Pay For Performance and Deforestation: Evidence from Brazil*

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Abstract

This paper studies Brazil's Bolsa Verde program, which has a unique incentive structure. Instead of paying land owners or forest managers, the program pays extremely poor households for forest conservation evaluated at the regional level. We use a difference-in-differences approach to identify the environmental impact of the program, and find that deforestation in treated areas fell by 44-53 percent of the counterfactual forest loss. These program benefits in terms of reductions in carbon dioxide emissions are valued at approximately USD 335 million between 2011 and 2015, about 3 times the program costs. Additionally, we find that the treatment effects increase in the number of beneficiaries and are driven by action on non-private properties in the treated areas. In particular, the program increases the number of fines, especially in areas far away from where satellite alarms could inform the authorities about illegal deforestation. Together, these findings suggest that the BV program reduced deforestation by providing poor households with incentives to monitor and report on deforestation activities in their areas of residency.

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1 Introduction

When an economic agent does not bear the full cost of his actions, a moral hazard problem may arise in which the agent, by doing what is privately optimal, behaves sub-optimally from a social standpoint [Holmström, 1979]. How to remove moral hazard in communal ownership and management of natural resources has been considered one of the main challenges for sustainable management of natural resources, e.g. forests. Under communal ownership, it is difficult to infer the actions of individual deforesters from observations on ambient levels of deforestation. Direct regulation of individual actions is also challenging because of costly monitoring and poor enforcement of existing laws and regulations, particularly in developing countries where institutions are weak.

In this paper, we examine if the delegation of monitoring to local communities can mitigate moral hazard and overcome collective action problems associated with management of communal resources [Lichbach, 1996]. Our analysis utilizes a quasi-experimental setting of Brazil's Bolsa Verde (BV), a conditional cash transfer program in effect between 2011 and 2018 to rural populations living in extreme poverty. The BV has a unique incentive structure. Instead of paying land owners or forest managers, the program pays extremely poor households living in rural areas with significant amounts of remaining forests, regardless of the form of land tenure or ownership. Instead of individual behavior or payoff, the BV imposes a conditionality based on an aggregate outcome: forest cover at the regional level.[1] If the total forest cover of an area violates the Forest Code, which requires at least 80 percent of lands permanently maintained as legal reserves (forest), then every BV beneficiary in the area exits the program. This condition implies that any conservation or deforestation activity within the area has consequences on all BV participants, who sign a contract to commit to implementing conservation activities and using natural resources sustainably in their areas of residence. This incentive structure is similar to that proposed by theoretical models in the the non-point source pollution literature [Segerson, 1988].[2] More broadly, this mechanism is similar in spirit to the monetary incentives structure in the management and organization theory literature, in which worker compensation is tied directly to the firm's outcome via performance pay to align the interests of workers and the firm [Holmström, 1982].

Understanding the causal relationships between the local's incentives, community participation, and sustainable resource management faces many challenges for identification.[3] Self-

[1]The feature of the BV program that rewards are conditional on overall performance rather than individual one in terms of resource conservation is an important distinction from other cash transfer programs with an environmental conditionality, often known as Payments for Ecosystem Services (PES). There is a large and growing literature which investigates the effectiveness of the PES programs in different contexts. We will discuss how our results contribute to that literature in more details below.

[2]Non-point source pollution can not be traced to individual emitters due to monitoring costs. Consequently, moral hazard problems arises and the contracts to reduce pollution must target a group of emitters.

[3]Empirical work from both the lab and the field in the past few decades has demonstrated numerous examples of successful management of resources by communities who self-organize and mutually enforce against exploitative

selection, for example, is a potential threat. Participation in conservation activities is unlikely to be exogenous with respect to the overall performance and community's governance characteristics. Using the setting of the BV program to analyze the ability of communities (and mechanisms) to transmit the BV's restrictions to all households is attractive because the program provides plausibly-exogenous variation in the local's incentives to self-organize and manage a natural resource.

In our main empirical analysis, we use three quasi-experimental strategies. First, we adopt a generalized difference-in-differences framework to compare deforestation in areas with and without BV beneficiaries. Using panel data at the regional level from 2009 to 2015, we identify the causal effects of the program on deforestation with variation in participation across regions and over time. Second, we use an event study design to study the dynamics of participation in the BV and deforestation. This approach allows us to investigate how quickly deforestation responds to the BV program, and whether the impact expands, remains constant, or reverts to the mean. Third, we implement a triple difference strategy at the grid cell level to account for the potential of selection in Priority Areas into the BV program. The third difference comes from deforestation in grid cells lying just outside receiving versus non-receiving areas.

