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Abstract

The perpetuity and improvement of REDD+ projects for curbing deforestation require rigorous impact evaluations of their effectiveness. Today, a number of global and regional remote sensing (RS) products are publicly available for detecting changes in forest cover worldwide. In this study, we assess the suitability of using these readily available products to evaluate the impact of REDD+ local projects targeting smallholders in the Brazilian Amazon. Firstly, we reconstructed forest loss for the period between 2008 and 2018 of 21,492 farms located in the Transamazonian region, using data derived from two land-cover change datasets: Global Forest Change (GFC) and Amazon Deforestation Monitoring Project (PRODES). Secondly, we evaluate the consistency between the two sources of data. Lastly, we estimate the long-term impact of a local REDD+ initiative using both datasets. We found that the estimates of deforestation at the farm level vary considerably from one dataset to another. However, using microeconometric techniques that use pre-treatment outcomes to construct counterfactual patterns of participants in the REDD+ program, we found that an average of about 2 hectares of forest were saved on each of the 348 participating farms during the first years of the program, regardless the source of data used. Moreover, we found that deforestation decreased on plots surrounding participating farms, suggesting that the program had a positive spillover effect on neighbouring farms. Finally, we showed that the participants returned to the business-as-usual pattern at the end of the program. The environmental gain generated during the four years of the program was, however, not offset by any catch-up behaviour. By evaluating the monetary gain of the delayed carbon dioxide emissions, we found that the program's benefits were ultimately greater than its costs.

Keywords: REDD+, remote sensing products, additionality, deforestation, Brazilian Amazon.

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1 Introduction

Forest cover change is a leading cause of Brazil's greenhouse gas emissions.[1] As a result, there has been a proliferation of sub-national initiatives financed by the United Nation's REDD+ (Reducing Emissions from Deforestation and forest Degradation) mechanism in the Brazilian Amazon for some years (Sills et al., 2014). Brazil currently hosts about 50 REDD+ projects targeting small farmers and financed by REDD+ funds or carbon markets (Simonet et al., 2015). The perpetuity and improvement of REDD+ projects require rigorous impact evaluations of their effectiveness. Yet, robust evidence about their effectiveness on reducing deforestation remains scarce (Jayachandran et al., 2017; Simonet et al., 2018b; Roopsind, Sohngen, and Brandt, 2019). One of the reasons for this lack of evidence is related to the high cost to access the data needed for impact analysis (Blackman, 2013; Pagiola, Honey-Rosés, and Freire-González, 2016).

Over the past 20 years, however, remotely-sensed data for detecting changes in land cover worldwide has evolved dramatically, which offered new opportunities for the evaluation of forest conservation programs. In particular, a number of derived and modelled remote sensing (RS) products that extract information from raw earth observation (EO) data became publicly available (Kugler et al., 2019). Though these RS products represent a great opportunity to measure changes in forest cover at a large scale, the suitability of these readily available data-sets to perform proper impact evaluations of sub-national REDD+ initiatives has rarely been questioned so far (Bos et al., 2019).

For the present study, we focus on two well-known data-sets: the Global Forest Change (GFC) dataset provided by the University of Maryland and the PRODES data-set provided by the National Institute for Space Research (INPE) of Brazil. GFC provides free of charge global historical record of annual tree-cover loss and has already been used to assess the effectiveness of forest conservation policies in Ecuador (Jones and Lewis, 2015; Jones et al., 2017) and French Guyana (Roopsind, Sohngen, and Brandt, 2019). In the Brazilian context however, the most often used deforestation data-set has been PRODES, an accessible and transparent RS product, provided free of charge as well. In particular, it has been employed in particular to study the effectiveness of protected areas on avoiding deforestation in the Amazon (Nolte et al., 2013; Herrera, Pfaff, and Robalino, 2019).

In this study, we assessed the applicability of these two RS datasets to evaluate the impact of REDD+ local projects targeting smallholders in the Brazilian Amazon. To do so, we concentrated on a Brazilian REDD+ flagship project for curbing deforestation, the Sustainable Settlements in the Amazon (SSA) project, which offered technical assistance and conditional payments to 350 households for maintaining forest cover on at least half of their land between 2012 and 2016 (see SI Appendix for details). We focused on a local REDD+ program

[1] Although the annual deforestation rate in Brazil fell by 70 percent between 2005 and 2013 (Nepstad et al. 2014), more than 9,700 square kilometers of the Brazilian Amazon were cleared between 2018 and 2019, representing an increase of 30 percent in the annual deforestation rate and the highest rate since 2008 (INPE, 2019a).

implemented in a country characterized by the highest annual loss of forest in the world. This project has already been evaluated by Simonet et al. (2018a) using survey data collected at the early stage of the program. The authors found that an average of 4 ha of forest were saved on each participating farm in 2014.[2] A potentially important caveat in this study, however, is the extent to which participants might have under-declared their actual deforestation (compared to non-participants). RS data does not suffer from such problem.[3]

RS data also have at least three additional advantages over survey data. First, using RS data generally makes it possible to run analysis from larger samples than those available from surveys, thus affording increased statistical power, for a much lower access cost. In the case of the SSA project, this means that we can estimate the forest loss on the individual plots of the entire population of participants, rather than a sample of them.

Second, using RS data allows us to estimate what would have been the forest loss on these farms in the absence of any program (the so-called counter-factual situation) with more precision. To make valid inferences about participants, there must be a sufficient number of non-participants with a high potential to be selected as matched counterparts. Using RS data allows access to a larger pool of candidates for the matching procedure, which increases the probability of finding good matches.[4]

Third, the use of RS data allows us to study the effects of the program several years after its end. It is very expensive to collect information in the field repeatedly, over a long period. For this reason, the analysis based on survey data generally do not provide evidence of the permanence of the effects of conservation programs. On the contrary, RS data make it possible to study the long-term effects of conservation programs, from their early stage of implementation to the most recent period, by highlighting, if they exist, the effects of attenuation, rebounds, or compensation, which may arise after the program ends.

