rural credit policy should be encouraged, as well as options for improving these policies by identifying transmission mechanisms that could condition access to rural credit or direct the purpose of the investment made by rural producers.

In addition to this introduction, this work is structured as follows. Section 2 discusses recent literature regarding the role of rural credit in the Brazilian agricultural sector. Section 3 presents the empirical strategy. Section 4 discusses the dataset used in this study and the descriptive statistics, and Section 5 presents the findings and discussion of our analysis. In Section 6 we present our concluding remarks.

2. Theoretical foundation

Brazil has become one of the largest producers and exporters of agricultural products in the world in recent decades, as a result of technological advances, the expansion of the agricultural frontier, greater productivity, and competitiveness. In addition to advances in research developed by the Brazilian Agricultural Research Company – Embrapa (*Empresa Brasileira de Pesquisa Agropecuária*), Araújo et al. (2020b) emphasize that rural credit has been fundamental in achieving these positive results, even in light of a series of difficulties, such as infrastructure deficiencies, high interest rates, and a devalued currency. According to these authors, rural credit has remained the main instrument to support rural producers, since the enactment of the National Rural Credit System –SNCR (*Sistema Nacional de Crédito Rural*) by Law nº 4,829 of 1965. Also in this regard, Servo (2019) highlighted the existence of a historical dependence of the agricultural sector in Brazil on rural credit, making this instrument of support for rural producers one of the main determinants of Brazilian agricultural GDP.

Impacts of rural credit have been widely investigated in the literature, in which the effects are measured on different outcome variables of the agricultural sector (economic and environmental) through different methodological approaches. In the Brazilian case, for example, evidence can be found on the effect of rural credit on agricultural or agribusiness GDP (Araújo et al., 2021; Borges & Parré, 2022; Gasques et al., 2017), on Total Factor Productivity (TFP), land or labor productivity and/or technical efficiency (Araújo & Vieira Filho, 2018; Costa & Freitas, 2018; Figueira, 2020; Freitas et al., 2020; Garcias & Kassouf, 2016; Gasques et al., 2017); on the quantity produced (Costa & Vieira Filho, 2018; Figueira, 2020; Souza et al., 2021); and on the income of rural producers (Araújo et al., 2020a). Furthermore, recent studies have investigated the effects of rural credit on environmental aspects such as land use, and planted and harvested areas (Araújo & Vieira Filho, 2018; Assunção & Souza, 2019; Costa & Vieira Filho, 2018; Figueira, 2020; Souza et al., 2021).

The evidence also highlights the positive and significant effects of rural credit on the gross value of production, which is the variable of interest in this work (Araújo et al., 2020a; Araújo & Vieira Filho, 2018; Assunção & Souza, 2019; Costa & Vieira Filho, 2018; Eusébio et al., 2020; Figueira, 2020; Freitas et al., 2020; Garcias & Kassouf, 2016; Gasques et al., 2017; Magalhães et al., 2006; Maia et al., 2019; Souza et al., 2021). Using different methodological approaches, most of these studies assumed that rural credit has homogeneous impacts on Brazilian agricultural production.

However, research that has focused on the heterogeneity of the effects of rural credit on Brazilian agricultural production is still scarce. Among those who aimed to estimate causal relationships, Eusébio et al. (2020), Garcias & Kassouf (2016) and Maia et al. (2019) found evidence of the heterogeneous effects of rural credit across Brazilian regions. Using data from the 2006 Agricultural Census, the latter two works used approaches based on propensity scores to estimate the effects of rural credit.

In this context, this work contributes by providing new evidence of heterogeneous regional effects, considering the intensity of access to rural credit as treatment, by using an alternative empirical strategy to models based on propensity scores with advantageous statistical properties, and by exploring potential mechanisms of rural credit transmission neglected in previous studies.

Table 1 details the evidence on the effects of rural credit, highlighting the type of rural credit considered, the methodology, the units of the analysis, the period, the source of the data, and the outcome variables in which the authors assessed the impact in order publication chronology.

Table 1 – Previous evidence on the effect of rural credit in Brazil

Authors	Rural Credit	Methodology	Analysis Units	Period	Source	Variables of interest
Magalhães et al. (2006)	Pronaf beneficiaries and non-beneficiaries	OLS and Propensity Score	Family farmers in the state of Pernambuco	2001	Primary	1 – Production value; 2 – Production value per hectare; 3 - Production value per person;
Garcias & Kassouf (2016)	Greater and lesser restrictions to credit	Propensity score matching	Brazilian municipalities	2006	Agricultural Census / IBGE	1 – Land productivity; 2 – Labor productivity
Gasques et al. (2017)	Total rural credit	Transfer functions in time series with AR and MA components	Brazil	1996 to 2015	Central Bank; IBGE; Cepea/USP e MAPA	1 - Gross value of production; 2 - Agribusiness GDP; 3 – Agricultural GDP; 4 - TFP
Araújo & Vieira Filho (2018)	Quantity and total value of Pronaf agriculture and livestock contracts	Panel vector autoregressive	26 states and Federal District in Brazil	2007 to 2016	Central Bank and IBGE	1 - Planted area; 2 - Gross value of agricultural and livestock production; 3 - Land productivity
Costa & Freitas (2018)	Access to rural credit	stochastic frontier and sample selection model	Farmers in Brazil	2006	Microdata-Agricultural Census / IBGE	1 – Technical efficiency
Costa & Vieira Filho (2018)	Quantity and value of contracts by segment (agriculture or livestock)	Panel vector autoregressive	26 states and Federal District in Brazil	2007 to 2016	Central Bank and IBGE	1 - Planted area; 2 - Quantity harvested; 3 - Value of agricultural production; 4-Number of cattle;
Assunção & Souza (2019)	Total rural credit	Shift-share models in panel data	Brazilian municipalities	2002 to 2015	Central Bank, IBGE, MapBiomas and RAIS	1 – Municipal GDP; 2 Agricultural GDP; 3 –Land and labor productivity; 4 – Planted area
Araújo et al. (2020a)	Pronaf beneficiaries and non-beneficiaries	Propensity score matching	Farmers in Brazil	2014	PNAD/IBGE	1 – Agricultural income; 2 – Land productivity
Eusébio et al. (2020)	Access to rural credit	Two-Stage Estimation Method	Non-family farmers in Brazil	2006	Microdata - Agricultural Census / IBGE	1 - Total production value
Figueira (2020)	total rural credit for agricultural activity	Panel data: pooled, fixed and random effect	Rural Development Offices in São Paulo (municipalities)	1995 to 2012	Central Bank	1 – Area planted with sugar cane; 2 – Sugarcane productivity

Source: Prepared by the authors.

Table 1 – Continued...

Authors	Rural Credit	Methodology	Analysis Units	Period	Source	Variables of interest
Freitas et al. (2020)	Greater and lesser access to rural credit by resource source	OLS and Entropy Balancing; Stochastic frontier	Brazilian municipalities	2017	Agricultural Census / IBGE	1 – Value of agricultural production; 2 – Technical efficiency
Maia et al. (2019)	Pronaf beneficiaries and non-beneficiaries	Propensity score matching	Farmers in Brazil and Regions	2006	Microdata - Agricultural Census / IBGE	1 – Value of agricultural production;
Araújo et al. (2021)	Total value of MODERFROTA program	Structural vector error correction	Brazil	2002 to 2019	IPEA; BNDES; IBGE;	1 – Agricultural GDP; 2 – Harvested area
Souza et al. (2021)	Total rural credit	Shift-share models in panel data	Brazilian municipalities–by biomes	2002 to 2018	Central Bank, IBGE, MapBiomas	1–Planted areas; 2–Agricultural production; 3–Land productivity.
Borges & Parré (2022)	Total rural credit and by purpose	Vector autoregressive		1999 to 2018	Central Bank, IBGE	1 - Agricultural GDP

Source: Prepared by the authors.

