RESR Revista de Economia e Sociologia Rural

ISSN 1806-9479

ARTICLE

Impact of a crop insurance mechanism on credit obtained by smallholders: evidence from "*Proagro Mais*" in Paraná

Impacto de um mecanismo de seguro agrícola no crédito na agricultura familiar: evidência do "Proagro Mais" no Paraná

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How to cite: Oñate-Paredes, C., & Ozaki, V. A. (2025). Impact of a crop insurance mechanism on credit obtained by smallholders: evidence from "*Proagro Mais*" in Paraná. Revista de Economia e Sociologia Rural, 63, e266252. https://doi.org/10.1590/1806-9479.2025.266252

Abstract: This research analyzes a public compulsory crop-credit public insurance program, *Proagro Mais*, which is one of the largest agricultural risk management programs in Brazil and is also focused on smallholder producers. In particular, this study assesses the influence of the program on the amount of credit obtained per hectare by smallholder corn producers in the state of Paraná, Brazil. The primary dataset is a comprehensive database of agricultural credit borrowers comprising 93.303 individuals. The methodology incorporates the propensity score matching (PSM) at the endline year, employing three distinct matching algorithms, and PSM at the baseline, coupled with the difference-in-differences method. The results indicate that the treatment had ambiguous effect on the treated, with reduced impacts when compared with the outcome variable means. This suggests that the control group may have employed agricultural risk management tools other than *Proagro Mais* to mitigate the effects of low production on the average credit per hectare. It should be noted that this research represents one of the few impact evaluation studies on crop insurance in Latin America.

Keywords: crop insurance mechanism, impact evaluation, Brazil.

Resumo: Esta pesquisa analisa o programa público compulsório (com crédito) de seguro agrícola *Proagro Mais*, que é um dos maiores programas de gestão de risco rural no Brasil, que também é focado nos produtores de pequena escala. Especificamente, foi avaliado o impacto deste programa no valor do crédito obtido por hectare pelos pequenos produtores de milho no Estado do Paraná. O principal componente da informação é um grande banco de dados de mutuários de crédito agrícola composto por 93.303 indivíduos. A metodologia inclui pareamento por escore de propensão (PSM) no ano final (usando três algoritmos de pareamento diferentes) e PSM (na linha de base) juntamente com diferenças em diferenças. Os resultados mostram efeitos ambíguos do tratamento nos indivíduos tratados, porém todos eles com impactos reduzidos quando comparados com as médias da variável de resultado. Isso sugere que o grupo de controle pode ter utilizado outras ferramentas de gestão de risco agrícola além do *Proagro Mais* para mitigar os efeitos da baixa produção no crédito médio por hectare. Cabe ressaltar que, esta pesquisa é um dos poucos estudos de avaliação de impacto sobre seguro agrícola na América Latina.

Palavras-chave: mecanismos de seguro agrícola, avaliação de impacto, Brasil.

1. Introduction

The agricultural sector in Brazil plays a significant role in the national economy, accounting for 25% of the country's gross domestic product (GDP) in 2022 (Universidade de São Paulo, 2023). Brazil is also a prominent player in global agricultural production and is ranked among the top five producers for 23 agricultural crops. Brazil is the leading producer of coffee, soybeans, cashew apples, Brazil nuts, oranges, sisal, and sugar cane (Food and Agriculture

Organization of the United Nations, 2023). The significance and scale of Brazilian agricultural production have prompted the establishment of public and private risk management strategies, including futures and option contracts, minimum support prices, mechanisms for smallholder commercialization, debt renegotiations, crop information systems, infrastructure and logistics for crop production and storage, and private and public crop insurance (Arias et al., 2015). The latter group comprises the Farm Activity Guarantee Program for Smallholders *(Proagro Mais*), which was implemented in 2004 (Brasil, 2004) and is the focus of this article.

Proagro Mais, also referred to as Family Farming Insurance (*SEAF* – in Portuguese), is a compulsory crop credit public insurance program provided by the Brazilian Federal Government. The program is targeted towards smallholders who adhere to the Brazilian National Program for Strengthening Family Agriculture (*Pronaf*[1]). As Iturrioz & Arias (2010) observe, *Proagro Mais* offers a "multi-peril yield-shortfall policy", which indemnifies smallholders by "the amount that actual crop revenue falls short of the sum insured" (Iturrioz & Arias, 2010, p. 54). The program covers a wide range of crops and insures against several climatic risks associated with farming activities. In return for the payment of a premium to the Federal Government, farmers who adhere to the program receive indemnification from the Federal Government in the event of agricultural disasters (Brasil, 2018a).

Proagro Mais is a significant program in terms of the number of operations and the amount of capital allocated to address crop losses. As indicated in the *Proagro* reports (Brasil, 2018b, 2018c, 2018d, 2018e, 2023), from its inception in 2004/05 to 2021/22[2], *Proagro Mais* has disbursed BRL 131,905 BRL million (approx. USD 45,345 million) across 7,704,868 operations, distributed among 154 crops and 27 states of the federation. These figures illustrate the considerable scale and eventual impact of *Proagro Mais* on smallholders' agricultural risk management. Furthermore, *Proagro Mais* has distributed a greater amount of resources than another Brazilian public program for smallholders, which is based on the crop insurance mechanism (Crop Warranty - *Garantia Safra*), over the 2004/05 to 2017/2018 period (Brasil, 2019).

Notwithstanding the considerable investment and the size of the beneficiary population, the *Proagro Mais* insurance premium over indemnity indicator remains a point of improvement. As posited by Raviv (1979), the limitation on the policies provided by a risk-neutral insurer can be expressed by the following equation: $P \geq (1+l)E\left[I(x)\right]$, where P is the premium, $I(x)$ is the coverage or indemnity function, and l is the fixed percentage of insurance costs. This implies that the expected indemnity, in conjunction with the associated costs, must be equal to or less than the insurance premium. In the case of *Proagro Mais*, the total insurance premium was observed to be lower than the indemnity in 15 of the 18 available data seasons (2004/05-2021/22). Additionally, the ratio I/P was less than or equal to 1 in only three periods: 0.96 in 2006/07; 0.34 in 2009/10; and 0.74 in 2010/11. Thus, the largest Brazilian smallholder agricultural risk management program is not consistently financially self-sustaining over time, which reinforces the importance of this study as a contribution to the analysis of Brazilian agricultural policy.

In a regional context, Iturrioz & Arias (2010) indicate that a minority of Latin American and Caribbean (LAC)[3] countries have developed crop insurance programs that focus on smallholders. Chile has the Small Farmer Lending Bank (INDAP), Peru has Agro Protégé, México has Agroasemex, Argentina has multiple-peril crop insurance (MPCI) state government schemes, and Brazil has

[1] *Pronaf* has its primary objective to "stimulate income generation and improve the use of family labor through the financing of agricultural activities and services and non-agricultural services developed in rural establishments or nearby community areas" (Brasil, 2012, p. 2).

[2] The crop season spans from July to June of the following year.

[3] According to Iturrioz & Arias (2010), the LAC region includes some of the world's leading agricultural and livestock producers. It is a region where agricultural insurance is relatively well developed in comparison with Africa and Asian countries.

Proagro Mais, which is the only program that is compulsory. The Brazilian Federal Government offers *Proagro Mais* on a national scale and it is publicly funded, with no participation of private agricultural insurance companies.

The objective of this study was to evaluate the impact of *Proagro Mais* on a sample of smallholder producers of corn in the state of Paraná, Brazil. The outcome of interest is the amount of credit per hectare. To reach that objective, we used information from *Proagro Mais*' beneficiary and non-beneficiary farmers from Paraná State, which was obtained from an agricultural credit database.

Although *Proagro Mais* is a compulsory program, the credit database indicates that between 2004 and 2008, not all smallholders were automatically incorporated into the program. This may have been due to technological and operational challenges faced by the financial institution responsible for implementing the program. Therefore, the baseline was established as the year preceding the program inception, in this case 2003, while 2005 was designated as the endline, as it was a year following a notable decline in corn production within the analyzed region. In addition to the outcome, the relevant variables matrix includes crop and smallholder characteristics such as the financed area, complementary economic activities for additional income, education, and expected yield. Furthermore, meteorological and regional variables from other public sources were incorporated as controls for geographical heterogeneity.

For analysis, the corn crop and the state of Paraná were selected due to their significance in Brazilian agriculture and in the program under study. As reported by the Brazilian Geography and Statistics Institute (Instituto Brasileiro de Geografia e Estatística, 2023), during the study period (2003-2005), corn was the second most harvested crop (38 million ha) and the third largest source of agricultural income (USD 12,244 million) in Brazil. Additionally, Paraná State was the leading corn producer in the country. Furthermore, in terms of beneficiaries under *Proagro Mais*, corn producers constituted 47.9% of the total, with their covered value accounting for 40.5%. This illustrates that corn was the most significant crop within the context of the analyzed program during the 2004/05 season (Brasil, 2018c). Furthermore, Paraná is the second most representative state in terms of beneficiaries of *Proagro Mais*, with 95,915 beneficiaries accounting for 17.3% of the total enrolled in the program in the 2004/05 season. Additionally, it is the second most active state in terms of covered value, with USD 0.52 million (26.8% of the total) disbursed during the same period.