So far, a number of programs for forest conservation or reforestation have been evaluated applying microeconometric methods to RS data (see Pattanayak, Wunder, and Ferraro (2010); Samii et al. (2014); Alix-Garcia and Wolff (2014); Börner et al. (2017) for reviews of the literature). Most studies have been conducted in Costa Rica (Sanchez-Azofeifa et al., 2007; Arriagada et al., 2012; Garbach, Lubell, and DeClerck, 2012; Robalino and Pfaff, 2013) and Mexico (Honey-Rosés, Baylis, and Ramirez, 2011; Scullion et al., 2011; Alix-Garcia, Shapiro, and Sims, 2012; Sims et al., 2014; Alix-Garcia, Sims, and Yañez-Pagans, 2015; Costedoat et al., 2015).[5]

[2]Simonet et al. (2018a) moreover showed that this conservation came at the expense of pastures rather than croplands. This amounts to a decrease in the deforestation rate of about 50 percent. They find no evidence of within-community spillovers.

[3]RS deforestation data can suffer from measurement and classification errors, but there is no reason a priori for these errors to be more frequent on the plots enrolled in conservation programs.

[4]This is referred to as the common support assumption. Those non-participants who displayed a pattern identical to that of the participants during the period preceding the program typically have high potential to be selected as counter-factual in the matching procedure. The larger the pool of non-participants, the more likely the common support hypothesis is to hold.

[5]Those programs typically offer conditional payments to participants. Overall, the results of these studies

As for REDD+ programs, recent impact evaluations include a study by Jayachandran et al. (2017) in Uganda using remote-sensed data developed from QuickBird satellite images, Mohebalian and Aguilar (2018) in Ecuador using remote-sensed data developed from Landsat TM images, and Roopsind, Sohngen, and Brandt (2019) in Guyana using the GFC data-set. Overall, the results of these studies suggest that the impact of REDD+ programs on forest loss may be large. Jayachandran et al. (2017) indeed find that tree cover in Uganda declined by 4.2 percent during the two-year period under study in treatment villages, compared to 9.1 percent in control villages, thus reporting a 54 percent decrease in deforestation rates. Roopsind, Sohngen, and Brandt (2019) estimate that the annual tree cover loss was 0.056 percent in Guyana against 0.087 percent in the synthetic counter-factual, thus reporting a 35 percent decrease in annual deforestation rates thanks to the program.

Our study adds to the existing literature by providing new evidence on the effectiveness of REDD+ programs, focusing on a region characterized by the highest annual loss of forest in the world, while previous studies were on areas where deforestation may appear less pressing. To the best of our knowledge, despite the abundance of REDD+ initiatives in Brazil, there are no studies assessing the long term impacts of such projects, combining ready-to-use RS products and property-level data. Our study aims at filling this gap. Furthermore, this is the first study assessing the effectiveness of a Brazilian REDD+ local project conservation program using two different sources of remotely-sensed deforestation data to cross validate impact assessment results.

2 Remote-Sensing products

The Amazon Deforestation Monitoring Project (PRODES)

PRODES was created in 1988 by the Brazilian National Institute for Space Research (INPE), with the main objective to quantify and geolocalize deforestation in the Brazilian Legal Amazon[6] and help the Brazilian government to make informed decisions and establish environmental and development public policies for the region[7] (Câmara, Valeriano, and Soares, 2006). Annual rates are estimated from the deforestation increments identified in Landsat images[8]. PRODES uses the seasonal year, starting on August 1st, to calculate annual deforestation, so images are selected as near to this date as possible. Next, the images are masked to exclude non-forest, previous deforestation, and water using the previous year's analysis.

suggest that the impact of the programs on the average annual forest cover varies substantially across regions (Simonet et al., 2018a).

[6]The Brazilian Legal Amazon occupies an area that corresponds to 59 percent of the Brazilian territory.

[7]PRODES' data are employed in: (1) certification of agribusiness supply chains such as the Soy Moratorium; (2) national inventory reports on GHG Emissions; and (3) monetary donations from the Amazon Fund uses PRODES's data as a reference for deforestation activity in the Legal Amazon.

[8]PRODES uses mainly Landsat series images, but when there's too much cloud coverage, analysts employ SENTINEL-2 and CBERS-4 images.

Finally, the identification of deforestation is done by photo-interpretation, where analysts delineate deforested polygons in the intact forest of the previous year - the patterns of clear cutting are based on three main observable elements present in the images: tone, texture and context (see INPE (2019b) for a detailed description of PRODES' methodology).

Like any RS product, PRODES has some technical limitations because its methodology (entirely done by visual photo-interpretation) can only detect contiguous areas of cleared forest that are greater than 6.25 hectares. Therefore, smaller deforestation patches and forest degradation due to logging are not recorded in the dataset unless accumulated over several years. Also, deforestation estimates only consider primary forests and do not account for secondary or regenerating forests, and, since it relies on optical imagery, constant cloud coverage prevents Landsat sensors from capturing land cover imagery.

The Global Forest Change dataset (GFC)

The most known global deforestation dataset currently available is the University of Maryland's Global Forest Change data-set (GFC) – also popularly called Hansen data. This dataset has the objective to produce annual globally consistent characterizations of tree cover loss (Hansen et al., 2013). GFC maps annual forest loss starting in 2001. The maps produced by the GFC initiative are also based on the Landsat satellite images, but the classification process is 100% automated. The classification process of cloud-free Landsat image mosaics is carried out using decision tree algorithms. As the classification is carried out pixel by pixel, the minimum area mapped by this product is 900 square meters (30 x 30 meters).

For this dataset tree-cover is defined as all vegetation taller than 5 meters in height across a range of canopy densities (from 0 percent to 100 percent) for an area of approximately 0.1 hectare (equivalent to a Landsat pixel). Therefore, this layer can represent primary and secondary natural forests as well as tree plantations. Also, this data-set require users to choose a percentage threshold value to determine whether a pixel is considered forest or not. Forest loss is defined as the complete removal of tree cover canopy at the Landsat pixel scale (see Hansen et al. (2013) for complete methodological explanation).

While GFC is a major progress in the understanding and quantification of global forest change research and conservation planning there exist limits of this dataset. First, tree cover loss can be the result of human activities (e. g., plantation harvesting, selective logging and clear-cut) as well as natural causes (such as disease, storm and fire damage). Second, plantations such as, cocoa, palm oil or eucalypt are included as forests (Tropek et al., 2014), though they are not considered forest according to the Brazilian Forest Code.

