Impacts of Rural Credit on Family Farming Income in Brazil: Insights from a Novel Survey of Rural Establishments*

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Abstract

Family farming is an important source of income in rural Brazilian areas, playing a crucial role in food supply. Brazil's most important rural credit program is the National Program to Strengthen Family Farming (PRONAF), established in 1995. In this paper, we investigate the role of rural credit in improving income. One of the novelties of our work is to use a new data set from a longitudinal survey that took place in the state of Bahia between 2017 and 2022. By applying a Propensity Score Matching approach, our analysis reveals statistically significant evidence that PRONAF positively affects rural family income.

Keywords: PRONAF; Family Farming; Rural development, Matching.

Área: POLÍTICAS PÚBLICAS: GÊNERO, RAÇA, INCLUSÃO

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1 Introduction

Family farming is a crucial financial resource for many families in Brazil and worldwide, and it also plays a key role in the food supply. The 2023 Statistical Yearbook of Family Farming, released by the National Confederation of Rural Workers and Family Farmers (Contag), in partnership with the Inter-Union Department of Statistics and Socioeconomic Studies (Dieese), argues that Brazilian family farming is the major contributor to the country's domestic food market supply, ranking as the eighth largest food producer globally when considering the output by family farmers (CONTAG, 2023).

According to the Brazilian Institute of Geography and Statistics (IBGE, in Portuguese), 77% of rural establishments in Brazil (3.9 million properties covering 23% of the Brazilian area) are classified as family farming establishments, with a production value of about 107 billion BRL (IBGE, 2017). According to CONTAG (2023), in 90% of Brazilian municipalities with up to 20 thousand inhabitants (accounting for 68% of all Brazilian municipalities), family farming represents 40% of the income of the economically active population.

In addition to its overall economic importance, family farming is essential for low-income families who rely on it for subsistence and income generation. In that sense, the promotion and implementation of public policies to improve the social and economic aspects of rural families engaged in family farming are of utmost importance.

Rural credit programs are particularly relevant for financing families engaged in agriculture, serving as a vital tool to reduce inequality within the rural population (Lu et al., 2023). In June 2023, the Brazilian federal government announced the 2023/2024 Family Farming Plan, allocating R$71.6 billion to the National Program for Strengthening Family Agriculture (PRONAF), marking the highest amount in its historical series (CONTAG, 2023). Established in 1995, PRONAF is one of Brazil's most important rural credit programs, aimed at expanding the productive and financial capacities of rural family groups below the poverty line and fostering financial and social equilibrium among families in the family farming sector (Schneider, 2003).

The objective of this article is to investigate the role of rural credit in improving the income of PRONAF beneficiaries. Previous literature has relied chiefly on data from the IBGE's Agricultural Census. In contrast, we utilize a novel dataset obtained from a longitudinal survey conducted in Bahia between 2017 and 2022 as part of the *Bahia Produtiva* project tailored to family farmers. This dataset comprises over sixteen thousand interviews, providing detailed information about beneficiaries and the technology employed in production.

The Bahia Sustainable Rural Development Project (2015-2023), also known as "Bahia

Produtiva", results from a cooperation between the World Bank and the Bahia Government through a state-level developing company (CAR-Companhia de Desenvolvimento e Ação Regional). This project is embedded within a context of public policies geared toward rural development in Bahia, reaching 342 municipalities and 170 thousand beneficiaries. Primarily targeted at family farmers, the project aimed to enhance market integration, net revenues, and food security among beneficiaries organized into cooperatives or associations, alongside improving access to water supply and household sanitation services.

This project boasts a comprehensive database, with a standout feature being the data collection effort for monitoring and tracking the over 34 thousand project beneficiaries who received rural technical assistance, utilizing an administrative dataset known as CAD (Cadastro Cidadão in Portuguese). The monitoring efforts of "Bahia Produtiva" include a survey conducted between 2017 and 2023, comprising many questions, among which is information regarding rural credit, income, technology, and several socioeconomic characteristics of families engaged in family farming. This dataset is a crucial source of information in our research, allowing us to conduct longitudinal analysis and study the impact of PRONAF on rural income among family farmers in Bahia.

Utilizing this novel dataset, we bring fresh insights into PRONAF's role, underscoring the importance of rural credit within the family farming context. The first step of our analysis is an ordinary Least Squares regression, with household per capita income as the dependent variable and PRONAF as the primary explanatory variable. To mitigate potential biases, we further employed a Propensity Score Matching procedure. In both cases, we observe a positive correlation between PRONAF and rural income among family farmers.

Next, we provide a non-exhaustive review of pertinent literature on the subject.

2 Literature Review

According to the most recent agricultural census (IBGE, 2017), family farming comprises the largest number of productive units in Brazil, accounting for a significant portion of jobs related to agricultural activities. Besides that, family farming has played a prominent role in ensuring national food security.

Despite the advancements of public policies aimed at the agricultural sector, significant socio-economic disparities persist in Brazilian rural. The existence of target policies that consider this usually prioritizes improving agricultural productivity, fostering social inclusion by promoting income generation, and improving food security. The population dependent on agriculture is diverse and, when the government intends to target low-income groups, family farmers have become crucial when directing economic policies.

There is evidence of substantial economic and productive inequality in Brazil's rural areas, with a considerable portion of family farmers living below the poverty line (Pires, 2013; Mattei, 2014; Bianchini, 2015). These findings underscore the need for governments to focus their approach towards this group. As important as the design of target programs, it is very important to implement a culture of evaluating these programs to understand better their outcomes (Gasson, 1988).

Family farming has emerged as a priority for governments due to the significance of their economic activities to the economy and as a source of social inclusion for families in rural areas. Among the various policies tailored to this group, rural credit stands out. Specific lines of credit aimed at family farming enable the provision of financial services to rural families, fostering the exploitation of productive opportunities. Financing the agricultural sector through subsidized rural credit is a popular sort of social policy in many developing countries to grant low-income producers access to credit markets in a context where greater institutional changes, such as land reform, are challenging to implement (Braverman & Guasch, 1989; Yadav & Sharma, 2015; Khan et al., 2024).

In this regard, conducting analyses and evaluations of existing public policy impact is highly relevant, given that policymakers are keen on understanding whether and how their objectives are being achieved, thereby justifying public investments. In this section, we conducted a non-exhaustive review of the literature regarding family farming and rural credit, with particular emphasis on investigations regarding PRONAF.