This article is organized as follows: Section Two provides a theoretical background and review of the literature; Section Three presents the econometric methods; Section Four describes the data and empirical model; Section Five presents the results; and Section Six contains the concluding remarks.

2. Theoretical foundation

2.1 Crop insurance and agricultural credit

The research hypothesis posits that following a period of low production, smallholders who participated in *Proagro Mais* should demonstrate a highetened average credit per hectare compared to the control group. This could enable them to repay or reduce their debts, thereby averting credit default and sustaining their debt capacity at similar levels prior to crop failure. To substantiate this hypothesis, two theoretical models, as presented in Ben-Yashar et al. (2018) and Cai (2016), respectively, have been employed.

In their study, Ben-Yashar et al. (2018) present a theoretical model that elucidates the interrelationship between credit decision-making structures of banks and the role of government guarantees in covering loans granted for investment in projects. Although the scheme presented by Ben-Yashar et al. (2018) does not belong to a specific sector, Ifft et al. (2019) used these foundations to explain the mechanism in the field of crop insurance. These financial mechanisms can be considered as a proxy of the government guarantee, as they offer a payment (to the banks) in the case of drops in yield or market prices, as shown in Equation 1:

$$P_y R + \left(1 - P_y\right) g - C > 0 \tag{1}$$

Where: P_y represents the probability of a successful agricultural project, $R > 1$ is the loan repayment, $C \geq 0$ is the cost of lending, Y is the project return, and g is the guarantee of governmet repayment, which is represented by subsidy crop insurance mechanisms as *Proagro Mais*. One model assumption is that the loan must be used only for investing in the agricultural project.

In the event of crop losses, the probability of loss, P_y, declines, indicating the activation of the crop insurance mechanism (g increases). Consequently, the potential factors that could reduce P_y, such as yield and price risks, become less significant to the financial institution (lender). As posited by Ifft et al. (2019, 4), this would engender an augmented willingness on the part of lenders to extent loans to farmers, thereby precipitating an increase in the supply of credit. This conclusion is corroborated by Hazell et al. (2017), who posit that farmers who purchase insurance and borrow to finance new projects that ultimately succeed due to an insured loss would elect to repay the loan out of the indemnity funds received.

Furthermore, Cai (2016) utilized a two-period, two-state model (good state - no disaster; bad state - disaster), wherein the author illustrated and contrasted the value of agricultural credit that optimizes individual utility with and without the inclusion of crop insurance. Specifically, she compared the initial consumption (C1) with the expectation of future consumption (C2). To this end, the above-mentioned author set up an optimization model, using a return-on-investment function $F(\cdot)$ and three variables (C1, family savings – S, and agricultural credit – B). The solution to the maximization problem revealed that the optimum level of agricultural credit increases once insurance is offered.

The positive impact of insurance provision on agricultural credit allows farmers who have adopted insurance to demand larger amounts of credit from financial institutions. This is because such action is taken to support the current farmer's growth or at least to maintain similar investments in production. This is a consequence of having a risk management program that minimizes the losses caused by crop failure.

2.2 Impact evaluation of crop insurance programs

This section presents a selection of key studies on the impact evaluation of crop insurance, with a particular focus on to those that utilize agricultural credit as an impact variable. While there is a substantial body of literature on quasi-experimental impact evaluation in agricultural projects and crop insurance mechanisms, there is a paucity of studies that examine these topics together. It is notable that only one study specifically addresses the Latin American context.

In their studies, DeLay et al. (2023), Tsiboe & Turner (2023), Mishra et al. (2021), Cariappa et al. (2020), Cai (2016), Cole et al. (2013), Varadan & Kumar (2012), Winters et al. (2010), and Giné & Yang (2009) assessed the influence of insurance programs on a range of indicators, including agricultural credit.

DeLay et al. (2023) employed data from the Kansas Farm Management Association to estimate the impact of insurance indemnities and crop insurance liability on farm debt. Their findings indicated a positive and statistically significant relationship, thereby supporting the notion that farms with substantial crop insurance coverage tend to exhibit increased debt levels. Similarly, Tsiboe and Turner (2023) employed data from the United States agricultural insurance system, particularly from the Federal Crop Insurance Program (FCIP), spanning the period from 1948 to 2020, in their analysis. The objective was to identify the impact of the total per-acre premium on farm debt. The results from both models used (OLS, 2SLS) indicate a positive and significant impact of the FCIP on the total farm financial debt variable.

Mishra et al. (2021) investigated the influence of integrating index insurance with agricultural loans on access to credit of smallholder farmers in northern Ghana between 2015 and 2017. The results from all the models consistently indicated that insurance interventions increased the probability of farmers securing loans in subsequent periods. Furthermore, the authors postulated that insured loans could impact credit market accessibility through their effects on both the behavior of farmers and the behavior of banks.

In their study, Cariappa et al. (2020) investigated the factors influencing the adoption of crop insurance and its subsequent impact on debt and farm income. The researchers employed nationally representative data from the National Sample Survey Office (NSSO) in India during the period 2012-2013, encompassing 35,200 farming households. The findings regarding farm debt indicated that households with access to crop insurance exhibit significantly lower levels of outstanding debt. One plausible explanation for these results is that, in contrast to the United States, Indian crop insurance policies provide coverage for yield risk rather than price risk exclusively. Furthermore, as previously observed, only a limited number of farmers are covered by crop insurance, and an even smaller number receive indemnity payments.

Cai (2016) employed a panel database comprising nine years of data (2000–2008) and encompassing 5,746 tobacco farmers from Jiangxi Province, China. The objective was to assess the influence of an agricultural insurance program on household production, borrowing, and saving behavior. The findings indicated that insurance provision exerts a positive impact on crop production and borrowing, yet does not affect household savings. Other studies have employed primary data to examine the relationship between credit, impact evaluation, and crop insurance. Winters et al. (2010) evaluated the impact of the implementation of an index insurance program called “Agro-Positiva” on credit, input use, and welfare. The study employed a sample of 800 cotton smallholders in Peru. The findings indicated that the low demand for agricultural insurance among farmers, the inherent weaknessed of the instrument and challenges associated with the local branch of the financial institution impeded the realization of the experiment objectives.

In their study, Giné & Yang (2009) conducted an evaluation to ascertain whether the provision of crop insurance to farmers induces them to take out loans to adopt new crop technologies. The study sample was composed of eight hundred randomly selected maize and peanut producers in Malawi, Africa. Half of the participants were offered credit to purchase high-yielding maize and groundnut seeds for the 2006 harvest, while the remainder were offered the same credit package, but were required to purchase weather insurance. The results demonstrated that the take-up rate was 13% lower among farmers who were offered insurance in conjunction with the loan. This can be explained by the notion that farmers had an implicit insurance policy inherent in the loan contract, such that the weather insurance premium represented an additional cost on top of the loan interest rate.

In other contexts, Cole et al. (2013) and Varadan and Kumar (2012) have analyzed the relationship between crop insurance and credit. In the first article, the authors evaluated the impact of increased liquidity on the purchase of rainfall insurance. This study used randomized samples from two Indian states to test the importance of price and nonprice factors, such as trust, financial literacy, liquidity constraints and other behavioral factors.

The results pertaining to liquidity constraints indicated that positive liquidity among selected smallholders exerted a positive influence on insurance demand, with this effect being particularly pronounced among the poorest individuals. According to the authors, the evidence that liquidity constraints affect crop insurance demand would imply that “a potential side effect of credit expansion...would be an increase in insurance demand” (Cole et al., 2013, p. 125).

In a case study conducted by Varadan & Kumar (2012), the impact of a crop insurance program for rice in India on farmers’ revenue was assessed. The results demonstrated that insured farmers exhibited higher returns than their uninsured counterparts. Additionally, the researchers identified loan accessibility as a significant factor influencing the adoption of crop insurance.

It is important to note that the results found in the literature differ according to the authors. With regard to our hypothesis (positive impact of insurance on credit), the results of Giné & Yang (2009) indicate an opposing effect. Conversely, the study of Cai (2016), which is similar to this study in terms of the large sample size and the impact variable used (“borrowing”), presents a positive impact evaluation of insurance.

Furthermore, although the studies conducted by Cole et al. (2013) and Varadan & Kumar (2012) relate crop insurance and credit in a causality that is contrary to the one proposed in this study, their findings indicate a positive correlation between these two variables.

