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Paying smallholders not to cut down the Amazon forest: Impact evaluation of a REDD+ pilot project *

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Abstract

We estimate the additional effects of a REDD+ pilot project offering Payments for Environmental Services to reduce deforestation by smallholders in the Brazilian Amazon. We collected original data from 181 individual farmers. We use DID-matching and find evidence that supports the parallel trend assumption. We estimate that an average of 4 ha of forest have been saved on each participating farm in 2014, and 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. We find no evidence of leakage effects. Finally, we find that the project is cost-effective.

Keywords: REDD+, Payments for Environmental Services, Brazilian Amazon, treatment effects, quasi-experiment
JEL: Q23, Q57, D12

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1 Introduction

Tropical deforestation and degradation play an important role in anthropic emissions of carbon dioxide (CO2), with an annual emission rate estimated at 7-14 percent of global CO2 emissions (Harris *et al.*, 2012; Grace *et al.*, 2014). Among forested countries worldwide, Brazil has been one of the main sources of loss of global tree cover (Hansen *et al.*, 2013). For many years now, programs and policies designed to reduce tropical deforestation have featured highly on the political agenda. Afforestation and reforestation projects were included in the Clean Development Mechanism of the Kyoto Protocol signed in 1997 and a mechanism aimed at Reducing Emissions from Deforestation and forest Degradation, known as REDD, was established during the 11th Conference of the Parties of Montreal in 2005.[1] Since that time, satellite imagery has enabled the Brazilian government to further tighten regulatory policies and to improve forest monitoring. The implementation of command-and-control measures, the expansion of protected areas, and interventions in the soy and beef supply chains, such as the Soy Moratorium established in 2006, have significantly curbed deforestation in the Amazon in recent years. Between 2005 and 2013, the annual deforestation rate in Brazil fell by 70 percent (Nepstad *et al.*, 2014).

Despite this overall improvement, however, deforestation rates have stabilized at 5,000-7,000 km^2 year^{-1} since 2009 (Godar *et al.*, 2014). Furthermore, the reduction in deforestation rates achieved prior to 2009 can mainly be attributed to large farms, as evidence shows that small farms had a limited role in the improvements recorded during this period (Godar *et al.*, 2014). Indeed, until recently, the Brazilian Institute for the Environment and Renewable Natural Resources (IBAMA), which operates as the national environmental and legal enforcement authority, has primarily targeted areas that are dominated by larger properties.[2] The reason for this is threefold. Firstly, large tracts of forest are easier to de-

[1] The core mechanism of the REDD project is to offer financial rewards to developing countries in exchange for emissions reductions achieved through decreased deforestation. In 2009, this mechanism was expanded to include provisions addressing conservation, the sustainable management of forests, and the enhancement of forest carbon stocks. This expanded strategy was renamed REDD+. As of 2014, there are more than 300 REDD+ projects around the world (Simonet *et al.*, 2014).

[2] In 2004, Brazil began implementing a federal Plan for the Protection and Control of Deforestation in the Amazon based on three pillars: (i) Tenure regularization; (ii) Environmental monitoring, control, and enforcement; and (iii) Incentives for sustainable production. The second pillar, enforced via a satellite-based monitoring system that enables the identification of deforestation hot spots, was actually the first to be im-

tect in satellite images than small ones. Secondly, it is less expensive to regulate several large landowners than many small landowners who may be scattered over a vast territory. Thirdly, targeting forests in areas dominated by small landowners living in poverty would have posed certain ethical problems. After a decade of command-and-control regulation, there is now a consensus that new mechanisms targeting small landowners are required in order to achieve additional reductions in deforestation in the Amazon rainforest (see Borner *et al.* (2015), Godar *et al.* (2014), Gebara & Thault (2013), Ezzine-de-Blas *et al.* (2011), Chhatre & Agrawal (2009) among others). For this reason, Brazil has integrated REDD+ in its environmental policy portfolio, notably through the Amazon Fund, which finances projects that align with the federal priorities. As a result, subnational REDD+ projects are emerging with the aim of promoting forest conservation among small landowners, an important step towards ensuring the respect of the Brazilian Forest Code, which requires that farmers maintain at least 50 percent of land in forest (commonly referred to as Legal Reserve), [3] and the conservation of permanent protection areas (hilltops, mountain slopes, mangroves, and riparian forests), which are to be left intact to preserve biodiversity, maintain water quality, and stabilize soils. Within this context, offering Payments for Environmental Services (PES) to small landowners conditional on the respect of the Forest Code, has emerged as a potential strategy that may achieve both equity and conservation goals in the Trans-Amazonian region. Although a bill to create a national PES program is currently being debated in Congress, PES programs in Brazil have so far been implemented mainly by Non-Governmental Organizations (NGOs) and local governments. In this article, we evaluate the effectiveness of one the first PES-based REDD+ project ever launched in Brazil.

A question of primary importance is therefore: to what extent can a PES program contribute to avoided deforestation? There are a variety of reasons why voluntary programs (like PES) may not be effective in curbing deforestation rates. Firstly, farmers who face the lowest costs for decreasing deforestation are the most likely to enter such a program. As a result, the program may end up paying some farmers for doing nothing differently from

plemented.

[3]The Brazilian Forest Code actually requires that private properties maintain 80 percent of land located in the Amazon as forestland, but the legal reserve has been lowered to 50 percent in some so-called Environmental Economic Zoning (ZEE) areas in order to encourage economic development.

what they would have done in the absence of any payment. In this case, the additional impact of the program may be quite small. This is likely to occur when the probability of being audited by IBAMA is high enough to encourage farmers to engage in alternative agricultural systems that are less dependent on forest clearing. Secondly, additionality of the program, if there is any, may be entirely offset by leakage. Leakage occurs when the program happens to increase deforestation among non-participants through market equilibrium effects such as a change in the demand for cattle products, or when a forest-owner shifts all planned deforestation activities from a PES-enrolled plot to a non PES-enrolled plot. In the most extreme cases, for example if some landowners use all PES payments to buy chainsaws to clear more forest in order to create grassland for cattle, leakage effects may well exceed additional effects (Wunder, 2007).

The use of PES to prevent the deforestation and degradation of forest lands is not new,[4] but there have been few rigorous evaluations of such PES programs so far (see Pattanayak *et al.* (2010) and Alix-Garcia & Wolff (2014) for a review of the literature). Most of these works are quasi-experimental analyses that have been conducted in Costa Rica (Robalino & Pfaff, 2013; Arriagada *et al.*, 2012; Sims *et al.*, 2014) and Mexico (Alix-Garcia *et al.*, 2012, 2015; Costedoat *et al.*, 2015). Overall, their results suggest that the environmental impact of PES is significant but modest.[5]

This study builds on and extends this literature by providing the first impact analysis of a REDD+ pilot project that offers PES in order to reduce deforestation rates in an area that has come to be considered the quintessential example of deforestation - the Brazilian Amazon. We collected data from a representative sample of small landowners living in the state of Para, where a REDD+ program called Projeto Assentamentos Sustentaveis na Amazonia (PAS) provides conditional incentives to 350 households. The PAS program, launched in 2012, is funded by the Amazon Fund until 2017. It provides enrolled landowners with annual payments contingent on their compliance with the Forest Code. In the Brazilian context, these payments should be considered as transitional assistance designed to encourage

[4]Mexico, Costa Rica, and Ecuador have already established systems in which payments are made in exchange for avoiding deforestation.

[5]Results from these studies are not readily comparable because initial deforestation levels vary across countries and the environmental outcomes are expressed in different units.

the poorest farmers to comply with the Forest Code. In addition to conditional incentives, the program provides administrative support that enables farmers to register for the Rural Environmental Registry, and technical assistance to adopt sustainable agricultural practices such as agroforestry, intensive cattle ranching, or fish farming.

We ran a two-phase survey among 181 households from intervention (where the program was offered) and comparison (where the program was not offered) communities. Before the program started, only 15 percent of the surveyed households did not meet the 50 percent legal forest reserve requirement,[6] but annual deforestation rates were high enough - above 3 percent per year on average - to justify the implementation of a PES program. Given deforestation rates observed in the area, it was indeed expected that most households would cross the threshold of 50 percent of land as legal reserve in a few years in the absence of intervention.[7]

We show that the process of self-selection into the program led to the involvement of a particular group of landowners. Before the program started, participants had smaller farms and a smaller number of cows compared to non-participants, although they had similar deforestation rates. They also derived more money from wage labour.

Using difference-in-difference (DID) matching, we estimate the additional and leakage effects that occurred as a result of the PAS project. We show that the additional effect of the program on participants is significant. We find evidence supporting the parallel trend assumption and show that participants devoted an average of 66 percent of their land to forest in 2014 while it would have been 61 percent without the program. We thus estimate that an average of approximately 4 ha of forest have been conserved on each participating farm as a result of the program. Although forest cover continues to decline in both participant and control groups after 2010, we highlight a clear break in the trend of deforestation rates among participants, which we attribute to the program. After 2010, the deforestation rate among participants decreases to 1.8 percent per year, which means that the program led to an approximate decrease of 50 percent in the average deforestation rate. Our esti-

[6] Three quarters of them, however, did not fulfill the 80 percent legal forest reserve criterion.

[7] Our data show that the average landowner from comparison communities indeed reached the threshold of 50 percent of land as legal reserve in 2014.

mates also suggest that without the program, the average participant would have attained the legal threshold of 50 percent of land as forest in only a few years.

We moreover show that this decrease in deforestation occurs at the expense of pastures versus cropland. We find no evidence of a leakage effect among non-participants living in intervention communities. Extrapolating the estimated ATT to the 350 participants of the program, we calculate that the PAS project has succeeded in avoiding the emission of around 647,400 tCO2. Comparing the monetary value of these gains to the costs of the implementation, our results indicate that the PAS project is likely to be cost-effective at this stage, although nothing can be said about the longer-term effects.

The remainder of the article is structured as follows: Section 2 presents the context and the project under study, Section 3 our data collection process, and Section 4 our estimation methodology. The main results are presented in Section 5. Section 6 discusses cost-effectiveness, and Section 7 concludes and discusses the likely long term impact of the program.