3. Methodology and data

We are interested in measuring the effect of the intensity of access to rural credit (where the treatment dummy is an indicator variable for municipalities with greater access to rural credit) on agricultural production (gross production value) in Brazil and its regions. This issue is a problem in the evaluation literature, where only the potential outcomes of rural credit-intensive municipalities (treated group) and non-intensive municipalities (control group) can be observed. To estimate the true effect of this treatment, however, it would be necessary to compare the potential outcome of the treated municipalities against the potential outcome of the treated municipalities if these municipalities had not received the treatment (counterfactual group). Since the potential results of the counterfactual group were not observed, the alternative found was to use information from the control group to derive the counterfactuals, that is, we seek to compare the value of agricultural production in municipalities with greater coverage in access to rural credit (treated group) in relation to municipalities with lower coverage in access to credit (control group), as long as the latter group presents observed characteristics similar to the characteristics of the treated group.

Specifically, we are interested in estimating the parameter that measures the effect of the intensity of access to credit in municipalities that were indeed treated (Average Effect of Treatment on the Treated - ATT). Therefore, this parameter will inform the increase in the value of the municipality’s production resulting from greater access to rural credit, making it possible to guide policy makers whether being intensive in rural credit has any impact. A simple way to measure ATT is to estimate a standard linear regression by Ordinary Least Squares (OLS), according to Equation 1 below, which establishes a relationship between the value of agricultural production (Y) and having greater coverage in access to rural credit (T):

$$Y_i = \alpha_i + \beta T_i + \gamma' X_i + \varepsilon_i \tag{1}$$

where, Y_i is the gross value of agricultural production in the *i-th* municipality; X_i is a vector of observable characteristics; T_i is a treatment indicator variable that assumes the value 1 if the municipality is intensive in accessing rural credit, and 0 otherwise; β is the parameter of interest to be estimated, equivalent to the ATT.

However, as the distribution of municipalities into groups of highest and lowest coverage was not randomly assigned (using, for instance, a lottery), it is likely that the ATT estimated in Equation 1 is biased by omitting unobserved characteristics which may be correlated with the variable T. For example, it is possible that in certain municipalities rural producers are risk lovers and are more willing to make investments via financing, while in other municipalities risk-averse rural producers may predominate, and therefore would avoid financing. As the degree of risk aversion in financing is not a characteristic observed in the data, it is possible that municipalities have greater coverage in access to rural credit because they have rural producers who are more likely to take on financing risks and municipalities with lower coverage in access to credit rural areas have producers who are less likely to take on financing risks. Thus, the effect of having greater coverage on access to rural credit could be confused with the effect of risk propensity. This self-selection makes the variable T endogenous, which could overestimate the effect of rural credit by capturing part of the effect of these unobserved characteristics.

Instrumental variable estimators are suitable options for estimating the ATT. However, the use of this approach is limited to the availability of good instruments.[6] Another alternative would be the use of approaches based on propensity scores, as in Rosenbaum & Rubin (1983). This approach assumes that selection by unobservable variables would not affect the outcome variable in the absence of treatment. Under this hypothesis, known as the conditional independence hypothesis, comparisons between the potential outcomes of the treated group and the control group, provided that groups are similar in observable characteristics (*i.e.*, groups balanced in observable characteristics), would provide unbiased estimates of the ATT. The propensity score matching (PSM) technique has been widely used in the literature in this regard, allowing to improve the distribution of observable characteristics, making them independent of the treatment. These techniques, however, can result in low levels of balance.

Thus, Hainmueller (2012) proposed the Entropy Balancing approach, which involves a weighting scheme of the units of analysis for later estimation of the treatment effect. The propensity score-based scheme requires large samples and an estimated propensity score close to the actual one, which is often unknown. Thus, poorly specified propensity scores can increase bias in subsequent estimates of the treatment effect by failing to balance the covariates. Furthermore, they achieve balance only asymptotically. In this sense, the Entropy Balancing method appears as a more accurate alternative to find the balance of covariates. This means that balancing the covariates using the entropy method would make the distribution of municipalities between the two groups independent of the outcome variable (Production Value) and their observed characteristics, similar to what would happen if the distribution of groups were defined by lottery.

We adopted, thus, the following empirical strategy. Initially, the balancing of the covariates was performed using the Entropy Balancing technique proposed by Hainmueller (2012), and the conditional independence hypothesis was tested by reporting the absence of differences in the means of the observable characteristics. Then, to determine the effects of rural credit on the value of production in Brazil and in the different regions, the ATT were estimated by standard OLS regressions after weighting the data by the entropy weight.

[6] According to Wooldridge (2002), a valid instrument must be correlated with the probability of being treated, but it cannot be determined by confounding factors that affect the outcome variable. However, the second condition cannot be tested. Thus, the choice of a valid instrument largely depends on intuitive and economic reasons. For the case of this study, we could think of the Municipal Institutional Quality Index, adapted by Oliveira et al. (2022), as a candidate instrument for greater intensity of access to rural credit. Municipalities with higher institutional quality and, therefore, better reputation or composed of more reliable agents due to financial balance could be associated with a greater probability of the municipality having greater coverage in access to rural credit. However, institutional quality is constantly associated with higher levels of regional economic development (Nakabashi, 2021), which could also favor the development of the agricultural sector. In this way, the instrument would also be endogenous, increasing the endogeneity problem.

In practice, we assumed that the treatment corresponds to the intensity of access to rural credit, considering representative farms, which are described in the next section, as the unit of analysis. Therefore, representative farms with greater intensity in access to rural credit belonged to the treated group, and representative farms with less intensity belonged to the control group.

As previously described, the ATT is given by the difference in the expected results of the treated rural establishments, $\left(E\left[Y(1)|T=1\right]\right)$, and the counterfactuals $\left(E\left[Y(0)|T=1\right]\right)$:

$$\tau_{ATT} = E\left[Y(1)|T=1\right] - E\left[Y(0)|T=1\right] \tag{2}$$

where Y is the result of interest (value of agricultural production), and T is an indicator of treatment (T=1, treated; T=0, control). The second term on the right side of equation (2) cannot be observed. Entropy Balancing, however, gets around that by rebalancing the control units, *i.e.*, the sample units of the control group were weighted by w_i, such that the estimate of $E\left[Y(0)|D=1\right]$ can be determined, as in Equation 3:

$$\widehat{E[Y(0)|T=1]} = \frac{\sum_{\{i|T=0\}} Y_i w_i}{\sum_{\{i|T=0\}} w_i}, \tag{3}$$

The w_i weights were assigned to each control unit and were obtained through an optimization problem subject to equilibrium and normality constraints. Balancing constraints were imposed to equalize the average of the covariates between the two groups, ensuring that the control group contained, on average, units of analysis that are as similar as possible to the treated units.[7] The w_i weights were used to weight the units of analysis in subsequent regressions, containing the treatment indicator variable (T) as an explanatory variable, according to Equation 1. This way, the estimated coefficient β was the unbiased ATT measure. To verify the sensitivity of the estimated coefficient, Equation 1 was estimated before and after weighting the data by the entropy weight. Furthermore, the ATT was estimated for Brazil and regions, making it possible to verify whether the effect of rural credit was heterogeneous between regions.

3.1 Data

Data from the 2017 Agricultural Census were used, which are available at the IBGE website, through the IBGE Automatic Recovery System (*Sistema de Recuperação Automática* - SIDRA) (Instituto Brasileiro de Geografia e Estatística, 2023b). This database contains microdata, making it possible to identify, at the individual level, the characteristics of rural producers and rural establishments, in addition to the technologies and agricultural practices adopted. Information on financing and its sources is also available, which facilitated the identification of treated and control groups in order to estimate the effect of rural credit. However, these microdata are not readily accessible, given the confidential nature of the information and, therefore, this work made use of aggregate data at the municipal level, which are publicly available.[8]

[7] For details on obtaining the weights, see Hainmueller (2012).

[8] Microdata can be accessed upon approval of a research project. However, these data can only be accessed in a confidential room located in Rio de Janeiro, substantially increasing research costs.

The use of aggregate data may represent a limitation as they disregard all heterogeneity within the municipality. Thus, if farms are very different, aggregation would not allow exploring this variation between the units of analysis. We therefore adopted the concept of representative farms, following previous literature (Freitas et al., 2020; Helfand et al., 2015). Each unit of analysis thus symbolizes a 'representative' rural property within the municipality, where the variables correspond to the average. These representative units were obtained by dividing all the municipal level variables by the total number of rural establishments. For example, the area of a representative establishment is given by the sum of the areas of all rural establishments divided by the total number of rural establishments in municipality *i*.