Additionally, the methodological approach varies across the studies. Cariappa et al. (2020) estimated the average treatment effect on the treated (ATET) using logit and propensity score matching (PSM) with three different algorithms: nearest neighbor matching, caliper, and kernel-based matching. Mishra et al. (2021) and Cai (2016) employed the difference-in-difference methodology, while Cai (2016) also utilized the triple difference technique. Winters et al. (2010) employed a randomized experimental design that included an instrumental variable (IV), which was represented by a discount coupon that lowered the price of the insurance premium. Tsiboe & Turner (2023) and DeLay et al. (2023) employed both ordinary least squares (OLS) and two-stage least squares (2SLS) models, with DeLay et al. (2023) additionally utilizing a fixed effect model. As in the two previously cited research studies, Giné & Yang (2009) employed a fixed effect panel data regression, wherein the dependent variable was a dummy variable that assumed a value of 1 if the individual took out the loan to purchase the hybrid seed and 0 otherwise. Varadan & Kumar (2012) estimated a probit model to identify the variables that influence participation in the insurance scheme, where one of the variables was access to loans. Finally, Cole et al. (2013) used a linear probability model. It is notable that no standard econometric methodology was employed by all the authors. The use of panel data techniques, such as difference-in-difference or fixed effects, represents interesting alternatives to be considered when examining different periods.

As previously stated, the existing literature on the impact evaluation of crop insurance programs is limited in scope and does not focus on a specific geographic area, econometric methodology, or source of data. The aforementioned studies assessed the impact of crop insurance programs in Asia, Africa, United States and Latin America. They employed a range of econometric techniques, including propensity score matching (PSM), difference-in-differences, fixed effects models, triple difference, instrumental variable (IV), and endogenous treatment regressions, utilizing both primary and secondary data. It is noteworthy that, despite crop insurance being an agricultural risk management tool that is widely utilized in Latin America, its economic evaluation has not been adequately analyzed. There is a paucity of studies that address this subject matter within this region; therefore, this research, which is based on a substantial Brazilian crop insurance public program, is foundational, particularly at the regional level.

3 Methodology

3.1 Econometric methods

The impact of *Proagro Mais* on the amount of credit per hectare is measured by the outcome approach, which is also known as the Roy-Rubin model. This approach is based on three fundamental pillars: individuals, treatment, and potential outcomes (Caliendo & Kopeinig, 2008). In a binary treatment, D_i is equal to 1 if smallholder i is a *Proagro Mais* beneficiary and 0 otherwise. The potential outcome is defined as Y_i, where $i = 1,..., N$. Thus, the treatment effect or causal effect for smallholder i (δ_i) is defined by:

$$\delta_i = Y_i^T - Y_i^C \tag{2}$$

Where: Y_i^T is the potential outcome of the treatment, and Y_i^C is the potential outcome in the absence of the treatment.

Given that Y_i^T and Y_i^C are not observed for the same smallholders, it is not possible to estimate the individual treatment effect (δ_i). Consequently, the impact evaluation focuses on the ATET, which is the most common evaluation parameter (Caliendo & Kopeinig, 2008; Smith & Todd, 2005). This is defined as follows:

$$ATET = E\left[Y_i^T - Y_i^C \mid S_i = 1\right] = E\left[Y_i^T \mid S_i = 1\right] - E\left[Y_i^C \mid S_i = 1\right] \tag{3}$$

Where: S is the treatment status, then $S = 1$ implies treated. As noted by Sanglestsawai et al. (2015), it was not possible to observe the outcome of *Proagro Mais* smallholders if they had not contracted this insurance, $E\left[Y_i^C \mid S_i = 1\right]$. If the selection of the program were randomly assigned, the variable S would be statistically independent from the outcome.

It was not possible to randomize in this study due to the use of a bank database that reflects the behavior of a sample of smallholders who borrow *Pronaf* credit with and without contracting *Proagro Mais*. The adoption of program was not randomly assigned, which could result in biased estimators due to selection bias.

One method for controlling selection bias in observable characteristics is to utilize PSM techniques. Additionally, it is crucial to highlight certain aspects of the database to minimize bias. Primarily, *Proagro Mais* is a compulsory crop insurance program targeting a specific group of smallholders, all of whom are borrowers from a particular public credit program (*Pronaf*). This results in a notable degree of uniformity in the farmers’ socioeconomic characteristics.

Secondly, although our database includes both treated and non-treated individuals, it is possible that the primary motivation for all farmers is access to credit. However, some farmers elected to participate in *Proagro Mais*, while others did not. During the initial stages of *Proagro Mais*, the financial institution responsible for implementing the program may have lacked the requisite capacity to effectively manage it. Technological and operational challenges could have emerged during that period[4]. Given that the individuals in our database share similar characteristics (as *Pronaf* clients) and only a portion accessed *Proagro Mais*, it is reasonable to assume that the issue of selection bias may have been minimized.

[4] Although *Proagro Mais* has been mandatory since its inception, data from our database indicate that this legal requirement was only effectively enforced after 2008.

To estimate the ATET, we employed the use of PSM in conjunction with difference-in-differences (DiD) technique, which is a method of matching with difference-in-differences, henceforth referred to as MMDiD (Blundell & Costa Dias, 2000).

The propensity score matching (PSM) proposes that treated and untreated farmers differ in their treatment and other characteristics that affect participation and the outcome. This technique matches treated and untreated farmers using conditional probabilities to participate in the project (propensity scores), thereby replicating the project selection using observable factors (Winters et al., 2010; López & Maffioli, 2008). In conclusion, as stated by Cariappa et al. (2020, p. 4), the propensity score can be defined "as the selection probability conditional on confounding variables".

The propensity score is calculated using a logit or probit model, with the dependent variable (dummy) taking the value of 1 if the observation is part of the treatment group and 0 otherwise. Furthermore, the vector of covariates should be exogenous to the evaluated program (Winters et al., 2010).

Once the propensity score has been estimated, the treatment group farmers can be matched with the nonenrolled individuals that have the closest propensity score, thereby becoming the comparison group (Gertler et al., 2016). There are numerous matching algorithms that can be employed, including nearest neighbor, radius matching with a specified caliper or maximum propensity score distance, five nearest neighbors, and nonparametric kernel and local-linear matching (Heinrich et al., 2010; Winters et al., 2010). In this study, we employed the nearest neighbor 1-1 without replacement (NNM), radius caliper, and kernel as matching algorithms to estimate PSM in 2005 (endline year). This approach aligns with the methods utilized by Cariappa et al. (2020) and Priscilla & Chauhan (2019) in their respective studies.

The difference-in-differences (DiD) technique employs a combination of cross-sectional and temporal variation to facilitate a comparison of changes in the outcome variable. This approach offers a significant advantage in terms of controlling for unobserved heterogeneity in the baseline characteristics of the treatment and control groups (Aerts & Schmidt, 2008; Winters et al., 2010). In this manner, the MMDiD corrects the selection biases pertaining to observable characteristics (PSM), and moreover, it eliminates the bias associated with unobservable and time-invariant characteristics of the farmers across both groups (López & Maffioli, 2008; Winters et al., 2010; Gertler et al., 2016). In this study, we employed the MMDiD with panel data, utilizing the same NNM, radius caliper, and kernel matching algorithms described above for the PSM models.

The ATET estimated by the MMDiD with panel data (MMDiD_{LD}[5]) is defined based on the following expression (Blundell & Costa Dias, 2000; Khandker et al., 2010):

$$\hat{\alpha}^{LD}_{MMDID} = \frac{1}{N^T}\sum_{i\in T}\left[\left(Y_{it_1}{}^{T} - Y_{it_0}{}^{T}\right) - \sum_{j\in C} w_{ij}\left(Y_{jt_1}{}^{C} - Y_{jt_0}{}^{C}\right)\right] \tag{4}$$

Where: t_0 and t_1 are the baseline and endline, respectively, and w_{ij} is the weight for the matching between *i* and *j*.

In this technique, the treated group was defined as smallholders who took out loans to produce corn without contracting *Proagro Mais* in 2003 and subsequently took out loans with *Proagro Mais* in 2004 and 2005. The control group consisted of corn smallholders who took out loans throughout the period 2003-05 but did not hire *Proagro Mais*.

Once the primary sample has been defined, the new control group was obtained using PSM in the baseline. Subsequently, matched individuals were identified in 2004 and 2005. Consequently,

[5] The suffix LD means "longitudinal data".

a balanced panel comprising three years (2003-05) was generated for both groups. The ATET can be calculated using the following expression (Athey & Imbens, 2006; Khandker et al., 2010):

$$Y_{it} = \alpha + \gamma P_{it} + \rho T_{it} + \beta T_{it} P_{it} + \varepsilon_{it} \quad i = 1, \ldots, n; \; t = 0,1 \tag{5}$$

Where: Y_{it} is the impact indicator, that is, credit per hectare; P_{it} is equal to 1 if the farmer is in the treatment group (*Proagro Mais* beneficiary), and 0 if the farmer is in the control group; T_{it} is the time dummy variable, which is equal to 0 if at baseline and equal to 1 after treatment; ε_{it} is the error term.