The main findings of the paper are as follows. First, the BV is associated with an approximately 0.11 percentage point higher reduction in deforestation, or 92 hectare (ha), in receiving areas. The magnitude of this reduction is 44 percent of the counterfactual forest loss.[4] Despite concerns of free riding, the treatment effect increases in the number of beneficiaries: a 10 percent increase in the number of beneficiaries is associated with a 0.24 percentage point decrease in deforestation, or approximately 15 ha per beneficiary. Additionally, we show that the BV program has higher impacts in extremely poor areas than in wealthier ones, indicating the importance of the payment as a financial incentive for program compliance, as poor regions are more likely to have beneficiaries for whom the cash transfer is a more sizable addition to the household budget. These results speak to the debate on whether social programs should target poor citizens [Banerjee et al., 2017], by providing an example where doing so is effective in improving social welfare at large.

To investigate mechanisms, we utilize information from Brazil's recent rural property registry (CAR) for private properties in combination with high resolution deforestation data. We find that the reductions of deforestation related to the BV program take place in those parts of receiving areas that are not registered in the CAR. Among registered rural properties, we find nil

behavior (see Ostrom [2000] for an overview). Specifically, co-management regimes of resources seem the most likely to counter collective action problems in the presence of well-defined property rights and incentives for monitoring at the local level [Berkes et al., 2006].

[4] On average, deforestation in all eligible areas during the pre-program period is 0.25 percent. Therefore, a 0.11 percent higher reduction in deforestation among receiving areas represents approximately 44 percent of the counterfactual forest loss. The estimate we obtain from a matched sample is 0.12 percentage point, or 53 percent of the counterfactual deforestation. These effect sizes are in line with the finding of 41 to 50 percent in Alix-Garcia et al. [2015].

effects of the program in small, medium and large properties whereas the smallest properties (mini) show, if anything, some signs of increased deforestation. These results indicate that the program effect does not arise from reductions in deforestation at the recipients properties. Instead, we find some evidence that reporting of illegal deforestation to the authorities is a likely channel. We do so by studying geo-located fines issued across our sample area. Conditional on deforestation taking place, we find that the number of fines increases significantly in treated areas. Taking advantage of geo-located satellite based deforestation alarms used by the enforcement authorities, we find that the effect on fines is, if anything, larger in areas that are far away from where an alarm went off. This indicates that the authorities learned about the offenses through some other channel, such as reporting from the BV households.

This paper is related to two strands in the literature. First, we add to the limited existing evidence on mechanisms for improvements in environmental outcomes due to PES and large-scale avoided deforestation programs.[5] Building on the ideas of the economics of crime [Becker, 1968], we develop a simple framework to motivate empirical analysis, where we use data on fines against deforestation and other environmental offenses, and test the underlying mechanisms of the BV program. Here there are two forces at work. On one hand, the BV could lead to more monitoring and more reporting and consequently to more fines and less deforestation. On the other hand, the higher *threat* or *expectation*[6] of being reported to authorities by BV beneficiaries could lead to less deforestation and less fines. So, a priori the relationship between deforestation and fines is ambiguous, but bringing data on fines on other illegal activities, we concluded that actual monitoring (and reporting) is plausible mechanism which drives the effectiveness of the BV program.

Second, our results about the effectiveness of the BV program to reduce deforestation resonate with the literature on improving governance and public sector delivery through community-based monitoring. In terms of health services provision, empirical evidence suggests that local controls are effective only when they engage broader community participation to develop a

[5]The literature examining avoided deforestation programs is emerging but mostly focus on small-scale projects. In Brazil, the only paper that examines the effectiveness of a PES program on deforestation is one that evaluates a REDD+ pilot project implemented in the state of Para on 181 farmers [Simonet et al., 2018]. A randomized-control trial in Uganda was conducted to estimate a causal program effect of 50 percent and is the one of the most rigorous evaluations to date [Jayachandran et al., 2017]. Prior to this recent line or work, most of the literature focus on large-scale programs and face various identification challenges. Using retrospective data, some studies are limited in space [Alix-Garcia et al., 2018] and some are limited in time (Alix-Garcia, Shapiro, and Sims 2012). Few studies identify changes in avoided deforestation at the national level with sufficient variation over time, except for Costa Rica's program [Arriagada et al., 2012].