2.1 Rural credit and development

Among the policies aimed at rural development, support for agriculture has always been relevant in generating employment in rural areas and promoting increased agricultural production, thus playing a crucial role in alleviating poverty and reducing the risks associated with agricultural work (Ghinoi et al., 2018). Many works have studied the connection between rural credit policies and development, addressing the effects of these policies on various indicators such as income, productivity, and the well-being of beneficiaries, as well as on economic growth. This literature is particularly prolific in developing countries[1].

Chen et al. (2022) investigated the effects of formal rural credit in China using two national survey databases and employing the Tobit model combined with a propensity score matching approach. They found evidence of an improvement in the operational performance of Chinese family agriculture associated with rural credit. Chen et al. (2021) also conducted a study related to rural credit in China, focusing directly on poverty and utilizing a sample

[1] [See, for example, Khandker & Faruqee (2003), Mazumder & Lu (2015), Chen et al. (2021) and Lu et al. (2023).

of microdata from 592 families in six nationally designated poverty-stricken counties in the provinces of Yunnan, Guizhou, and Shaanxi during the period 2012, 2015, and 2018. Their results demonstrated that implementing formal credit is a good strategy for reducing poverty in underdeveloped areas.

Zhu et al. (2021), using a panel dataset of 30 provinces in mainland China from 1997 to 2015, examine the effect of rural credit on poverty reduction. Their approach differs from the previous ones regarding the unit of analysis since these authors did not use microdata but province-level data of the proportion of rural credit concerning agricultural output value. Employing a spatial panel model, they found evidence that rural financial development reduces poverty with a positive spatial spillover effect on poverty alleviation.

Luan & Bauer (2016) examining the impacts of credit on different groups in Vietnam. Using survey data from 1338 households in 2012 and combining a bootstrapping approach with a propensity score matching procedure, they found evidence that credit access affects groups heterogeneously, with evidence of a positive impact on non-farm income but no effect on farm income. Overall, their results suggest that, in Vietnam, households with favorable economic conditions tend to benefit from accessing rural credit.

Regarding rural credit in Brazil, recent works include Nascimento et al. (2023), Moreira-Dantas et al. (2023), Carrer et al. (2020), Maia et al. (2020), Neves et al. (2020) and Ely et al. (2019)

Nascimento et al. (2023) using a time series approach for aggregated data, examined the relationship between rural credit and the gross value added of agricultural production, both in the short and long term, using a Vector Error Correction Model. They find evidence of a positive long-term relationship between agricultural production and rural credit, showing that a 1%

Moreira-Dantas et al. (2023) examined the factors influencing the credit received at the regional level in the 103 micro-regions of the Brazilian Legal Amazon, using a spatial Durbin error model. Their results suggest a relationship between the locality where PRONAF microcredit is provided and the allocated values, meaning micro-regions with commercial banks present and higher production receive more significant microcredit amounts, with favoritism towards wealthier farmers in these locations. The work suggests expanding policy actions aimed at poorer farmers in this area.

Carrer et al. (2020) focused their research on understanding the role of PRONAF in increasing the adoption of more sustainable ways of production, in particular Integrated Crop-Livestock Systems (ICLS) and Integrated Crop-Livestock-Forestry Systems (ICLFS). Using a survey with 175 farmers, they find evidence that rural credit has positive and relevant impacts on the adoption of sustainable ways of production.

Maia et al. (2020) assess the role of rural credit on development with a similar approach to the one we use. Employing a propensity score matching procedure to the 2006 Brazilian Agricultural Census, with information on about 4.1 million family farmers in Brazil, they find evidence of a positive impact of PRONAF on family farming production. Their results also suggest a stronger impact among families living in the poorest regions.

Neves et al. (2020) focused their research on the impact of PRONAF on income inequality. Using data from the most important National Household Sample Survey (PNAD - Pesquisa Nacional por Amostra de Domícilios in Portuguese) they estimate the influence of credit on income inequality in Brazilian rural areas. Their results suggest that PRONAF is not associated with an increase in inequality.

Ely et al. (2019) also using data from the National Household Sample Survey (PNAD) investigated the PRONAF's impact on individuals' time allocation. Applying a propensity score matching approach, they find evidence of a positive relationship between PRONAF and beneficiaries' productivity improvements due to increased working hours. However, their results also suggest that rural credit also stimulates female partners and female adolescents to engage in unpaid work, a negative side effect of the policy.

Our contribution builds upon previous literature as we aim to investigate the impact of rural credit on rural development. Specifically, we focus on assessing the impact of PRONAF on rural income among family farms in the state of Bahia. Like several previous studies, we employ a quasi-experimental method, utilizing a propensity score matching procedure. In the next section, we present details about our empirical strategy and the dataset.

3 Data, method, and research design

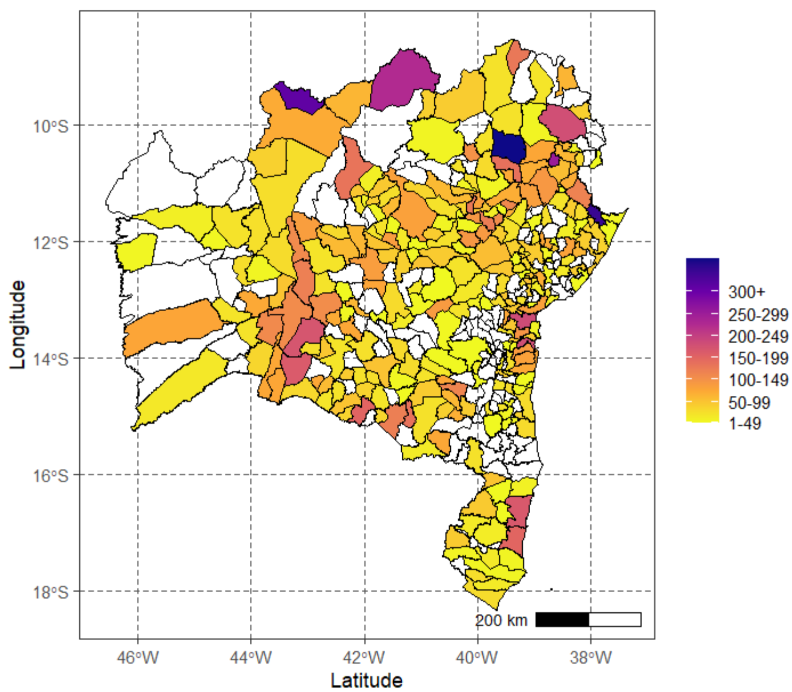
3.1 Data

Our dataset is an unbalanced longitudinal dataset from a survey realized between[2] 2017 and 2022 across 287 of the 417 municipalities in Bahia. This comprehensive survey encompasses 16,690 interviews, capturing data from numerous families engaged in family farming, some of whom have been interviewed across multiple years. Bahia is the fourth most populous state in Brazil according to the 2022 census, with approximately 14.1 million residents. It has a Human Development Index (HDI) of 0.691. Covering an area of 564,760 square kilometers, Bahia is nearly as large as France.