The purposes and methodologies of PRODES and GFC are quite diverging (Table 1). Firstly, GFC includes forest changes in every type of vegetation greater than 5 m in height while PRODES only focuses on primary forest loss. Secondly, GFC is a global dataset while PRODES only focuses on the Brazilian Amazon. Finally, PRODES's methodology is based on contextual classification (i. e., image segmentation and analyst interpretation) and GFC's methodology is grounded on pixel-based classifications (i. e., automated decision tree). There is therefore no reason a priori for the information relating to the loss of forest provided by the two products to coincide.

3 Results

Comparing deforestation estimates from both data-sets

A paired t-test of annual differences in deforestation revealed significant difference between the PRODES and GFC data for the years 2008 to 2018, the only exception is the year of 2015 (SI Appendix, Table 1). Furthermore, GFC detects higher rates of deforestation than PRODES for all years except 2010 and 2011.

Also, several spatial differences emerged when comparing the GFC and PRODES data. To highlight these differences, we aggregated deforestation pixels for the 2008-2017 period from PRODES and GFC data into binary raster layers. To measure the spatial consistency between the two RS products, we overlapped both layers and performed validation samples of the areas of agreement and conflict between the two input map products. Overall, the extent of the match between the two products appears rather small. We found that datasets have a 39 percent agreement at the municipality scale, a 36 percent agreement at the settlement scale and a 27 percent agreement at SSA plot's scale.

This low spatial agreement between the two products suggests that one or both products may not be suitable for monitoring deforestation under REDD+ programs. This, however, does not necessarily call into question the interest of these products for evaluating the effectiveness of REDD+ programs in curbing deforestation. Indeed, it is possible that the level of precision of the forest loss measurement is nevertheless sufficient for a significant difference to be detected between the participating plots and the control ones (if this difference exists).

Additionality of the REDD+ initiative

We identified the causal effect of the SSA program using a matching approach that uses pre-treatment outcomes to correct for selection bias. The results of the estimates of the ATT are displayed in Table 2 in Appendix. According to GFC data, the ATT ranges between -0.38 and -0.57 hectares for the year 2013, between -0.76 and -0.91 ha for the year 2014 and between -0.42 and -0.77 ha for the year 2015, suggesting that the SSA project prevented about 1.86 hectares of forest, on average, from being cleared on each participating farm during the first three years of the SSA program. Similarly, we find significant negative point estimates using PRODES data. The ATT ranges between -0.48 and -0.57 ha for the year 2014, between -0.87 and -1.19 ha for the year 2015 and between -0.59 and -0.93 ha for the year 2016, implying that the program prevented around 2.24 of forest from being cleared during these years on each enrolled plot.

The results for the estimations are shown graphically on Figure 1. According to GFC dataset, the participant group deviates significantly from the trajectory of the control group from 2012, until 2015. The same phenomenon is demonstrated with PRODES data (with one-year lag). Under the hypotheses that we made when constructing the control groups, this clear break in the deforestation trend among participants can be attributed to the SSA program.

Permanence of the effects of the REDD+ initiative

We failed to detect a significant impact of the program for the years 2016, 2017 and 2018 using GFC data and for the years of 2017 and 2018 using PRODES data. The fact that the ATT becomes insignificant as the program comes to an end, indicates that the treated group, whose trajectory had diverged from that of the control group, go back to the same behaviour after three years. This is clearly illustrated in Figure 1, which shows that the trajectory of the treated group joined that of the control group – the two curves overlap again – from 2016 (or 2017, depending on the dataset used).

These results suggest that the gains achieved by the program until 2018 represent a 3-year delay in the deforestation that otherwise would have occurred in the absence of the program. This mean that we are in the scenario where the program participants consented to modify their behaviour during the duration of the program, only to return to the business-as-usual pattern after the end of the program. This suggests that the intervention was not sufficient to trigger long-lasting change in farmers' behaviour. It is however important to mention that we do not detect a higher rate of deforestation in the participating group than the control group after the end of the program, meaning that participants did not catch up on their postponed deforestation (at least not until 2018). Thus, the environmental gain generated during the three first years of the program was not subsequently destroyed. It lasts at least until 2018, when our analysis ends.

Spillover effects of the REDD+ initiative

In any conservation program targeting individuals, the possible presence of spillover effects, i.e. an impact of the program on individuals who were not initially targeted by the program but were exposed to, must be considered. In the case of the SSA program, these individuals are farmers who have not signed any PES contracts, but who have been able to benefit from some non-financial components of the program, such as information campaigns or free registration in the rural registry (see SI Appendix for details about the SSA program). Moreover, the development of low deforestation activities among participants in the PES program may have benefited surrounding families on the adoption of new practices, access to inputs, and increasing labour demand.

To test for the presence of such spillovers, we focused on the deforestation that may have occurred in the plots surrounding participating farms. Therefore, we assessed the impact of the program on those 3,793 farm-holds that were less than three kilometres distant from a treated one. We applied the same identification strategy to these potential beneficiaries of the program as that applied to the treated plots. The results are displayed in Table 3 in the SI Appendix. We found that that tree cover loss on plots surrounding participating farms between 2013 and 2015 was lower than forest loss on control plots, suggesting that the program indeed had a positive spillover effect of avoiding about one hectare of deforestation on average on each surrounding plot.

Cost effectiveness of the REDD+ initiative

Following to Jayachandran et al. (2017) and Simonet et al. (2018a), we calculated the value of the carbon benefit over the 2013 to 2018 period using the Social Cost of Carbon (SSC) and compared this value to the program's costs. The benefits of the SSA project were computed by using our estimates of the additionality in terms of hectares of forest saved thanks to the program. We computed the average stock of carbon in our study area, using the estimates of biomass provided by the World Resources Institute, i.e. 116 tons of CO2 aboveground per hectare of forest with at least 50 percent tree cover. We found that the program had avoided the emission of 309,746 tons of CO2.

The costs of the PES component of the SSA project were computed using the amount disbursed to participants from 2014 to 2017 (626 USD per participant), which lead to 838,849 USD of discounted costs (using a 3 percent discount rate). By relating this expenditure to the emissions avoided, we found that the cost of the project was thus 2.8 USD per ton of CO2 emissions avoided. By then computing the value of the carbon benefit using the SSC, we finally found that the discounted benefit of the avoided emissions was about 1,255,976 USD, which gives us a benefit/cost ratio of about 1.5, meaning that one dollar invested in the program would have translated into a dollar and a half of environmental gain.

