No-Tillage System adoption and Brazilian forest areas: What can a Propensity Score Matching Analysis tell us?*

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Abstract
The agrotechnology adoption has direct effects on the management of land use. This article analyzes the relationship between the adoption of the No-Tillage System (NTS) and its effects on land use in Brazil, with special attention to its impacts on forest areas. For that, the Propensity Score Matching method (PSM) was used. Our econometric results shows that the NTS adoption had a negative effect on forest area of the treated municipalities. We argue that, the high productivity and consequent profitability generated by NTS, has a direct influence on the farmer's land use decision. The possibility of greater profit encourages the expansion of the agricultural frontier, thus promoting the degradation of natural areas.
Keywords: No-Tillage System, Forest Areas, Propensity Score Matching

Resumo
A adoção de agrotecnologias tem efeitos diretos sobre o gerenciamento do uso da terra. Este artigo analisa a relação entre a adoção do Sistema de Plantio Direto (SPD) e seus efeitos sobre o uso da terra no Brasil, dando atenção especial aos impactos sobre as áreas de floresta. Para tanto, foi utilizado o método de Propensity Score Matching (PSM). Nossos resultados econométricos mostram que a adoção de SPD teve um efeito negativo sobre a área de floresta de municípios tratados. Argumentamos que, a alta produtividade e consequente lucratividade gerada pelo SPD, influencia diretamente a decisão de uso da terra por parte do agricultor. A possibilidade de maior lucro estimula a expansão da fronteira agrícola, promovendo a degradação das áreas naturais.
Palavras-chave: Sistema de Plantio Direto, Áreas Florestais, Propensity Score Matching

JEL code: Q15, Q55

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1. Introduction

Brazil figures as the largest producer of agricultural goods in the world. According to data from the National Food Supply Company (Conab) in 1980 the production was 50.8 Mton, reached 123.1 Mton in 2000 and 237.6 Mton in 2017. Another information that shows the trajectory of expansion of Brazilian agriculture is the values of planted area. Also according to data from Conab, in 1980 40.1 Mha of land were used and about 60.8 Mha in 2017. Much of this production serves the foreign market. The sector stands out in the national accounts, with the agricultural trade balance in 2018 totaling 81.6 billion dollars, while the total balance was 50.9 billion, according to the World Trade Organization (WTO). Sugar, soy, corn, orange juice, coffee, cotton, pork, poultry and cattle are the main products exported. In addition to the natural advantages (availability of agricultural land, water and adequate climatic conditions), the use of agricultural technology in the form of products and practicals more efficient, explain the increase in production and productivity in Brazilian agriculture. The synergy created from the 1970s, which involves the participation of the Brazilian Agricultural Research Corporation (Embrapa), research centers at universities and farmers, is at the center of this process (Suzigan & Albuquerque, 2011).

The adoption of technology and the consequent economic-productive advancement of agriculture has direct effects on the management of land use. The recovery of previously non-agricultural soils, the possibility of switching to more profitable crops (e.g. soybeans, corn) are examples of agricultural technology acting on space. But, certainly, the relationship between agriculture and forest areas is the most worrying point, in view (i) of the greater need to retain Greenhouse Gases (GHG), directly related to global climate change (Miles & Kapos, 2008; Reay, et al. 2012; Schmitz, et al. 2012; Havlík, et al. 2013; Lamb, et al. 2016; Mayer, et al. 2018); (ii) avoid changes in hydrological cycles (Pielke Sr, et al. 2007; Sterling, et al. 2013; Bagley, et al. 2014) and (iii) the preservation of the biodiversity present in natural areas (Reidsma, et al. 2006; Oliver & Morecroft, 2014; Kehoe, et al. 2017; Marques, et al. 2019; Fastré, et al. 2020).

In this way it is possible to establish a link between technology adoption and forest areas. Thus, in addition to increases in productivity, agricultural technology used should target the sustainability.