2 Context and PAS project

The PAS project is implemented by a Brazilian NGO called the Amazon Environmental Research Institute (IPAM).[8] The participants in the PAS project live in 13 settlements located in the municipalities of Anapu, Pacaja and Senador Jose Porfirio, located near the BR-230 Trans-Amazonian Highway, an area that has historically suffered from pronounced levels of deforestation and continues to do so today (Figure 1).

Agricultural settlers arrived in the area in the early 1970s during the early stages of the National Integration Plan for the colonization of the Brazilian Amazon. As a part of this plan, Amazonian colonists received land and in-kind support to settle along the Trans-Amazonian Highway, which rapidly became part of the arc of deforestation that now characterizes the area. Indeed, during this time, settlers were formally encouraged by governmen-

[8] IPAM is a recognized national actor in the implementation of REDD+ projects in the Brazilian Amazon (Gebara *et al.*, 2014). Although IPAM is responsible for the implementation of the PAS project, two other Brazilian partners are involved: the National Institute of Colonization and Agrarian Reform (INCRA) and the Brazilian Foundation Live, Produce and Preserve (FVPP).

tal authorities to deforest more than half of their plots in order to secure their ownership of the land. The National Institute for Colonization and Agrarian Reform (INCRA) was created in order to manage the creation of these first agricultural settlements (Valverde, 1989; Menton *et al.*, 2009). In the mid-1970s, the government prioritized support for large-scale agribusiness and abandoned the small landowners in the area, putting them in a precarious living situation, which has remained largely unchanged since then. Today, the livelihoods of small landowners in this area still depend on swidden agriculture and extensive cattle ranching, which constitute two primary drivers of deforestation(Smith *et al.*, 1996; Soares-Filho *et al.*, 2006). The cultivation of cocoa in agroforestry systems (recognized as Legal Reserve under certain conditions) is expanding in the area due to guaranteed markets and higher prices, as well as to the interventions of several NGOs and private firms that provide technical assistance to farmers. Further adoption of this crop, however, is often limited by poor soil fertility.

In 2008, the Brazilian government blacklisted municipalities in the Amazon in an attempt to better target their efforts to reduce deforestation. Not only were law enforcement and monitoring activities intensified, but economic sanctions and political pressures were also imposed in blacklisted municipalities (Assunção & Rocha, 2014). The three municipalities included in our study were added to the blacklist in 2009 and 2012. Although landowners are aware that IBAMA monitors the blacklisted municipalities more closely, they often have no other choice but to clear and burn the forest in order to maintain a subsistence living. For this reason, promoting the adoption of agro-ecological practices was the main objective of the first PES-based federal program, called Proambiente, that was launched in 2003. However, Proambiente was halted in 2006 due to funding cuts. Some years later, the NGO IPAM launched the PAS project, with the goal of helping smallholders to comply with the law in the near future. The PAS project offers PES conditional on forest conservation (that is compliance with the Forest Code, which requires having at least 50 percent of land as legal reserve, and conserving 15 meter-wide forest on riparian zones) and on the adoption of an environmentally sustainable production system.[9]The annual payment may reach

[9]The first step toward a more sustainable management of the forest is the regularization of land tenure through registration under the Rural Environmental Registry, which is also part of the program.

a maximum of USD 626[10] and is paid quarterly.

Additional information about the implementation of the program should be mentioned. Firstly, the switch towards more sustainable agricultural production systems was not a requirement for receiving PES in 2014, a decision that the NGO took because of the delay in implementing technical assistance. Our study thus focuses mainly on the issue of deforestation. Secondly, the first payments were made in 2014, a few weeks after the final survey. Therefore, if there is any impact of the program (and there is one, as we shall see), this may be due to the fact that the participants reduced deforestation in anticipation of such payments. That of course does not exclude the possibility that this result arises because the participants had been convinced of the necessity of decreasing deforestation during awareness meetings organized in the framework of the program or during discussions with technical assistants of the NGO.

3 Data

3.1 Surveys

We ran two surveys in eight communities, four of which were offered the program, and the remaining four were used for comparison (Figure 1). A total of 181 households were interviewed twice. The first survey took place in June-July 2010, before the PAS project began. The second survey took place in February-March 2014, approximately 18 months after the official start of the project. In all communities, interviewed households were selected randomly. In the intervention communities, a stratified randomization was used in order to include approximately half of the households that had previously participated in Proambiente. The four comparison communities were selected from a list of accessible communities located in the project's area (Sunderlin *et al.*, 2010). From the 181 households that are included in this study, 106 households were surveyed in the intervention communities and 75 households were surveyed in the comparison communities. Two years after the first sur-

[10] 1680 Reais converted to USD by applying a conversion rate of 0.3724 (average conversion rate of Brazilian Real to American dollars in 2014).

vey, half of the 106 households living in the intervention communities became involved in the PAS project.

Table 1 reports summary statistics for the entire sample in 2010 and 2014. All data is based on declarations made by the interviewed households, including data on land use. It is worth-mentioning that the proponent intended to use satellite images for assessing the respect of the Forest Code, but such data were not available at the time we conducted the surveys. Therefore, during both surveys, each respondent was asked to make a detailed sketch of his or her landholding. The consistency of the responses given between the two phases of the survey was assessed. Moreover, independence between the research team and the project proponent was clearly stated at the beginning of each questionnaire. Respondents were informed that the data would not be used by the proponent for land use assessments of participants in the PES program. They were also told that the proponent relies on satellite images and field visits for these assessments and that the anonymity of all responses was guaranteed.

The sample includes small rural families that own less than 100 hectares on average[11] and are representative of the colonist small farmers of the Transamazon highway (Moran, 1981; Perz *et al.*, 2006). In 2010, these landowners devote about 67 percent of their land to forest and about 25 percent to pasture. Most of the remaining land is dedicated to the cultivation of rice, cassava, or cocoa. While they derive income mainly from crops and livestock products, other sources of income such as wage labour from agricultural work on neighboring farms, and government social programs, particularly *Bolsa Familia* and retirement pensions, are not negligible. In our sample, the deforestation rate between 2008 and 2010 was above 3 percent per year on average, amounting to almost 3 hectares of forest cleared each year, which is similar to other estimates in the literature (see Godar *et al.* (2014) for an example). Between 2010 and 2014, the main change relates to a decrease in forest cover, with forests mainly being converted to pasture.

[11] Börner *et al.* (2010) estimate that around 13 percent of the Brazilian Amazon is occupied by formal rural settlements, where people own less than 100 hectares in average. According to INCRA, there are 969,640 families living in these settlements in early 2016, covering a surface area of around 88.3 million hectares. The remaining land includes Indigenous land (22 percent), protected areas (17 percent), private land (24 percent) and unclassified public land (24 percent).

Table 2 displays the summary statistics for several variables corresponding to the pre- and post-program surveys in the intervention and comparison groups. Households in intervention communities do not differ much from households in comparison communities in terms of mean age (about 50 years), education (about 2.5 years), family size (about 5 members) and total amount of land owned (about 90 ha). However, in both surveys, intervention communities are characterized by owning more land in forest and crops, less land in pasture, and more revenue from wage labour than comparison communities. The two groups also differ in land use changes over time, with less conversion from forest to pasture in the intervention communities. Our goal is to assess to what extent such changes can be attributed to the PAS project.

3.2 Determinants of participation in the program

In order to identify the determinants of participation in the PAS project, we compare participating households in the intervention communities to non-participating households in the same communities. We perform tests on the equality of means between these two groups for a variety of variables measured in 2010. Results are displayed in Table 3. Before the start of the project, participating households on average had smaller plots, owned less livestock, and earned more money from wage labour (e.g. agricultural labour) and government social programs (including *Bolsa Familia*) than non-participating households. However, participants did not differ significantly from non-participants in terms of the proportion of forestland owned (about 70 percent of the land area), deforestation rates (around 3 percent annually), agricultural land (almost 10 percent), or pasture land (around 20 percent). This indicates that adverse selection in the program was low.

In addition to this analysis, we fit a maximum-likelihood logit regression including all observable factors[12] presented in Table 3. In this model, the dependent variable takes on the value one if the farmer is a participant and takes on the value zero if he/she belongs to the group of non-participants living in intervention communities. Table 4 displays the results expressed in terms of odds ratios. Only the income derived from wage labour appears to

[12] We do not include the dummy variable that captures participation in the previously run project, Proambiente, because no farmers in the comparison communities participated in the Proambiente project.

play a significant role in determining participation in the project, and its effect remains small in size: holding other variables constant, the odds of being a participant is on average 1 percent greater for farmers who earn 500 Reais more from wage labour than for others. No other factors seem to drive participation in a significant way.

4 Estimation Methodology

4.1 Parameters of interest

We seek to capture various impacts of interest. The households from the comparison communities (which we hereafter refer to as the untreated group) are used to construct valid control groups. First, we aim to measure the impact of the program on forest conservation among participants. This impact is measured as the average amount of forestland saved by participating farmers as a result of the program. Second, we investigate a possible cumulative effect triggered by a farmer's participation in past conservation projects. In our case, this refers to the impact of participating in the PAS program among those who had previously participated in the Proambiente program. Finally, we study the indirect (or leakage) effects of the PAS project, which refers to the changes in the amount of forestland owned by non-participating farmers who reside in an intervention community. We can expect both positive and negative leakage effects of the program on these households. On the one hand, they may be more likely to slow deforestation on their own plots if they had the opportunity to attend awareness meetings and discuss land use issues with participants after the start of the project in 2012. This may have convinced some of the importance of respecting the Forest Code even without the added incentive of PES. On the other hand, the program may increase deforestation among non-participants if market equilibrium effects occur (such as a change in the demand for cattle products) or if some participants seek to compensate for a possible loss of income by working as a labourer on the plots of non-participant neighbours.

In order to determine the average amount of forestland conserved among participants as a result of the project, we need to calculate the difference between the amount of forestland observed on participating farms in 2014 and the amount of forestland that would have been observed in those farms in 2014, had they not been involved in the PAS project. This is the so-called average treatment effect on the treated (ATT), defined as $ATT = E(y^1 - y^0|D = 1)$, where y^1 denotes the amount of a farmer's forestland in the presence of the project, y^0 denotes the amount of a farmer's forestland in the absence of the project, and D is a dummy variable which takes on the value of one when the farmer participated in the project and zero otherwise. We use DID and DID-matching methods to estimate the outcome level in the unobserved state, namely $E(y^0|D = 1)$.