Such estimate, however, does not take into account the start-up and operational costs of the program, nor the gains generated by the spillover effects. When all the costs are included, [9] the total (discounted) project costs over the 2012-2017 period reaches 8,607,246 USD. On the other side, the total of avoided emissions including the positive spillover gain, reaches 1,924,490 tons of CO2. This brings us to a new estimate of the cost of the program, which this time would amount to 4.47 USD per ton. Using again the SSC, we find that the discounted benefit of the avoided emission would be about 9,086,840 USD, that is to say a benefit/cost

[9] Source: Amazon Fund (http://www.fundoamazonia.gov.br/pt/projeto/Assentamentos-Sustentaveis-na-Amazonia/).

ratio of about 1.1. Again, this suggests that the program may well have been cost-effective.

4 Discussion

Remote-Sensing products

The divergence that we found between the two RS products can be partially explained by methodological differences in the construction of the products. First, small deforestation is not incorporated within PRODES estimates (because deforestation activities are only reported if they accumulate beyond the 6.25-hectare threshold), while it can be detected more easily in GFC. Second, GFC estimates detects secondary forest clearings, while PRODES does not. Third, some of the cover loss reported in GFC dataset may be due to forest degradation (e.g. such as forest fires and selective logging), something that is less likely to occur with PRODES estimates. All this may explain why GFC often detects higher rates of deforestation than PRODES.

This result calls for at least two comments. The first one is that neither of the two products seems to completely outperform the other. PRODES estimates are validated in the field but are not able to account for small deforestation operations. GFC, on the other hand, can detect small patches, but sometimes wrongly, when it is not strictly deforestation. This should encourage REDD+ project evaluators to cross-validate their results using multiple datasets when available.

The second comment relates to the suitability of PRODES and GFC products for the evaluation of REDD+ programs. Incontestably, any deforestation RS product may contain classification errors and deforestation area estimates that diverge from reality. Does this mean that these products are of no use in properly estimating the impact of PES programs targeting smallholders who own a hundred hectares or less? Although these products do not seem suitable for the fine monitoring of this type of program, our analysis nevertheless suggests that they make it possible to assess the effectiveness of a PES program. This can be done provided that (i) the impact of the program is large enough to be detected despite the lack of precision of the RS products and (ii) the noise caused by the imprecision of the RS product estimates is distributed normally between the treated and control plots, so that it is net out through the comparison between the two groups.

Local REDD+ effectiveness

We assessed the impact of SSA project over 2013-2018 and estimated that an average of about 2 hectares of forest were saved during the early years of SSA project on each participating farm, regardless the source of deforestation data used. Even though the size of the estimated effect is smaller than the one estimated using survey data by Simonet et al. (2018a), it is quite similar in magnitude to those found for other PES-based forest conservation programs run in Latin America (Robalino and Pfaff, 2013; Alix-Garcia, Shapiro, and Sims, 2012).

We failed to detect a positive impact of the program during its last year (the difference between participants and the counterfactual group vanishes even before the end of the program), suggesting that the program's effects were primarily realized in its first years. Evidence thus suggests that the SSA project may have failed on prompting a transition to more sustainable agricultural practices on the following years. Similarly, Giudice et al. (2019) and Fiorini et al. (2020) found that Peru's Natural Forest Conservation Program and Water and Forest Producers Program succeeded in increasing forest cover only in the program's first years. One possible explanation for that is that the opportunity costs of complying with the program requirements increased during the period when the program was in place, leading farmers to return to their business-as-usual practices even before the end of the program. As we can see in SI Appendix, Figure 2, the price of cattle sharply increased from 97 BRL per arroba in January 2013 to 144 BRL in January 2015. This hasty increase in cattle prices may have played a determining role on the decision of deforestation, by increasing the relative profitability of expanding pastures compared to complying with the program requirements.

Finally, it should be stressed that the SSA program had several components, other than the PES, which may have played a role in the effects we estimated. Actually, we are unable to disentangle the effects of each of these components on the detected impact on forest cover among participant plots. However, our results, which show that deforestation decreased on farm-holds surrounding treated plots between 2013 and 2015, suggest that non-monetary components of the program may have been at play too.

5 Conclusion

In sum, the four key messages one can take away from this analysis relate to (i) the suitability of RS products for evaluating conservation program effectiveness, (ii) the likely short-term and long run effectiveness of PES programs, (iii) the likely spillover effects of such programs and ultimately (iv) their cost-effectiveness.

Overall, our findings suggest that despite the disagreement between GFC and PRODES on forest cover loss estimates at the individual plot-level, such datasets represent a valuable source of data to evaluate forest conservation projects.

We found evidence that the local REDD+ initiative was effective in reducing deforestation during its early years of implementation in the Transamazon region, an area with historically high deforestation rates. This suggests that PES program targeting smallholders in the Brazilian Amazon may well be effective at least in the short-run. We moreover found evidence that farm-holds located close to enrolees were somehow impacted by the program, as they decrease deforestation also during the early years of program implementation as a consequence of the program. This suggests that PES program may change the behaviour of farmers who are not the primary beneficiaries of the program – although we are not able to show by which channel such phenomenon occurs.

In addition, we found that the participants resumed their normal rate of deforestation even before the end of the program. Our findings suggest that the SSA project have failed in generating permanent effects on farmers' decision about deforestation and inducing more sustainable agricultural practices on the following years. Despite this, we valued the three-year delayed CO2 emissions highlighted by the impact assessment and found that the SSA program benefit were larger than its costs.

6 Materials and Methods

Reconstructing forest loss on individual plots

We used property boundaries from the Environmental Rural Registry (CAR in the original Portuguese acronym)[10] of 21,492 titled households in our study area (SI Appendix, Figure 1). We delimited a 50-kilometer buffer around the Transamazonian highway for the municipalities of Altamira, Senador Jose Porfirio, Anapu and Pacaja in order to delimit the rural properties that would be included in our initial sample. Georeferenced data on deforestation and registered private rural properties were overlapped to enable identification of patches cleared inside properties boundaries. We used information from GFC and PRODES to determine the location of forest clearings at an annual basis. All geographical datasets were re-projected to a common spatial reference (SIRGAS 2000/UTM 22S). Our sample covers the 2008-2018 period. Since we did not have information about changes in properties' borders during our sample period, we assumed that they were constant throughout this period. For this study we used a threshold of 75 percent of vegetation cover for GFC tree cover layer as a definition of the forest - average threshold used in studies in Amazonian context (Baker and Spracklen, 2019; Gasparini et al., 2019).