The concept of agricultural technology must be understood as the application of knowledge, science and engineering in agricultural and animal production systems (Zilberman, et al. 2014). This term can represent the adoption of simple and widely spread products and techniques in the field such as, use of tractors, harvesters, irrigation pivots, planting systems (conventional, NTS, etc.), fertilizer and pesticide use, and more complex and less widespread techniques such as GPS monitoring, genetic engineering, biotechnology and nanotechnology (Rocha, et al. 2020).

Certainly each of them establishes a type of relationship with land use management. This article is limited to analyzing the relationship between the adoption of the No-Tillage System (NTS) and its effects on land use in Brazil, with special attention to its impacts on forest areas.

NTS is a form of soil management that involves techniques recommended to increase agricultural productivity. The main techniques used in the NTS are: minimal soil turning, soil cover with straw and crop rotation. In NTS, straw and residues from other crops are kept on the soil surface, ensuring coverage and protection against harmful processes, such as erosion. The soil is manipulated only at the time of planting, when furrows are opened where seeds and fertilizers are deposited. The most important control in this cultivation mode is that of weeds through integrated pest management. Finally, for the success of the system, crop rotation is necessary.

According to the 2017 Brazilian Agricultural Census available by the Brazilian Institute of Geography and Statistics (IBGE), NTS is adopted by about 19% of farmers. At around 45%, traditional cultivation is still the most used. Higher productivity, the "less environmental impact" label and the incentive of government agricultural agencies (Ministry of Agriculture, State Agricultural Institutes, etc.), drives the expansion of NTS adoption in Brazil.

Soil erosion and the consequent loss of productivity and increased costs are the main motivations for farmers to adopt NTS. However, the practice of NTS was included in the Sectoral Plan for Mitigation and Adaptation to Climate Change for the consolidation of a Low-carbon Economy in Agriculture (ABC Plan)[1]. This plan is an important part of the commitment to reduce GHG emissions, undertaken by Brazil at the 15th Conference of the Parties (COP15), held in 2009. The relationship between the adoption of NTS and the reduction of GHG must (i) its ability to retain carbon dioxide in the soil (via straw remaining in the soil); (ii) less use of agricultural machinery and (iii) less use of fertilizers and pesticides (via crop rotation).

However, there is a possibility of a reverse effect. The adoption of NTS can lead to increases in productivity and profitability for the farmer. The consequence of this economic incentive can be seen in the form of land use. In other words, the adoption of NTS can indirectly lead to advances in agriculture over forest areas, thus undermining possible environmental gains from the technique. This article opens that discussion.

The question that guides this study is:

- What is the impact of adopting the NTS on the Brazilian forest areas?

In addition to this introductory section, this article is divided as follows. The second describes the theoretical model, empirical implementation and database. The third presents the results.

[1]More details about the ABC Plan are available at Brazilian Ministry of Agriculture (2016).

Finally, The fourth section concludes.

2. Method

2.1. Economic land-use model

Following Rocha et al. (2020), the land use model is derived from the problem of profit maximization of the farmer. The production function for each land use category is described as:

$$g_j = F_j(y_j, TechAdoption, X), \quad j = 1, 2, ..., J \tag{1}$$

where j is the land use category, g_j is the product of the origin of land type j, y_j is the area of land use j, $TechAdoption_i$ are the technological components (products and practices) used in for production of g_j, and X are other control variables.

The profit function (Π_j) associated with production for each category of land use is given by:

$$\Pi_j = \sum_{j=1}^{J} p_{gj} y_j - \sum_{j=1}^{J} p_{Fj} F_j = \Pi_j(p_{gj}, p_{Fj}, F_j) \tag{2}$$

where p_{gj} and p_{Fj} represent the price of the good produced in land type j and the price of the inputs, respectively. As a hypothesis, we consider that the relative prices between regions are effectively determined by technological condition ($TechAdoption$) and other control variables (X). We therefore disregard the presence of relative prices in our modeling, since price is an endogenous argument, for example, the technology variable. In addition, we consider $F =< TechAdoption, X >$. It is possible to write the following problem of profit maximization conditioned to the total amount of land as follows:

$$max_{y_1,y_2,...,y_J}(\sum_{j=1}^{J} \Pi_j(y_j, F_{j(-y_j)})) \qquad s.a. \qquad \sum_{j=1}^{J} y_j = Y \tag{3}$$