[6]Similar mechanism worked in other contexts. For instance, Shimshack and Ward [2005] provide an example of the spillover effect from regulation policies when water polluters who are not fined react to fines issued on other actors. They claim this is due to the regulator's enhanced reputation, as fines credibly signal the regulator's ability to levy penalties on other plants. Andrade and Chagas [2016] find that deforestation also decreased in municipalities next to the "blacklisted" (targeted) municipalities and argue that this is due to expectation channel of stricter enforcement. Decker and Pope [2005] report that unregulated firms under Clean Air Act respond to regulation of their rivals.

monitoring plan.[7] Consistent with this, we demonstrate that monitoring of pubic goods delivery is effective only when there is larger sense of community and consequently broader involvement of members of community, by exploiting differences in institutional structure between SUCs and Settlements. SUCs have managers and community councils while Settlements often do not have community management in place. Also, migrants from the South were allocated plots of land to farm in Settlements during the 1970s, hence it is likely that residents in these areas make the majority of their living from agriculture and potentially use deforestation as a means for clearing land. We show that the BV is more effective in SUCs than Settlements, and this may reflect one or more of the following traits if SUCs: (i) larger sense of community in the SUCs to engage into sustainable activities; (ii) existence of potential infrastructure (managers) for reporting to be feasible in the SUCs; (iii) alignment between monetary rewards and underlying incentives is greater in the SUCs, and (iv) weaker incentives to deforest in SUCs than in Settlements.

More broadly, our findings speak directly to the discussion of the effective ways of implementing targets of the United Nations' Sustainable Development Goals (SDG). A core objective of the Goals is to address all great challenges mankind is facing, and specifically including eradication of poverty and protecting the environment through climate action. The SDGs have been embraced by about 193 countries and they have become concrete policy issue for governments around the world. Since the targets are expensive, and given limited budgets, especially in developing countries[8], the key policy issue is to prioritize those targets which have significant beneficial impacts on other targets as well. An example in point is the issue of reducing deforestation [Dasgupta et al., 2017]. Forest conservation contributes to several targets of the SDGs: food security, health, poverty alleviation, hunger reduction and climate action [Seymour and Busch, 2016]. In particular, the BV program is a good example of a cost-effective policy that addresses the above objectives.

The rest of the paper is organized as follows: Section 2 provides a brief history of deforestation in the Brazilian Amazon and describes the Bolsa Verde program; Section 3 provides insights from the theoretical literature on mechanisms of the program. Section 4 presents the main data sources and summary statistics; Section 5 outlines the empirical strategy, discusses the estimation results and sources of heterogeneity. Section 6 investigates the plausible mechanisms and Section 7 concludes.

[7] For instance, Banerjee et al. [2004] evaluate a project in Rajasthan in India, where a member of community was paid to check whether the nurse-midwife assigned to the health centre was present at the centre. However, this intervention had no impact on attendance and the authors argue that the key reason for this to happen is that the member of community did not manage to utilize the information on absenteeism to engage broader participation from the community. In contrast, Björkman and Svensson [2009] address participation constraint and show that in this case communities managed to hold their local health providers accountable.

[8] Schmidt-Traub [2015] estimate that the low- and middle-income countries will need to spend about $1.4 trillion per year, or about 4% of their GDP, to meet the goals of the SDGs.

2 Background

2.1 The Bolsa Verde Program: 2011 to 2018

The BV program was first implemented in 2011, exclusively in Priority Areas within the Brazilian Legal Amazon (BLA), covering an area that is approximately 61 percent of Brazil.[9] The program has been expanded to Priority Areas in the rest of Brazil in 2012, with 64 percent of the program areas in the north, 26 percent in the northeast; 6 percent in the southeast; and 4 percent in the central-west [Bindo, 2012]. Priority Areas eligible for the program are Sustainable Use Conservation Zones (SUCs) and Environmentally Distinctive Agrarian Reform Settlements.[10]