Identification strategy for the impact assessment

In this section, we describe our empirical approach and its key assumptions to estimate the mean difference between the deforestation extent observed on participating farms and the deforestation extent that would have been observed in those farms if they were not enrolled in the program, the so-called average treatment effect on the treated (ATT). Estimating treatment effects using observational data brings the problematic of selection bias, because participants self-select into the program, so that the treated and untreated units might be differ-

[10]The CAR is a mandatory and self-declaratory registry for all Brazilian rural properties. To obtain CAR, landholders must document georeferenced property's boundaries, as well as within-property areas of native vegetation. CAR has a public consultation module where data from properties, detaining either temporary or permanent registrations, are available for download in vector format at http://www.car.gov.br/publico/municipios/downloads.

ent for many reasons other than the treatment itself. This bias occurs because some of the factors that influence the selection of participants also determine the outcomes of interest. Observations of pre-treatment outcomes might help to correct for selection bias because they contain information on these confounding factors. Thus, matching treated and untreated groups on pre-treatment deforestation outcomes allows to correct for selection bias (Abadie, Diamond, and Hainmueller, 2010).

In addition to pre-treatment outcomes, we also selected a number of covariates that were likely to drive both the participation in the SSA project as well as decisions regarding deforestation, in order to improve the matching procedure. These covariates include: the forest cover as observed in 2000, the farm size, the distance to the main road (Transamazon highway), the distance from the main navigable river (Xingu river), the distance from the main market (Altamira city), and the distance from the nearest small village (local market).

We performed an estimation for the ATT using the Nearest Neighbour Matching (NNM) and the Propensity Score Matching (PSM) estimators. We apply both matching estimators to our data to estimate the average effect of the SSA project on the deforestation rate of participants, using the comparison group to estimate the counter-factual level of deforestation (SI Appendix, Table 4).

To deal with the Stable Unit Treatment Value Assumption (SUTVA), we excluded from the untreated group those plots that were less than 3 km distant from a treated plot, thus creating a kind of buffer zone between treated plots and potential control ones. By doing so, we ended up with 11,466 observations. We performed the same procedure when estimating the impact of the program on those farms that did not receive any PES but were located close enough to enrolled plots to indirectly benefit from the program. In practice, we again created a buffer zone between beneficiaries (whether direct or indirect) and potential controls, by excluding from the sample of untreated plots those farm-holds located between 3 and 6 kilometres from an enrolled plot.

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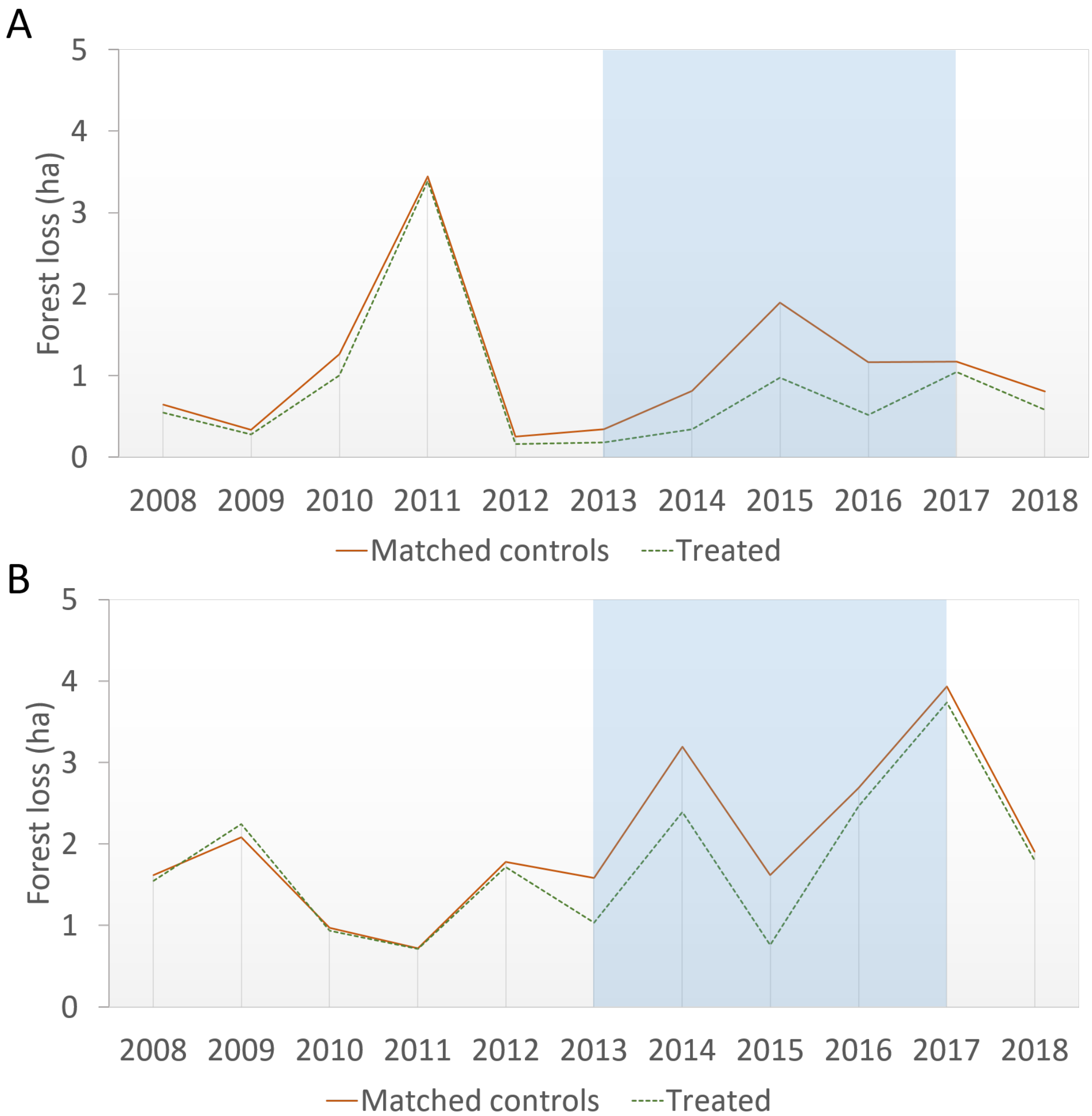
Figure 1: Effect of the SSA program on avoided deforestation on enrolled farms



Notes: Mean difference in forest loss (hectares) between participants (n=348) and control group (n=696). (A) Nearest neighbor matching (NNM) estimates using PRODES dataset. (B) NNM estimates using PRODES dataset. The SSA REDD+ program was implemented from 2013 to 2017 (blue panel). The difference between treated and controls is significant for the early years of program implementation.