The Lagrangian of the optimization problem expressed in (3) is written as follows:

$$\mathcal{L} = \sum_{j=1}^{J} \Pi_j(y_j, F_{j(-y_j)}) + \mu(Y - \sum_{j=1}^{J} y_j) \tag{4}$$

From the first-order conditions extracted from (4), we can derive the optimal land allocations for each use type j, represented by the symbol y_j^*. These optimal areas are determined by the total area of the establishment (Y) and by the vector of explanatory variables (F_j), i.e. $y_j^* = \mathcal{F}(Y, F_j)$.

2.2. Estimation strategy

There are several theoretical reasons we can believe why adopting NTS can affect land use - including forest use. But how can we be sure that forest degradation or conservation compared to non-adopters is caused by the use of NTS? Ideally, using experimental data could provide us with counterfactual information, which would solve the problem of causal inference. This is not our case because we will use observed data (Blundell & Costa Dias, 2000). We must avoid some statistical inference pitfalls in order to isolate the effect of NTS adoption on forest use. This has to do with the more general problem of "self-selection", i.e. when farmers decide to adopt a new technology (in particular, NTS) it will be related to the benefits/losses of this adoption, due to reduction/increase of forest area. In other words, there may be a two-way relationship between NTS and forest conservation/degradation.

In this context, it is difficult to establish the causal effect of agricultural technology, in particular, the use of NTS on forested areas, but at the same time this is necessary if we are to understand better how much NTS can be an instrument of environmental preservation/degradation.

If NTS adoption were randomly assigned among farmers (as in the case of a controlled experiment) we could assess the causal effect of technology adoption on land use as the average difference between adopters and non-adopters. However, with observational data, we need to use some statistical solutions to make a causal inference (Blundell & Costa Dias, 2000; Abadie & Imbens, 2006; Caliendo & Kopeinig, 2008).

In a counterfactual approach, a value of interest is the average treatment effect (ATE) defined by Rosenbaum & Rubin (1983) as:

$$\alpha_{ATE} = E[Y^1 - Y^0] \tag{5}$$

Heckman et al. (1999) notes that, in practice, this estimate may have no relevance, as it includes the effect in the municipalities where the treatment was not intended. Thus, the most important assessment parameter is the average treatment effect on the treaties (ATT), which explicitly focuses on the effects on those for whom the treatment is actually intended. It is given by:

$$\alpha_{ATT} = E[Y^1 - Y^0 | T = 1] \tag{6}$$

where Y^T denotes the municipality's land use pattern (e.g. forest area participation in the municipality) which adopts or not NTS (T=1 or 0). Then, Y^1 and Y^0 denote respectively the forest area participation in municipalities that adopts and does not adopt the NTS technique.

As the counterfactual mean for those being treated – $E[Y^0|T = 1]$ – is not observed, one has to choose a proper substitute for it in order to estimate ATT. Using the mean outcome of untreated municipalities $E[Y^0|T = 0]$ is in nonexperimental studies usually not a good idea, because it is most likely that components which determine the treatment decision also determine the outcome variable of interest (Caliendo & Kopeinig, 2008). Thus, the outcomes of individuals from the treatment and control groups would differ even in the absence of treatment leading to a "selection bias". With a zero-sum operation, we rewrote the ATT as:

$$\alpha_{ATT} = E[Y^1|T = 1] - E[Y^0|T = 1] + E[Y^0|T = 0] - E[Y^0|T = 0] \tag{7}$$

The difference between the $(E[Y^1|T = 1] - E[Y^0|T = 0])$ and α_{ATT} is the so-called "selection bias". The true parameter α_{ATT} is only identified if:

$$E[Y^0|T = 1] - E[Y^0|T = 0] = 0 \tag{8}$$

In experiments where assignment to treatment is random this is ensured and the treatment effect is identified. In observational studies, we must rely on some identifying assumptions to solve the selection problem. That said, we proceed with the description of the Propensity Score Matching (PSM) procedure, that will be used in our estimates of the impact of NTS adoption on land use - especially the forest areas.