Table 1 summarizes the annual income statistics from the survey, expressed in Brazilian

[2] In instances where a family was interviewed multiple times within the same year, we retained only the most recent data, as families are typically interviewed once annually.

Figure 1: Number of interviews by Municipalities - families interviewed at least once between 2017 and 2022.



Source: CAR/BAHIA PRODUTIVA — Author's elaboration

Reais (BRL). Data from the National Household Sample Survey (PNAD-IBGE) indicates that in December 2023, the state of Bahia reported a monthly average household per capita income of R$1,139.00, while the national figure for Brazil was R$1,893.00. Table 1 reveals that, within our dataset, the average monthly household per capita income was approximately R$507.00 in 2022. When converted to current US dollars for December 2023, these figures correspond to a state-level monthly per capita income of around USD 230.00, a national-level income of approximately USD 382.00, and a monthly per capita income of about USD 102 within the survey.

Table 1: Annual Income Summary

	Household Income		**Per capita Income**		
	Mean	**SD**	**Mean**	**SD**	**n. obs.**
2017	14,883.68	18,547.54	4,389.31	7,107.39	941
2018	18,041.71	25,293.39	5,275.92	8,150.13	3311
2019	17,504.29	25,314.92	5,174.82	8,018.36	3919
2020	20,728.39	29,927.55	6,177.39	10,368.76	4107
2021	18,806.85	17,327.17	5,608.24	5,900.73	2022
2022	20,358.95	27,792.82	6,088.11	8,896.64	2390

Values in Brazilian Reais as of December 2023, adjusted by CPI (IPCA-IBGE) Source: CAR/BAHIA PRODUTIVA | Author's elaboration

This picture is consistent with the stylized facts regarding the level of development in Bahia, especially in rural areas. A poor state with a significant part of its population receiving income from cash transfer programs and a high level of informality. It is important to notice that the total income we reported in Table 1 is composed of the income from the family's rural activities, other sources of income, and income from cash transfer programs. In this paper, we are particularly interested in the effects of PRONAF on income from the family's rural activities, from now on just rural income. Table 2 summarizes information about rural income in our data. Household and per capita household income from rural activities is about half the total income in Table 1. This difference is partly due to the importance of cash transfer programs in Bahia's rural areas. While the average annual average per capita rural income was R$ 3,108.79 in 2022 the average per capita income from cash transfers was R$ 2,085.10 in Reais of December of 2023, about 35% of the total per capita income. There is also a big heterogeneity in terms of rural income within our data, while the minimum rural income reported in the data in 2022 was zero, probably due to subsistence rural activities, the maximum value for the annual per capita rural income was R$ 163,271.81, about USD 33,000.00 in current dollars as of December 2023.

Table 2: Annual Rural Income Summary

	Household Income		**Per capita Income**		
	Mean	**SD**	**Mean**	**SD**	**n. obs.**
2017	5,695.56	14,642.66	1,687.76	5,375.66	941
2018	8,223.76	21,262.03	2,440.29	6,894.21	3311
2019	7,352.18	21,263.82	2,159.84	6,380.25	3919
2020	9,689.06	25,828.41	2,894.72	8,668.99	4107
2021	8,011.23	13,445.65	2,411.67	4,457.54	2022
2022	10,431.72	25,395.15	3,108.79	7,900.12	2390

Values in BRL as of December 2023, adjusted by CPI (IPCA-IBGE)
Source: CAR/BAHIA PRODUTIVA | Author's elaboration

Our main interest is analyzing if receiving PRONAF credit is associated with the income level, i.e., if, controlling for a set of characteristics, family farms receiving PRONAF have a higher income than those that do not receive this sort of rural credit. Table 3 describes the variables we use in our econometric analysis, where the Per capita income originating from family farming is the dependent variable (Rural_income), PRONAF is our main explanatory variable, and the rest of the variables a group of characteristics of the household head and the farm.

Table 3: Variables

Name	Type	Description	Additional information
Rural_income	**Numeric**	Per capita income from the family farm activity	Brazilian Reais as of December 2023
PRONAF	Binary	Received any sort of PRONAF credit in the current year	0 (no) / 1 (yes)
Educ_pre_school	Binary	Household head with pre-school education	0 (no) / 1 (yes)
Educ_elementary	Binary	Household head with elementary education	0 (no) / 1 (yes)
Educ_secondary	Binary	Household head with secondary education	0 (no) / 1 (yes)
Educ_illiteracy	Binary	Illiterate household head	0 (no) / 1 (yes)
Educ_technical	Binary	Household head with technical education	0 (no) / 1 (yes)
Educ_higher	Binary	Household head with high education	0 (no) / 1 (yes)
Age	Numeric	Age of the household head	-
Electricity	Binary	Access to electricity	0 (no) / 1 (yes)
Irrigation	Binary	Use of irrigation	0 (no) / 1 (yes)
Insecticides	Binary	Use of Insecticides	0 (no) / 1 (yes)
Fertilization	Binary	Use of fertilization	0 (no) / 1 (yes)
Burning	Binary	Presence of burning practice	0 (no) / 1 (yes)
Insecticides	Binary	Use of insecticides	0 (no) / 1 (yes)
Animal_Traction	Binary	Use of animal traction work	0 (no) / 1 (yes)
Automobile	Binary	The household owns an automobile	0 (no) / 1 (yes)
Aquatic_Vehicles	Binary	Use of aquatic vehicles	0 (no) / 1 (yes)
Large_Vehicles	Binary	Use of large vehicles work	0 (no) / 1 (yes)
Motorcycle	Binary	The household owns a motorcycle	0 (no) / 1 (yes)
Livestock	Binary	Family involved in livestock farming	0 (no) / 1 (yes)
Household_head_race	Binary	Household head self-identified as white	0 (no) / 1 (yes)
Household_head_gender	Binary	Household head female	0 (no) / 1 (yes)

Source: Author's elaboration

3.2 Method and research design

We face a typical public policy analysis problem where we desire to evaluate the effect of an intervention on a variable of interest Y, in the sense that a group of people is subject to this intervention/treatment and another group is not. In a regression setup, we can express this as follows:

$$Y_{it} = \beta_0 + \delta_{it} D_{it} + \beta_k X_{ij} + u_{it} \tag{1}$$

where Y_{it} represents the variable of interest, such as rural income in our context; β_0 the regression intercept; D_{it} a treatment dummy variable; δ the parameter associated with the dummy variable; X_{ij} the vector of control variables; β_k the parameters associated with the control variables; and u_{it} the error term, where i and t denote the individuals and the time index, respectively.