Data at the municipal level did not allow us to identify whether the establishment had access to rural credit, which was another limitation of the data. Therefore, we created a dummy variable that indicated the treatment condition (T) of the representative farms, using as a basis the variable *proportion of establishments that obtained financing (Z)*:

$$T = 1 \, if \; Z > mean(Z) + 1 * standard\ deviation(Z)$$

$$T = 0 \, if \; Z \leq mean(Z) + 1 * standard\ deviation(Z)$$

Thus, representative farms whose proportion of establishments that obtained any financing greater than the mean, added by a standard deviation, assumed a value of 1, and 0 otherwise.[9] This was a proxy for the treatment variable that indicated the intensity of access to rural credit. In this case, we are working with a binary treatment, which represents the extensive margin of rural credit (having access or not). Furthermore, since the definition of the treatment variable follows an *ad-hoc* approach, we also check the robustness of the estimated treatment effect by testing two variations of the condition that defines the treatment variable. In the first variation, we reduced the treatment intensity grade to 0.75 standard deviation of *Z*, thus increasing the number of treated units. In the second variation, we increased the treatment intensity grade to 1.25 standard deviation of *Z*, reducing the number of representative farms treated.

The sample size varied depending on the region analyzed and the missing values of the variables. Of the 5563 municipalities registered in the Agricultural Census, 127 were excluded from the sample.[10] Figure 1 shows the frequency distribution and the mean of the proportion of rural establishments that received any kind of funding, and the number of treatment and control representative farms according to the regions of interest.

The data revealed a certain heterogeneity regarding access to rural credit among the regions considered, which could suggest different regional effects of rural credit on agricultural performance. The North and Northeast regions, respectively, had lower averages of the proportion of rural establishments with access to rural credit, especially in comparison with the South region. Garcias & Kassouf (2016) showed that in 2006 the North and Northeast regions predominated as the areas of greater credit restriction in Brazil.[11]

[9] This criterion was adopted in Freitas et al. (2020) for rural credit, and by Costa et al. (2020) for the case of cooperativism. Garcias & Kassouf (2016), on the other hand, defined the treatment if most establishments faced credit restrictions in the municipality.

[10] Six municipalities were excluded due to the absence of gross agricultural production values, 42 due to lack of information on the number of establishments that obtained financing, and an additional 79 for lacking information on the number of establishments with irrigation. Missing values were considered the following: absolute zero, not resulting from a rounded value; values omitted so as to not identify the informant; when not applicable; or when value was not available.

[11] According to Garcias & Kassouf (2016), the concept of credit restriction must take into account whether the rural establishment applied for credit, but had its request denied, since producers who did not demand credit cannot be considered restricted. Unfortunately, data from the 2017 Agricultural Census do not allow the identification of establishments that had their request denied and, therefore, the variable of proportion of establishments that obtained credit, used in this study, does not strictly represent the concept of restriction.

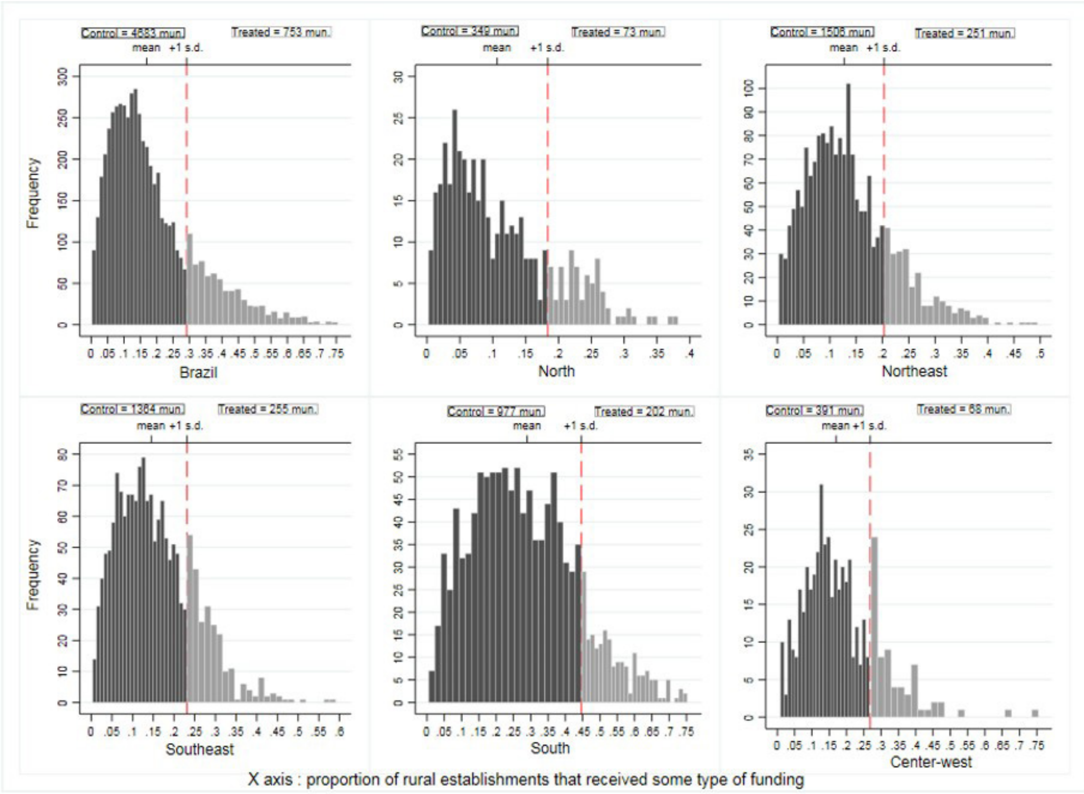

Figure 1 - Frequency distributions of the proportion of rural establishments with financing – Brazil and Regions – 2017.
Source: 2017 Agricultural Census.

The natural logarithm of the gross value of agricultural production (animal and plant) was used as the outcome variable. Statistics on the value of agricultural production, according to the region of interest and treatment condition, are shown in Figure 2. Differences in means between the treated and control groups are plotted in the first column of Figure 2.

Statistics show regional heterogeneity in terms of agricultural production. The Center-west region, due to the comparative advantages in the production of temporary crops, stood out as the one with the highest average agricultural production. On the other hand, the Northeast and North regions, respectively, have lower levels of agricultural production (see second column, Figure 2).

Positive and significant differences in agricultural production, favorable to the treated representative farms, were found, meaning that municipalities with greater coverage in access to rural credit performed better in terms of agricultural production in relation to municipalities with lower coverage (considered here as control units). These results are valid for both Brazil as a whole and considering its regions, except for the Northeast, where the control group presented better performance in relation to the treated group, but this result is not statistically significant. However, these differences may not reflect the true effect of rural credit, since access to rural credit among rural establishments may not occur randomly. Thus, potential differences in observable and unobservable characteristics between the two groups may explain part or a large part of these differences, and not necessarily the treatment effect. In this sense, it was necessary to use methods capable of attenuating these problems.