Figure 2: Localization of treated and matched plots used for estimating counterfactual levels of forest loss

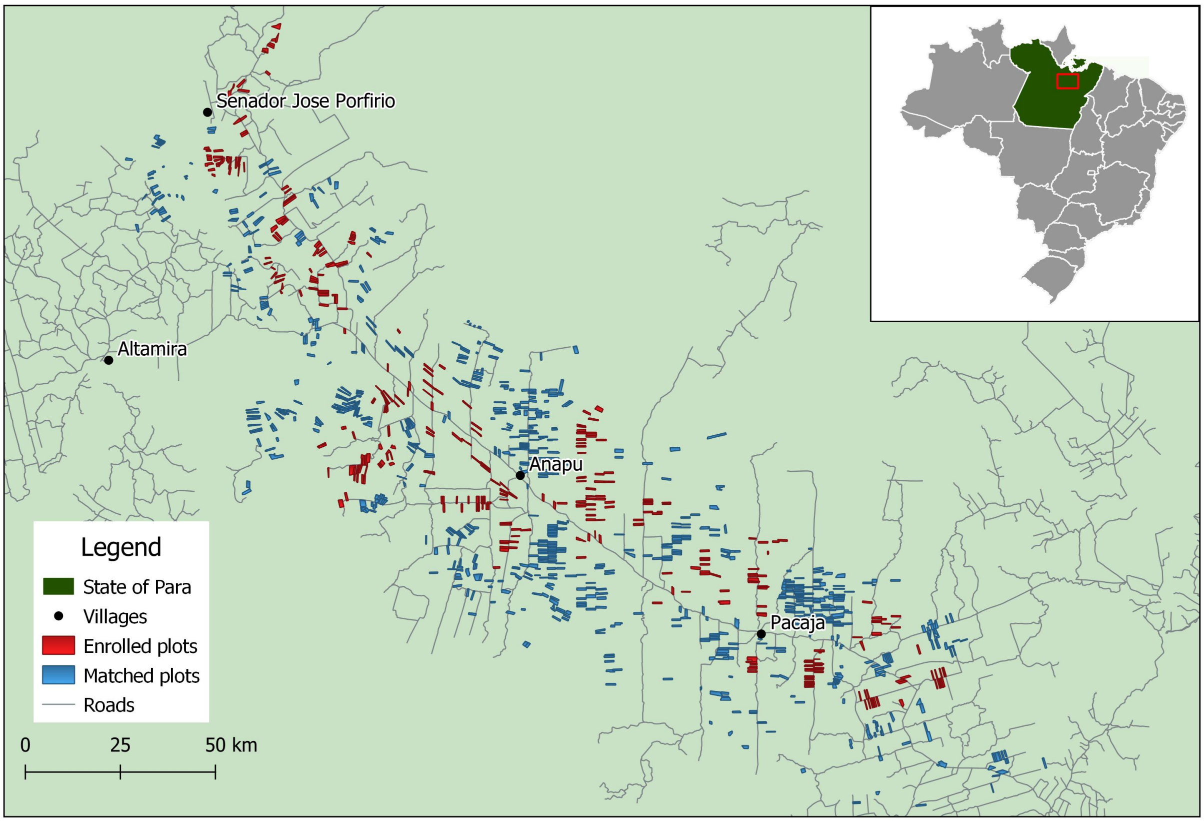


Table 1: Comparison between GFC and PRODES

	PRODES	GFC
Data source	Mainly Landsat	Landsat
Resolution	30 meters	30 meters
Minimum patch size	6.25 hectares	0.09 hectares
Coverage	Brazilian Amazon	Global
Tree cover definition	Primary forest	Vegetation taller than 5 meters
Method	Image segmentation and analyst interpretation	Automated decision tree
Observation Period	August 1 to July 31	January 1 to December 31

Supplementary Information

Description of the REDD+ Case Study

The SSA project is a sub-national REDD+ initiative implemented by the Amazon Environmental Research Institute (or IPAM), a Brazilian non-governmental organization involved in the design and implementation of several forest conservation programs in Brazil (Cromberg et al., 2014). The SSA project started in 2012 and was financed by the Amazon Fund[1] until 2017. The program has offered a mix of interventions to reduce deforestation rates to smallholders living in settlements located in the Transamazon highway (Figure 1). According to IPAM, about 2700 families have benefited from the program through a series of interventions such as: i) Awareness-raising meetings on environmental legislation and tenure regularization that were held between 2013 and 2017, benefiting an unknown number of participants, since those were open to the local community; ii) Administrative support for registration under the rural registry (or CAR) to 1300 smallholders between 2012 and 2014; iii) Development of low deforestation activities (e.g., intensive cattle ranching, agroforestry and horticulture) benefiting 650 families between 2014 to 2017; and iv) Payments for Ecosystem Services (PES) scheme to 350 smallholders.

Our analysis focuses on the 350 farm-holders[2] that benefited from all the above-mentioned components. These small landowners live in land reform settlements located in the municipalities of Anapu, Pacaja, and Senador Jose Porfirio (Simonet et al., 2018). These three municipalities, located close to the Transamazon highway, still figure in the ranking of the 10 ten critical municipalities for their deforestation rates until today[3]. The value accessed

[1]The Amazon Fund is a REDD+ instrument designed to raise donations for non-reimbursable investments in efforts to curb deforestation as well as to promote sustainable use of resources in the Brazilian Amazon.

[2]The map with the localization of the farm-holds enrolled in SSA program is publicly available at IPAM's website (http://www.pas-simpas.org.br/). Therefore, we used this available data to geolocalize 348 plots from the 350 that received payments conditional on forest conservation.