4.2 DID-matching approach

The matching approach is widely used when evaluating voluntary programs (Todd, 2007). The main concerns when evaluating the impact of such programs relates to the fact that sometimes intervention communities are not randomly selected and participants in intervention communities may self-select into the program given its voluntary nature. In our pre-program data, we indeed find evidence that intervention and comparison communities significantly differed from each other in terms of land use and sources of income (Table 2). We moreover show that farmers in intervention communities who participated in the program differ from non-participants before the start of the project (Table 3). A crucial step is thus to control for observable factors X that are likely to drive both the decision to participate in the PAS project as well as decisions regarding the conservation of forestland in 2014.

It is important that the observable factors X are not affected by the project (Imbens, 2004), which is why we use pre-treatment values from 2010 (and from 2008 when available). We include in the set of observable factors X extracted from the baseline 2010 survey: the total land area in hectares in 2010, the amount of forestland as a share of the total land area in 2010 and in 2008 (the forestland variable in 2008 was constructed from recall-type questions), the agricultural land as a share of the total land area in 2010, pastures as a share of the total land area in 2010, the market value of total agricultural production in 2010 (which includes sales and self-consumption), the market value of owned livestock in 2010, the amount of other sources of income received in 2010, such as those derived from wage labour, government social programs, retirement pensions, and outside businesses (in Reais), as well as family size and the age and education level (in school years) of the head of the household.

Matching eliminates selection bias due to observable factors X by comparing treated farmers (i.e. participants) to observationally identical untreated ones (Imbens, 2004). We apply the DID-matching estimator as defined in Heckman *et al.* (1997) because, even after conditioning on observable factors X, there may still be systematic differences between treated and matched untreated farmers' outcomes that could lead to a violation of the identification conditions required for matching. This estimator allows for temporally invariant differences in outcomes between participants and their X-matched untreated counterparts. This requires that $E(\Delta y^0|X, D = 1) = E(\Delta y^0|X, D = 0)$, meaning that the average difference in forestland between the two matched groups must be constant through time in the absence of treatment. In other words, this means that observationally identical treated and untreated individuals must exhibit the same change in forestland in the absence of treatment. This is the so-called parallel trend assumption. Applied to our data, this identification strategy consists in comparing the change in participants' forest cover between 2010 and 2014 with the change in forest cover among matched untreated farmers. Forest cover is expressed as a share of the total land area.

Another key assumption for the validity of the DID-matching approach is that the treatment received by one farmer must not affect the outcome of another farmer. This assumption is referred to as the Stable-Unit-Treatment-Value-Assumption (Rubin, 1978). In our analysis, the validity of this assumption is not likely to be threatened because the connection between communities is extremely limited due to the poor quality of transportation infrastructure.

4.3 Estimators

We use the nearest-neighbour matching estimator and the kernel-based matching estimator (Abadie *et al.*, 2004). The general form of the DID-matching estimator is:

$$E(y^1 - y^0|D = 1) = \frac{1}{n1} \sum_{i \in I_1} \left(y^1_{it} - y^0_{it'} - E(y^0_{it} - y^0_{it'}|D = 1, X_i) \right) \tag{1}$$

with

$$E(y^0_{it} - y^0_{it'}|D = 1, X_i) = \sum_{j \in I_0} \lambda_{ij} (y^0_{jt} - y^0_{jt'}) \tag{2}$$

where I_1 denotes the group of treated farmers, I_0 denotes the group of untreated farmers, and n_1 is the number of treated farmers in I_1. Matching estimators differ in how matched untreated farmers are selected through the matching procedure. This difference is driven by the weights λ_{ij} that we assign to potential matches given their characteristics X. The nearest-neighbour matching estimator we use in the analysis matches each participant to the closest untreated farmer or the four closest untreated farmers from the comparison communities, according to the vector X. We also apply the matching procedure to the summary statistic $\Pr(D_i = 1|X_i)$, the so-called propensity score (Rosenbaum & Rubin, 1983).

Another, computationally easier, way to generate an estimate of the ATT is to regress D on Δy, controlling for X (or for the propensity score), by using ordinary least squares.[13] We run these linear regressions as a robustness check. Finally, we also provide results of the simple DID estimator, which simply consists in regressing D on Δy.

We use the asymptotically-consistent estimator of the variance of the nearest-neighbour matching estimator provided by Abadie & Imbens (2006), and we implement a bootstrap procedure (500 repetitions) in order to obtain an estimator of the variance of the kernel matching estimator. In addition, we test for the autocorrelation of the deforestation rates within communities and find that the size of the intra-cluster correlation for this variable is actually small (3.5 percent).[14] We thus choose to ignore the correlation and analyze the data

[13]In addition to the assumption of linearity, this requires us to assume that the gain associated with the program is constant across X, meaning that the impact of the program is the same for all treated farmers.

[14]This result is not surprising since communities as defined in our study cannot be thought like communities as defined in African studies for example, where there is evidence that the households that are members of the same villages behave the same way. In the present study, households living in the same communities

in a standard way.[15]

5 Results of the impact analysis

5.1 Impacts on participants

We first apply the matching procedure to the group of participants (the treated group) and to the group of farmers living in the comparison communities (the untreated group). Conditional probabilities for participation in the project (or propensity scores) are computed by estimating a probit model where the dependent variable is D and which includes all of the aforementioned covariates X. Figure 2 shows that densities in both groups are high enough for a wide range of propensity scores, meaning that the matching procedure is likely to perform well. The matching procedure is considered successful when significant differences in observable factors X among the treated and matched-untreated are removed.

We compare the extent of balancing between the two groups before and after the matching procedure. Table 5 shows that, before matching, the treated group significantly differs from the untreated group in terms of land use and wage income: treated households own more forest cover both in 2010 and in 2008, and less pasture in 2010, compared to untreated households; additionally, they derive more income from wage labour in 2010. The matching procedure was successful in removing important sources of bias, such as differences in land use between groups. Although the gap between groups in terms of wage income was considerably diminished, it remains statistically significant at the 5 percent level. There is evidence that farmers who derive more income from wage labour are more likely to participate in the PAS project (see Section 3.2). However, these farmers do not have lower deforestation rates: their forest cover is statistically the same as that of their matched counterparts in 2010 (about 71 percent of land) as well as in 2008 (about 76 percent of land), which supports the parallel trends assumption underlying our difference-in-differences approach. This sug-

actually live very far from each other and thus have very limited interactions.

[15]With eight clusters only, standard errors might prove too wide and too conservative. We nevertheless obtain still significant estimates when using clustered standard errors in the estimates for which the sample is large enough, i.e. when we apply our identification strategy to intervention communities taken as a whole (see Section 5.3). Results are available from authors upon request.

gests that wage labour should not be seen as a confounding variable.

We examine the validity of the parallel trends assumption further by using a placebo test that applies the identification strategy at a pre-treatment year, 2008, when no effect should be detected. Specifically, we test the parallel trends assumption by matching individuals in the treatment group with individuals in the comparison group using control variables measured in 2010 in the same manner that we estimate the ATT in 2014, except that we evaluate the ATT in 2008 instead. Using this procedure, we find no significant difference in forest cover between participants and their matched counterparts (Table 6). Note that applying the simple DID approach to the data leads to the same result (a zero impact of the program in 2008). We conclude that our identification strategy is valid.

Column 1 of Table 7 gives the estimates of the impact of the program on forestland owned among participants. The estimated ATT range between 5.4 and 8 percentage points. Using the smallest significant impact estimator generated from the matching analysis (ATT= 5.4 percentage points), it represents the difference in 2014 between the average land area devoted to forests among participants (66 percent) and the average land area devoted to forests among controls (60.6 percent). Given that average land area equals 79.3 hectares, this indicates that an average of approximately 4.3 hectares of forests were saved on each participating farm, compared to the counterfactual scenario of no program.

This result is shown graphically in Figure 3. We observe that the amount of forest cover continues to decline in both participant and control groups after 2010. However, we see a clear break in the deforestation trend among participants, which we can attribute to the PAS project. After 2010, the deforestation rate among participants decreased to 1.8 percent, which means that the PAS project has led to an approximately 50 percent decrease in the average deforestation rate in these farms, compared to the control group, where the deforestation rate is still around 3.5 percent in 2014.

We also observe that the deforestation rate among controls is similar to that in comparison communities, around 3.5 percent between 2010 and 2014, and that it appears to have followed the same trend since 2008. This is why applying the DID approach to the data leads to results that are very similar in size to those obtained from the DID-matching approach (see first row of Table 7). Finally, Figure 3 shows that the average landowner from comparison communities reached the threshold of 50 percent of land as legal reserve in 2014, and that the average participant would have crossed this threshold in just a few years in the absence of the program.

Applying the same identification strategy to the total land area, we find no difference between participant and control groups in 2014 (Table 8). We conclude that less deforestation among participants necessarily caused some changes to the way that other owned land is used. We thus apply our identification strategy to the proportion of land devoted to crops and to pastures. We find no evidence of any impacts on cropland (Table 9). In contrast, we do find evidence that the project had a significant impact on pastures. Column 1 of Table 10 displays the estimates of the impact of the program on participants in terms of amount of total land as pasture. The estimated ATT range between -6 and -11.3 percentage points. This means that the creation of an average of 4.8 hectares of pastures (taking ATT=-6 percentage points) may have been avoided in each participating farm compared to a scenario without the PAS project. These results fit well with our estimates of the program's impact on forest cover. We thus conclude that an average of about 4 to 5 hectares of forest have been saved on each participating farm in 2014, and that this conservation came at the expense of pastures rather than cropland.

Finally, since participants did not receive the PES until 2014, we investigate whether the changes in land use that occurred due to the program, i.e. more forests and less pastures, prompted participating farmers to seek alternative sources of income outside the farm. To do so, we apply our identification strategy to the variable that measured wage labour in 2014. Most estimators do not allow us to reject the null hypothesis of no impact (Table 11). We thus conclude that participants did not seek new sources of income during the PES contract. We also apply this identification strategy to the variable that measured the value of total livestock owned in 2014.[16] The point estimate is negative but lacks precision, and we are not able to reject the null hypothesis of no impact (Table 12). Taken together, these results suggest that participants in the PAS project simply devoted less pasture land to their

[16]The average value of all cattle owned by participants in 2014 is about 15,000 Reais, which corresponds to about 15 cows. In 2010, they owned an average of about 11 cows per farm.

cattle as a result of the program.