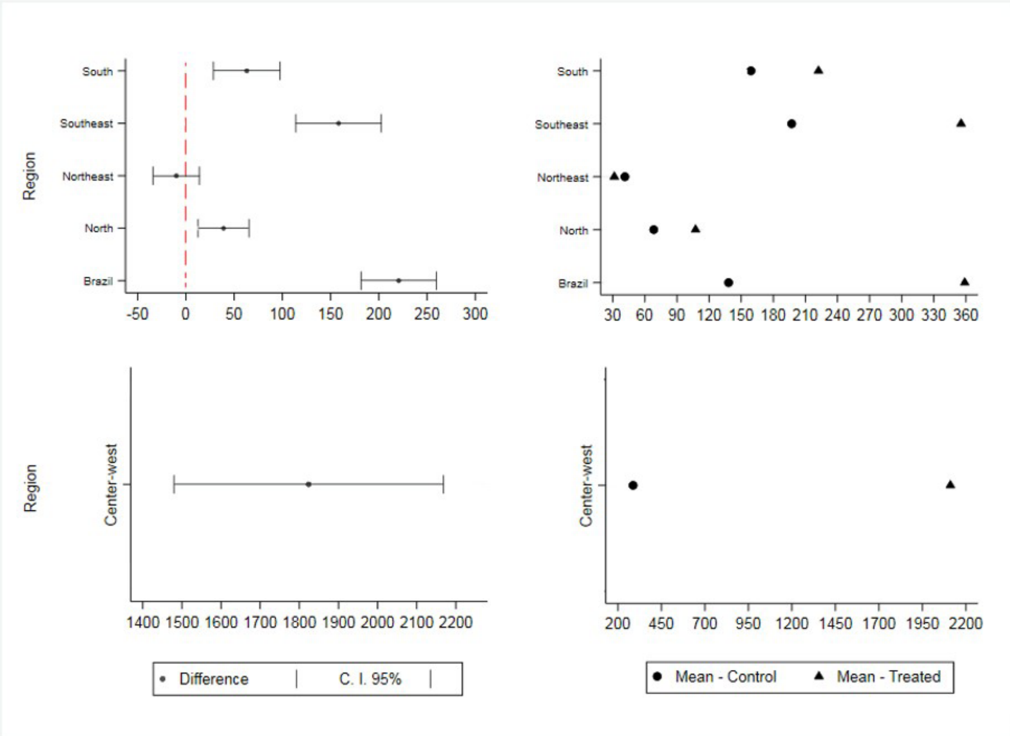

Figure 2 - Differences in the means of the gross value of agricultural production - Brazil and Regions – 2017. **Source:** 2017 Agricultural Census.

Estimates of the rural credit effect were controlled by a set of variables, which were incorporated in the modeling. We selected four vectors of observed characteristics. The first vector is composed of mesoregions dummy variables which were identified based on the municipal codes, and subsequently associated with the codes of the mesoregions provided by the IBGE.[12]

The second vector contains climatic variables obtained from the Terrestrial Hydrology Research Group (THRG), according to the procedures of Sheffield et al. (2006). Towards this end, monthly average temperature (°C) and monthly accumulated precipitation (mm) data were used between 1980 and 2006, and then averages were calculated for the summer (December to February) and winter (June to August) for this period. We chose to transform these data into natural logarithms. The strategy based on climatic seasons, used in previous studies on agriculture (Cunha et al., 2015; Pereda, 2012; Reyna et al., 2020), is justified by the significant change in climate between the two seasons.

The third vector is comprised of individual characteristics of the managers of rural establishments, namely the number of male managers; the number of managers aged 65 or over, and the level of education of the managers (never attended school; know how to read and write; attended adult education classes; attended primary school).

The fourth and final vector is formed by variables that reflect the characteristics of the property and/or practices adopted by the manager, which were the size of the area of the rural establishment (in hectares), the number of producers who owned the land, the number of producers residing on the establishment, the number of people employed at agricultural establishment, the number of producers who do not belong to the family farming category, and the number of producers associated to cooperatives and/or class entities.

[12] These codes were generated from the combination of the two-digit codes of the Units of the Federation (UF) and the two-digit codes of the 2017 mesoregions, provided by the Instituto Brasileiro de Geografia e Estatística (2023a).

Two other variables were also included in our model: the number of establishments using some type of irrigation method, and the number of establishments that received some type of technical assistance. All variables extracted from the 2017 Agricultural Census were divided by the total number of rural establishments in the municipalities, following the strategy of representative rural establishments. The area and employed persons variables were transformed into natural logarithms, given the different scale of the other variables.

The entropy weight was calculated using the third and fourth covariate vectors, as they are variables related to both treatment and agricultural production, based on previous literature on determinants of access to rural credit and agricultural production functions (Dias et al., 2021; Freitas et al., 2020). In addition to these variables, we incorporated state dummy variables in the calculation of entropy weights. This is because regional differences in access to rural credit can also be influenced by issues specific to each state of the country, such as decisions by public managers, credit supply or by structural issues of rural producers, among others.

However, only the dummy variables of mesoregions and climatic variables were included in the regression, acting exclusively as a control of the estimates. The irrigation and technical assistance variables, which also determine agricultural production, were incorporated in the model to test potential transmission mechanisms of effects of rural credit on agricultural production.

Table 2 below provides the means of the covariates according to the treatment condition, in addition to the mean difference tests between the groups. Significant differences violate the covariate balancing hypothesis and therefore, for the third and fourth vector variables, these statistics are expressed before (panel A) and after (panel B) entropy weighting to test this hypothesis. For simplicity, only the statistics of the variables at the Brazil level are presented. The first column contains the mean values of the treated, the second column contains the mean values of the control observations, the third column expresses the difference between the groups, and the fourth column provides the p-value, whose null hypothesis is the non-existence of significant differences. Descriptive statistics by region are available in the Appendix (see Table A1).

Before weighting the data, it was possible to identify significant differences in the covariates between the groups. The treated group is characterized by a higher incidence of male managers, a lower proportion of managers over the age of 65, and a lower proportion of managers with low education in relation to farms that are less intensive in rural credit.

Furthermore, representative farms with intensive access to rural credit had a higher proportion of owners and producers residing on the establishment, a greater proportion of associated producers, and family farmers. The location of the representative farm, in the vast majority of cases, also seems to matter when comparing the proportions of treated and controls in each State.

These differences could confound the treatment effect. Rural credit-intensive units may, for example, present higher levels of production simply because they have more educated producers than less rural credit-intensive units. This bias could be reduced if representative farms were similar in their observed characteristics. In Table 2, all covariates were accurately balanced after entropy balancing, eliminating the differences previously observed for the variables that jointly determine the variable of interest and the treatment, thus fully meeting the balancing hypothesis.

Table 2 - Differences in characteristics before and after entropy balancing - Brazil – 2017

Variables	Before entropy weighting (A)				After entropy weighting (B)			
	T	C	diff	p-value	T	C	diff	p-value
Rondônia	0.004	0.010	-0.006	0.018	0.004	0.004	0.000	0.999
Acre	0.000	0.004	-0.004	0.000	0.000	0.000	0.000	0.010
Amazonas	0.000	0.013	-0.013	0.000	0.000	0.000	0.000	0.000
Roráima	0.000	0.003	-0.003	0.000	0.000	0.000	0.000	0.006
Pará	0.000	0.029	-0.029	0.000	0.000	0.000	0.000	0.000
Amapá	0.000	0.003	-0.003	0.000	0.000	0.000	0.000	0.012
Tocantins	0.008	0.025	-0.017	0.000	0.008	0.008	0.000	0.999
Maranhão	0.000	0.045	-0.045	0.000	0.000	0.000	0.000	0.000
Piauí	0.013	0.045	-0.032	0.000	0.013	0.013	0.000	0.999
Ceará	0.004	0.038	-0.034	0.000	0.004	0.004	0.000	0.999
Rio Grande do Norte	0.024	0.031	-0.007	0.249	0.024	0.024	0.000	0.998
Paraíba	0.036	0.041	-0.005	0.486	0.036	0.036	0.000	0.998
Pernambuco	0.001	0.038	-0.037	0.000	0.001	0.001	0.000	0.994
Alagoas	0.001	0.020	-0.019	0.000	0.001	0.001	0.000	1.000
Sergipe	0.003	0.014	-0.011	0.000	0.003	0.003	0.000	0.999
Bahia	0.005	0.088	-0.082	0.000	0.005	0.005	0.000	1.000
Minas Gerais	0.078	0.166	-0.088	0.000	0.078	0.078	0.000	0.997
Espírito Santo	0.004	0.016	-0.012	0.000	0.004	0.004	0.000	0.999
Rio de Janeiro	0.000	0.018	-0.018	0.000	0.000	0.000	0.000	0.003
São Paulo	0.045	0.125	-0.080	0.000	0.045	0.045	0.000	0.998
Paraná	0.197	0.053	0.144	0.000	0.197	0.196	0.000	0.997
Santa Catarina	0.181	0.033	0.148	0.000	0.181	0.181	0.000	0.998
Rio Grande do Sul	0.337	0.051	0.286	0.000	0.337	0.337	0.000	0.996
Mato Grosso do Sul	0.011	0.015	-0.004	0.296	0.011	0.011	0.000	0.999
Mato Grosso	0.027	0.026	0.001	0.882	0.027	0.027	0.000	0.998
Goiás	0.021	0.048	-0.027	0.000	0.021	0.021	0.000	0.998
Distrito Federal	0.000	0.000	0.000	0.317	0.000	0.000	0.000	0.319
Male’	0.888	0.825	0.063	0.000	0.888	0.888	0.000	0.996
Age ≥ 65 years’	0.231	0.253	-0.022	0.000	0.231	0.231	0.000	0.994
Low education level’	0.438	0.487	-0.049	0.000	0.438	0.438	0.000	0.997
Ln (area)’	3.871	3.807	0.064	0.124	3.871	3.871	0.000	0.997
Establishment owner’	0.867	0.806	0.061	0.000	0.867	0.867	0.000	0.995
Resides on the establishment’	0.729	0.666	0.064	0.000	0.729	0.729	0.000	0.997
Ln (workers)’	1.125	1.109	0.017	0.310	1.125	1.125	0.000	0.999
Non-family farming’	0.236	0.279	-0.043	0.000	0.236	0.236	0.000	0.999
Association’	0.600	0.349	0.251	0.000	0.600	0.600	0.000	0.995