The PSM technique originates from the papers by Rosenbaum & Rubin (1983, 1984, 1985a, 1985b). To ensure that the PSM estimators identify and consistently estimate the treat, we assume: (i) unconfoundedness, i.e. assignment to treatment is independent of the outcomes, conditional on the covariates (X) - $(Y^0; Y^1) \perp T|X$. This implies that the selection of NTS adoption is random and is not correlated with the land use pattern, as we control by the vector of observed variables; (ii) commom support condition, i.e. the probability of assignment is bounded away from 0 and 1 - $0 < p(T = 1|X) < 1$. This hypothesis show that, as long as the NTS adoption is random, we can compare the land use pattern (e.g. share of forest area) from similar municipalities with different technological status (i.e. treaties and controls), defining similar municipalities according to the values of X. However, due to the high size of X, the PSM method reduces the dimensionality of the problem by comparing municipalities with the same probability of adopting NTS, given the controls X (Rosenbaum & Rubin, 1983). This conditional probability is the propensity score, which we use to identify "similar" municipalities.

After estimating the propensity score that captures the similarities, we need to use these to match each adopter with the "nearest" non-adopter. There are different methods to do this. In this article we will use the Mahalanobis distance. In it we identify for each municipality the "closest twin" in the opposite technological status, we then calculate an estimate of the technological effect as the average difference in land use pattern (i.e. share of forest area) between each pair of "matched municipalities".

The effect of adopting NTS for municipalities with scores of similar propensity can be written as:

$$\alpha(p(X)) = E[Y^1|T = 1, p(X)] - E[Y^0|T = 0, p(X)] \tag{9}$$

where the average effect of treatment on treaties is described by:

$$\alpha_{ATT}^{PSM} = E[\alpha(p(X))] \tag{10}$$

In other words, the PSM estimator is a difference in the average of outcomes in relation to common support, properly weighted by the distribution of the propensity score. The implementation of PSM models follows the steps described in Caliendo & Kopeinig (2008)[2].

2.3. Database

In order to implement the model proposed above, we now describe the dependent variable, variable of interest and control variables used in our empirical experiment.

Depedent variable (Y)

• *Land use*: three types of land use were considered - forest, cropland and pasture. Percentages of these uses (share) were calculated in relation to the total area. Total area refers to the sum of forest, cropland and pasture. We consider the $ln(1 + Y_i)$ of this variable. The data for 4448 Brazilian municipalities were extracted from the 2017 Agricultural Census provided by the Brazilian Institute of Geography and Statistics (IBGE).

Treated variable (T)

• *NTS adoption:* the adoption of NTS was captured by observing the number of establishments that confirmed using NTS and in relation to the total of area of municipality (variable NTS_i). In addition, we consider the ln of this variable. The data for 4448 Brazilian municipalities were extracted from the 2017 Agricultural Census provided by the Brazilian Institute of Geography and Statistics (IBGE). In the baseline model we consider that the treated municipalities are those that are above national average in terms of NTS adoption ($ln(1 + NTS_i)$), i.e.

[2]The econometric implementation of the main model as well as the robustness tests occurred in the R environment using essentially the "Matching" (Sekhon, 2011) and "rbounds" (Keele, 2010) packages. Codes are available upon request.

$$\text{if } ln(NTS_i) \geq \sum_i^I ln(NTS_i)/I; \text{ is considered treated } (T_i = 1)$$
$$\text{if } ln(NTS_i) \leq \sum_i^I ln(NTS_i)/I; \text{ is considered control } (T_i = 0)$$

where $i \in I$ represents the municipal unit.

We also use other rules for treaty/control classification, with threshold values of 1^{st} and 3^{rd} quartiles. Both will be used to robustness checks. For more details, contact the authors.

Table 1 shows the treated/control sample distribution in the experiments performed. In turn, Figure 1 shows the geographical representation of the treated and controls municipalities considered in the baseline model.