Our treatment variable is receiving credit from PRONAF in a given time, with the rural per capita income being the variable we suspect could be positively affected by the supply of credit. If the error term is not correlated with the explanatory variables, we can estimate equation (1) by Ordinary Least Square, with no consideration for the Panel structure of the data. However, this is a strong assumption since families receiving PRONAF are not randomly selected.

Let's think about our question again, using the idea of potential outcome. In our research, we are interested in investigating the effect of PRONAF on rural income. Therefore, we should ask: What is the potential outcome for a family that received PRONAF in the absence of the program? What is the potential outcome for a family that did not benefit from the program, assuming they have received PRONAF? We can express this as in the following equation:

$$E(Y_i|Z=1) - E(Y_i|Z=0) = \delta_i \tag{2}$$

$Z = 1$ indicates that the household is receiving PRONAF credit; when $Z = 0$, the household did not receive PRONAF credit. The variable Y represents the rural income and i is the household unit. This is not observable, because we do not observe the same unit i (at the same time) in these two different scenarios, we should find a counterfactual scenario for each unit.

When working with experimental data, one usual approach involves randomly dividing the units into treated and non-treated (control units) before the experiment and observing the outcomes. However, we cannot conduct such randomized experiments in most social science situations. Instead, we aim to replicate the experiment's rationale using statistical methods suitable for non-experimental data, particularly when household selection for treatment/policy is not random.

A popular way to deal with this selection bias problem is by approaching the econometric modeling with a panel difference in difference approach [see Cunningham (2021) for details], however, a challenge in our research design is addressing the unbalanced longitudinal data structure, where surveyed households do not consistently appear across all years. Additionally, a significant number of the households/farms 'treated' with PRONAF have received credit every year they are included in the survey. This, altogether, makes the usual panel data fixed effects differences in differences setup unsuitable in our research. Propensity score matching (PSM) methods, as proposed by Rosenbaum & Rubin (1983), are a suitable option in this case.

The propensity score is defined as the probability of receiving treatment (receiving Pronaf credit), conditional on the covariates described in 3. Considering the matched group, this method enables us to match units and proceed with a regression such as in equation 1. For our analysis, we will follow the approach proposed by Ho et al. (2011) using the R stats package *matchit*, which estimates the propensity score with a logit regression by default and builds match groups by different methods. In this paper, we use the full matching method [see Hansen (2004)] that generates better statistics for the adjusted sample when compared to other matching methods for our data set.

Matching units with pooled data could be tricky since units can appear in more than one year in the dataset, and we want to avoid the possibility of units matching with themselves. To overcome this, we performed a propensity score matching within each year of the survey and then pooled the resulting data in a new data set before performing with OLS regressions considering matching groups.

Additionally, as a robustness check, we select households from the last year that appear in the dataset in a way each family appears in this new sample only once. By doing that we also could create the variable PRONAF_lag, which indicates the status of receiving PRONAF during the previous time the household appeared in the data, often corresponding to two years prior. With this data set, we performed the propensity score matching and the OLS regression for matching units and reported it in the Appendix.

4 Results and discussion

First, we will analyze OLS results without considering matching units. Table 4 describes the outcomes for these regressions. We included all control covariates from Table 3, and dummies for years, with 2017 as a year base. We also included an interaction between the dummy for 2022 (the last survey year in the survey). We highlight that coefficients associated with gender (woman household head) and illiteracy are both negative and significant at 5% in all the models. Coefficients associated with race (white household head) are positive and significant at 5% in all the models. The age of the household head has the usual coefficient signal, positive for Age and negative for Age^2, statistically significant in both cases. The coefficients for PRONAF, our main interest variable, are positive and significant at 5% in all specifications, showing a positive association between receiving rural credit from PRONAF and the per capita income generated by rural activities.

Dealing with a possible selection bias issue, our next step involves estimating propensity scores. As mentioned earlier, we conducted household matching within each survey year. Before presenting the results, it is worthwhile to compare the per capita rural income between households receiving Pronaf credit and those not benefiting from the program. This information is in Table 5.

Now, we estimate a propensity score by estimating the probability of receiving Pronaf on the covariates described in Table 3. This is done by a logistic regression like in equation (3), where $P(Z = 1|X_1, X_2, ...X_k)$ is the probability of a household receiving the rural credit from Pronaf and X is the vector of covariates [see Cameron & Trivedi (2005) for details].

$$P(Z = 1|X_1, X_2, ...X_k) = (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k) \tag{3}$$

We plot in Figure 2 a chart with the distribution of estimated scores among treated and non-treated units throughout the years and investigate the so-called common support region, visualizing the propensity score range for which we have individuals in the control group and the treatment group. These distributions indicate we have enough units to pair.

One way of estimating the treatment effect is to pick observations from the common support region, dividing up these individuals by propensity score quantiles [see Rosenbaum & Rubin (1983)]. We do that differently, however, by applying the Ho et al. (2011) algorithm from *matchit* package using the full matching method (Hansen, 2004).

Figure 3 presents a graphical representation of covariate balance before and after matching. In this plot, we observe the standardized mean difference between covariates for the treated and untreated groups, both before and after the matching process. If the matching process succeeds we expect to see the covariates' mean difference approaching (statistically) to zero.

Now we have a new sample generated by propensity score matching, we re-estimated our regression model and reported it in Table 6.