In employing this regression, is the constant term is represented by α, while γ serves to control differences between the control and treatment groups. The role of ρ is to control for trends over time, and β provides an estimation of the ATET.

3.2 Data and empirical application

The primary data source utilized in this research is a database of agricultural credit borrowers, provided by the Federal Accounting Court of Brazil (TCU – Tribunal de Contas da União in Portuguese), which includes a sample of farmers who received credit to produce corn in the state of Paraná between 2003 and 2005. To supplement the TCU data, we incorporated agroclimatic variables at the micro-region level[6] from the Agro-meteorological Brazilian Monitoring System (*Agritempo*) and geographical identification variables at the municipality level from IBGE and BACEN.

The TCU database contains two categories of agricultural credit borrowers: those who also received *Proagro Mais* and those who did not. This database excludes observations made outside the main corn season or "summer corn" (*milho verão*[7]). Consequently, all extemporaneous corn crops (called *safrinha* in Brazil) planted between January and April are not included in the sample, leaving only observations from the main corn season. The main corn seasons were sown between August and November.

The TCU database comprises 93,303 individuals, of whom 67,607 constitute the control group (comprising 25,107, 14,087, and 28,413 in 2003, 2004 and 2005, respectively) and 25,696 are part of the treated group (17,117 and 8,579 in 2004 and 2005, respectively).

The sampling method of proportions and percentages (Cochran, 1977) was employed to verify the statistical relevance of the samples in 2004 and 2005 in the context of *Proagro Mais*. The populations under consideration in the aforementioned periods were 43,786 and 49,521 operations, respectively (Brasil, 2018b). With a 95% confidence interval, the sampling error was 0.58% and 0.96% in 2004 and 2005, respectively, indicating that the sample was statistically significant.

The empirical analysis was conducted over the period 2003-2005 for two reasons. First, 2003 is the year preceding the beginning of *Proagro Mais*, and therefore represents an appropriate period for the evaluation of the impact of the program. *Proagro Mais* employs a coverage mechanism similar to that of crop insurance, specifically multiple peril crop insurance. This entails the provision of indemnity in instances where a decline in agricultural yield is of a discerned within a specific region. The year 2005 was selected as the endline, as it marked the conclusion of a notable decline in corn production in the state of Paraná. According to Instituto Brasileiro de Geografia e Estatística (2021), the loss in this state reached -40.43% between 2003 and 2005.

The second reason for selecting the 2003-2005 period was the availability of data from the control group. Banco Central do Brasil (Brasil, 2014) stipulates that all *Pronaf* borrowers are obliged to contract *Proagro Mais*, thereby rendering this crop insurance public program a

[6] A micro-region is a geographical unit established by IBGE, which is defined as the grouping of neighboring municipalities.

[7] See Franco et al. (2015) for more information about the "summer corn" season in the state of Paraná.

compulsory condition of *Pronaf*. However, the information from the TCU database indicated that this legal condition was only effective from 2008 onwards, when the number of *Pronaf* borrowers who did not contract *Proagro Mais* was negligible.

Thus, given the aforementioned aspects and the lack of evidence of substantial evidence indicating a decline in corn production in Paraná between 2005 and 2008 (Instituto Brasileiro de Geografia e Estatística, 2021), it is evident no other period than those examined in this study can provide an adequate evaluation of the impact of *Proagro Mais*.

From the TCU database, we obtained the following variables: treatment (*PM*), outcome (credit per hectare, *CH*), period (*YR*), and a few control variables (*EY*, *ED*, and *AA)*. These variables were all at the farmer level. As *CH* is affected by inflation, we deflated it as suggested by Aerts & Schmidt (2008), assuming 2005 as the base year, and designated it *credit_per_hectare_05*[8]. Furthermore, we incorporated agroclimatic and geographical identification variables to obtain more precise PSM estimations.

The mean annual temperature and precipitation values for each microregion were collected from Agritempo (Brasil, 2015b). Additionally, three variables related to agricultural production at the municipal level were incorporated based on IBGE information (Instituto Brasileiro de Geografia e Estatística, 2021). Finally, the number agricultural funding credit agreements in each municipality of Paraná was calculated using data from the Statistical Yearbook of Rural Credit (Brasil, 2015a).

The microdata utilized in this study are drawn exclusively from the TCU database, due to the unavailability of disaggregated public *Proagro Mais* and *Pronaf* data. Table 1 provides a comprehensive overview of the variables incorporated into both econometric techniques (endlie PSM and MMDiD_{LD}), while Table 2 presents the bibliographic support of the control variables.

Table 1 – Definition of variables

Variable	Unit	Definition	Source
CH	BRL*	Credit value per hectare (BRL/ha) in nominal terms	TCU database
credit_per_hectare_05	BRL*	Credit value per hectare (BRL/ha) in real terms	TCU database
PM	Dummy	1 if a smallholder belongs to the treated group (those who hired *Proagro Mais*)	TCU database
YR	Dummy	0 = 2003, 1 = 2005	TCU database
EY	Tons/hectares	Expected yield, which is the mean of the last five years of yield	TCU database
ED	Years	The smallholders' educational level	TCU database
AA	Dummy	1 if a smallholder with at least one additional agricultural credit allocated for the production of a crop other than corn	TCU database
TP	Celsius degrees	Microregion annual mean temperature	Agritempo (Brasil, 2015b)
PCP	Millimeters	Microregion annual mean rainfall	Agritempo (Brasil, 2015b)
NF	Number of farms	Number of corn farms by municipality	Instituto Brasileiro de Geografia e Estatística (2021)
MY	Tons/hectares	Municipality corn yield	Instituto Brasileiro de Geografia e Estatística (2021)
MC	Number of contracts	Credit agreements by municipality	Brasil (2015a)
HVA	%	Harvested area of corn/total harvested area of temporary crops by municipality	Instituto Brasileiro de Geografia e Estatística (2021)

Note: *BRL represents the Brazilian Real (Brazil's currency), and the annual average exchange rates (USD/BRL) for 2003, 2004 and 2005 were 3.08, 2.53, and 2.43, respectively (Brasil, 2016).

[8] IGP-DI was used as a deflation indicator.

Table 2 – Bibliographic support for control variables

Variable	Document	Description of variables in referenced documents
EY	Mishra et al. (2021)	**Maize yield (kg/acre).**
ED	Cai (2016)	Education: 0 = illiterate, 1 = primary, 2 = secondary, 3 = high school, 4 = college.
	Varadan & Kumar (2012); Giné and Yang (2009)	Years of schooling.
	Spörri et al. (2012)	Levels of agricultural competence in farm management: 1 = none, 2 = vocational studies under way, 3 = skilled worker or technician, 4 = farm engineer, 5 = agricultural engineer.
	Cariappa et al. (2020)	Education: below primary school, below higher secondary school.
	Tsiboe & Turner (2023)	Education level.
AA	Cai (2016)	Share of tobacco production area in relation to the total area of agricultural production.
	Spörri et al. (2012)	1 = the farm does not have diversification of products.
	Cariappa et al. (2020)	1 = the cultivation is the primary income source.
TP, PCP, NF, MY, MC, HVA	Varadan & Kumar (2012); Spörri et al. (2012)	Dummy variables that identify distinct productive regions.
HVA	Cariappa et al. (2020)	Dummy variables that identify distinct land sizes.
	DeLay et al. (2023)	Total cropped areas

4 Results

4.1 Propensity score matching (PSM) results

In this subsection, we present the results of the impact of *Proagro Mais* on the amount of agricultural credit received by smallholders, using propensity score matching (PSM). The descriptive statistics of the dependent variable and covariates for the endline are presented in Table 3:

Table 3 – Descriptive statistics for variables included in the propensity score matching (PSM) models (endline)

Variables	Mean	Standard Deviation
	Beneficiaries (*N* = 8,579)	
credit_per_hectare_05	74.35	23.30
EY	1.93	0.97
ED	7.20	2.90
AA	0.05	0.22
TP	19.98	1.05
PCP	4.11	0.61
NF	1,060.59	887.36
MY	4.11	1.62
MC	1,805.30	1,399.99
HVA	0.37	0.20
	Control group (*N* = 28,413)	
credit_per_hectare_05	83.77	49.72
EY	2.80	2.48
ED	7.75	3.41
AA	0.10	0.31
TP	20.32	1.19
PCP	4.10	0.65
NF	1,020.13	683.31
MY	4.24	1.61
MC	1,442.55	1,002.96
HVA	0.35	1.18

The treatment group, comprising beneficiaries, represents smallholders who took out loans to produce corn and contracted *Proagro Mais*. The control group, which includes smallholders who also took out agricultural loans but did not contract the analyzed crop insurance program, serves as the comparison group.