[3]The first settlers arrived in the area during the Plan for National Integration (PIN) for the colonization of the Brazilian Amazon. At that time, poverty in north-eastern Brazil was the immediate issue, especially following the extreme drought of 1970 (Fearnside, 1984). The transfer of poor north-easterners to colonization areas along the Transamazon highway was raised as the solution by the Brazilian Government at that time. Encouraging quick installation of settlers and the construction of the Transamazonian highway has intensified deforestation in the area without achieving many of its development goals. Colonizers were explicitly encouraged by the government to deforest at least 50 percent of their plots to pledge ownership (Souza, 2006). The livelihoods of small landowners in this area still depend on slash-and-burn agriculture and extensive cattle ranching, which are the two primary drivers of deforestation in the Brazilian Amazon (Smith et al., 1996; Soares-Filho et al., 2006).

by the 350 households in the PES scheme was of who participated in the project received 1680 Brazilian reais (BRL) per month (about 526 USD[4]) from January 2014 to February 2017 (Pinto de Paulo Pedro, 2016). The payments offered to project participants were conditional on forest conservation and agricultural transition toward a fire-free production system [5]. The payments were made every three months, according to the compliance to the established guidelines. The monitoring of the compliance was made annually by IPAM , based on analysis of PRODES data for the forest cover and on the performance of the low-deforestation activities certified by the project technical assistance team (Pinto de Paulo Pedro, 2016).

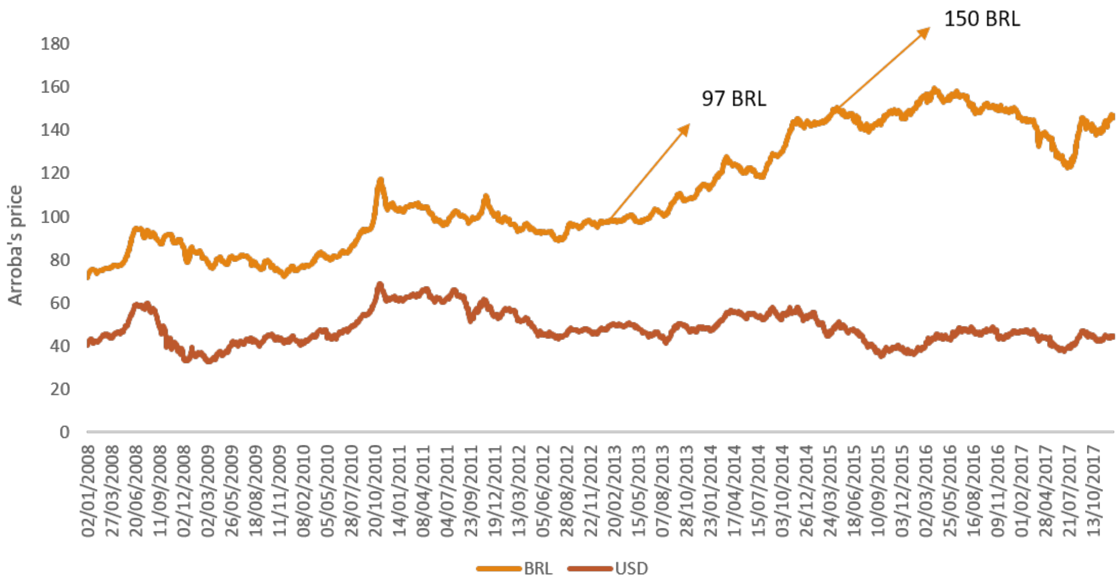
[4] 1,680 Reais converted to USD by applying the average conversion rate of Brazilian Real to American dollars in 2017

[5] Thirty percent of the payment was conditional on conserving forest on at least 50 percent of the farm, another thirty percent of the payment was conditional on the maintenance of 15-meter-wide forest riparian zones and the remaining 40 percent of the payment relied on the adoption of fire-free practices. A minimum of 30 percent of forest cover was required to be eligible for payments, but only participants with at least 50 percent of forest cover received the full payments (see Simonet et al. (2018) for a detailed description of the SSA program).

Figures

Figure 1: Localization of the study zone

Figure 2: Evolution of cattle price in Brazil



Source: Centro de Estudos Avancados em Economia Aplicada (CEPEA)

Tables

Table 1: Paired t-tests on the equality of deforestation means (ha)

Year	GFC	Std. Dev.	PRODES	Std. Dev.	ND	t	p-value
2008	3.27	7.52	1.98	6.76	0.126	23.07	0
2009	2.35	5.68	1.01	4.49	0.184	28.21	0
2010	1.44	3.99	1.98	5.93	0.074	-12.23	0
2011	1.45	3.65	2.86	7.07	0.178	-26.67	0
2012	2.42	5.58	0.46	2.22	0.325	45.86	0
2013	1.86	4.36	0.53	2.68	0.259	42.63	0
2014	3.10	7.09	0.78	3.73	0.289	49.73	0
2015	1.63	5.76	1.56	5.68	0.007	1.49	0.13
2016	2.94	6.94	1.29	5.52	0.185	39.61	0
2017	4.01	7.54	1.30	5.13	0.296	57.61	0
2018	2.66	6.49	1.17	4.59	0.187	41.27	0

Note: Mean forest loss (in hectares) of GFC and PRODES yearly estimates for individual farm-holds (n=21,492). A paired t-test of annual differences in deforestation revealed significant difference between the PRODES and GFC estimates for the period 2008-2018, the only exception is the year of 2015. Furthermore, GFC detects systematically higher rates of deforestation than PRODES (except for 2010 and 2011).