After pairing groups by propensity score matching, we see that the basic picture portrait before about the association between receiving PRONAF and per capita rural income remains consistent. If all the selection bias sources were due to observable covariates it could be implied in a causal relationship. As in the previous models, coefficients associated with gender (woman household head) and illiteracy are both negative and significant at 5% in all the specifications, and coefficients associated with race (white household head) are positive

Table 4: OLS Regression with no-matching groups

	Dependent variable:		
	log(Rural_income)		
	(1)	(2)	(3)
PRONAF	0.458***	0.463***	0.441***
	(0.033)	(0.033)	(0.033)
year_2018		0.369***	0.370***
		(0.073)	(0.073)
year_2019		0.101	0.101
		(0.074)	(0.074)
year_2020		0.373***	0.372***
		(0.073)	(0.073)
year_2021		0.518***	0.517***
		(0.079)	(0.079)
year_2022		0.404***	0.322***
		(0.078)	(0.078)
Pronaf:year_2022			0.147
Observations	13,837	13,837	13,837
R^2	0.105	0.111	0.111
Adjusted R^2	0.104	0.109	0.110
Residual Std. Error	1.852 (df = 13815)	1.846 (df = 13810)	1.846 (df = 13809)
F Statistic	77.308***	66.373***	64.024***

Notes: Robust standard errors. Symbols *,**, and *** indicate rejection of the null hypothesis at the significance level of 10%, 5%, and 1%, respectively. All covariates from Table 3 are included, see Table A1 in the Appendix for the rest of the coefficients.

Table 5: Per capita rural income vs. Pronaf

Year	Pronaf	Households	Mean	Std. Error
2017	0	338	1736.99	389.24
2017	1	402	2397.88	230.40
2018	0	1042	2022.11	152.10
2018	1	1688	3538.36	210.81
2019	0	1432	2094.06	159.92
2019	1	1815	3011.41	176.56
2020	0	1750	2623.29	175.70
2020	1	1726	4228.21	262.78
2021	0	829	2585.99	164.61
2021	1	889	3073.82	156.66
2022	0	925	2496.67	216.23
2022	1	1166	4391.59	276.68