In the initial stage of the PSM, the propensity scores were estimated using a logit model, with a binary dependent variable that takes the value of 1 if the observation belongs to the treatment group and 0 otherwise. The independent variables consist of the covariates described in Table 3, with the exception of *credit_per_hectare_05*, which is the impact variable utilized to estimate the ATET in the second step of the PSM. The estimated results of the logit model are presented in Table 4.

Table 4 – Logit results, propensity score matching (PSM) (endline)

Variables	Coefficient	Standard Error	z
EY	-0.33	0.01	-28.62***
ED	-0.04	0.004	-8.37***
AA	-0.71	0.06	-12.88***
TP	-0.16	0.01	-11.79***
PCP	-0.05	0.02	-2.27**
NF	-0.0004	0.00002	-16.87***
MY	-0.03	0.01	-3,07***
MC	0.0004	0.00002	28.55***
HVA	0.91	0.08	11.28***
constant	2.70	0.32	8.55***
Treatment variable: *PM*			
Number of observations: 36,992			
χ^2= 3,162.58			
$p > \chi^2 = 0.0000$			
Pseudo $R^2 = 0.08$			

* p<0.10; ** p<0.05; *** p<0.01

To guarantee the reliability of the estimation outcomes, three matching algorithms were employed: NNM, radius caliper, and kernel. The common support of propensity scores (Table 5) demonstrates that the selection of variables fulfills the balance criteria in all models.

Table 5 – Common support for propensity score estimations, propensity score matching (PSM) (endline)

Matching method	Treatment assignment	Off support	On support	Total
NNM	Untreated	0	28,413	28,413
	Treated	0	8,579	8,579
	Total	0	36,992	36,992
Radius caliper matching	Untreated	0	28,413	28,413
	Treated	378	8,201	8,579
	Total	378	36,614	36,992
Kernel matching	Untreated	0	28,413	28,413
	Treated	0	8,579	8,579
	Total	0	36,992	36,992

Based on the propensity scores calculated from the logit model and validated to ensure common support, we estimated the ATET. The effects were measured using the credit value per hectare in real terms as a dependent variable. The estimated results for the PSM using the three matching algorithms previously mentioned are shown in Table 6, and the quality indicators before and after the matching are shown in Table 7.

Table 6 – Empirical results of PSM in endline

Matching method	Non-beneficiaries of *Proagro Mais*	Beneficiaries of *Proagro Mais*	ATET
NNM	76.83	74.35	-2.48***
Radius caliper matching	76.92	74.26	-2.66***
Kernel matching	77.09	74.35	-2.74***

* p<0.10; ** p<0.05; *** p<0.01

The estimated results of the PSM are consistent across the three matching methods, and all are significant at 1%. These results indicate that, on average, the smallholders in the state of Paraná who contracted *Proagro Mais* as crop insurance received approximately BRL 2.5 (USD 1) less in credit per hectare to cultivate corn in 2005 than smallholders who did not contract *Proagro Mais*. It is noteworthy that all the results rejected the proposed hypothesis.

Table 7 – Matching quality indicators before and after matching

Matching method	LR χ^2 before matching	LR χ^2 after matching	p > χ^2 before matching	p > χ^2 after matching	Mean bias before matching	Mean bias after matching
NNM	3,161.40	41.02	0.000	0.000	18.7	2.2
Radius caliper matching	3,161.40	36.70	0.000	0.007	18.70	2.0
Kernel matching	3,161.08	27.75	0.000	0.001	18.7	1.9

As demonstrated in Table 7, irrespective of the matching method employed, the average standardized bias difference for all covariates was significantly reduced after matching, from 18.7 to a minimum of 2.2 for NNM, 2.0 for radius caliper, and 1.9 for kernel. This demonstrates that the utilization of propensity score estimators effectively reduced the bias in observable characteristics between the *Proagro Mais* beneficiaries and non-beneficiaries in 2005.

4.2 Results for the method of matching with difference-in-differences ($MMDiD_{LD}$)

The initial phase of the method of matching with difference-in-differences with longitudinal data ($MMDiD_{LD}$) entailed the construction of the balanced panel in 2003, 2004, and 2005, encompassing both the treatment and control groups. Utilizing this sample, we present the descriptive statistics of the model's variables in the baseline year in Table 8. Furthermore, in Table 9, we present the descriptive statistics of the outcome variable in real terms for the baseline and endline.

Table 8 – Descriptive statistics for variables included in the $MMDiD_{LD}$ (baseline)

Variables	Mean	Standard Deviation
Beneficiaries (N = 410)		
EY	1.99	1.14
ED	7	2.60
AA	0.08	0.28
TP	20.09	1.12
PCP	3.67	0.45
MY	5.08	1.25
MC	1,472.09	1,038.49
HVA	0.43	0.20

Table 8 – Continued...

Variables	Mean	Standard Deviation
Control Smallholders (N = 2,135)		
EY	2.00	1.65
ED	6.99	2.79
AA	0.05	0.22
TP	21.17	0.91
PCP	3.97	0.41
MY	4.52	1.02
MC	1,233.68	854.16
HVA	0.61	0.24

Table 9 – Mean and standard deviation of *credit_per_hectare_05* for the treatment and control groups in the $MMDiD_{LD}$ (baseline and endline)

Group	Year	Mean (BRL)	Standard Deviation (BRL)	Number
Treatment	2003	70.55	34.83	410
Control	2003	78.11	29.36	2,135
Treatment	2005	78.36	29.37	410
Control	2005	80.52	33.77	2,135

Following the generation of the 2003 and 2005 panels, an estimation of the PSM for the baseline was conducted using a logit model, resulting in the scores (Table 10)[9]. It is noteworthy that *NF* was not used in the PSM, as this variable lacks data in the baseline year[10].

Table 10 – Logit results, MMDiDLD with NNM (baseline)

Variables	Coefficient	Standard Error	*Z* value
EY	-0.24	0.04	-5.28***
ED	0.03	0.02	1.20
AA	0.12	0.23	0.52
TP	-0.89	0.07	-12.63***
PCP	-0.33	0.16	-2.06**
MY	-0.34	0.07	-4.70***
MC	-0.0002	0.00007	-2.73***
HVA	-3.27	0.40	-8.10***
constant	21.79	1.46	14.90***
Treatment variable: *PM*			
Number of observations: 2,545			
χ^2= 462.53			
$p > \chi^2 = 0.0000$			
Pseudo $R^2 = 0.21$			

* p<0.10; ** p<0.05; *** p<0.01

The results indicate that two variables exhibit p values that do not reject the null hypothesis. However, when considered collectively, the vector of probabilities or propensity score generated from the logit model is statistically significant at a level of 1% (χ^2 test).

By employing the vector of probabilities generated with the logit model and applying the NNM criterion, we were able to ascertain the counterfactual outcome for the 2003 treatment group. As a result of the matching procedure, one observation was excluded ("off support"), reducing the size of the new treatment group sample to 409 individuals. The 2003 NNM

9 A probit model was tested; however, the PSM exhibited a better quality of fit with the logit model.

10 The variable *NF* is only presented in the 2006 Brazilian Agricultural Census (Instituto Brasileiro de Geografia e Estatística, 2021). Therefore, its use in this study was restricted to estimated scores for the endline period (2005), as this was the year closest to the census data.

balancing test results indicate that the majority of variables do not reject the *t*-test null hypothesis of equal means. Additionally, the results demonstrate a reduction in bias between the means of control and treatment groups following the implementation of the treatment, as illustrated in Table 11.

Table 11 – NNM balancing test

Individual Test							
Variable	Sample	Mean		% bias	% reduction in bias	*t*-test	
		Treatment	Control			*t* value	*p* > t
EY	Unmatched	1.99	2.01	-1.3	-1,337.4	-0.22	0.828
	Matched	1.99	2.26	-18.8		-2.53	0.011
ED	Unmatched	7.00	6.99	-0.0	-12,458.8	-0.01	0.993
	Matched	7.00	7.15	-5.8		-0.81	0.418
AA	Unmatched	0.08	0.05	12.6	14.9	2.54	0.011
	Matched	0.08	0.11	-10.7		-1.30	0.193
TP	Unmatched	20.09	21.17	-105.3	96.0	-21.08	0.000
	Matched	20.09	20.14	-4.2		-0.54	0.588
PCP	Unmatched	3.67	3.97	-69.5	99.9	-13.33	0.000
	Matched	3.67	3.67	0.0		0.01	0.995
MY	Unmatched	5.09	4.52	49.8	77.6	9.91	0.000
	Matched	5.09	5.21	-11.1		-1.45	0.147
MC	Unmatched	1,474.6	1,233.7	25.3	86.4	5.04	0.000
	Matched	1,474.6	1,441.8	3.4		0.44	0.663
HVA	Unmatched	0.43	0.61	-79.3	89.5	-13.98	0.000
	Matched	0.43	0.41	8.4		1.25	0.210

Model test			
Sample	χ^2	$p > \chi^2$	Mean bias
Unmatched	458.62	0.000	42.9
Matched	13.29	0.102	7.8

Following the acquisition of the 2003 control group sample, a new balanced panel was constructed, comprising 409 observations in each group and year (yielding a total of 1,636. individuals) . This new database serves as a basis for estimating MMDiD_{LD} ATET (via Equation 6), with the resulting data presented in Table 12.