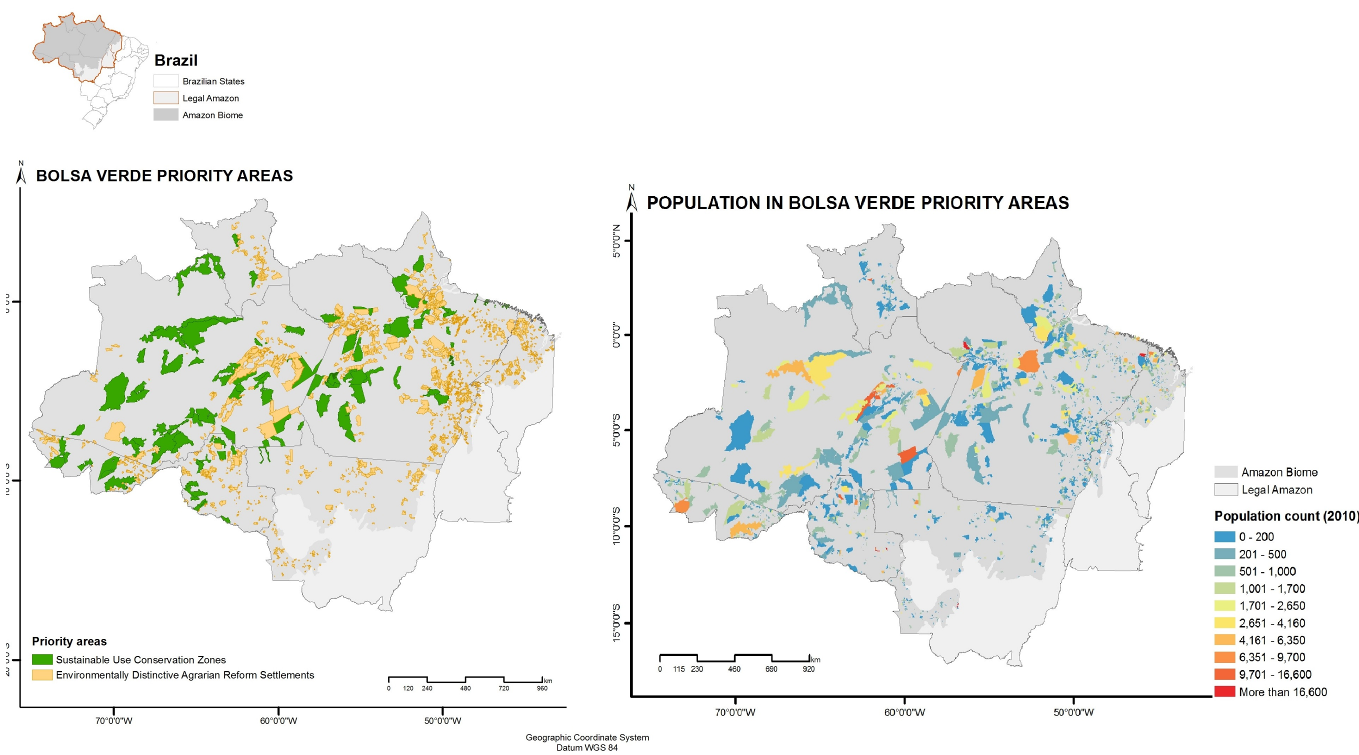

Figure 1: Bolsa Verde Priority Areas by Category and Population

Notes: The figure on the left shows the spatial distribution of Sustainable Use Conservation Zones and Settlements in the Legal Amazon. The figure on the right plots the population in each of the Priority Area using data from the 2010 Census.

[9] Between 1998 and 2000, Brazil's Ministry of the Environment (MMA) identified 900 areas as Priority Areas in terms of biodiversity conservation. For more details on the initiative and details of the selection, see `http://www.mma.gov.br/estruturas/chm/_arquivos/Prioritary_Area_Book.pdf`.

[10] SUC are protected areas created after the 1988 Federal Constitution. Settlements are areas of independent agricultural units that belong to smallholder farmers relocated to the Amazonia under the government-induced migration since the 1970s.

One motivation for launching the BV is the recognition that 7.5 million people who live in extreme poverty, or almost half of the country's extremely poor, reside in rural areas [Bindo, 2012].[11] A household is eligible for the program if it (i) lives in extreme poverty - defined as having per capita monthly income under 77 Brazilian Real (approximately 30USD); and (ii) resides in an eligible priority rural area, which has vegetation level that is in accordance with the Forest Code: at least 80 percent of the land is forested.[12] Figure 1, left panel, shows the spatial distribution of BV-eligible zones by category in the BLA, our study area. The right panel demonstrates the population of these areas in 2010 based on the 2010 Census. On average, Settlements are more populated than conservation zones. The quarterly payment is 300 Brazilian Real (BRL), or $154 in 2012 U.S. dollars. These benefits, which are approximately $51 per month, account for 13 percent of the per capita household income in the BLA in 2015. [13]

In terms of entry into the program, the administrative process through which an eligible household becomes a beneficiary has minimal selection. A list of households who are eligible for the BV is sent to the Ministry of the Environment (MMA) for evaluation and fact checks. The majority of eligible households become beneficiaries because there are no selection criteria beyond the conditions that determine eligibility. Moreover, the reasons for eligible households to be denied the grant, such as deaths of the responsible family member, missing signature, and incomplete forms, are likely uncorrelated with income level of the household or underlying propensities to deforest. Since there is no selection in the assignment of beneficiary status based on observed or unobserved household characteristics, we rule out concerns about endogeneity in the number of beneficiaries in each Priority Area.