Values in BRL as of December 2023
Source: Author's elaboration

Figure 2: Common support region

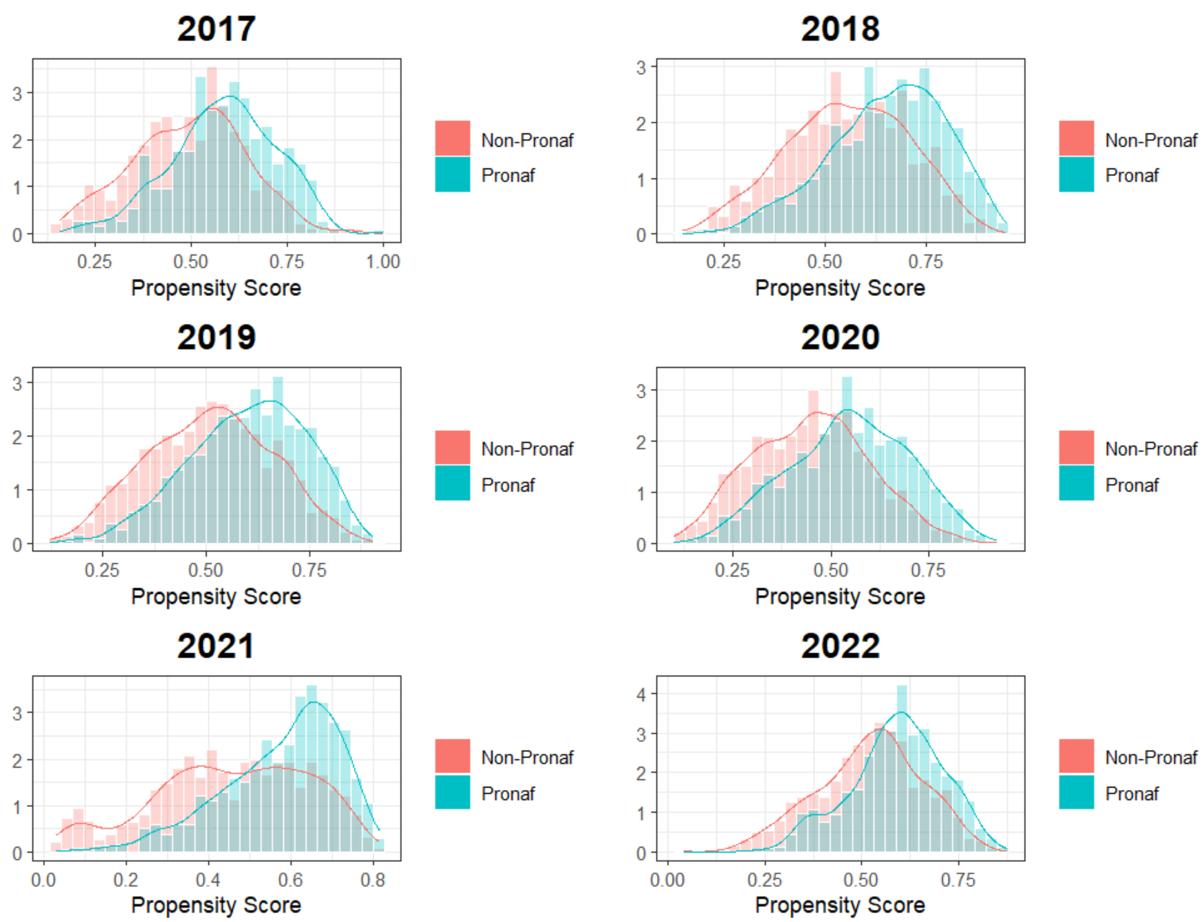


Figure 3: Adjusted versus unadjusted sample

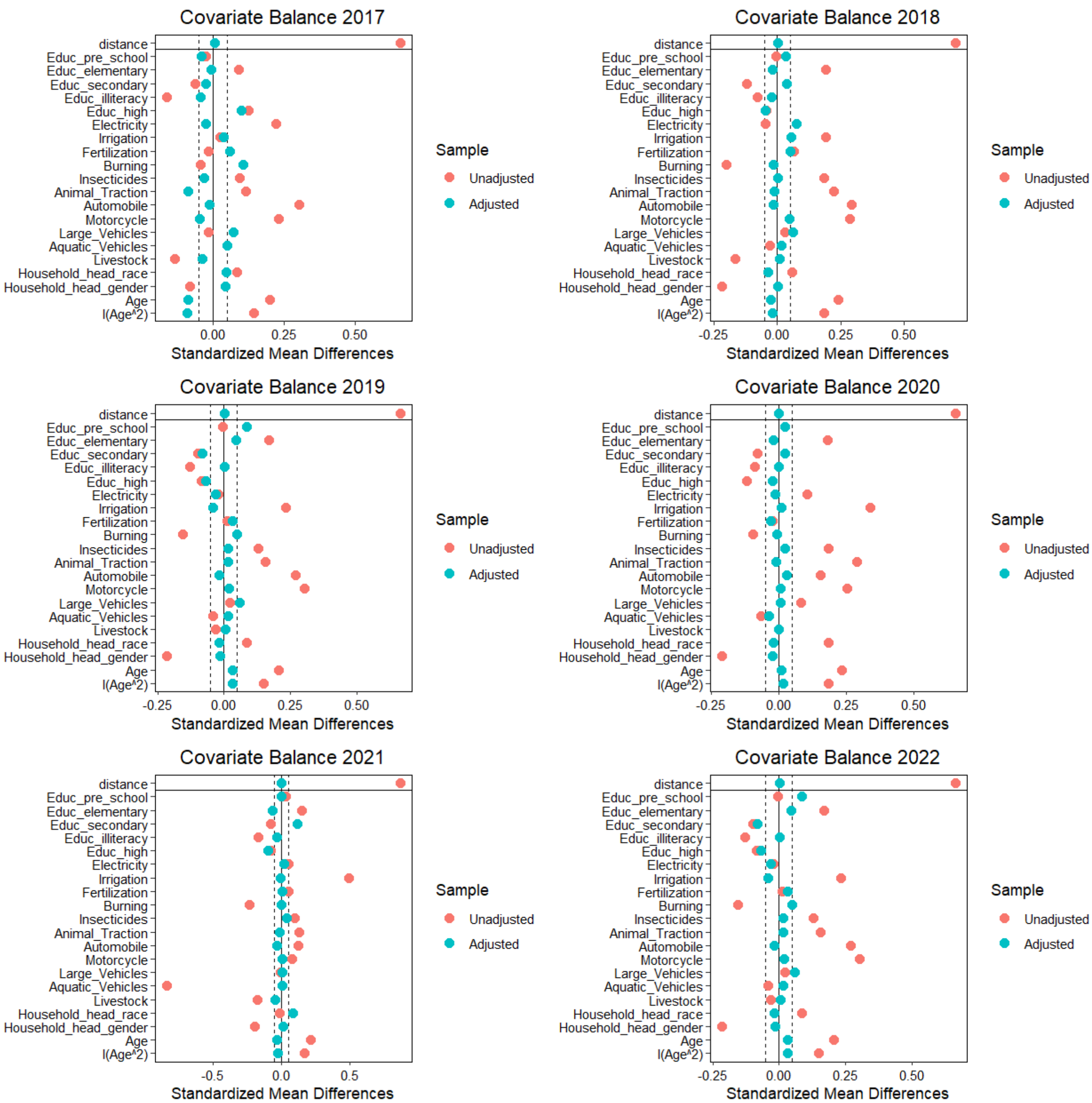


Table 6: OLS Regression with matching groups on PRONAF status

	Dependent variable:		
	log(Rural_income)		
	(1)	(2)	(3)
PRONAF	0.469***	0.473***	0.459***
	(0.044)	(0.044)	(0.049)
year_2018		0.358***	0.359***
		(0.115)	(0.115)
year_2019		0.107	0.107
		(0.115)	(0.115)
year_2020		0.394***	0.393***
		(0.114)	(0.114)
year_2021		0.408***	0.408***
		(0.124)	(0.124)
year_2022		0.426***	0.375***
		(0.118)	(0.143)
Pronaf:year_2022			0.092
			(0.110)
Observations	13,837	13,837	13,837
R^2	0.099	0.104	0.104
Adjusted R^2	0.097	0.102	0.102
Residual Std. Error	1.804 (df = 13815)	1.799 (df = 13810)	1.799 (df = 13809)
F Statistic	71.937***	61.592***	59.353***

Notes: Robust standard errors. Symbols *,**, and *** indicate rejection of the null hypothesis at the significance level of 10%, 5%, and 1%, respectively. All covariates from Table are included, see Table A2 in the Appendix for the rest of the coefficients.

and significant at 5% in all the models. Again, the age of the household head has the usual coefficient signal, positive for Age and negative for Age^2.

5 Conclusions

Credit plays a crucial role in market economies, being especially important in agriculture. PRONAF is a public credit program designed to support family farming. In this paper, benefiting from a recent novel survey of family farming units, we are interested in investigating the impact of PRONAF on the per capita income generated by family farming activities in Bahia.

A usual issue when evaluating social programs is the possibility of selection bias, since, in the absence of randomly selected treated units, we cannot guarantee that the differences in the unit's outcome, in this case, the per capita income, are due to the policy. We approach this by applying a propensity score matching procedure.

We performed OLS regressions without considering matching groups and after matching groups. The econometric results indicate a positive association between PRONAF and the household per capita income in family farms. Despite the usual parsimony necessary in cases like that, if most bias sources are due to characteristics in observable covariates, results could indicate that PRONAF credit causes an improvement in rural income.

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Appendix

Table A1: OLS Regression with no-matching groups (all coefficients)

	Dependent variable:		
	log(Rural_income)		
	(1)	(2)	(3)
PRONAF	0.458*** (0.033)	0.463*** (0.033)	0.441*** (0.033)
Educ_pre_school	−0.641*** (0.120)	−0.628*** (0.120)	−0.628*** (0.120)
Educ_elementary	−0.371*** (0.108)	−0.362*** (0.108)	−0.362*** (0.108)
Educ_secondary	−0.232** (0.107)	−0.232** (0.107)	−0.232** (0.107)
Educ_illiteracy	−0.762*** (0.128)	−0.768*** (0.127)	−0.766*** (0.127)
Educ_high	−0.086 (0.130)	−0.097 (0.130)	−0.096 (0.130)
Electricity	0.285*** (0.092)	0.247*** (0.092)	0.248*** (0.092)
Irrigation	0.289*** (0.037)	0.267*** (0.037)	0.268*** (0.037)
Fertilization	0.363* (0.204)	0.355* (0.205)	0.354* (0.205)
Burning	0.010 (0.045)	−0.010 (0.045)	−0.011 (0.045)
Insecticides	0.225*** (0.034)	0.225*** (0.034)	0.226*** (0.034)
Animal_Traction	0.235*** (0.037)	0.238*** (0.037)	0.238*** (0.037)
Automobile	0.409*** (0.037)	0.406*** (0.037)	0.407*** (0.037)
Motorcycle	0.258*** (0.032)	0.258*** (0.032)	0.258*** (0.032)
Large_Vehicles	0.733*** (0.149)	0.713*** (0.147)	0.718*** (0.147)
Aquatic_Vehicles	0.814*** (0.136)	0.689*** (0.136)	0.688*** (0.136)
Livestock	−0.093*** (0.036)	−0.055 (0.036)	−0.054 (0.036)
Household_head_race	0.344*** (0.043)	0.358*** (0.043)	0.357*** (0.043)
Household_head_gender	−0.463*** (0.033)	−0.468*** (0.033)	−0.468*** (0.033)
Age	0.051*** (0.008)	0.051*** (0.007)	0.051*** (0.007)
I(Age^2)	−0.0003*** (0.0001)	−0.0003*** (0.0001)	−0.0003*** (0.0001)
year_2018		0.369*** (0.073)	0.370*** (0.073)
year_2019		0.101 (0.074)	0.101 (0.074)
year_2020		0.373*** (0.073)	0.372*** (0.073)
year_2021		0.518*** (0.079)	0.517*** (0.079)
year_2022		0.404*** (0.078)	0.322*** (0.078)
Pronaf:year_2022			0.147
Constant	4.268*** (0.288)	4.032*** (0.294)	4.040*** (0.294)