5.2 Cumulative effects of a previous PES program

In our sample, almost 80 percent of participants in the PAS project had previously participated in the Proambiente project, a PES-based program run by the same NGO from 2003 to 2006. Although Proambiente was abandoned after only six months of payments, the landowners who had participated in that program were nevertheless already familiar with PES contracts when the PAS project started. They had additionally participated in a number of briefings about agro-ecological practices run by the NGO. Consequently, one might expect that the impact of the project on these farmers will be strong.

We apply our identification strategy to this subset of farmers in order to estimate the impact of having participated in both projects. Balancing tests are shown in Table 13. The matching procedure was successful in removing all significant sources of bias, including the gap between groups in terms of wage income.

Column 2 of Table 7 gives the estimates of the impact of the PAS program on participants Proambiente. The estimated ATT range between 5.6 and 9.8 percentage points. Using the smallest significant impact estimator (ATT= 5.6 percentage points), this result represents the difference between the average land area devoted to forests among the treated (68.6 percent) and the average land area devoted to forests among controls (63 percent) in 2014. This indicates that an average of approximately 4.5 hectares of forests may have been saved on farms that participated in both projects, compared to a scenario in which neither program would have been implemented.

Same results hold as well for other land uses. We find no evidence of an impact on cropland. In contrast, we find evidence that participation in both programs had a significant impact on pastures. Column 2 of Table 10 provides point estimates expressed in terms of pastures as a share of total land area. The estimates range between -7.4 and -12.4 percentage points. This means that the creation of an average of about 6 hectares of pastures may have been avoided on each farm that participated in both projects, compared to a no-program situation. Given the proportion of Proambiente participants among PAS participants, we cannot rule out the possibility that the impacts that we estimate for the PAS project actually reflect the cumulative impacts of both projects.

5.3 Leakage effects

We test for the presence of leakage effects within intervention communities by applying our DID-matching procedure to the non-participants living in these communities. Column 3 of Table 7 shows the estimates of the impact of the program on non-participants. The null assumption (ATT= 0) cannot be rejected whatever the estimator considered, which indicates that, if there is any spillover effect it is too small to be detected using our data. We are, however, able to show that, if there is any spillover effect it is too small to entirely offset the additional impact of the program on forest cover. To do so, we apply our identification strategy to intervention communities taken as a whole, meaning that we considered both participants and non-participants living in intervention communities as members of the treated group. Again, we compute conditional probabilities of living in an intervention community for each individual (see the distribution of propensity scores on Figure 4).

Column 4 of Table 7 gives the ATT we obtained for this group. Overall, the impact of the program on the treated group remains significantly different from zero. The ATT values range from 4.2 to 5.4 percentage points, which means that an average of approximately 4 hectares of forests may have been saved on farms located in intervention communities. Again, we find that the average amount of new pasture land that was avoided as a result of the program is very similar in size, around 4.2 percentage points (Column 4 of Table 10). We can thus safely conclude that, even in presence of leakage inside intervention communities, the PAS project had a significant and positive net impact on forest cover in intervention communities, and that this change occurred to the detriment of new pasture land.

6 Cost-benefit analysis

Finally, we use our estimates of the ATT to perform a cost-benefit analysis of the project. Given that participants saved an average of approximately 4 ha of forest on their farm since the beginning of the project in 2012,[17] we expand this point estimate to the 350 households involved in the project and estimate that a total of 1,400 hectares of forest were saved as a result of the program. Using the estimated carbon sequestration capacity of 126 tC per hectare of forest provided by the Intergovernmental Panel on Climate Change (IPCC), we calculate the impact of the forestland conserved in tCO2 (1 tC =3.67 tCO2), and determine that the PAS program led to around 647,400 tCO2 in avoided emissions.

Depending on the carbon price chosen, we reach differing conclusions regarding the cost-effectiveness of the project. In the relevant literature, carbon prices range from USD 5.2 per tCO2, the price in the voluntary carbon market[18](Hamrick, 2015), to USD 11 and USD 56 per tCO2, when using the social cost of carbon [19] (IWGSCC, 2015). The costs of the PAS project can be estimated using either the amount of PES disbursed to participants in 2014, or alternatively, the total cost of the project over two years, which includes start-up as well as operational costs.[20] Table 14 provides the difference between the gains and the costs of the PAS project using each of these methods. Our results indicate that the project appears to be cost-effective even when assuming the smallest possible value for benefits and the largest possible value for costs[21].

7 Conclusion

Subnational REDD+ programs and projects are expanding in many areas around the world, and particularly in Brazil. However, the impacts of these projects have been largely under-

[17]Participants in the project received PES only in 2014, but we do not rule out the possibility that the numerous public meetings regarding the significance of the upcoming environmental regulations that took place in 2013 may have played a role in the decrease in deforestation we measure. As a result, we assume that the gains in terms of retained forest cover should be distributed over both years.

[18]We report here the average price for REDD+ credits over the 2007-2014 period. Transactions of REDD+ credits mainly occur on the over-the-counter (OTC) voluntary carbon market, which prevents transparency on data. The surveys led by Forest Trends Ecosystem marketplace provide the best estimate of the mean exchange price of these voluntary transactions.

[19]The social cost of carbon (SCC) is an estimate of the monetized damages associated with an incremental increase in carbon emissions in a given year. We report here the estimates made by the Interagency Working Group on Social Cost of Carbon (United States Government) in July 2015, using discount rates of 5 percent (SCC of USD 11) and 2.5 percent (SCC of USD 56).

[20]Sills *et al.* (2014) calculated a total annual cost of the PAS project of USD 769 per household per year, including the start-up (awareness meetings, baseline analysis, etc.) and recurrent (administrative, monitoring, technical assistance, etc.) costs of the project.

[21]This analysis does not take into account the risk of non-permanence of the benefits. We further discuss this concern in the conclusion.

studied. This article fills this gap by providing the first impact assessment of a REDD+ pilot program that offers PES as well as technical and administrative support to facilitate farmer compliance with the Forest Code in the Brazilian Amazon. We estimate additional and leakage effects of the program using original data collected from 181 individual farmers in the state of Para. We apply DID-matching to our data and find support for the parallel trend assumption underlying our identification strategy. We estimate that an average of approximately 4 ha of forest have been saved on each participating farm in 2014 compared to a control group. Although the amount of forest cover continues to decline in both participant and control groups after 2010, we highlight a clear break in this trend among participants, which we are able to attribute to the PAS project. After 2010, the deforestation rate among participants decreases to 1.8 percent, which means that the program led to a decrease in the average deforestation rate by approximately 50 percent.

Our estimates also suggest that without the program, the average participant would have crossed the threshold of 50 percent of land as legal reserve within just a few years. We moreover show that decreases in deforestation occurred at the expense of pastures over cropland. Given the proportion of former Proambiente participants among PAS participants, we cannot rule out the possibility that the impacts that we estimate for the PAS project reflect the cumulative impacts of both projects. We find no evidence of leakage effects among non-participants living in intervention communities. Finally, we perform a cost-benefit analysis and obtain results indicating that after two years of implementation, the PAS project appears to be cost-effective by even the most conservative estimates.

Our results suggest that REDD+ projects that include a PES component constitute a promising strategy to reduce deforestation rates among small landowners. The long term on-the-ground presence of the project proponent and the gradual implementation of command-and-control measures in the most remote areas probably helped obtaining such encouraging results. It should be noted, however, that the PAS project is still in the early stages of implementation and that our data do not allow us to determine whether participants will be able to eliminate their reliance on deforestation activities altogether by switching towards more sustainable agricultural production systems before the program's expiration date. Our results indicate that participants in the program were able to reduce their deforestation activities by devoting less pastureland to their cattle in the first year of the program, and that they may not have suffered from a loss of income as a result of less deforestation.

Taken together, these results raise several questions. Will participating farmers adopt more intensive cattle ranching systems in the long run? Are there other strategies available to farmers that would enable them to reduce their dependence on deforestation activities? Among the possible alternative practices, the expansion of cocoa production emerges as a promising alternative to cattle farming and swidden agriculture because cocoa is grown in an agroforestry system (as such, it can be recognized as Legal Reserve), and because it has the potential to be more profitable than extensive cattle ranching (Schneider *et al.*, 2015; Sablayrolles *et al.*, 2012). A limitation, however, is that cocoa production requires fertile soils, high start-up costs, as well as technical agricultural support in order to obtain good quality cocoa. Towards this end, the PAS project includes provisions aimed at providing technical assistance for the adoption of such sustainable practices. An evaluation of the project in the longer run is thus likely to provide evidence on participants' ability to entirely eliminate their dependence on the deforestation of mature forest and switch toward more sustainable agricultural production systems. Understanding the effectiveness of monetary payments on smallholders conservation decisions, in the context of their broader strategies, is indeed fundamental to understand the implications of PES programs in the long run.

References

Abadie, A., Drukker, D., Herr, J. L., & Imbens, G. W.: Implementing matching estimators for average treatment effects in stata, *Stata journal*, 4, (2004), 290–311.

Abadie, A., & Imbens, G. W.: Large sample properties of matching estimators for average treatment effects, *Econometrica*, 74(1), (2006), 235–267.

Alix-Garcia, J., Sims, R., Katharine, & Yañez-Pagans, P.: Only one tree from each seed? environmental effectiveness and poverty alleviation in mexico's payments for ecosystem services program, *American Economic Journal: Economic Policy*, forthcoming.

Alix-Garcia, J., & Wolff, H.: Payment for ecosystem services from forests, *Annual Review of Resource Economics*, 6(1), (2014), 361–380.

Alix-Garcia, J. M., Shapiro, E. N., & Sims, K. R. E.: Forest conservation and slippage: Evidence from mexico's national payments for ecosystem services program, *Land Economics*, 88(4), (2012), 613–638.