Source: 2017 Agricultural Census. ’Variables used in the entropy weight calculation.

Significant differences in covariates were also found for Brazilian regions. Although few of the differences observed did not reveal statistical significance and/or maintained the same direction, the South and Center-west regions were the most similar in relation to the national context. However, these results also show relative heterogeneity among regions, especially regarding treatment status. For example, while the representative untreated farms in the South and Center-west regions showed a higher proportion of less educated managers, managers over the age of 65, and fewer people employed, the farms in the North and Northeast regions moved in the opposite direction (see Appendix A, Table A1).

4. Results and discussion

The following analysis will essentially determine whether there was an effect, whose treatment is given by the level of how much farms have access to rural credit, of rural credit on Brazilian agricultural production, and whether these effects are heterogeneous among regions. Furthermore, we explored potential transmission mechanisms of this treatment.

However, before estimating the effects of intensity on access to rural credit, we analyzed the factors that would explain the heterogeneity observed in access to rural credit across regions. Thus, we estimate a probit model of the treatment dummy variable based on the characteristics of the producer and the rural establishment, as well as interactions between a categorical variable that defines the Brazilian regions with some of these characteristics, namely: low level of education, non-family farming and association. The estimates of this binary choice model are reported in Table A2, in Appendix A.

The results of this model suggest, as expected, that most characteristics of producers and rural establishments are positively associated with the probability of being intensive in access to rural credit, except for the proportion of rural managers aged over 65, whose relationship estimate was negative. Some of these results, for example in relation to land ownership, are in line with the results found by Dias et al. (2021), who suggest positive effects of land ownership on access to rural credit.

We also identified that some of these characteristics are related to the likelihood of treatment differently across regions. For example, we observed that the low level of education of rural managers in the North and Midwest regions seem to negatively influence the probability of farms having intensive access to rural credit, while in the Southeast and South regions, the low level of education seems to make no difference. On the other hand, the proportion of rural establishments that do not belong to family farming in the Southeast and South regions is negatively associated with the probability of having intensive access to rural credit, while in the North and Northeast regions this characteristic does not seem to matter. The proportion of associated rural establishments is positively correlated with the probability of treatment in all regions, and more strongly in the South region.

The main results of this work are shown in Table 3, where the ATT of rural credit on agricultural production is presented after weighting the data by the entropy weight. Eight different specifications were estimated to verify the sensitivity of the ATT to the inclusion of covariates. In column [1], in addition to the treatment dummy variable, only the dummy variables from the mesoregions were included in the regression. In the second specification [2], temperature and precipitation variables were added. In column [3], producer characteristics were incorporated in the model. In specification [4], the variables of the establishment were added. In the fifth model [5], the irrigation variable was added to verify whether part of the ATT was capturing the irrigation effect. In the same way, in the sixth specification, column [6], the irrigation variable was removed and the technical assistance variable was added. In column [7], all covariates were included in the regression. Finally, in column [8], we disaggregate the technical assistance variable into public and private assistance (full specification), which is the representation of the base specification of this study.

Table 3 is divided into six panels, where each panel provides the ATT for each region. The coefficients of the covariates and intercept, except for the coefficients of the variables irrigation (columns [5] and [7], [8]), technical assistance (columns [6] and [7]) and public and private technical assistance (column [8]), were purposely omitted due to space limitations and to simplify the presentation of the ATT.[13] Each regional panel also contains the r-square statistic for each specification. The complete specification (column [8]) presented an r-squared which varied between 0.68 and 0.89, depending on the region, suggesting a strong explanatory power.

The result in Table 3 shows that rural credit had positive and significant effects on the value of agricultural production in Brazil. In other words, representative farms with intensive access to rural credit were positively associated with greater agricultural production results. This corroborates previous and recent findings on the effect of rural credit in Brazil (Eusébio et al., 2020; Freitas et al., 2020). However, the results found for Brazil are not necessarily the same when analyzed by individual regions. The estimated effects were positive and significant for those regions where rural credit was more accessible, *i.e.*, in regions with a greater proportion of rural establishments that obtained some financing, such as the South and Center-west regions. On the other hand, in regions where access was more restricted, such as in the North, Northeast, and Southeast regions, the effect of rural credit was statistically null. Therefore, our estimates indicate the existence of heterogeneous regional effects of rural credit on agricultural production in Brazil.

This regional heterogeneity of the effects of rural credit may be strictly associated with imbalances between supply and demand for rural credit. Although our treatment measure compared municipalities with greater and lesser rural credit access coverage, it is noteworthy that the intensity of treatment was different between regions. While in the South and Center-west regions the maximum coverage of rural establishments that received rural credit reached 75.4% of establishments, in the North and Northeast regions this percentage did not exceed 50% (see Figure 1). Furthermore, the volume of rural credit from the Brazilian National Program to Strengthen Family Farming (PRONAF - *Programa Nacional de Fortalecimento da Agricultura Familiar*) was proportionally more significant in the North and Northeast regions. However, this line of credit generally provides small amounts per individual.

Our results are supported by findings of previous studies. Assunção et al. (2018), for example, showed that imbalances between supply and demand for credit had important consequences for producers and for the regions in which they live. Thus, the credit available to producers is generally not the most appropriate for their respective circumstances and needs. Furthermore, Freitas et al. (2020) emphasized that a lower financial constraint provided by the amount of credit available to the municipality would allow producers to acquire modern inputs more easily, adopt more productive technologies and services, and thus have greater productive performance.

Although the mesoregion dummy variables controlled part of the regional heterogeneity, some issues should be mentioned. The effect of rural credit may vary depending on the particularities of the type of financial support considered and between regions. The variable used to measure the intensity of access to rural credit in municipalities did not consider the differences in the various types of rural credit, such as the source of funding (public/private), the type of funding (to cover initial costs, capital investments, commercialization, etc.) or differences in the volume of credit obtained by the establishments. Freitas et al. (2020) found positive and significant effects of rural credit, regardless of the source of funding. However, the effect of rural credit from other sources was higher in comparison with credit from PRONAF. In addition, our model did not consider efficiency regarding the source of funding, meaning that producers may be technically more efficient regarding the source of funding in one region than in others.

[13] Complete estimates can be provided upon request.