*p<0.1; **p<0.05; ***p<0.01

Table A2: OLS Regression with matching groups (all coefficients)

	Dependent variable:		
	Rural_income		
	(1)	(2)	(3)
PRONAF	0.469*** (0.044)	0.473*** (0.044)	0.459*** (0.049)
Educ_pre_school	−0.590*** (0.218)	−0.600*** (0.213)	−0.598*** (0.213)
Educ_elementary	−0.286 (0.208)	−0.297 (0.203)	−0.296 (0.203)
Educ_secondary	−0.143 (0.204)	−0.153 (0.199)	−0.152 (0.200)
Educ_illiteracy	−0.693*** (0.224)	−0.716*** (0.219)	−0.714*** (0.219)
Educ_high	−0.064 (0.227)	−0.087 (0.223)	−0.087 (0.223)
Electricity	0.426*** (0.156)	0.405** (0.158)	0.405** (0.158)
Irrigation	0.272*** (0.048)	0.240*** (0.048)	0.240*** (0.048)
Fertilization	0.216 (0.242)	0.200 (0.250)	0.200 (0.249)
Burning	0.042 (0.054)	0.017 (0.054)	0.017 (0.054)
Insecticides	0.251*** (0.046)	0.247*** (0.047)	0.247*** (0.047)
Animal_Traction	0.239*** (0.050)	0.235*** (0.051)	0.234*** (0.051)
Automobile	0.444*** (0.051)	0.449*** (0.051)	0.449*** (0.051)
Motorcycle	0.225*** (0.044)	0.229*** (0.044)	0.229*** (0.044)
Large_Vehicles	0.795*** (0.173)	0.758*** (0.170)	0.759*** (0.170)
Aquatic_Vehicles	0.362* (0.193)	0.318 (0.199)	0.319 (0.198)
Livestock	−0.074 (0.047)	−0.037 (0.046)	−0.037 (0.046)
Household_head_race	0.361*** (0.057)	0.373*** (0.056)	0.373*** (0.056)
Household_head_gender	−0.520*** (0.041)	−0.523*** (0.041)	−0.523*** (0.041)
Age	0.047*** (0.009)	0.046*** (0.009)	0.046*** (0.009)
I(Age^2)	−0.0003*** (0.0001)	−0.0003*** (0.0001)	−0.0003*** (0.0001)
year_2018		0.358*** (0.115)	0.359*** (0.115)
year_2019		0.107 (0.115)	0.107 (0.115)
year_2020		0.394*** (0.114)	0.393*** (0.114)
year_2021		0.408*** (0.124)	0.408*** (0.124)
year_2022		0.426*** (0.118)	0.375*** (0.143)
Pronaf:year_2022			0.092 (0.110)
Constant	4.315*** (0.386)	4.095*** (0.393)	4.101*** (0.393)