Arriagada, R. A., Ferraro, P. J., Sills, E. O., Pattanayak, S. K., & Cordero-Sancho, S.: Do payments for environmental services affect forest cover? a farm-level evaluation from costa rica, *Land Economics*, 88(2), (2012), 382–399, matching sur PES au Costa Rica.

Assunção, J., & Rocha, R.: Getting greener by going black: The priority municipalities in brazil, Tech. rep., Climate Policy Initiative Working Paper, 2014.

Borner, J., Marinho, E., & Wunder, S.: Mixing carrots and sticks toconserve forests in the brazilian amazon: A spatial probabilistic modeling approach, *PloS one*, 10(2), (2015), e0116846.

Börner, J., Wunder, S., Wertz-Kanounnikoff, S., Tito, M. R., Pereira, L., & Nascimento, N.: Direct conservation payments in the brazilian amazon: Scope and equity implications, *Ecological Economics*, 69(6), (2010), 1272–1282.

Chhatre, A., & Agrawal, A.: Trade-offs and synergies between carbon storage and livelihood benefits from forest commons, *Proceedings of the National Academy of Sciences*, 106(42), (2009), 17667–17670.

Costedoat, S., Corbera, E., Ezzine-de Blas, D., Honey-Rosés, J., Baylis, K., & Castillo-Santiago, M. A.: How effective are biodiversity conservation payments in mexico?, *PloS one*, 10(3), (2015), e0119881.

Ezzine-de-Blas, D., Börner, J., Violato-Espada, A.-L., Nascimento, N., & Piketty, M.-G.: Forest loss and management in land reform settlements: Implications for redd governance in the brazilian amazon, *Environmental science & policy*, 14(2), (2011), 188–200.

Gebara, M. F., Fatorelli, L., May, P., & Zhang, S.: Redd+ policy networks in brazil: constraints and opportunities for successful policy making, *Ecology and Society*, 19(3).

Gebara, M. F., & Thault, A.: Ghg mitigation in brazil's land use sector: an introduction to the current national policy landscape, *World Resource Institute Working paper*.

Godar, J., Gardner, T. A., Tizado, E. J., & Pacheco, P.: Actor-specific contributions to the deforestation slowdown in the brazilian amazon, *Proceedings of the National Academy of Sciences*, (p. 201322825).

Grace, J., Mitchard, E., & Gloor, E.: Perturbations in the carbon budget of the tropics, *Global Change Biology*.

Hamrick, K.: State of the voluntary carbon markets 2015. ahead of the curve, Tech. rep., Forest Trends Ecosystem Marketplace, 2015.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., Thau, D., Stehman, S., Goetz, S., Loveland, T., *et al.*: High-resolution global maps of 21st-century forest cover change, *Science*, 342(6160), (2013), 850–853.

Harris, N. L., Brown, S., Hagen, S. C., Saatchi, S. S., Petrova, S., Salas, W., Hansen, M. C., Potapov, P. V., & Lotsch, A.: Baseline map of carbon emissions from deforestation in tropical regions, *Science*, 336(6088), (2012), 1573–1576.

Heckman, J. J., Ichimura, H., & Todd, P. E.: Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme, *The review of economic studies*, 64(4), (1997), 605–654.

Imbens, G. W.: Nonparametric estimation of average treatment effects under exogeneity: A review, *Review of Economics and statistics*, 86(1), (2004), 4–29.

IWGSCC: Update of the social cost of carbon for regulatory impact analysis under - interagency working group on social cost of carbon, Tech. rep., United States Government, 2015.

Menton, M. C. S., Merry, F. D., Lawrence, A., & Brown, N.: Company-community logging contracts in amazonian settlements: impacts on livelihoods and ntfp harvests, *Ecology and Society*, 14(1).

Moran, E. F.: *Developing the Amazon.*, Indiana Univ. Press, 1981.

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., Seroa da Motta, R., Armijo, E., Castello, L., Brando, P., Hansen, M. C., McGrath-Horn, M., Carvalho, O., & Hess, L.: Slowing amazon deforestation through public policy and interventions in beef and soy supply chains, *Science*, 344.

Pattanayak, S. K., Wunder, S., & Ferraro, P. J.: Show me the money: Do payments supply environmental services in developing countries?, *Review of Environmental Economics and Policy*, 4(2), (2010), 254–274.

Perz, S. G., Walker, R. T., & Caldas, M. M.: Beyond population and environment: Household demographic life cycles and land use allocation among small farms in the amazon, *Human Ecology*, 34(6), (2006), 829–849.

Robalino, J., & Pfaff, A.: Ecopayments and deforestation in costa rica: A nationwide analysis of psa's initial years, *Land Economics*, 89(3), (2013), 432–448.

Rosenbaum, P. R., & Rubin, D. B.: The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70(1), (1983), 41–55.

Rubin, D. B.: Bayesian inference for causal effects: The role of randomization, *The Annals of statistics*, (pp. 34–58).

Sablayrolles, P., Oliveria, C., & Pinto, C.: Adequação ambiental e políticas públicas para a agricultura familiar do alto xingu, Tech. rep., GRET, 2012.

Schneider, C., Coudel, E., Cammelli, F., & Sablayrolles, P.: Small-scale farmers' needs to end deforestation: Insights for redd+ in são felix do xingu (pará, brazil), *International Forestry Review*, 17(S1), (2015), 124–142.

Sills, E. O., Atmadja, S. S., de Sassi, C., Duchelle, A. E., Kweka, D. L., Resosudarmo, I. A. P., & Sunderlin, W. D.: *REDD+ on the ground: A case book of subnational initiatives across the globe*, CIFOR, 2014.

Simonet, G., Karsenty, A., de Perthuis, C., Newton, P., & Schaap, B.: Redd+ projects in 2014: an overview based on a new database and typology, *Cahiers de la Chaire Economie du Climat - Information and Debates Series*, 32. Working Paper.

Sims, K., , Alix-Garcia, J., Shapiro-Garza, E., Fine, L., Radeloff, V., Aronson, G., Castillo, S., Ramirez-Reyes, C., & Yañez-Pagans, P.: Improving environmental and social targeting through adaptive management in mexico's payments for hydrological services program, *Conservation Biology*, 28(5), (2014), 1151–1159.

Smith, N. J., Falesi, I. C., Alvim, P. d. T., & Serrao, E. A. S.: Agroforestry trajectories among smallholders in the brazilian amazon: innovation and resiliency in pioneer and older settled areas, *Ecological Economics*, 18(1), (1996), 15–27.

Soares-Filho, B. S., Nepstad, D. C., Curran, L. M., Cerqueira, G. C., Garcia, R. A., Ramos, C. A., Voll, E., McDonald, A., Lefebvre, P., & Schlesinger, P.: Modelling conservation in the amazon basin, *Nature*, 440(7083), (2006), 520–523.

Sunderlin, W. D., Larson, A. M., Duchelle, A., Sills, E. O., Luttrell, C., Jagger, P., Pattanayak, S., Cronkleton, P., & Ekaputri, A.: *Technical guidelines for research on REDD+ project sites with survey instruments and code book*, CIFOR, 2010.

Todd, P. E.: Evaluating social programs with endogenous program placement and selection of the treated, *Handbook of development economics*, 4, (2007), 3847–3894.

Valverde, O.: *Grande Carajás: planejamento da destruição*, Forense Universitária, 1989.

Wunder, S.: The efficiency of payments for environmental services in tropical conservation, *Conservation biology*, 21(1), (2007), 48–58.

8 Tables

Table 1: Main sample characteristics in 2014 and 2010

Variables in 2014	Obs.	Mean	Median	Std dev.
Total land area (ha)	181	92.9	87.3	63.2
Forest cover (% of land area)	181	58.8	58.8	21.1
Crop land (% of land area)	181	7.5	4.8	8.3
Pasture land (% of land area)	181	32.3	29.4	21.7
Crop value (Reais)	181	11,990	5,908	19,484
Cattle value (Reais)	181	26,790	12,570	50,649
Bolsa Familia (Reais)	181	1,856	1,400	2,322
Retirement pension (Reais)	181	3,952	0	5,964
Wage labour (Reais)	181	4,696	720	9,630
Business (Reais)	181	1,734	0	6,827
Age (years)	181	52.9	55	12.7
Education (school years)	181	2.6	2	3.1
Family members (number)	181	4.7	4	2.6
Variables in 2010	**Obs.**	**Mean**	**Median**	**Std dev.**
Total land area (ha)	181	93.0	95.0	66.2
Forest cover (% of land area)	181	66.5	68.5	18.9
Crop land (% of land area)	181	7.6	4.8	8.5
Pasture land (% of land area)	181	25.0	20.2	18.9
Crop value (Reais)	181	6,682	3,651	10,518
Cattle value (Reais)	181	13,674	6,805	21,557
Bolsa Familia (Reais)	181	994	810	1,612
Retirement pension (Reais)	181	2,019	0	4,007
Wage labour (Reais)	181	2,402	400	5,200
Business (Reais)	181	352	0	2,029
Age (years)	181	50.4	52	12.4
Education (school years)	181	2.6	2	2.6
Family members (number)	181	5.0	5	2.4

Table 2: Main characteristics of intervention and comparison groups

Variable	Mean values comparison	intervention	pvalue	
Total land area (ha)	88.3	96.4	0.39	
Forest cover in 2008 (% of land area)	67.3	74.3	0.02	**
Forest cover in 2010 (% of land area)	62.3	69.5	0.01	**
Forest cover in 2014 (% of land area)	52.6	63.2	0.00	***
Crop land in 2010 (% of land area)	6.3	8.4	0.10	*
Crop land in 2014 (% of land area)	6.5	8.2	0.17	
Pasture land in 2010 (% if land area)	30.4	21.2	0.00	***
Pasture land in 2014 (% if land area)	39.9	26.9	0.00	***
Crop value in 2010 (Reais)	5,299	7,660	0.11	
Cattle value in 2010 (Reais)	14,399	13,161	0.68	
Bolsa Familia in 2010 (Reais)	777	1,147	0.09	*
Retirement pension in 2010 (Reais)	2,690	1,544	0.07	*
Wage labour in 2010 (Reais)	1,270	3,203	0.01	***
Business in 2010 (Reais)	225	441	0.42	
Age in 2010 (years)	50.9	49.9	0.60	
Education in 2010 (school years)	2.3	2.8	0.15	
Family members in 2010 (number)	4.8	5.2	0.38	