For our research design and estimation procedures, two elements of the BV program are crucial. First, the BV is a cash transfer program with an environmental conditionality, unlike typical PES programs where payment is conditional on the flow of environmental services and unconditional on recipient income. PES households who become more well-off over time continue to receive payments for the ecosystem services they provide. A beneficiary household under BV, however, exits the program when the per capita household income no longer falls below the extreme poverty threshold. Therefore, the BV is a social program as much as it is an environmental program in that its objective is to have fewer beneficiaries in subsequent years as their

[11] The federal government defines the extreme poverty line to be 77 BRL (approximately 30 USD) of per capita income per month.

[12] Examples of Priority Areas defined by the program include categories within sustainable use conservation zones: Extractive Federal Reserves (RESEX), the Sustainable Development Federal Reserves (RDS), and the Naitonal Forests (Flonas); Environmentally Distinctive Agraian Reform Settlements, managed by the National Institute of Colonization and Agricultural Reform (INCRA); as well as territories occupied by extractivists and indigenous groups. We do not consider territories occupied by riparian, extractivists, quilombolas and other traditional communities in our analysis due to lack of spatial information. In addition, no territories occupied by indigenous people have received Bolsa Verde payments.

[13] Brazilian Institute of Geography and Statistics (IBGE), `ftp://ftp.ibge.gov.br/Trabalho_e_Rendimento/Pesquisa_Nacional_por_Amostra_de_Domicilios_continua/Renda_domiciliar_per_capita/Renda_domiciliar_per_capita_2015_20160420.pdf`.

livelihoods gradually improve to the point where their income rises above the extreme poverty line. Second, the only observable cost for an eligible household to become a beneficiary is the commitment to engaging in conservation and using natural resources in sustainable ways. This commitment is made in the form of a contract, which sets out details of the program, as well as the responsibilities of the families in terms of maintaining the zone's vegetation level and using natural resources in sustainable manners (Figure A1 in the Appendix A).

2.2 Deforestation in Brazil: 1960s to 2000s

The Brazilian Amazon hosts 40 percent of the world's tropical forests. When the local economy relied on extraction of forest resources in the 1960s, Brazil implemented policies that encouraged the occupation of the Amazon. In the 2000s, however, government policies have shifted focus to promoting reductions in deforestation. In fact, the deforestation rate in 2014 is approximately 75 percent lower than the average from 1996 to 2005 [Tollefson, 2015]. Our study area is the Legal Amazon region, where the trends in deforestation are consistent with the national scale. As Figure 2 shows, total deforestation rate in the Legal Amazon from 2002 peaks in 2003 and has since fallen annually. While there is a lack of consensus among economists as to what drives this large drop in deforestation in the mid-2000s, one of the popular views attributes this reduction to regulatory efforts and conservation policies of the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA).[14]

With respect to Figure 2, the BV is relevant for the period 2011 to 2015, and for areas designated as Priority Areas, where the program is exclusively implemented. While the level of deforestation inside Priority Areas has always been low relative to the national average, deforestation activities that remain from 2011 are nonetheless non-trivial. In fact, the remaining annual forest loss inside Priority Areas from 2011 to 2015 averages approximately 850 km^2, which is the size of New York City.

The upward trend in deforestation from 2012, however, raises concern. Unlike areas outside Priority Areas where much of the deforestation is likely driven by economic activities of large landowners, whose contribution to deforestation has fallen by 63 percent since 2005, much of the deforestation inside are due to farmers with smallholdings, whose contribution to deforestation has increased by 69 percent [Godar et al., 2014]. Against the somewhat rosy backdrop of large reductions in deforestation on the national scale, policies that target the increasing deforestation activities of small-scale farmers and households, such as the BV, may become more important in sustaining the overall reductions in deforestation in the years to come.

[14] See, e.g. Gibbs et al. [2015] and Nepstad et al. [2014] for their analysis on the roles of interventions in the supply chain of soy and beef in reducing deforestation; Pfaff et al. [2014] and Assunção et al. [2015] for their evaluation of conservation policies as a driver of reduced deforestation; and Burgess et al. [2017], who analyze the power of the Brazilian state in shaping deforestation over time.