Table 1: Treated and controls in the database

	Treated ($T_i = 1$)	Control ($T_i = 0$)
Baseline model		
$ln(NTS_i) >$ average	1922	2526
Robustness checks		
$ln(NTS_i) > 1^{st}$ quartile	3336	1112
$ln(NTS_i) > 3^{rd}$ quartile	1112	3336

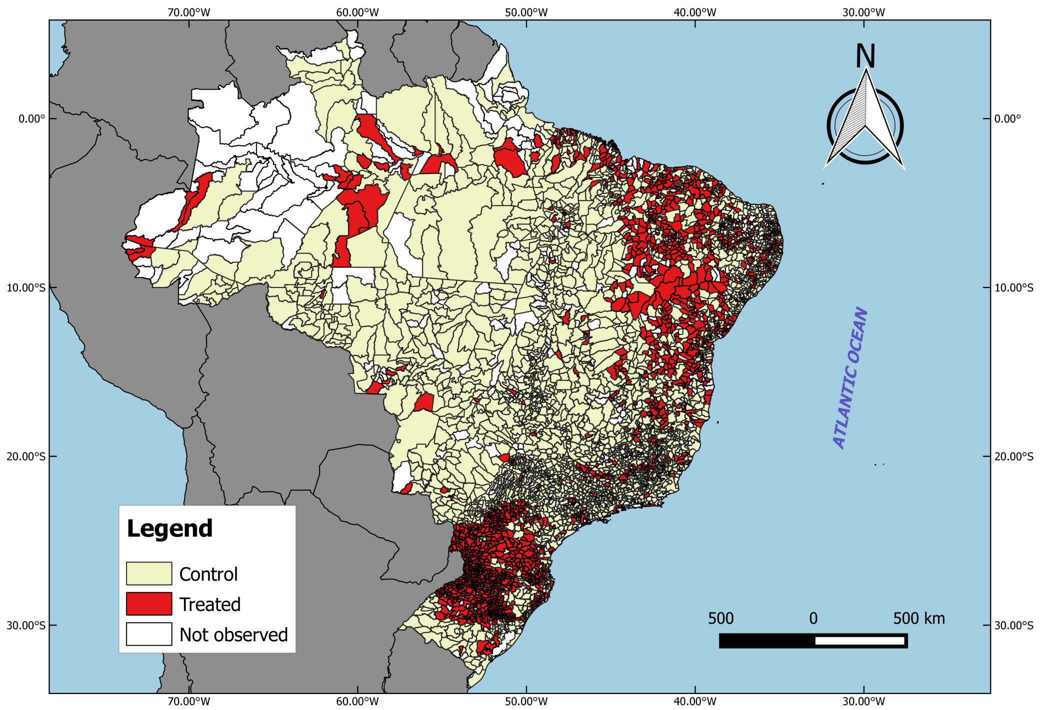

Figure 1: Treated and control municipalities(treatment criteria: $ln(NTS_i) >$ average)

Control variables (X)

• *Land use in neighborhood*: we calculated the participation of land use (forest, cropland and pasture) in the neighborhood. For this, we use a neighborhood matrix (W) whose radius reaches 1000 km. Such a variable will give us a sense of the land use pattern in a given region.

• *Farm characteristics*: we selected the following variables to characterize the situation of the farms: (i) number of tractors by farm; (ii) number of agronomists by farm; (iii) percentage of farmers with some education and (iv) percentage of farms using pesticide. The first expresses the use of physical agricultural technological capital. For this, the ratio between the number of tractors (with more than 100 hp) and the total area of each municipality was adopted as proxy. As source, we used the 2017 Agricultural Census, available by IBGE. The second represents agricultural human capital. The ratio between the total number of skilled workers in the agricultural sector (agricultural engineers, agronomy engineers and researchers in agronomic sciences) and the total area of each municipality was used as a metric. The data used were provided by the Annual Social Information Report (RAIS), published by the Brazilian Ministry of Labor and Employment (MTE), where 2017 is the reference year. In the third we calculate the percentage of farmers in the municipality with education, that is, those who have ever attended school. Information from the 2017 Agricultural Census, provided by IBGE, was used. The fourth variable assesses pesticide use on farms. We calculated the percentage of pesticide farms in each municipality analyzed. We use data from the 2017 Agricultural Census, provided by IBGE. We hope that all of these variables that make up the characteristics of farms will help us partly explain the pattern of land use in the municipalities.