Table 3 – The effect of rural credit in Brazil and regions – 2017

	Dependent variable:	**After entropy weighting (B)**							
Regions	Gross Production Value	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Brazil	ATT	0.324***	0.328***	0.293***	0.202***	0.194***	0.111**	0.108**	0.083*
		[0.049]	[0.048]	[0.050]	[0.031]	[0.031]	[0.037]	[0.037]	[0.039]
	Irrigation	No	No	No	No	0.475**	No	0.339*	0.395*
						[0.166]		[0.159]	[0.156]
	Technical assistance	No	No	No	No	No	0.838***	0.818***	No
							[0.120]	[0.123]	
	Public Technical assistance	No	No	No	No	No	No	No	0.084
									[0.118]
	Private Technical assistance	No	No	No	No	No	No	No	0.722***
									[0.112]
North	ATT	0.025	-0.03	-0.02	0.079	0.079	0.069	0.07	0.058
		[0.115]	[0.107]	[0.106]	[0.069]	[0.069]	[0.072]	[0.072]	[0.072]
	Irrigation	No	No	No	No	0.682	No	0.64	0.371
						[0.526]		[0.524]	[0.522]
	Technical assistance	No	No	No	No	No	0.507	0.48	No
							[0.484]	[0.482]	
	Public Technical assistance	No	No	No	No	No	No	No	-0.104
									[0.496]
	Private Technical assistance	No	No	No	No	No	No	No	1.627
									[1.010]
Northeast	ATT	-0.02	0.018	0.01	0.006	-0.002	-0.007	-0.012	-0.014
		[0.055]	[0.053]	[0.051]	[0.042]	[0.041]	[0.041]	[0.041]	[0.040]
	Irrigation	No	No	No	No	1.447***	No	1.386***	1.293***
						[0.192]		[0.190]	[0.189]
	Technical assistance	No	No	No	No	No	0.612**	0.468*	No
							[0.201]	[0.189]	
	Public Technical assistance	No	No	No	No	No	No	No	-0.201
									[0.216]
	Private Technical assistance	No	No	No	No	No	No	No	1.664***
									[0.436]
Southeast	ATT	-0.005	0.048	0.028	0.104*	0.105*	0.058	0.066	0.041
		[0.065]	[0.063]	[0.060]	[0.047]	[0.046]	[0.046]	[0.045]	[0.044]
	Irrigation	No	No	No	No	1.091***	No	0.983***	0.960***
						[0.222]		[0.212]	[0.211]
	Technical assistance	No	No	No	No	No	0.690***	0.586***	No
							[0.158]	[0.149]	
	Public Technical assistance	No	No	No	No	No	No	No	0.095
									[0.176]
	Private Technical assistance	No	No	No	No	No	No	No	0.853***
									[0.118]
South	ATT	0.343***	0.296***	0.292***	0.209***	0.211***	0.160***	0.162***	0.145***
		[0.057]	[0.052]	[0.052]	[0.032]	[0.032]	[0.033]	[0.033]	[0.034]
	Irrigation	No	No	No	No	0.292*	No	0.274+	0.322*
						[0.137]		[0.162]	[0.163]
	Technical assistance	No	No	No	No	No	0.391***	0.386***	No
							[0.094]	[0.091]	
	Public Technical assistance	No	No	No	No	No	No	No	-0.059
									[0.094]
	Private Technical assistance	No	No	No	No	No	No	No	0.339***
									[0.068]
Center-west	ATT	0.739***	0.696***	0.596***	0.390***	0.393***	0.256**	0.256**	0.228**
		[0.156]	[0.158]	[0.149]	[0.082]	[0.082]	[0.082]	[0.081]	[0.081]
	Irrigation	No	No	No	No	-0.214	No	-1.119	-0.568
						[1.015]		[0.998]	[0.847]
	Technical assistance	No	No	No	No	No	1.334***	1.474***	No
							[0.352]	[0.352]	
	Public Technical assistance	No	No	No	No	No	No	No	-0.884
									[0.776]
	Private Technical assistance	No	No	No	No	No	No	No	1.513***
									[0.343]
X	*Mesoregion Dummies*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Temperature and precipitation	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Producer characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
	Establishment characteristics	No	No	No	Yes	Yes	Yes	Yes	Yes

Source: 2017 Agricultural Census. Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Robust standard errors in brackets. Entropy-balance weighted regression estimates.

The estimates without data weighting were performed, although they are not reported in the table.[14] Before weighting the covariates in the entropy sense, the estimates were relatively similar to the estimates after weighting the data. On the other hand, the effect estimated before weighting the data for the South region significantly underestimated the effect of rural credit, going from 2.8% before weighting (statistically null) to 14.5% after weighting. The bias on observed characteristics thus underestimated the ATT estimate. This result however shows the importance of balancing the covariates in the entropy sense.

Furthermore, the estimated effect was sensitive to the model specification, when significant. There was a significant reduction in the estimated effect after the inclusion of the characteristics of the rural establishment (column [4]). Another significant reduction was observed after the inclusion of the technical assistance variable, but this does not happen after the inclusion of the irrigation variable. In other words, for both models [5] and [7], the estimated effect did not change after the inclusion of the irrigation variable in relation to the previous models [4] and [6], respectively. On the other hand, the variation observed in the ATT, after the inclusion of the technical assistance variable (specification [6] and [7]), suggests an overestimation of the rural credit effect in light of the absence of this variable. Furthermore, in the complete specification (column [8]), when disaggregating the technical assistance variable between public and private assistance, no significant variations are observed in the ATT parameter.

The behavior of the ATT remained for all regions. For regions where the estimated effect of rural credit was significant, when the technical assistance variable was inserted (models [6] and [7]), the ATT coefficient and its significance changed in relation to models that did not contain this variable. In the case of the Southeast region, in addition to the variation in the ATT, all the statistical significance found in specifications [4] and [5] was lost after the inclusion of the assistance variable.

To check the sensitivity of these estimates presented in Table 3, we estimated the specification [8] considering different variations in the treatment intensity condition (Table 4). Panel A of Table 4, for example, reports the estimated effect (ATT) when we reduce from 1 standard deviation of the variable (Z) to 0.75 standard deviation. Panel B, on the other hand, reports the estimated effect (ATT) when we increase from 1 standard deviation of (Z) to 1.25 standard deviation of the variable (Z). Overall, the estimated effects for different treatment conditions remain similar to the estimates reported in Table 3, both for Brazil and its regions.

Although the irrigation and technical assistance variables were positively and significantly associated with agricultural production, except for the North and Center-west regions where irrigation was not statistically significant, these results may indicate that technical assistance is an important transmission channel of rural credit (Table 3). Thus, part of the effect of rural credit on the value of production may be explained by the indirect effect of rural credit on technical assistance, which in turn is also positively and significantly associated with the value of agricultural production. Furthermore, specification [8] reveals that this mechanism may depend on the type of technical assistance, since only private technical assistance has a significant influence on the gross value of agricultural production.

[14] Estimates without data weighting can be provided upon request.

Table 4 – Sensitivity of the ATT to variations in the treatment condition

Dependent variable: Gross Production Value	After entropy weighting (B) - T = mean(Z)+0.75*SD(Z) - Panel A					
	BR	NO	NE	SE	S	CO
ATT	0.088**	0.054	-0.034	0.031	0.135***	0.343***
	[0.028]	[0.071]	[0.037]	[0.041]	[0.032]	[0.074]
Irrigation	0.665***	0.543	1.315***	0.879***	0.285+	-0.28
	[0.135]	[0.530]	[0.175]	[0.190]	[0.166]	[0.957]
Public Technical assistance	0.072	-0.082	-0.148	0.024	-0.041	-0.152
	[0.088]	[0.483]	[0.209]	[0.170]	[0.082]	[0.695]
Private Technical assistance	0.764***	2.516*	1.791***	0.869***	0.420***	1.069***
	[0.075]	[1.060]	[0.399]	[0.110]	[0.065]	[0.317]
Dependent variable: Gross Production Value	**After entropy weighting (B) - T = mean(Z)+1.25*SD(Z) - Panel B**					
	BR	**NO**	**NE**	**SE**	**S**	**CO**
ATT	0.073*	-0.005	-0.035	0.035	0.129***	0.324**
	[0.035]	[0.072]	[0.040]	[0.046]	[0.037]	[0.100]
Irrigation	0.288+	0.447	1.422***	0.986***	0.244	-0.423
	[0.161]	[0.561]	[0.214]	[0.238]	[0.148]	[1.007]
Public Technical assistance	0.011	-0.304	-0.275	0.315	-0.086	-0.412
	[0.102]	[0.540]	[0.218]	[0.215]	[0.089]	[0.866]
Private Technical assistance	0.673***	1.348	1.517***	0.925***	0.297***	1.141***
	[0.091]	[0.967]	[0.451]	[0.128]	[0.079]	[0.344]

Source: 2017 Agricultural Census. Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

To test this hypothesis, complementary regressions were designed to verify the influence of rural credit on technical assistance (see Table 5, Panel A) in Brazil and its regions.[15] Furthermore, as suggested by previous results, the type of technical assistance (public or private) exerts a distinct influence on agricultural production. Thus, we also checked the influence of rural credit on public (Panel B, Table 5) and private (Panel C, Table 5) technical assistance.