Table 2: Additional effects of the REDD+ initiative

Y ear	Estimator	ATT PRODES		SE	ATT GFC		SE
2013	NNM (4X)	-0.19	**	0.10	-0.57	***	0.15
	NNM (2X)	-0.21		0.11	-0.47	***	0.19
	NNM (1X)	-0.11		0.13	-0.41	**	0.21
	PSM (4N)	-0.06		0.08	-0.38	***	0.15
	PSM (2N)	-0.02		0.08	-0.42	***	0.18
	PSM (1N)	-0.09		0.11	-0.71	***	0.29
2014	NNM (4X)	-0.54	***	0.15	-0.79	***	0.25
	NNM (2X)	-0.57	***	0.21	-0.91	***	0.29
	NNM (1X)	-0.90	***	0.30	-0.70	**	0.33
	PSM (4N)	-0.48	***	0.12	-0.82	***	0.24
	PSM (2N)	-0.50	***	0.15	-0.76	***	0.26
	PSM (1N)	-0.58	***	0.19	-0.55		0.30
2015	NNM (4X)	-0.95	***	0.28	-0.64	***	0.22
	NNM (2X)	-1.19	***	0.33	-0.77	***	0.31
	NNM (1X)	-1.38	***	0.39	-0.95	**	0.45
	PSM (4N)	-0.87	***	0.24	-0.50	***	0.13
	PSM (2N)	-0.90	***	0.28	-0.42	***	0.16
	PSM (1N)	-0.98	***	0.35	-0.59	***	0.22
2016	NNM (4X)	-0.59	***	0.18	-0.28		0.28
	NNM (2X)	-0.64	***	0.20	-0.38		0.32
	NNM (1X)	-0.78	***	0.26	-0.27		0.33
	PSM (4N)	-0.93	***	0.19	-0.36		0.27
	PSM (2N)	-0.83	***	0.24	-0.23		0.29
	PSM (1N)	-1.00	***	0.32	-0.32		0.34
2017	NNM (4X)	-0.20		0.25	-0.61		0.33
	NNM (2X)	-0.36		0.30	-0.88	***	0.41
	NNM (1X)	-0.25		0.34	-0.74		0.46
	PSM (4N)	-0.06		0.23	-0.87	***	0.33
	PSM (2N)	-0.06		0.24	-0.69		0.37
	PSM (1N)	-0.14		0.28	-0.25		0.39
2018	NNM (4X)	-0.15		0.16	-0.15		0.19
	NNM (2X)	-0.24		0.18	-0.21		0.22
	NNM (1X)	-0.27		0.23	-0.43		0.26
	PSM (4N)	-0.06		0.13	0.02		0.20
	PSM (2N)	-0.06		0.16	-0.19		0.22
	PSM (1N)	0.01		0.18	-0.24		0.28

Note: ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level. ATT is the Average Treatment effect on the Treated. NNM(4X) (resp. 2X and 1X) refers to the nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls.

Table 3: Spillover effects of the REDD+ initiative

Outcome	Estimator	ATT		S.E.
PRODES 2013	NNM (4X)	-0,164	***	0,054
	NNM (2X)	-0,213	***	0,071
	PSM (4N)	-0,149	***	0,059
	PSM (2N)	-0,122	**	0,060
PRODES 2014	NNM (4X)	-0,426	***	0,108
	NNM (2X)	-0,348	***	0,117
	PSM (4N)	-0,428	***	0,112
	PSM (2N)	-0,383	***	0,151
PRODES 2015	NNM (4X)	-0,410	***	0,163
	NNM (2X)	-0,432	***	0,191
	PSM (4N)	-0,436	***	0,181
	PSM (2N)	-0,479	***	0,206
PRODES 2016	NNM (4X)	-0,080		0,118
	NNM (2X)	-0,028		0,130
	PSM (4N)	-0,798	***	0,281
	PSM (2N)	-0,947		0,585
PRODES 2017	NNM (4X)	0,140		0,126
	NNM (2X)	0,198		0,136
	PSM (4N)	-0,417		0,308
	PSM (2N)	-0,308		0,625
PRODES 2018	NNM (4X)	-0,023		0,098
	NNM (2X)	-0,029		0,114
	PSM (4N)	-0,010		0,082
	PSM (2N)	0,016		0,087

Note: ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level. ATT is the Average Treatment effect on the Treated. NNM(4X) (resp. 2X and 1X) refers to the nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls.

Table 4: Balancing tests

	Means		Variances		Standardized differences		Variance ratio	
Covariates	Control	Treated	Control	Treated	Raw	Matched	Raw	Matched
Plot area (ha)	96.37	88.89	6350.9	3042.42	-0.11	0.04	0.48	1.09
Distance from nearest river	4208.36	4437.79	1.23E+07	1.62E+07	0.06	0.04	1.31	1.26
Distance from nearest village	29496.36	20531.42	2.65E+08	1.28E+08	-0.64	0.02	0.48	0.83
Distance from Altamira	171651.3	127081.4	9.52E+09	3.58E+09	-0.55	0.02	0.38	0.89
Distance from Belo Monte dam	148787.9	91124.94	6.93E+09	3.54E+09	-0.8	-0.04	0.51	1.04
Distance from Transamazon highway	27729.06	11796.57	3.80E+08	1.12E+08	-1.02	-0.11	0.3	1.21
Distance from Xingu river	119414.3	69856.78	7.12E+09	3.08E+09	-0.69	-0.02	0.43	1
Forest cover in 2000 (GFC)	92.7	91.01	6628.29	3254.36	-0.02	0.05	0.49	1.05
GFC 2008	3.26	2.13	58.49	20.72	-0.18	0.04	0.35	1.15
GFC 2009	1.89	2.75	24.54	23.29	0.18	0.06	0.95	1.06
GFC 2010	1.54	0.94	16.62	6.87	-0.17	0.07	0.41	1.04
GFC 2011	1.54	0.86	14.19	4.7	-0.22	0.06	0.33	1.2
GFC 2012	2.39	1.78	32.33	12.88	-0.13	0.09	0.4	1.13
PRODES 2008	2.02	1.24	47.98	14.69	-0.14	0.1	0.31	1.33
PRODES 2009	1.18	0.38	23.26	3.94	-0.22	0.05	0.17	1.31
PRODES 2010	1.94	1.23	33.67	14.21	-0.14	0.04	0.42	1.17
PRODES 2011	2.62	2.89	46.5	28.21	0.04	0.14	0.61	1.19
PRODES 2012	0.56	0.2	6.09	1.47	-0.19	0.03	0.24	1.33

The goal of matching is to make the covariate distributions of participants and non-participants similar. After we compare the extent of balancing between the participant and comparison groups before and after the matching procedure. We calculate the normalized difference between these two groups for the pre-treatment covariates. The normalized difference is the most commonly accepted diagnostic used to assess covariate balance (Rosenbaum and Rubin 1985).

The normalized difference is considered negligible when it is below of 0.25 standard deviations (Imbens and Wooldridge 2009). Column 6 of Table 4 shows that, before matching, the participant group (column 3) differs significantly from the comparison group (column 2) in terms of distance from nearest village, distance from Altamira, distance from Belo Monte dam, distance from Transamazon highway and distance from Xingu river Column 7 of Table 4 reports the normalized mean differences between participants and the constructed matched group. All normalized differences are below 0.25 standard deviations, which indicates that the matching procedure was successful in constructing a valid control group.

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- RePEc https://ideas.repec.org/s/hal/wpceem.html
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