• *Socioeconomic aspects*: the following variables were used to characterize the socioeconomic conditions of the analyzed municipalities: (i) rural population density; (ii) total population density; (iii) indigenous population density and (iv) the municipal agricultural GDP per capita. In the first, we calculated the ratio of the number of rural residents in relation to the total area of the municipality. We use data from the 2017 Agricultural Census, available from IBGE. In the second, we calculated the ratio between the total population of the municipality in relation to its area. We use data available from the 2017 Agricultural Census. Both variables give us a dimension of how inhabited the municipality is, directly influencing the way its land is used. In the third, we divided the number of indigenous people by the area of the municipality. We collected 2017 data estimated by IBGE. There is scientific evidence that indigenous peoples acting positively on environmental preservation. Thus, we hope that this variable will capture how protected it is, the forest area of the municipality. Finally, municipal agricultural GDP per capita will give us how important agricultural activity is to the municipality. This information was extracted from the Brazilian Institute of Applied Economic Research (IPEA), with reference to 2017.

• *Climate and edaphic conditions*: the climatic condition of the Brazilian municipalities will be represented by temperature and precipitation information. The temperature data are from the NCEP-DOE Reanalysis 2 project (Kanamitsu, et al. 2002), while the precipitation information is from the Climate Hazards group Infrared Precipitation with Station (CHIRPS) (Funk, et al. 2015). The average annual and summer precipitation and temperature were considered (December/January/February (djf)) - to adapt climatic events to cultivation decisions. Data were selected for the year 2017. Climatic variables are included to verify the influence of temperature and precipitation changes on land use. In turn, the edaphic conditions were represented by a categorical variable of Brazilian biomes (Amazon Forest, Atlantic Forest, Cerrado, Caatinga, Pantanal and Pampa). The 4448 municipalities analyzed were classified into one of these categories.

All covariates have undergone a logarithmic transformation, i.e. $ln(1 + X_i)$.

3. Results

Table 2 presents the coefficients related to the effects of the adoption of NTS on forest, cropland and pasture land-uses, using the PSM approach. In the baseline specification, treated municipalities were those in which the NTS adoption was above average. In addition, we present the estimated coefficients using the Ordinary Least Squares (OLS) method. These are considered biased, but serve for purposes of comparison.

Table 2: Estimed effects of NTS adoption on land-use
(treatment criteria: $ln(NTS_i)$ > average)

	OLS (all covariates)	PSM (all covariates)
Dependent variable: ln(forest)		
	-0.012	-0.108
NTS adoption effect (ATT)	(0.022)	(0.053)
	[0.575]	[0.044]
Dependent variable: ln(cropland)		
	-0.043	0.246
NTS adoption effect (ATT)	(0.029)	(0.066)
	[0.142]	[0.000]
Dependent variable: ln(pasture)		
	-0.087	-0.179
NTS adoption effect (ATT)	(0.023)	(0.049)
	[0.000]	[0.000]

Table 2 continued from previous page

Obs. Treated	1922	1922
Obs. Control	2526	2526
Obs. Total	4448	4448

Note: (1) Standard-Error between parenthesis and p-value between brackets.
(2) Matching algorithms characteristics: (i) nearest neighbour criteria with replacement; (ii) oversampling with 5 nearest neighbour; (iii) weights for oversampling type Mahalanobis distance metric; (iv) maximum tolerance level=0.00001.

It is possible to observe that the NTS adoption had a negative average effect on the forest area of the treaties. Treated municipalities have a forest share 10.25% less than no-treated. This value is the result of the exponential transformation $1 - exp^{-0.108}$. In terms of area, this represents, on average, a negative difference of 1759.54 ha between treated and controls municipalities. The opposite happens with cropland land-use. Treated municipalities have a cropland share 27.88% ($exp^{0.246} - 1$) greater than municipalities that have not adopted the technology. This represents a positive difference of 5115.69 ha between treaties and controls. These results follow the line of validation of the Jevons paradox (Hertel, 2012). In other words, the use of agricultural technology, in this case NTS adoption, expands agricultural areas and degrades forest areas.