Our estimates show that rural credit was positively and significantly associated with technical assistance. As observed in the previous analysis, the effect of rural credit on the proportion of rural establishments that received technical assistance was also relevant for Brazil and for regions with greater intensity in rural credit access, such as the Southeast, the Center-west, and to a greater extent, the South region of the country.

Table 5 - Effect of rural credit on technical assistance - Brazil and regions – 2017

Dependent variable	Treatment: Acess rural credit	Brazil	North	Northeast	Southeast	South	Center-west
Technical assistance (A)	ATT	0.111***	0.017	0.019*	0.058***	0.140***	0.109***
	S.E.	[0.014]	[0.015]	[0.009]	[0.014]	[0.023]	[0.016]
Public technical assistance (B)	ATT	0.008	0.006	0.015+	0.001	0.001	-0.004
	S.E.	[0.011]	[0.015]	[0.008]	[0.012]	[0.025]	[0.009]
Private technical assistance (C)	ATT	0.159***	0.014+	0.009	0.073***	0.224***	0.125***
	S.E.	[0.016]	[0.008]	[0.006]	[0.012]	[0.026]	[0.022]
X	*Mesoregion Dummies*	Yes	Yes	Yes	Yes	Yes	Yes
	Producer characteristics	Yes	Yes	Yes	Yes	Yes	Yes
	Establishment characteristics	Yes	Yes	Yes	Yes	Yes	Yes
N	-	5436	422	1757	1619	1179	459

Source: 2017 Agricultural Census. Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[15] We chose variables that determine access to technical assistance. Therefore, climate and irrigation variables were not considered in this analysis. The estimated coefficients of the other covariates were purposely omitted to simplify the presentation of the results and can be provided upon request.

Thus, our estimates suggest that technical assistance may be an important transmission mechanism through which rural credit influences agricultural production. Agricultural production, therefore, is positively and directly affected by rural credit, and indirectly through technical assistance.

In other words, producers in municipalities with greater access to rural credit may be seeking more information and knowledge regarding the activity and/or the best choice and use of inputs, machinery, equipment and agricultural implements through technical assistance, which in turn promotes more efficient agricultural production. Freitas et al. (2020), for example, show that municipalities with greater access to rural credit were more efficient in agricultural production and emphasize that technical assistance was associated with a reduction in inefficiency of representative establishments.

Furthermore, Costa & Freitas (2018) suggested that the combination of technical assistance and rural credit was more beneficial to producers, since technical assistance allowed the efficient use of financed resources, indirectly increasing the return of the rural credit. Additionally, our estimates show that the transmission mechanism through which rural credit operates essentially takes place through private technical assistance, and this result is valid both for Brazil and for its regions where access to rural credit is more intensive.

5. Conclusions

Rural credit in Brazil has become the main instrument to support rural producers, including family farmers. This financial support, among other factors, has contributed to Brazilian rural development, allowing the agricultural sector to maintain its relative importance in the Brazilian economy and in the international scenario. However, access to rural credit in Brazil has been persistently more restrictive in certain regions. This work, therefore, sought to explore issues related to the intensity of access to rural credit and the heterogeneous effects of rural credit on agricultural production across Brazilian regions. Furthermore, this study also investigated potential channels through which rural credit influenced agricultural performance.

The regional effects of rural credit on agricultural production, whose treatment was defined by the intensity of access to credit, were calculated by estimating the Average Treatment Effects on the Treated (ATT), using data from the Brazilian Agricultural Census of 2017 and climate variables. To reduce bias, estimates were obtained using standard regressions weighted by entropy balancing, taking into account robust standard errors. Entropy balancing provides significant advantages over propensity score models by allowing an exact balance of observed characteristics between treated and control groups regarding known sample moments.

Thus, the significant differences in observed characteristics between treated and control groups found in this study were removed after weighting the data by entropy balancing, making the observed characteristics independent of the treatment. This allowed us to isolate the effect of greater coverage on access to rural credit in relation to the effect of other observed characteristics that also affect agricultural production and that could be confused with the effect of greater coverage on access to rural credit.

On the one hand, the results suggest that greater access to rural credit increased the gross value of agricultural production in Brazil. Thus, municipalities that are more intensive in accessing rural credit produce more when compared to less credit intensive municipalities. In general, the results of this work support the hypothesis that rural credit contributes to rural development and the maintenance of competitiveness in the agricultural sector. A practical recommendation associated with this result consists of expanding the supply of rural credit throughout the national territory, since rural credit tends to increase agricultural productivity. Therefore, it is sensible to encourage the provision of rural credit in order to promote agricultural production.

On the other hand, the results also show that the effect of rural credit was heterogeneous across Brazilian regions. This result is important for those regions that have greater access to rural credit, namely the South and Center-west regions. However, for Brazilian regions characterized by greater restrictions in access to credit, the results do not seem to be encouraging. Greater availability of credit promotes the implementation of new production technologies, and thus the effect of rural credit is stronger in regions with more mechanization.

This important result indicates to policy makers which regions require more attention in terms of the supply of rural credit. The lack of effect for the North and Northeast regions may be associated with the inefficient use of financed resources or the coverage rate for access to rural credit itself, which is relatively low, even among municipalities with the highest coverage rate in these regions. Thus, these findings converge on the need to improve monitoring of the use of these resources, as well as indicating which regions access to credit should be expanded.

Furthermore, technical assistance proved to be an important mechanism for transmitting the effect of rural credit in Brazil and regions, whose effect was significant. Rural credit thus directly improves agricultural production of the treated establishments, and indirectly through technical assistance, since greater access to technical assistance makes it possible to reduce technical production inefficiencies. Therefore, this result has a practical implication that can favor rural credit policy in Brazil, either by associating or conditioning access to rural credit to a policy of access to technical assistance, with the aim of increasing the efficiency of the use of financed resources, especially public financing.

Thus, our results suggest that greater intensity in the access to rural credit is fundamental for Brazilian rural development. Although the results are not encouraging for all Brazilian regions, it is important to emphasize that imbalances between supply and demand for credit, as well as other factors between regions, such as access to technical assistance, can limit the effects of rural credit in regions with higher levels of restriction. Reducing these imbalances in these regions can allow their producers to acquire adequate and modern inputs for production, more sophisticated machinery and equipment which, combined with technical assistance, may promote more efficient use of production inputs.

Despite the methodological rigor adopted in this work, it is important to highlight that our estimates may still be subject to self-selection problems in unobserved variables. Therefore, future studies need to move towards reducing endogeneity problems. This issue may be addressed by using panel data which would allow the removal of the effects of unobserved variables that are constant over time, which could be investigated in further research.

Other future works could consider variations in the types of financing. Credit destined for capital investments generally mobilizes a considerable volume of resources for the acquisition of agricultural implements that improve land and labor productivity. Therefore, it would be reasonable to expect that the effect of this modality will be different in relation to the others. Also, by using the total value of production, our study disregards the fact that agricultural and livestock products can vary greatly between one microregion and another. Thus, an analysis for specific sectors could provide increasingly detailed results.