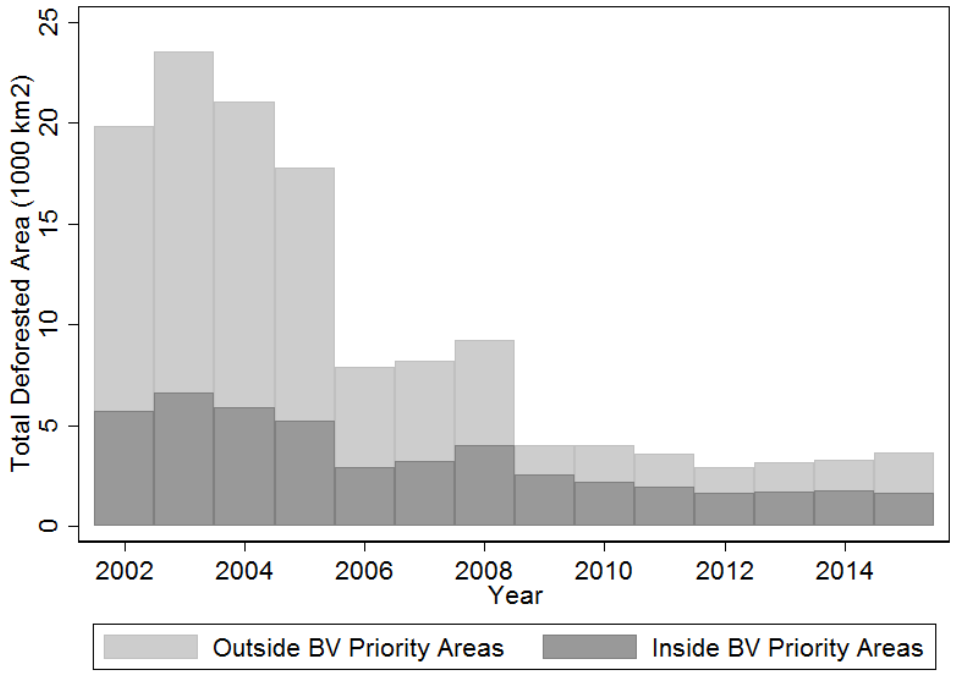

Figure 2: Annual Deforestation from 2002 to 2015 in the Legal Amazon

Notes: The figure plots total deforestation (km^2) per year inside and outside Priority Areas eligible for the BV in the Legal Amazon. Areas eligible for the BV are subcategories within SUC or Settlements (see Table 1).

3 Theoretical background

In this section, we draw conceptual insights from the relevant theoretical literature to understand mechanisms through which the BV could reduce deforestation. Globally about one-third of forest area in developing countries is under some form of community ownership [Gilmour, 2016]. This proportion is likely to increase given ongoing efforts to delegate forest management to local communities in many countries [Agrawal et al., 2008]. Management of natural resources at communal level faces well known barriers such as moral hazard problem. This is because the actions of individuals are not observable and under such situations, individuals choose levels, sub-optimal from social standpoint.

Two broad theoretical approaches in the literature explore how the moral hazard problem can be addressed in similar settings. One strand of research suggests that moral hazard in teams, when only the joint output is observed and it is fully shared among the agents, could be eliminated through the appropriate design of regulatory threats or payments. The key is to design the payment or threat so that all external costs and benefits are fully internalized. This goal could be achieved either through adjusting marginal incentives or through forcing contracts that provide sufficient penalties for suboptimal behaviour [Holmström, 1982]. The same idea has been applied to non-point ambient pollution problem by Segerson [1988]. Non-point source pollution cannot be traced to individual emitters due to monitoring costs or environmental stochasticity. Only ambient levels are measured. Consequently, moral hazard problem arises and the contracts to reduce pollution must target group of emitters. And the incentive structure is set in such way that there is no incentive to free-ride and there is an incentive to provide the level of abatement to ensure the level of ambient pollution as set by a principle.

The second approach focuses on contracts that exploit social ties to induce individuals to behave in the interests of a broader society. One branch of this research has developed theoretical models, which stress the role of peer monitoring in deterring moral hazard in credit contracts applied to micro-lending in developing countries e.g., [Stiglitz, 1990, Banerjee et al., 1994, Besley and Coate, 1995]. The underlying idea behind this peer monitoring is to delegate monitoring to borrowers themselves who have more knowledge and information about each other than the principal (banks). This makes monitoring less costly to the agents and they could also apply social sanctions on each other.

Peer monitoring is also an efficient mechanism in the theory of the firm [Carpenter et al., 2009, Kandel and Lazear, 1992]. To understand effectiveness of peer pressure, Kandel and Lazear [1992], for instance, distinguish between the notions of external peer pressure (e.g., mental or physical harassment) and internal peer pressure (gilt, or fear of being caught and be ashamed). They further stress the role of shame arising when workers produce less than the group average as an important mechanism to reduce shirking. There is also related theoretical literature in social psychology, which suggests that many activities are motivated by either intrinsic incentives (e.g., sense of duty) or extrinsic incentives (e.g., punishment, monetary reward), e.g., Bowles and Polania-Reyes [2012].