In turn, the NTS adoption reduces the participation of pasture areas. On average, treated municipalities have 16.38% ($1 - exp^{-0.179}$) less pasture area share. This represents a negative average difference of 5017.9 ha between treated municipalities and controls. This result indicates that the farmer who uses the NTS is linked to planting activity and not livestock.

The question that remains is: What is the channel that links NTS adoption and deforestation? Our hypothesis is that higher productivity and consequent profitability has a direct influence on the farmer's land use decision. The possibility of greater profit encourages the expansion of the agricultural frontier, thus promoting the degradation of natural areas. To verify the veracity of this, we performed a PSM analysis using the productivity of the municipalities' agricultural sector as a dependent variable. For this, information on agricultural production and agricultural area (cropland + pasture) was used. The results are shown in Table 3.

Table 3: Estimed effects of NTS adoption on productivity
(treatment criteria: $ln(NTS_i) >$ average)

	OLS (all covariates)	PSM (all covariates)
Dependent variable: ln(productivity)		
NTS adoption effect (ATT)	0.049 (0.026) [0.053]	0.132 (0.075) [0.077]
Obs. Treated	1922	1922
Obs. Control	2526	2526
Obs. Total	4448	4448

Note: (1) Standard-Error between parenthesis and p-value between brackets.
(2) Matching algorithms characteristics: (i) nearest neighbour criteria with replacement; (ii) oversampling with 5 nearest neighbour; (iii) weights for oversampling type Mahalanobis distance metric; (iv) maximum tolerance level=0.00001.

The result of a positive sign (0.132) and statistically significant confirms our hypothesis. That is, the NTS adoption increases the productivity of the treated municipalities. The economic benefits generated by the technology have direct effects on the conservation of forest areas.

It is worth highlighting the limitations of our analyzes. Most of them are of methodological aspects: (i) when working with experiments using observational data, we run the risk of measurement errors in the database used; (ii) the calculation of the propensity score is conditional on the variables X. Therefore, the PSM only reduces the bias caused by observable characteristics and (iii) the internal validity (i.e., when the results reveal the true impact of the program) is limited by the pairing condition.

4. Conclusion

By 2050, the world population will reach 9.1 billion. This fact implies the need for greater production of food. To reach a level of food security, cereal production will need to be around 3 billion tons/year, and meat production is expected to reach 470 million tons/year. The adoption of technologies is the main outlet for greater productivity in the agricultural sector (FAO, 2009, 2013).

In this context, it is necessary to discuss the consequences of adopting these technologies on the environment. This article aimed to better understand the effects of adopting the NTS technique on forest areas in Brazil. Through a PSM approach, we found evidence that the NTS adoption can encourage, through increased productivity/profitability, the expansion of cropland to the detriment of the forest area.

By reducing erosion and retaining soil carbon, the NTS technique is seen in Brazil as an aid to reducing GHG emissions from agriculture. When we reveal a negative relationship between its use and the conservation of natural areas, we alert the existence of a rebound effect in terms of GHG emissions.

In the Brazilian Sectorial Plan for Mitigation and Adaptation to Climate Change for the Consolidation of a Low Carbon Economy in Agriculture - Plan ABC, which inserts the NTS as one of the mitigation actions, the Brazilian Government affirm:

> "(...) the ABC Plan aims to organize the planning of actions to be carried out to adopt the **sustainable production technologies** selected to respond to the commitments assumed by the country to reduce GHG emissions in the agricultural sector"
>
> (Brazilian Ministry of Agriculture, 2016)

Our evidence warns of the possibility of environmental unsustainability from the NTS adoption. Therefore, its insertion in the ABC Plan, in its current format, may have been wrong. We recommend to policy makers (i) to rethink the incentive mechanisms given to farmers, aiming at the adoption of NTS combined with environmental conservation and (ii) to continuously monitor farmers' actions.

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