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Appendix A

Table A1 – Differences in observable characteristics before and after entropy balancing – Regions – 2017

Regions	Covariadas	Before entropy weighting (A)				After entropy weighting (B)			
		T	C	diff	p-value	T	C	diff	p-value
North	Rondônia	0.493	0.046	0.447	0.000	0.493	0.492	0.001	0.993
	Acre	0.041	0.043	-0.002	0.942	0.041	0.041	0.000	0.998
	Amazonas	0.000	0.172	-0.172	0.000	0.000	0.001	-0.001	0.000
	Roráima	0.000	0.043	-0.043	0.000	0.000	0.000	0.000	0.003
	Pará	0.055	0.384	-0.329	0.000	0.055	0.055	0.000	0.998
	Amapá	0.000	0.043	-0.043	0.000	0.000	0.000	0.000	0.005
	Tocantins	0.411	0.269	0.142	0.024	0.411	0.410	0.001	0.994
	Male'	0.845	0.806	0.039	0.000	0.845	0.845	0.000	0.994
	Age ≥ 65 years'	0.209	0.177	0.031	0.000	0.209	0.208	0.000	0.993
	Low education level'	0.502	0.465	0.038	0.013	0.502	0.502	0.000	0.997
	Ln (area)'	4.949	4.329	0.620	0.000	4.949	4.948	0.001	0.994
	Establishment owner'	0.886	0.819	0.067	0.000	0.886	0.886	0.000	0.990
	Resides on the establishment'	0.781	0.756	0.026	0.038	0.781	0.781	0.000	0.995
	Ln (workers)'	1.175	1.241	-0.066	0.020	1.175	1.175	0.000	0.992
	Non-family farming'	0.248	0.200	0.047	0.005	0.248	0.248	0.000	0.996
	Association'	0.289	0.256	0.033	0.137	0.289	0.289	0.000	0.999
Northeast	Maranhão	0.048	0.133	-0.085	0.000	0.048	0.048	0.000	0.999
	Piauí	0.159	0.120	0.039	0.112	0.159	0.159	0.000	1.000
	Ceará	0.080	0.108	-0.028	0.140	0.080	0.080	0.000	1.000
	Rio Grande do Norte	0.219	0.072	0.147	0.000	0.219	0.219	0.000	1.000
	Paraíba	0.283	0.098	0.185	0.000	0.283	0.283	0.000	1.000
	Pernambuco	0.048	0.112	-0.064	0.000	0.048	0.048	0.000	1.000
	Alagoas	0.028	0.060	-0.032	0.008	0.028	0.028	0.000	1.000
	Sergipe	0.020	0.042	-0.022	0.032	0.020	0.020	0.000	1.000
	Bahia	0.116	0.256	-0.141	0.000	0.116	0.116	0.000	1.000
	Male'	0.813	0.782	0.031	0.000	0.813	0.813	0.000	1.000
	Age ≥ 65 years'	0.253	0.236	0.017	0.000	0.253	0.253	0.000	1.000
	Low education level'	0.626	0.608	0.018	0.011	0.626	0.626	0.000	1.000
	Ln (area)'	3.369	3.127	0.242	0.000	3.369	3.369	0.000	1.000
	Establishment owner'	0.770	0.757	0.013	0.210	0.770	0.770	0.000	1.000
	Resides on the establishment'	0.757	0.683	0.074	0.000	0.757	0.757	0.000	0.999
	Ln (workers)'	1.000	1.032	-0.032	0.069	1.000	1.000	0.000	1.000
	Non-family farming'	0.210	0.220	-0.010	0.111	0.210	0.210	0.000	1.000
	Association'	0.444	0.365	0.078	0.000	0.444	0.444	0.000	1.000
Southeast	Minas Gerais	0.549	0.511	0.038	0.264	0.549	0.548	0.001	0.983
	Espírito Santo	0.035	0.051	-0.015	0.240	0.035	0.035	0.000	0.996
	Rio de Janeiro	0.000	0.061	-0.061	0.000	0.000	0.002	-0.002	0.000
	São Paulo	0.416	0.378	0.038	0.257	0.416	0.415	0.001	0.987
	Male'	0.864	0.857	0.007	0.123	0.864	0.864	0.000	0.999
	Age ≥ 65 years'	0.280	0.287	-0.008	0.095	0.280	0.280	0.000	0.998
	Low education level'	0.388	0.403	-0.015	0.185	0.388	0.388	0.000	0.995
	Ln (area)'	4.385	3.991	0.394	0.000	4.385	4.384	0.001	0.991
	Establishment owner'	0.830	0.823	0.007	0.337	0.830	0.830	0.000	0.990
	Resides on the establishment'	0.546	0.587	-0.041	0.001	0.546	0.546	0.000	1.000
	Ln (workers)'	1.419	1.174	0.245	0.000	1.419	1.418	0.001	0.991
	Non-family farming'	0.357	0.337	0.020	0.028	0.357	0.357	0.000	0.995
	Association'	0.518	0.332	0.186	0.000	0.518	0.518	0.000	0.986
South	Paraná	0.228	0.358	-0.131	0.000	0.228	0.228	0.000	0.999
	Santa Catarina	0.178	0.261	-0.083	0.007	0.178	0.178	0.000	0.999
	Rio Grande do Sul	0.594	0.381	0.213	0.000	0.594	0.594	0.000	1.000
	Male'	0.917	0.867	0.050	0.000	0.917	0.917	0.000	0.995
	Age ≥ 65 years'	0.223	0.243	-0.020	0.000	0.223	0.223	0.000	1.000
	Low education level'	0.411	0.447	-0.036	0.001	0.411	0.411	0.000	0.999
	Ln (area)'	3.573	3.625	-0.052	0.272	3.573	3.573	0.000	0.999
	Establishment owner'	0.913	0.861	0.052	0.000	0.913	0.913	0.000	0.995
	Resides on the establishment'	0.763	0.756	0.007	0.536	0.763	0.763	0.000	0.999
	Ln (workers)'	1.036	1.000	0.036	0.013	1.036	1.036	0.000	1.000
	Non-family farming'	0.173	0.256	-0.083	0.000	0.173	0.173	0.000	0.998
	Association'	0.728	0.474	0.255	0.000	0.728	0.728	0.000	0.996
Center-west	Mato Grosso do Sul	0.250	0.156	0.094	0.094	0.250	0.250	0.000	0.999
	Mato Grosso	0.397	0.289	0.108	0.092	0.397	0.397	0.000	0.999
	Goiás	0.353	0.552	-0.199	0.002	0.353	0.353	0.000	0.999
	Distrito Federal	0.000	0.003	-0.003	0.318	0.000	0.000	0.000	0.325
	Male'	0.851	0.838	0.013	0.018	0.851	0.851	0.000	0.999
	Age ≥ 65 years'	0.238	0.259	-0.020	0.018	0.238	0.238	0.000	0.999
	Low education level'	0.317	0.383	-0.066	0.000	0.317	0.317	0.000	0.998
	Ln (area)'	6.207	5.292	0.916	0.000	6.207	6.207	0.001	0.996
	Establishment owner'	0.808	0.833	-0.026	0.150	0.808	0.808	0.000	1.000
	Resides on the establishment'	0.573	0.658	-0.084	0.000	0.573	0.574	0.000	0.998
	Ln (workers)'	1.639	1.165	0.474	0.000	1.639	1.638	0.000	0.997
	Non-family farming'	0.496	0.368	0.128	0.000	0.496	0.496	0.000	0.998
	Association'	0.371	0.242	0.129	0.000	0.371	0.371	0.000	0.996

Source: 2017 Agricultural Census. Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A2 - Probit model

Dependent variable: T	Coefficient	S.E.
Intercept	-7.917***	0.634
Male'	5.121***	0.572
Age ≥ 65 years'	-2.473***	0.512
Ln (area)'	0.255***	0.041
Establishment owner'	0.506*	0.237
Resides on the establishment'	0.423+	0.230
Ln (workers)'	0.249**	0.082
Region#Low education level		
North	-2.007*	0.891
Northeast	0.970***	0.329
Southeast	-0.631+	0.345
South	0.417	0.276
Center-west	-2.061***	0.623
Region#Non-family farming		
North	0.411	1.033
Northeast	-0.764	0.555
Southeast	-1.232**	0.452
South	-1.476***	0.393
Center-west	0.918+	0.491
Region#Association		
North	1.959*	0.879
Northeast	0.803**	0.287
Southeast	2.804***	0.300
South	3.957***	0.225
Center-west	2.461***	0.574

Source: 2017 Agricultural Census. Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in brackets.