Table 12 – MMDiD_{LD} ATET (BRL) using NNM

Variable	Coefficient	Standard Error	*t* value
Constant	80.00	2.03	39.47***
PM	-9.45	2.87	-3.29***
YR	10.69	2.87	3.73***
ATET	-2.92	4.05	-0.72
N = 1,636	*p* > F= 0.000	Adjusted R^2 = 0.0280	
Dependent variable: *credit_per_hectare_05*			

* *p*<0.10; ** *p*<0.05; *** *p*<0.01

Using as outcome *credit_per_hectare_05*, and similar to PSM results presented in Table 6, the MMDiD_{LD} ATET is negative, but in this case, it is not statistically significant.

To test the reliability of these findings, we employed caliper and kernel matching algorithms to estimate the MMDiD_{LD}. These results are presented in Table 13.

The ATET with caliper and kernel matching results demonstrate an inverse relationship with the NNM ATET; however, their magnitudes remain insignificant when compared with *credit_per_hectare_05* mean. Additionally, both results lack statistical significance.

Table 13 – MMDiD$_{LD}$ ATET (BRL) using caliper and kernel matching

Variable	Coefficient	Standard Error	*t* value	N
ATET with caliper matching	1.42	4.29	0.33	1,460
ATET with kernel matching	0,49	9.02	0.05	532
Dependent variable: *credit_per_hectare_05*				

* *p*<0.10; ** *p*<0.05; *** *p*<0.01

5 Discussion

This section presents a discussion of the results of the study, with particular attention to their statistical implications and a comparison with findings from the theoretical framework and literature review. Additionally, the section examines the empirical implications of the results for market practices and public policy.

The descriptive statistics of the variables in the first econometric model – PSM – presented in the Results chapter (Table 3) indicate that, on average in the endline, there is a lower propensity for credit among those who were beneficiaries of *Proagro Mais* (treatment group) compared to the non-beneficiaries (control group). This circumstance may be interpreted in a number of ways. The lower average credit per hectare of the treatment group may be indicative of a risk-averse characteristic among these small producers, despite the support of *Proagro Mais*. Alternatively, it could be linked to a potential sample selection bias (Heckman, 1990), a phenomenon that could be refuted when analyzing the dispersion data of the impact variable (using the standard deviation). The standard deviation results in *credit_per_hectare_05* indicate a greater dispersion in the control group relative to the treatment group. This implies the existence of a significant subset of smallholders who took out loans with values close to (and in some cases, lower than) the mean value of loans taken out by smallholders in the treatment group.

Given the econometric findings, the results of the ATET were statistically significant only in the PMS model (Table 6). Nevertheless, these results, which refute the proposed hypothesis, account for a mere 3.3% of the mean credit per hectare in 2005 and 10.6% of the standard deviation for the beneficiary group. This indicates that *Proagro Mais* had a limited negative impact, which does not support the claim that the results for credit per hectare of the non-treated group are superior to those of the treated group following a decline in corn production yield. Overall, these findings suggest that, during its initial years, *Proagro Mais* did not achieve the intended effect on the economic recovery of its beneficiaries, as measured by credit acquisition.

With regard to the state of the art, this study makes a contribution to the existing literature that analyzes the economic impacts of crop insurance programs on their beneficiaries. This is a particularly relevant topic, given the dearth of research focusing on the impact evaluation of the amount of rural credit. This body of literature includes studies by DeLay et al. (2023), Tsiboe & Turner (2023), Mishra et al. (2021), Cariappa et al. (2020), Cai (2016), Cole et al. (2013), Varadan & Kumar (2012), Winters et al. (2010), and Giné & Yang (2009). Notably, Winters et al. (2010) is one of the few evaluations of crop insurance impacts that focuses on a Latin American case study. Our findings diverge from those of DeLay et al. (2023), Tsiboe & Turner (2023), Mishra et al. (2021), and Cai (2016), while aligning more closely with the conclusions of Cariappa et al. (2020) and Giné & Yang (2009).

It is crucial to underscore the distinctive characteristics of the aforementioned studies, as these may elucidate the similarities or discrepancies in their findings when juxtaposed against those of the present investigation. The data employed by DeLay et al. (2023) and Tsiboe &

Turner (2023) is derived from the Federal Crop Insurance Program (FCIC)[11] in the United States. In contrast to *Proagro Mais,* which is a fully public initiative, this program operates through a public-private partnership. In this model, the government subsidizes the premiums that producers pay for their policies, while private companies provide the insurance. Consequently, the crop insurance evaluation studies conducted by these authors reflect mechanisms more similar to the Rural Insurance Premium Subsidy Program (*Programa de Subvenção ao Premio do Seguro Rural* – PSR – in Portuguese)[12], which highlight significant operational and market differences from *Proagro Mais* that could affect a comparative analysis of results.

As with the studies by DeLay et al. (2023) and Tsiboe & Turner (2023), Mishra et al. (2021) conducted research in which the insurance company was privately held. However, the study was limited by a small sample size of producers and focused on gathering primary data, similar to the approach taken by Giné & Yang (2009). This approach differs from the larger and more diverse sample used in the current research. Furthermore, despite the challenges associated with field research, Winters et al. (2010) also based their study on a private entity providing agricultural insurance, employing a controlled and relatively small sample of farmers. This differs significantly from the extensive sample used to evaluate *Proagro Mais*.

In contrast, studies by Cai (2016) and Cariappa et al. (2020) are more methodologically and informationally aligned with the current case study. The research conducted by Cai (2016) is centered on the People's Insurance Company of China (PICC), a public entity. However, it employs a longer analysis period of eight years, in contrast to the three years covered in the present study. Conversely, Cariappa et al. (2020) employed a considerably larger sample of 35,200 smallholders and discovered no impact on the uptake of agricultural insurance. This outcome was attributed to the type of coverage offered, which does not include price risk like *Proagro Mais*. This limitation may result in a small percentage of farmers receiving compensation through this mechanism.

Therefore, beyond the empirical and public policy aspects related to *Proagro Mais* (which will be examined in subsequent paragraphs), comparing the effects of this program with other crop insurance programs presents a significant challenge. This is due to the considerable heterogeneity in agricultural insurance programs, which vary considerably in terms of their underlying mechanisms, the institutions involved, the sample sizes, and even the period over which they are analyzed.

Once the results of this study have been analyzed comparatively with the works cited in the literature review, we proceed to discuss them in light of the theoretical findings by Ifft et al. (2019), Ben-Yashar et al. (2018), Cai (2016), and Hazell et al. (2017) regarding the relationship between crop insurance and agricultural credit.

The findings of this study challenge the theoretical proposal of Equation 1, which underscores the significance of a government-backed repayment mechanism to facilitate enhanced credit flow in the aftermath of the failure of an agricultural project. This is due to the fact that it enables the utilization of subsidized government insurance to settle outstanding productive debts. Similarly, the findings are not in accordance with the theoretical model and empirical conclusions presented by Cai (2016). Specifically, the adoption of the public agricultural insurance *Proagro Mais* does not appear to influence the growth of agricultural credit acquired.

The empirical implications of the results prompt a discussion of the effectiveness of the program as a fundamental tool for the economic development of smallholders, which can

[11] For more references on federal crop insurance programs, see: i) Congressional Research Service (2021); ii) U.S. Department of Agriculture (2023).

[12] For more references, see: Brasil (2022).

be explained in several ways. One of the primary factors is the potential for legislation to be enacted by the National Congress that would permit rural producers to renegotiate debts over extended periods. The possibility of renegotiating debts can be seen as a competitive instrument insofar as rural producers may choose not to take out insurance, such as *Proagro Mais*, to protect themselves against adverse weather conditions. In the event of a crop failure due to such events, renegotiating the debts may be a plausible solution.

To elucidate this point, it is essential to examine the Brazilian rural debt renegotiation in the context of the study, which is associated with the outcome variable (credit per hectare) of the research. As Távora (2014) notes, three laws represent this policy between 2003 and 2005: Law 10,696 of July 2 2003; Law 10,823 of December 22, 2003; and Law 11,011 of December 20, 2004. The first of these laws extended the period of the rural credit payment to ten years, with a two-year grace period and a rebate of 8.8% on the outstanding balance. The second law extended the deadline for the renegotiation of rural debts until May 31, 2004. With respect to the last mentioned law, the risk of loans granted with resources from the Constitutional Fund Financing to *Pronaf* beneficiaries from July 1, 2004, should have been fully assumed by its respective Constitutional Fund.