Note: Size of comparison group is 75. Size of intervention group is 106. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

Table 3: Main characteristics of participants and non-participants

Variable	Mean value non-participants	participants	pvalue	
Proambiente (yes/no)	0.26	0.79	0.00	***
Total land area in 2010 (ha)	114.5	77.6	0.01	**
Forest cover in 2008 (% of land area)	72.9	75.7	0.42	
Forest cover in 2010 (% of land area)	68.0	71.0	0.36	
Crop land in 2010 (% of land area)	8.0	8.9	0.62	
Pasture land in 2010 (% of land area)	23.2	19.2	0.23	
Crop value in 2010 (Reais)	9,128	6,136	0.21	
Cattle value in 2010 (Reais)	18,432	7,688	0.03	**
Bolsa Familia in 2010 (Reais)	845	1,460	0.12	
Retirement pension in 2010 (Reais)	1,733	1,348	0.56	
Wage labour in 2010 (Reais)	1,493	4,978	0.01	***
Business in 2010 (Reais)	791	78	0.15	
Age in 2010 (years)	51.6	48.2	0.14	
Education in 2010 (school years)	2.6	3.0	0.52	
Family members in 2010 (number)	4.8	5.5	0.17	

Note: Size of participant group is 52. Size of non-participant group is 54. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

Table 4: Logistic regression

Variable	Odds ratio	Std. Error	z	pvalue	
Total land area in 2010 (ha)	0.99	0.01	-0.85	0.393	
Forest cover in 2008 (% of land area)	0.96	0.04	-1.24	0.217	
Forest cover in 2010 (% of land area)	1.12	0.09	1.41	0.158	
Crop land in 2010 (% of land area)	1.11	0.08	1.32	0.187	
Pasture land in 2010 (% of land area)	1.07	0.07	0.98	0.329	
Crop value in 2010 (Reais)	1.00	0.00	0.25	0.803	
Cattle value in 2010 (Reais)	1.00	0.00	-1.08	0.280	
Bolsa Familia in 2010 (Reais)	1.00	0.00	1.49	0.137	
Retirement pension in 2010 (Reais)	1.00	0.00	0.59	0.554	
Wage labour in 2010 (Reais)	1.00	0.00	2.79	0.005	**
Business in 2010 (Reais)	1.00	0.00	-0.48	0.634	
Age in 2010 (years)	0.97	0.03	-1.15	0.252	
Education in 2010 (school years)	0.95	0.10	-0.51	0.608	
Family members in 2010 (number)	0.96	0.11	-0.36	0.720	

Note: The sample includes both participants and non-participants living in the intervention communities that were offered the program. Size of participant group is 52. Size of non-participant group is 54. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

Table 5: Balancing tests on pre-treatment variables

Variable		treated	untreated	t	pvalue	
Total land area in 2010	Unmatched	77.6	88.3	1.93	0.16	
(hectares)	Matched	77.6	75.4	-0.41	0.69	
Forest cover in 2008	Unmatched	75.7	67.3	1.73	0.01	**
(% of land area)	Matched	75.7	75.8	0.04	0.97	
Forest cover in 2010	Unmatched	71.0	62.3	1.67	0.01	*
(% of land area)	Matched	71.0	71.7	0.44	0.66	
Crop land in 2010	Unmatched	8.9	6.3	0.55	0.12	
(% of land area)	Matched	8.9	6.8	-1.74	0.09	
Pasture land in 2010	Unmatched	19.2	30.4	1.91	0.00	**
(% of land area)	Matched	19.2	20.7	0.90	0.37	
Crop value in 2010	Unmatched	6,136.4	5,298.9	1,29	0,51	
(Reais/year)	Matched	6,136.4	4,715.0	-1.70	0.10	
Cattle value in 2010	Unmatched	7,687.8	14,399.4	1.92	0.00	**
(Reais/year)	Matched	7,687.8	9,097.2	1.21	0.23	
Bolsa Familia in 2010	Unmatched	1,459.6	777.0	0.12	0.04	*
(Reais/year)	Matched	1,459.6	971.1	-1.65	0.10	
Retirement pension in 2010	Unmatched	1,348.2	2,689.6	1.98	0.06	
(Reais/year)	Matched	1,348.2	1,686.9	0.84	0.40	
Wage labour in 2010	Unmatched	4,977.8	1,270.3	0.08	0.00	**
(Reais/year)	Matched	4,977.8	3,145.6	-2.14	0.04	*
Business in 2010	Unmatched	77.7	225.3	3.30	0.23	
(Reais/year)	Matched	77.7	93.8	0.27	0.79	
Age in 2010	Unmatched	48.2	50.9	1.16	0.22	
(years)	Matched	48.2	51.6	2.25	0.03	*
Education in 2010	Unmatched	3.0	2.3	0.55	0.14	
(school years)	Matched	3.0	2.2	-2.30	0.03	*
Family size in 2010	Unmatched	5.5	4.8	0.93	0.14	
(number)	Matched	5.5	5.6	0.47	0.64	

Note: The treated group refers to participants in PAS project. *p-value* refers to the t-test of the null hypothesis that the means for both groups are equal. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

Table 6: ATT on forest cover in 2008 - Placebo test

Estimator	(1) PAS Participants	(2) Proambiente Participants	(3) Non-participants	(4) Intervention
DID (ols)	0.24	0.33	-0.01	0.12
	1.11	*1.23*	*1.14*	*0.96*
DID-matching				
nnm (2x)	-0.81	-0.88	-0.91	-1.08
	1.32	*1.51*	*1.37*	*1.07*
nnm (4x)	-0.76	-0.83	-0.99	-0.78
	1.23	*1.37*	*1.22*	*1.00*
nnm (2ps)	-1.21	-1.45	-1.33	-1.27
	1.24	*1.44*	*1.29*	*1.07*
nnm (4ps)	-1.30	-1.13	-1.07	-1.19
	1.15	*1.34*	*1.32*	*0.99*
psm (kernel)	-0.91	-0.62	-0.99	-1.07
	1.06	*1.27*	*1.10*	*0.76*
Linear regression				
ols (x)	0.50	0.43	-0.90	-0.11
	1.28	*1.43*	*1.17*	*1.00*
ols (ps)	-0.32	-0.54	-0.95	-0.28
	1.39	*1.58*	*1.19*	*1.04*

Note: ATT is expressed in percentage points. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,⋄) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 7: ATT on forest cover in 2014

Estimator	(1) PAS Participants		(2) Proambiente Participants		(3) Non-participants	(4) Intervention	
DID (ols)	5.41	*	6.53	**	3.05	4.21	*
	2.90		*3.18*		*2.98*	*2.35*	
DID-matching							
nnm (2x)	4.11		5.57	*	3.01	4.30	◇
	3.10		*3.32*		*3.65*	*2.76*	
nnm (4x)	7.10	**	7.96	***	4.76	5.36	**
	2.89		*3.00*		*3.25*	*2.54*	
nnm (2ps)	1.14		3.68		3.70	3.17	
	3.73		*4.28*		*3.90*	*2.98*	
nnm (4ps)	2.94		4.45		3.46	5.12	*
	3.38		*3.63*		*3.66*	*2.80*	
psm (kernel)	7.98	*	9.76	*	3.51	4.87	*
	4.82		*5.25*		*3.20*	*2.75*	
Linear regression							
ols (x)	6.22	*	8.15	**	3.30	4.64	*
	3.34		*3.64*		*3.14*	*2.48*	
ols (ps)	6.06	*	8.22	**	3.33	4.38	*
	3.65		*4.08*		*3.18*	*2.55*	

Note: ATT is expressed in percentage points. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,◇) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 8: ATT on total land in 2014

Estimator	(1) PAS Participants	(2) Proambiente Participants	(3) Non- participants	(4) Intervention
DID (ols)	1.44	1.56	-2.93	-0.78
	6.45	7.26	7.18	5.36
DID-matching				
nnm (2x)	-7.17	-4.86	0.02	-3.51
	5.33	*5.40*	*10.11*	*7.30*
nnm (4x)	-4.29	-3.34	1.97	-2.31
	4.72	*4.96*	*8.40*	*6.19*
nnm (2ps)	-2.82	-3.13	13.46	-2.30
	4.12	*4.45*	*12.12*	*6.25*
nnm (4ps)	-4.12	-3.69	3.24	6.55
	4.76	*4.98*	*9.20*	*8.27*
psm (kernel)	-2.28	-0.74	2.51	-0.70
	6.05	*6.77*	*14.59*	*7.56*
Linear regression				
ols (x)	-0.73	0.77	2.52	2.49
	6.23	*6.98*	*6.13*	*4.79*
ols (ps)	-0.26	0.81	2.37	2.23
	8.13	*9.36*	*7.55*	*5.82*

Note: ATT is expressed in percentage points. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,◇) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 9: ATT on cropland in 2014

Estimator	(1) PAS Participants	(2) Proambiente Participants	(3) Non-participants	(4) Intervention
DID (ols)	0.38	-0.17	-0.98	-0.31
	1.58	1.70	1.47	1.27
DID-matching				
nnm (2x)	0.17	-0.64	-2.84	-1.73
	2.28	*2.41*	*1.72*	*1.69*
nnm (4x)	-0.50	-1.24	-1.81	-1.11
	2.22	*2.42*	*1.64*	*1.64*
nnm (2ps)	2.06	0.45	-1.36	0.29
	2.51	*3.05*	*1.95*	*1.75*
nnm (4ps)	0.79	-0.08	-1.66	-0.57
	2.15	*2.53*	*1.79*	*1.72*
psm (kernel)	1.39	0.14	-0.39	1.00
	5.20	*5.60*	*1.91*	*2.22*
Linear regression				
ols (x)	1.14	0.21	0.01	0.59
	1.63	*1.73*	*1.35*	*1.16*
ols (ps)	0.54	-0.53	-0.04	0.58
	1.99	*2.19*	*1.55*	*1.38*

Note: ATT is expressed in percentage points. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,⋄) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 10: ATT on pastures in 2014