*p<0.1; **p<0.05; ***p<0.01

Figure A1: Common support region - robustness check

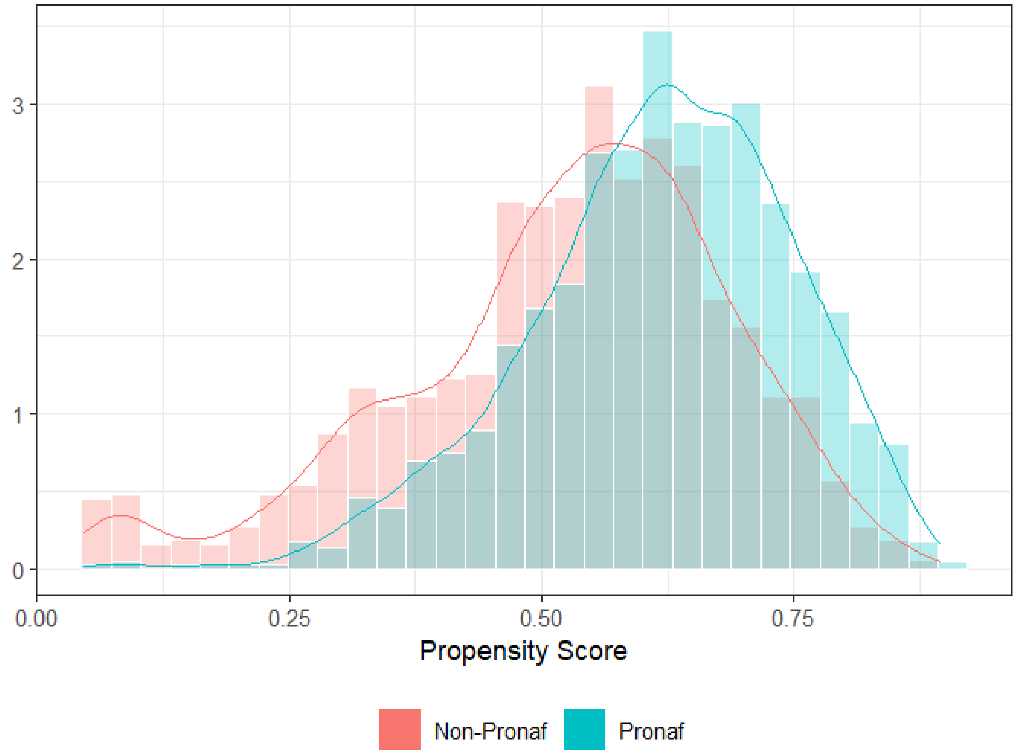

Figure A2: Adjusted versus unadjusted sample - robustness check

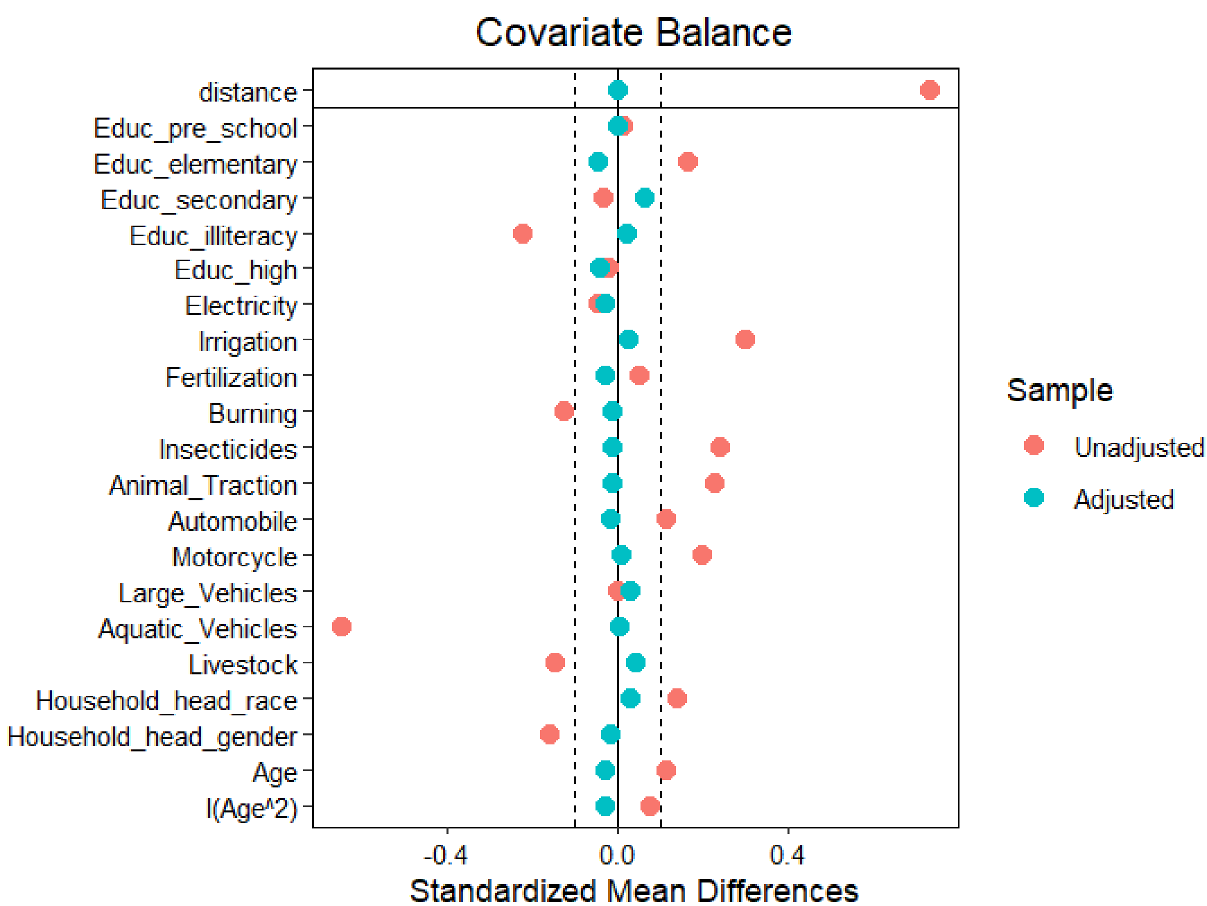

Table A3: OLS Regression with matching groups - robustness check

	Dependent variable:		
	log(Rural_income)		
	(1)	(2)	(3)
PRONAF	0.562*** (0.073)	0.531*** (0.073)	
PRONAF_lag			0.296*** (0.071)
Educ_pre_school	0.170 (0.260)	−0.246 (0.256)	−0.205 (0.258)
Educ_elementary	0.385 (0.242)	0.053 (0.233)	0.098 (0.235)
Educ_secondary	0.352 (0.246)	0.231 (0.236)	0.289 (0.237)
Educ_illiteracy	0.102 (0.273)	−0.312 (0.271)	−0.347 (0.273)
Educ_high	0.326 (0.299)	0.220 (0.290)	0.272 (0.292)
Electricity	0.553 (0.427)	0.650 (0.424)	0.616 (0.440)
Irrigation	0.205** (0.102)	0.186* (0.101)	0.228** (0.102)
Fertilization	2.433*** (0.548)	2.410*** (0.549)	2.431*** (0.554)
Burning	−0.028 (0.092)	−0.033 (0.092)	−0.049 (0.092)
Insecticides	0.203*** (0.070)	0.194*** (0.070)	0.211*** (0.071)
Animal_Traction	0.222*** (0.083)	0.216*** (0.083)	0.249*** (0.083)
Automobile	0.439*** (0.076)	0.416*** (0.076)	0.422*** (0.077)
Motorcycle	0.177*** (0.068)	0.189*** (0.068)	0.203*** (0.069)
Large_Vehicles	0.356 (0.322)	0.344 (0.315)	0.329 (0.316)
Aquatic_Vehicles	0.755*** (0.211)	0.789*** (0.211)	0.651*** (0.213)
Livestock	0.074 (0.087)	0.071 (0.086)	0.058 (0.087)
Household_head_race	0.265*** (0.101)	0.284*** (0.101)	0.306*** (0.102)
Household_head_gender	−0.533*** (0.070)	−0.501*** (0.070)	−0.517*** (0.071)
Age		0.063*** (0.016)	0.066*** (0.016)
I(Ageˆ2)		−0.001*** (0.0002)	−0.001*** (0.0002)
Constant	3.096*** (0.739)	1.569* (0.819)	1.561* (0.831)
Observations	2,701	2,701	2,701
R^2	0.107	0.117	0.104
Adjusted R^2	0.101	0.110	0.097
Residual Std. Error	1.717 (df = 2681)	1.708 (df = 2679)	1.720 (df = 2679)
F Statistic	16.955***	16.916***	14.821***

Robust Standard Errors — *p<0.1; **p<0.05; ***p<0.01