Another factor that serves to reinforce the aforementioned results pertains to the coverage mechanism of *Proagro Mais*. This program is designed to cover exclusively production losses, which may inadvertently exclude a subset of smallholders who encounter economic setbacks due to price fluctuations in agricultural commodities. Given the historical trend of the average spot price for a 60-kilogram bag of corn in the state of Paraná, a 32.95% decrease in the average price was observed between December 2003 and December 2005 (Universidade de São Paulo, 2016)[13]. It is thus probable that the crops of the smallholders discussed in this study were affected by both variations in production and shifts in product price.

The results of this study, regardless of the reasons that could support them, highlight certain characteristics of *Proagro Mais* that warrant attention and could stimulate a discussion about its significance as a public instrument for agricultural risk management. Firstly, *Proagro Mais* is a security instrument designed for financial agents. In the event of default, the Federal Government provides a guarantee of payment for the rural credit contracted by the rural producer with the financial institution. In other words, the ultimate beneficiary is the financial institution itself. In the event of crop loss, which would subsequently affect the ability to repay debt, the National Treasury assumes the financial responsibility for the loss. As a consequence of this operational model, the *Proagro Mais* bills increased significantly in 2022 and 2023, exceeding the budgetary allocations for the program. In 2023, the budgeted amount was R$2.7 billion (approximately USD 541 million), yet expenses reached R$9.4 billion (approximately USD 1.88 billion), indicating a significant deficiency in fiscal control (Agrometrópole, 2024).

A further significant issue is the apparent conflict of interest inherent to the program. The financial institution itself is responsible for reporting the claim and overseeing field inspections, while also receiving compensation. The lack of transparency in the surveys conducted by the experts is also a source of contention and has already been highlighted in a report produced by the TCU.

Finally, the Brazilian Federal Government is taking action to address some of these issues. One potential solution would be to gradually replace *Proagro Mais* with private insurance instruments, which are more efficient and less susceptible to operational fraud. Private insurance companies have accumulated extensive experience and expertise over many years in a range of areas, including field inspections, risk assessment, and the selection of these risks

[13] Real values for December 2010 using the IGP-DI price index (Brasil, 2016).

for insurance purposes. Insurers have more modern and rigorous procedures to address the weaknesses found in *Proagro Mais*, including more sophisticated pricing methods aligned with current methodologies and the use of geotechnology and climate information to monitor insured risks. Another advantage is that the insurance company itself bears the burden of paying indemnities, rather than the Federal Government, thereby greatly reducing the conflict of interest of financial institutions and relieving the government of this type of expense.

6 Conclusions

This research offers an overview of the significance of Brazil's public crop insurance program, *Proagro Mais*, which represents the first analysis of this agricultural risk management tool based on its impact on beneficiaries. Specifically, the study employs propensity score matching (PSM) and method of matching with difference-in-differences (MMDiD) estimators to assess the program's effects on a sample of corn producers in the state of Paraná, focusing on credit per hectare as the key impact variable. The analysis establishes 2003, the year prior to the launch od the program, as the baseline, while 2005, a year marked by a significant decline in corn yields in Paraná, serves as the endline for evaluating impact.

This study makes a significant contribution to the existing literature on the impact evaluation of agricultural insurance. It offers a valuable perspective as one of the few analyses focused on Latin American cases, particularly given its nature as a public mechanism and its significant scale. Additionally, the research explores a critical relationship in agricultural risk management: the interplay between credit financing for production and the procurement of insurance. By analyzing this relationship from a theoretical perspective, the study enhances the understanding of how these factors work together to promote agricultural resilience.

The results indicate a rejection of the null hypothesis, suggesting that, during the analysis period, *Proagro Mais* was ineffective as a compensation mechanism for losses in corn production among smallholders in Paraná. These findings diverge from, or align with, results from other similar studies, and suggest that the program may have been insufficient to address all the agricultural risks faced by small corn farmers in the region during the period analyzed from 2003 to 2005.

Furthermore, these findings provide valuable insights for future discussions regarding the role of the Brazilian government and its public policies in agricultural risk management. It is essential to consider the budgetary implications of investing in *Proagro Mais*, the limitations of its coverage with respect to both production and price risks, and the potential for strengthening public-private partnership models, such as the Rural Insurance Premium (PSR). These insights contribute to a deeper understanding of how state-generated instruments can enhance the sustainability of Brazilian agricultural production within a virtuous economic cycle.

Building on the preceding findings, this study identifies several potential avenues for future research regarding the relevance of *Proagro Mais* and its role in agricultural risk management in Brazil. Given its current compulsory nature, a quasi-experimental evaluation may not be feasible; however, various alternative methodological approaches can be explored. These may include primary data collection, cross-referencing databases from other public programs, and gathering qualitative insights based on expert assessments.

Moreover, researchers could examine the evolution of *Proagro Mais* in relation to the coverage provided by private insurers, as well as the government's interventions through models like the PSR. This comprehensive approach could provide valuable insights into the effectiveness and impact of *Proagro Mais* within the broader agricultural landscape in Brazil.

References

Aerts, K., & Schmidt, T. (2008). Two for the price of one? Additionality effects of R&D subsidies: a comparison between Flanders and Germany. *Research Policy*, *37*(5), 806-822. http://doi.org/10.1016/j.respol.2008.01.011

Agrometrópole. (2024). *Gastos com Proagro disparam, e governo e BC estudam mudanças.* Retrieved in 2015, March 12, from https://www.agrometropole.com.br/2024/02/03/gastos-com-proagro-disparam-e-governo-e-bc-estudam-mudancas/

Arias, D., Mendes, P., & Abel, P. (2015). *Revisão rápida e integrada da gestão de riscos agropecuários no Brasil: caminhos para uma visão integrada*. Brasília: Banco Mundial.

Athey, S., & Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, *74*(2), 431-497. http://doi.org/10.1111/j.1468-0262.2006.00668.x

Ben-Yashar, R., Krausz, M., & Nitzan, S. (2018). Government loan guarantees and the credit decision-making structure. *The Canadian Journal of Economics*, *51*(2), 607-625. http://doi.org/10.1111/caje.12332

Blundell, R., & Costa Dias, M. (2000). Evaluation methods for non-experimental data. *Fiscal Studies*, *21*(4), 427-468. http://doi.org/10.1111/j.1475-5890.2000.tb00031.x

Brasil. Banco Central do Brasil – BACEN. (2004). Resolução n° 3,234 de 31 agosto de 2004. Altera disposições do Proagro, constituindo no seu âmbito o "Proagro Mais", para atender aos pequenos produtores vinculados ao Pronaf. Retrieved in 2016, January 18, from https://www.bcb.gov.br/pre/normativos/busca/downloadNormativo.asp?arquivo=/Lists/Normativos/Attachments/46344/Res_3234_v1_O.pdf

Brasil. Banco Central do Brasil – BACEN. (2012). Resolução n° 4,107 de 28 de junho de 28, 2012. Altera as disposições do Programa Nacional de Fortalecimento da Agricultura Familiar (Pronaf), de que trate o Capítulo 10 do Manual de Crédito Rural (MCR), para aplicação a partir da safra 2012/2013. Retrieved in 2016, February 8, from https://www.bcb.gov.br/htms/normativ/RESOLUCAO4107.pdf

Brasil. Banco Central do Brasil – BACEN. (2014). Resolução n° 4,375 de 30 de setembro de 2014. Altera o Manual de Crédito Rural (MCR) com a finalidade de estabelecer, a partir de 1° de janeiro de 2015, novas condições para o Programa de Garantia da Atividade Agropecuária da Agricultura Familiar (Proagro Mais). Retrieved in 2016, April 20, from https://www.bcb.gov.br/htms/normativ/resolucao4375.pdf

Brasil. Banco Central do Brasil – BACEN. (2015a). *Anuário estatístico de crédito rural.* Retrieved in 2015, July 10, from http://www.bcb.gov.br/?RELRURAL

Brasil. (2015b). *Agritempo: sistema de monitoramento agrometeorológico.* Retrieved in 2015, February 9, from http://www.agritempo.gov.br/agritempo/produtos.jsp?siglaUF=PR

Brasil. Ipeadata. (2016). *Exchange rates.* Retrieved in 2016, May 27, from http://www.ipeadata.gov.br

Brasil. Banco Central do Brasil – BACEN. (2018a). *Manual de crédito rural.* Retrieved in 2018, June 20, from Retrieve from http://www3.bcb.gov.br/mcr