Deforestation at the community level (as under the BV program) is an example of nonpoint source pollution and thus, as in a general case considered theoretically by Segerson [1988], under such setting it is extremely difficult and costly, if not impossible, for the principle to monitor each agent and identify individual contributions. For that reason, the principle prefers to: (i) set rewards based depending upon the level of deforestation at the aggregate level (Priority area); (ii) provides incentives to agents (poor households in the BV program) to exert high effort for abatement; and (iii) delegate monitoring of the forest cover to the agents themselves (poor households), who face less monitoring costs.

Condition (ii) implies that the BV program incentivises households who benefit from payments more than from undertaking deforestation activities. We will examine this assumption in the data. In section 5.3.3, we provide suggestive evidence for this assertion by exploiting the heterogeneous effects of the BV program across poorer Priority Areas versus the wealthier ones.

Poor is incentivised to monitor forest cover in the priority area and to report illegal deforestation. Poor do not have, however, any means to exert any (external) peer pressure or social sanctions on richer households in their communities. As such, the BV program does not seem to work through peer pressure channel. Instead, richer household may feel *threat* or *expectation* of being monitored. Knowing that the priority area is now under stricter enforcement, deforesters may reduce their deforestation activities in response to the expectation that now personnel and federal agents could visit the area more often in response to monitoring and reporting by poor households.

To test this expectation channel, we use data on fines issued on illegal deforestation and other illegal environmental activities, as we discuss in more detail in Section 6.2. We will build a simple model, based on [Becker, 1968], to motivate our empirical analysis and to demonstrate that the relationship between fines and deforestation is theoretically ambiguous, and depends on whether (1) expectation channel or (2) actual monitoring and reporting channel dominates.

Sense of community or similar intrinsic incentives for sustainable use of natural resources might be strongly correlated with governance structure of communities. For instance, researchers have found a positive association between a community's governance characteristics and households resource use practices, e.g., [Ostrom, 2005, Ostrom and Nagendra, 2006, Chhatre and Agrawal, 2008]. Furthermore, some scholars expressed concerns that economic incentives could crowd out intrinsic incentives to collectively manage resource in sustainable way [Agrawal et al., 2015, Cardenas et al., 2000]. On the other hand, the success of community-based monitoring of provision of public goods services critically depends on the participation of a broader community [Banerjee et al., 2004, Björkman and Svensson, 2009].

Based on these arguments, we examine how a community's governance (and associated with it intrinsic motives) may influence the effectiveness of the program, by interacting with the above mentioned features (ii) and (iii) of the BV, by comparing the effectiveness of the BV program in Sustainable Use Conservation Zones (SUCs) versus Settlements. SUCs have managers and community councils while Settlements often do not have community management in place. Also, migrants from the South were allocated plots of land to farm in Settlements during the 1970s, hence it is likely that residents in these areas make the majority of their living from agriculture and potentially use deforestation as a means for clearing land. As such, in the SUCs, monetary rewards are likely very strongly aligned with incentives to monitor and report on illegal deforesters, especially if their managers present a point of contact to report illegal deforestation, enabling the monitoring and reporting feasible. In contrast, in the Settlements, underlying incentives are different as settlers were given land to do agriculture and, and there is also perhaps less intrinsic desire to report on neighbors since they live in the same area.

To sum up, the discussion above highlights two channels through which the BV program can reduce deforestation: (1) expectation channel or (2) actual monitoring and reporting channel. In addition, the effectiveness of both of these channels may be influenced by the community's governance structure through intrinsic motives of the members of the communities, and alignment of monetary rewards of the BV program with underlying incentives of the members of the community.

4 Data

Our main data is the PRODES project at the Brazilian National Institute of Space Research, which contains data on annual loss of primary forests and remaining forest cover in the Legal Amazon.[15] The area covers approximately 500 million ha of land across the northern and western parts of Brazil. Approximately 81 percent of the area is forested, 17 percent is cerrado (wooded grassland), and 1.8 percent is water [Skole and Tucker, 1993]. Using images from the Landsat LT-5, LT-7, and LT-8 satellites, PRODES calculates annual deforestation using the seasonal year, which starts from August in year t to July in year $t+1$.[16] We use data on deforestation in the period 2009 to 2015, which constitute three years before BV and the first four years of the program. The satellite data used in PRODES have spatial resolutions of approximately 30 meters. We process both the deforestation and remaining forest information from PRODES to generate a grid with 1 km^2 cells. We also assign geo-specific information, such as distances to the nearest city and paved road, to each grid cell based on the centroid. Overall, the annual deforestation rate is consistently below 278 ha from 2009 to 2015 (Figure 3). However, we observe both areas with increasing and decreasing deforestation since the start of the BV program from 2012. Our main identification strategy exploits this variation in deforestation over space and time for causal inference.