Estimator	(1) PAS Participants		(2) Proambiente Participants		(3) Non-participants	(4) Intervention	
DID (ols)	-6.91	**	-7.97	**	-0.78	-3.79	⋄
	2.89		*3.15*		*2.99*	*2.40*	
DID-matching							
nnm (2x)	-7.2	**	-7.98	**	-2.40	-4.89	*
	3.22		*3.40*		*3.86*	*2.84*	
nnm (4x)	-8.11	***	-9.19	***	-3.84	-5.57	**
	2.92		*3.13*		*3.42*	*2.65*	
nnm (2ps)	-5.78	⋄	-7.38	*	-3.31	-5.31	*
	3.74		*4.12*		*3.60*	*3.04*	
nnm (4ps)	-6.03	*	-7.58	**	-2.38	-5.92	**
	3.48		*3.55*		*3.38*	*2.65*	
psm (kernel)	-11.32	***	-12.37	***	-1.94	-6.13	**
	3.12		*3.52*		*3.08*	*2.52*	
Linear regression							
ols (x)	-7.82	**	-9.44	***	-2.46	-4.66	*
	3.2		*3.53*		*3.05*	*2.45*	
ols (ps)	-7.15	**	-8.52	**	-2.36	-4.40	*
	3.64		*4.06*		*3.17*	*2.62*	

Note: ATT is expressed in percentage points. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,⋄) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 11: ATT on wage labour in 2014

Estimator	(1) PAS Participants		(2) Proambiente Participants		(3) Non-participants	(4) Intervention	
DID (ols)	2,243		2,237		-309	955	
	1,935		*2,066*		*936*	*1,425*	
DID-matching							
nnm (2x)	3,447		3,792		-1,031	1,424	
	3,064		*3,275*		*1,191*	*1,801*	
nnm (4x)	2,893		2,970		-899	904	
	2,867		*3,190*		*976*	*1,711*	
nnm (2ps)	3,308		3,977		-8	1,740	
	2,934		*3,234*		*1,019*	*1,793*	
nnm (4ps)	2,741		3,487		-749	1,176	
	2,840		*3,171*		*967*	*1,700*	
psm (kernel)	4,032	⋄	2,689		-164	1,826	
	2,582		*3,149*		*1,071*	*1,399*	
Linear regression							
ols (x)	5,337	**	6,042	***	-190	2,502	*
	2,204		*2,189*		*976*	*1,511*	
ols (ps)	3,622	⋄	4,736	*	-164	1,821	
	2,430		*2,639*		*1,000*	*1,546*	

Note: ATT is expressed in Reais. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,⋄) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 12: ATT on the value of total livestock owned in 2014

Estimator	(1) PAS Participants	(2) Proambiente Participants	(3) Non-participants	(4) Intervention
DID (ols)	-8,485	-7,352	888	-3,755
	5,369	*6,081*	*8,356*	*6,050*
DID-matching				
nnm (2x)	-1,579	-1,405	2,506	882
	4,800	*5,617*	*10,223*	*6,732*
nnm (4x)	-525	107	3,836	2,316
	3,376	*3,905*	*9,775*	*6,202*
nnm (2ps)	-1,105	-632	2,365	-3,925
	2,817	*3,217*	*10,985*	*6,555*
nnm (4ps)	815	1,836	2,735	-98
	2,631	*2,977*	*10,383*	*5,939*
psm (kernel)	737	2,398	1,507	-911
	2,747	*2,945*	*9,073*	*4,759*
Linear regression				
ols (x)	-2,730	-1,320	1,812	653
	5,342	*6,066*	*8,476*	*6,177*
ols (ps)	-2,274	79	2,484	1,769
	6,704	*7,764*	*8,918*	*6,514*

Note: ATT is expressed in Reais. Standard errors are in italics below coefficients. Three asterisks *** (resp. **, *,⋄) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%, 15%) significance level. OLS refers to the linear regression using ordinary least squares (the DID estimator). OLS(X) refers to the linear regression using ordinary least squares and controlling for X. OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. NNM(2X) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the vector X. NNM(2PS) (resp. 4X) refers to the nearest neighbor estimator using 2 (resp. 4) matched observations and the propensity score. PSM (kernel) refers to the kernel-based propensity score matching estimator.

Table 13: Balancing tests on pre-treatment variables (Proambiente group)

Variable		treated	untreated	t	pvalue	
Total land area in 2010	Unmatched	79.4	88.3	1.77	0.32	
(hectares)	Matched	79.4	76.9	-0.45	0.65	
Forest cover in 2008	Unmatched	77.2	67.3	2.23	0.00	**
(% of land area)	Matched	77.2	76.7	-0.23	0.82	
Forest cover in 2010	Unmatched	72.6	62.3	1.72	0.01	**
(% of land area)	Matched	72.6	72.7	0.22	0.83	
Crop land in 2010	Unmatched	8.5	6.3	0.49	0.24	
(% of land area)	Matched	8.5	6.3	-1.48	0.15	
Pasture land in 2010	Unmatched	17.8	30.4	1.85	0.00	**
(% of land area)	Matched	17.8	20.1	0.84	0.40	
Crop value in 2010	Unmatched	6,434.5	5,298.9	1.09	0.42	
(Reais/year)	Matched	6,434.5	4,875.3	-1.52	0.14	
Cattle value in 2010	Unmatched	7,024.8	14,399.4	2.23	0.00	**
(Reais/year)	Matched	7,024.8	9,146.0	1.70	0.10	
Bolsa Familia in 2010	Unmatched	1,610.6	777.0	0.10	0.04	*
(Reais/year)	Matched	1,610.6	997.1	-1.74	0.09	
Retirement pension in 2010	Unmatched	1,405.5	2,689.6	2.07	0.09	
(Reais/year)	Matched	1,405.5	1,620.1	0.48	0.63	
Wage labour in 2010	Unmatched	5,132.6	1,270.3	0.07	0.01	**
(Reais/year)	Matched	5,132.6	3,159.5	-1.87	0.07	
Business in 2010	Unmatched	83.9	225.3	2.66	0.28	
(Reais/year)	Matched	83.9	90.2	0.09	0.93	
Age in 2010	Unmatched	48.9	50.9	1.32	0.39	
(years)	Matched	48.9	51.2	1.74	0.09	
Education in 2010	Unmatched	2.8	2.3	0.57	0.36	
(school years)	Matched	2.8	2.2	-1.55	0.13	
Family size in 2010	Unmatched	5.6	4.8	0.87	0.12	
(number)	Matched	5.6	5.7	0.07	0.94	

Note: The treated group refers to participants in Proambiente project. *p-value* refers to the t-test of the null hypothesis that the means for both groups are equal. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

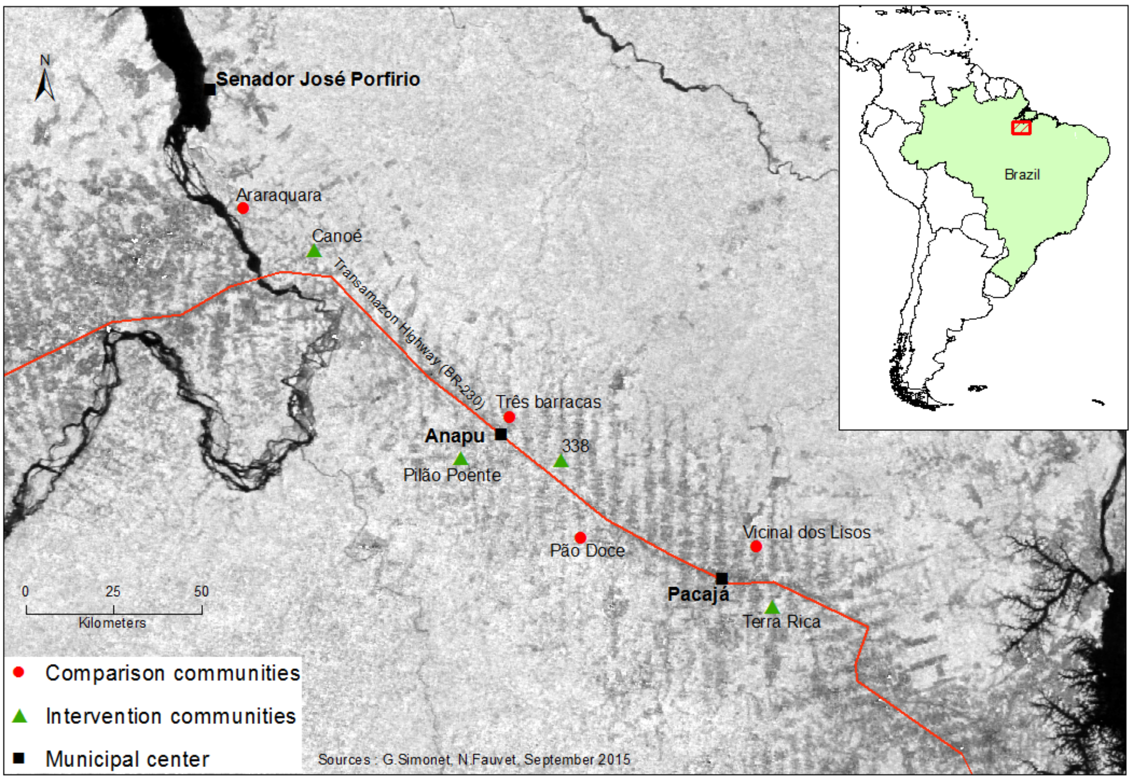
Table 14: Cost-effectiveness

Project Costs (USD)	Benefit (USD) USD 5.2/tCO2	USD 11/tCO2	USD 56/tCO2
USD 219,100 (PES only)	3,147,318	6,902,168	36,034,628
USD 538,300 (All costs)	2,828,118	6,582,968	35,715,428

Note: Benefits correspond to the monetized value of the avoided emissions achieved during the first two years of the project. They are calculated using the average exchange price of REDD+ credits on the voluntary carbon market over the 2007-2014 period (column 1, USD 5.2/tCO2, leading to a benefit of USD 3,366,418) or using the social cost of carbon at discount rates of 5 percent (column 2, USD 11/tCO2, leading to a benefit of USD 7,121,268) and 2.5 percent (column 3, USD 56/tCO2, leading to a benefit of USD 36,253,728). The costs during the first two years of the project amount to USD 219,100 when including only the cost of the PES (USD 626 for each participants, received only once) and to USD 538,300 when adding start-up and recurrent costs (USD 729 per household per year).