Brasil. Banco Central do Brasil – BACEN. (2018b). *Programa de Garantia da Atividade Agropecuária (PROAGRO): relatório circunstanciado 1999 a 2010.* Retrieved in 2018, July 2, from https://www.bcb.gov.br/htms/proagro/PROAGRO_Relatorio_Circunstanciado_1999-2010.pdf

Brasil. Banco Central do Brasil – BACEN. (2018c). *Programa de Garantia de Atividade Agropecuária (PROAGRO): relatório circunstanciado 2004 a 2012.* Retrieved in 2018, July 2, from https://www.bcb.gov.br/htms/proagro/PROAGRO-RelatorioCircunstanciado2004a2012.pdf

Brasil. Banco Central do Brasil – BACEN. (2018d). *Programa de Garantia de Atividade Agropecuária (PROAGRO): relatório circunstanciado 2011 a 2014.* Retrieved in 2018, July 3, from https://www.bcb.gov.br/htms/proagro/PROAGRO-RelatorioCircunstanciado2011a2014.pdf

Brasil. Banco Central do Brasil – BACEN. (2018e). *Programa de Garantia de Atividade Agropecuária (PROAGRO): relatório circunstanciado 2012 a 2015.* Retrieved in 2018, July 3, from https://www.bcb.gov.br/htms/proagro/PROAGRO-relatorioCircunstanciado2012a2015.pdf

Brasil. Ministério da Agricultura, Pecuária e Abastacimento – MDA. (2019). *Garantia-Safra Benefício condicionado da Agricultura Familiar.* Retrieved in 2023, June 28, from https://www.gov.br/agricultura/pt-br/assuntos/mda/garantia-safra/arquivos/dados-consolidados.pdf

Brasil. (2022). *Programa de Seguro Rural.* Retrieved in 2023, June 28, from https://www.gov.br/agricultura/pt-br/assuntos/riscos-seguro/seguro-rural

Brasil. Banco Central do Brasil – BACEN. (2023). *Matriz de dados do Proagro.* Retrieved in 2023, June 28, from https://www.bcb.gov.br/estabilidadefinanceira/proagro

Cai, J. (2016). The impact of insurance provision on household production and financial decisions. *American Economic Journal. Economic Policy*, *8*(2), 44-88. http://doi.org/10.1257/pol.20130371

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31-72. http://doi.org/10.1111/j.1467-6419.2007.00527.x

Cariappa, A. A., Mahida, D. P., Lal, P., & Chandel, B. S. (2020). Correlates and impact of crop insurance in India: evidence from a nationally representative survey. *Agricultural Finance Review*, *81*(2), 204-221. http://doi.org/10.1108/AFR-03-2020-0034

Cochran, W. (1977). *Sampling techniques* (3rd ed.). New York: John Wiley & Sons.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to household risk management: evidence from India. *American Economic Journal. Applied Economics*, *5*(1), 104-135. http://doi.org/10.1257/app.5.1.104

Congressional Research Service – CRS. (2021). *Federal crop insurance: a primer.* Retrieved in 2023, June 28, from https://sgp.fas.org/crs/misc/R46686.pdf

DeLay, N. D., Brewer, B., Featherstone, A., & Boussios, D. (2023). The impact of crop insurance on farm financial outcomes. *Applied Economic Perspectives and Policy*, *45*(1), 579-601. http://doi.org/10.1002/aepp.13223

Food and Agriculture Organization of the United Nations – FAO. (2023). *FAOSTAT statistics database.* Retrieved in 2023, June 27, from https://www.fao.org/faostat/en/#data/QCL

Franco, A., Marques, O., & Vidigal Filho, P. (2015). Sistemas de produção do milho safrinha no Paraná. In *Anais do Seminário de Milho Safrinha.* Retrieved in 2015, March 12, from http://www.cpao.embrapa.br/cds/milhosafrinha2013/palestras/13PEDROSOARESVIDIGALFILHO.pdf

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. (2016). *Impact evaluation in practice.* Washington, D.C.: World Bank Group.

Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: field experimental evidencefrom Malawi. *Journal of Development Economics*, *89*(1), 1-11. http://doi.org/10.1016/j.jdeveco.2008.09.007

Hazell, P., Meyer, R., & Varangis, P. (2017). *Unlocking smallholder credit: does credit-linked agricultural insurance work?* Washington, D.C.: World Bank Group.

Heckman, J. J. (1990). Selection bias and self-selection. In J. Eatwell, M. Milgate & P. Newman (Eds.), *Econometrics* (pp. 201-224). London: Palgrave Macmillan.

Heinrich, C., Maffioli, A., & Vazquez, G. (2010). *A primer for applying propensity-score matching.* Washington, D.C.: Inter-American Development Bank.

Ifft, J., Kuethe, T., & Schultz, A. (2019). Crop insurance's impact on agricultural lenders. In *2019 Agricultural & Applied Economics Association Annual Meeting*, Atlanta, GA.

Instituto Brasileiro de Geografia e Estatística – IBGE. (2021). *Censo agropecuário.* Retrieved in 2021, January 14, from https://www.ibge.gov.br/estatisticas/economicas/agricultura-e-pecuaria/9827-censo-agropecuario.html?=&t=o-que-e

Instituto Brasileiro de Geografia e Estatística – IBGE. (2023). *Produção agrícola municipal.* Retrieved in 2023, June 27, from https://sidra.ibge.gov.br/tabela/1612

Iturrioz, R., & Arias, D. (2010). *Agricultural insurance in Latin America: developing the market.* Washington, D.C.: World Bank Group. Retrieved in 2021, January 14, from http://documents.worldbank.org/curated/en/179701468277786453/Agricultural-insurance-in-Latin-America-developing-the-market

Khandker, S. B., Koolwal, G., & Samad, H. (2010). *Handbook on impact evaluation: quantitative methods and practices.* Washington, D.C.: World Bank Group.

López, F., & Maffioli, A. (2008). *Technology adoption, productivity and specialization of Uruguayan breeders: evidence from an impact evaluation.* Washington, D.C.: Inter-American Development Bank.

Mishra, K., Gallenstein, R. A., Miranda, M. J., Sam, A. G., Toledo, P., & Mulangu, F. (2021). Insured loans and credit access: evidence from a randomized field experiment in northern Ghana. *American Journal of Agricultural Economics*, *103*(3), 923-943. http://doi.org/10.1111/ajae.12136

Priscilla, L., & Chauhan, A. K. (2019). Economic impact of cooperative membership on dairy farmers in Manipur: a propensity score matching approach. *Agricultural Economics Research Review*, *32*(1), 117-123. http://doi.org/10.5958/0974-0279.2019.00010.7

Raviv, A. (1979). The design of an optimal insurance policy. *The American Economic Review*, *69*(1), 84-96.

Sanglestsawai, S., Rejesus, R. M., & Yorobe Junior, J. M. (2015). Economic impacts of integrated pest management (IPM) farmer field schools (FFS): evidence from onion farmers in the Philippines. *Agricultural Economics*, *46*(2), 149-162. http://doi.org/10.1111/agec.12147

Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, *125*(1-2), 305-353. http://doi.org/10.1016/j.jeconom.2004.04.011

Spörri, M., Baráth, L., Bokusheva, R., & Fertö, I. (2012, February). The impact of crop insurance on the economic performance of Hungarian cropping farms. In *123rd EAAE Seminar 'Price Volatility and Farm Income Stabilisation. Modelling Outcomes and Assessing Market and Policy Based Responses'* (pp. 23-24), Dublin.

Távora, F. L. (2014). *Renegociação de dívida rural: reflexões sobre o financiamento da agricultura brasileira.* Brasília: Senado Federal.

Tsiboe, F., & Turner, D. (2023). Econometric identification of crop insurance participation. *Agricultural and Resource Economics Review*, *52*(3), 476-497. http://doi.org/10.1017/age.2023.13

Universidade de São Paulo – USP. Centro de Estudos Avançados em Economia Aplicada – CEPEA. (2016). *Indicador de preços do milho ESALQ/BMFBovespa.* Retrieved in 2016, January 5, from http://cepea.esalq.usp.br/milho/

Universidade de São Paulo – USP. Centro de Estudos Avançados em Economia Aplicada – CEPEA. (2023). *PIB do agronegócio brasileiro.* Retrieved in 2023, June 27, from https://www.cepea.esalq.usp.br/br/pib-do-agronegocio-brasileiro.aspx

U.S. Department of Agriculture – USDA. (2023). Retrieved in 2023, June 27, from https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance/

Varadan, R. J., & Kumar, P. (2012). Impact of crop insurance on rice farming in Tamil Nadu. *Agricultural Economics Research Review*, *25*(2), 291-298.

Winters, P., Salazar, L., & Maffioli, A. (2010). *Designing impact evaluations for agricultural projects.* Washington, D.C.: Inter-American Development Bank.

Received: July 22, 2022
Accepted: September 26, 2024
JEL Classification: Q12; Q14; G22