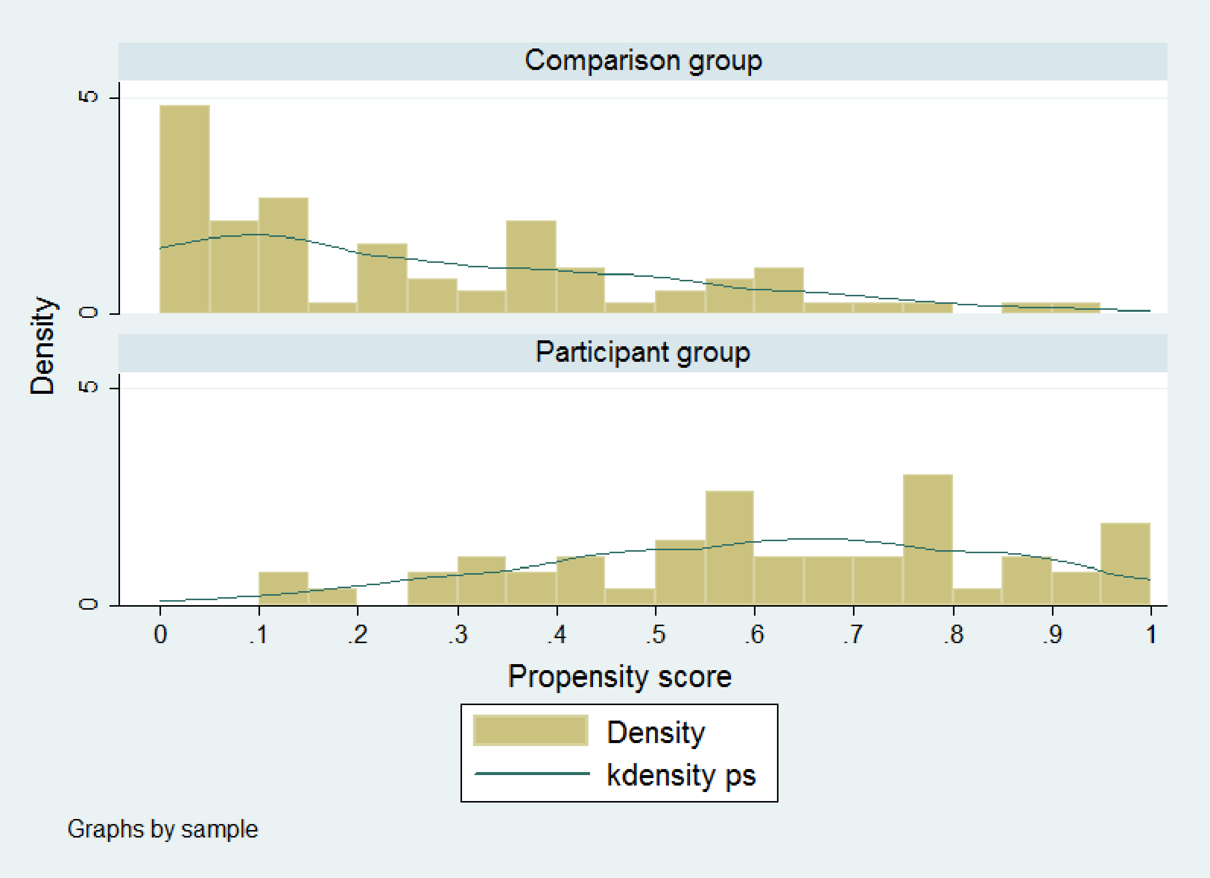
9 Figures

Figure 1: Location of interviewed communities



Note: Dark grey pixels correspond to deforested plots.

Figure 2: Propensity score distribution in the participant and comparison groups



Note: Comparison group refers to the communities that were not offered the program (75 households). Participant group refers to the households living in the intervention communities who were offered the program and accepted to enter it (52 households).

Figure 3: Forest cover as a share of land

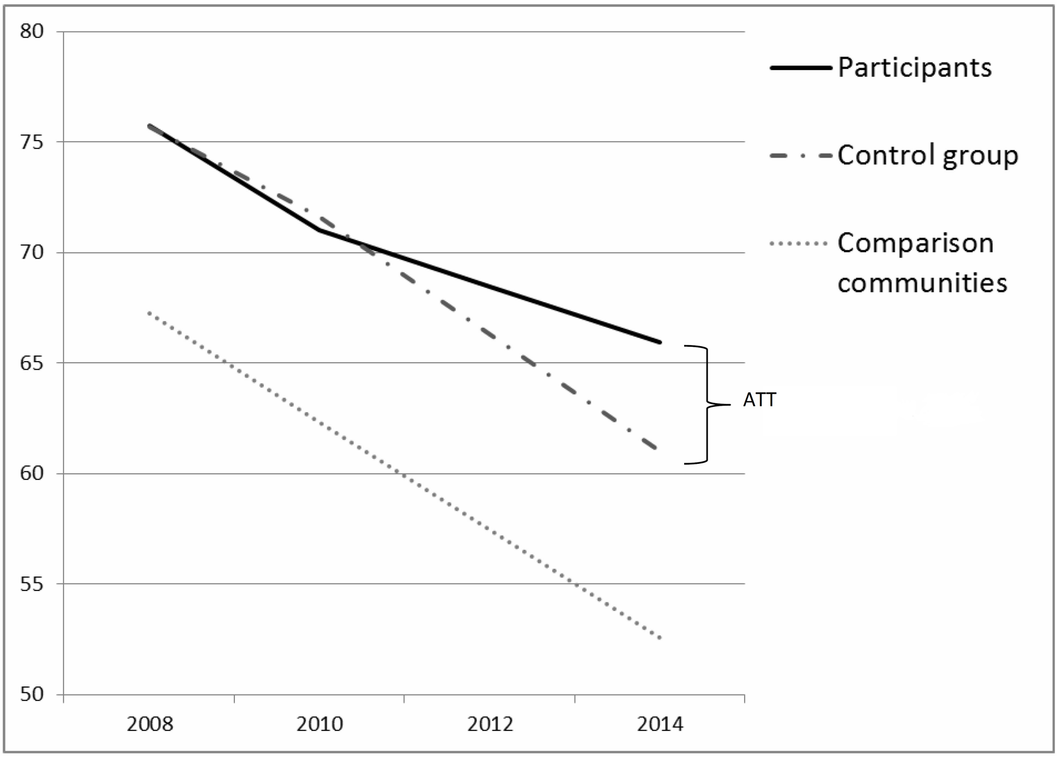
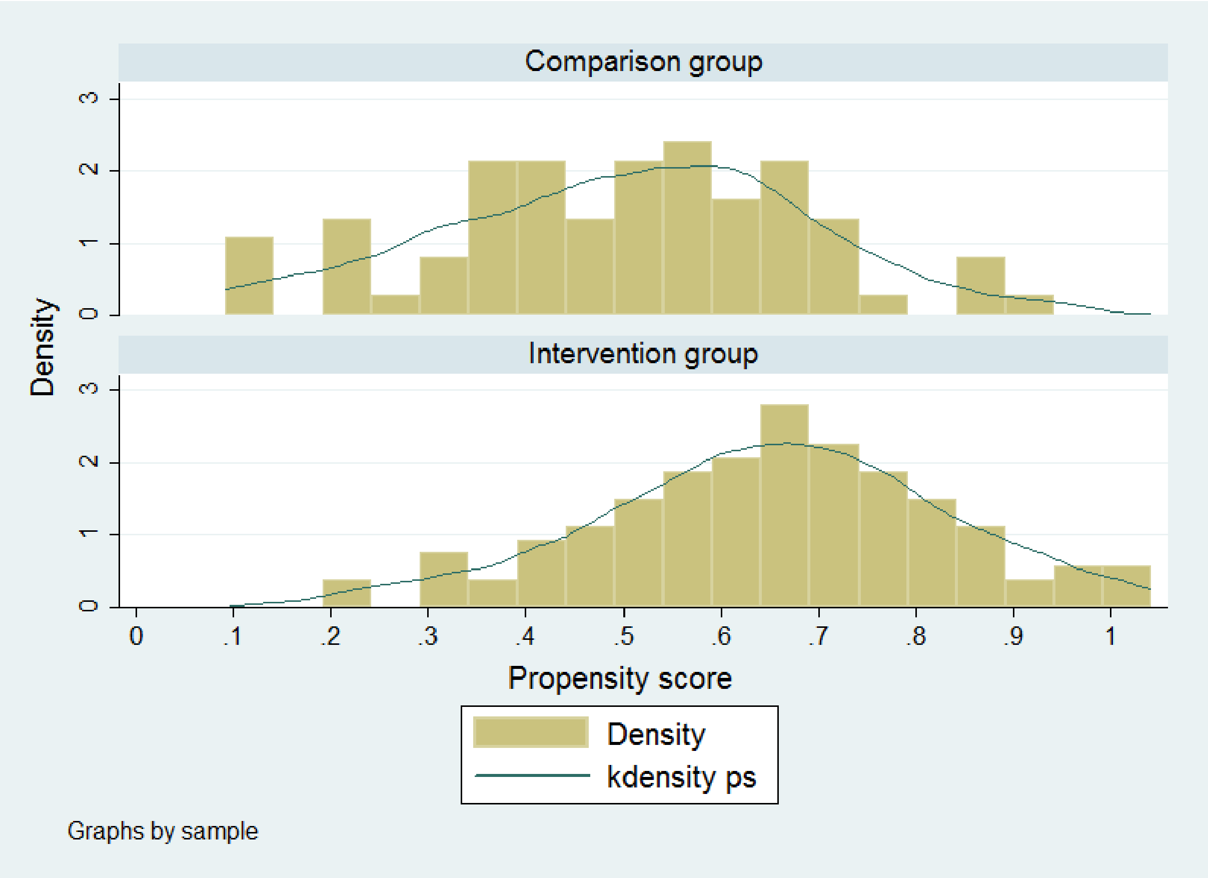


Figure 4: Propensity score distribution in the intervention and comparison groups



Note: Comparison group refers to the communities that were not offered the program (75 households). Intervention group refers to the communities that were offered the program (106 households, which includes both participants and non-participants).

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