Our analysis considers all eligible SUC and Settlements in the BLA with non-zero remaining forests at baseline (2009), an area of approximately 53 million ha. Examples of SUCs include national parks and extractive reserves, which are organized by the Chico Mendes Institute for Biodiversity Conservation (ICMBio). Each area has a manager and there are regular council meetings among residents. In contrast, Settlements are established by the National Institute of Colonization and Agrarian Reform but the management in many areas are met with obstacles [Ezzine-de Blas et al., 2011].

Table 1 presents the summary statistics of Priority Areas eligible for BV by receiving status. By August 2015, 266 areas (17 percent of the total) have received BV payments. Participation in the program was rolled out gradually over time, with 166 areas (62 percent of the sample) began receiving the grant by August 2012. Subsequently, 42 additional areas (16 percent of the sample) entered the program by August 2013, 53 new areas (20 percent of the sample) started receiving payments by August 2014, and 5 more areas (2 percent of the sample) entered the

[15]The PRODES project (http://www.obt.inpe.br/prodes/index.php) generates spatial data on deforestation in the Amazon that are used as the official governmental information to guide policy and local actions.

[16]Satellite images are selected as near to this date as possible for the calculation, generally from July, August, and September. PRODES only identifies forest clearings of 6.25 hectares or larger. Therefore, forest degradation or smaller clearings from fire or selective logging are not detected. For robustness, we will validate the analysis using Hansen et al. (2013)'s forest cover data.

program by August 2015.[17] Overall, the analysis sample covers 42,944,600 ha.

We also utilize data from the MMA, which provides an exhaustive list of households eligible for the BV program from 2012 to 2015, totaling 31,621 beneficiaries. The list contains information on the names of the representative household member, the Priority Area of residence, and the date of first BV payment or the reason for rejection.[18] To evaluate the success of the BV with respect to its environmental objective, we aggregate these data on eligible households up to the Priority Area level to match with the deforestation data.

The Brazilian government has established an electronic Rural Environmental Registry (CAR; Cadastro Ambiental Rural) since 2008, covering in principle all rural (private) properties in the entire country.[19]. We use data prepared by Bento et al. [2019], which has information deforestation at each property for each year. The data are based on a geo-referenced rural property map from CAR and the geo-referenced deforestation data from PRODES used elsewhere in this paper. We split the properties into four categories (mini, small, medium and large) based on fiscal modules, which is an official socioeconomic definition of properties. Fiscal modules strongly correlate with size, but vary across the country. For each zone or settlement, we aggregate the sum of deforestation per year.[20] We also investigate the impact of the BV on deforestation in subparts of SUCs and Settlements that are on not registered in CAR.

To explore whether the BV encourages participants to monitor illegal activities, we use data on federal fines issued for illegal environmental activities in these areas as outcomes.[21] A subset of these fines are issued against illegal deforestation, while the remaining fines are related to all types of illegal environmental activities, such as pollution, infringements of conservation rules, infringements against the administration of conservation zones, illegal acts against wildlife, including hunting and illegal fishing, as well as trafficking of exotic animals.[22]

[17] In the regression analysis, we exclude PAs, a sub-category within Settlements, due to low levels of program participation (only 1.9 percent of all PAs receive the BV) and low levels of remaining forests at baseline (less than 50 percent).

[18] The list includes households who start receiving the BV from November, 2011, when the program first launched. Since we combine the BV data with deforestation data, we assign deforestation years to each BV recipient. Given that deforestation from PRODES is calculated using the seasonal year starting in August, households who first received BV payments between September 2011 and August 2012 are matched with deforestation in the year 2011.

[19] The CAR was first implemented in Para and Mato Grosso

[20] As we only have the property boundaries at the end of the period (around year 2015-2016, depending on when the exact property was registered). Thus, the exercise is based on the assumption that property boundaries have not changed or properties have not merged or split within our sample period.

[21] There is growing literature on the effects of environmental enforcement on deterrence, see, e.g., Shimshack [2014] for through review and Muehlenbachs et al. [2016]. To our knowledge, this literature has focused on the incentives and behaviour of the enforcers, while we examine how delegation of monitoring to local communities (poor households) could influence deterrence.

[22] For more details on environmental fines and the source of the data, see http://www.ibama.gov.br/fiscalizacao-ambiental/autuacoes-ambientais.

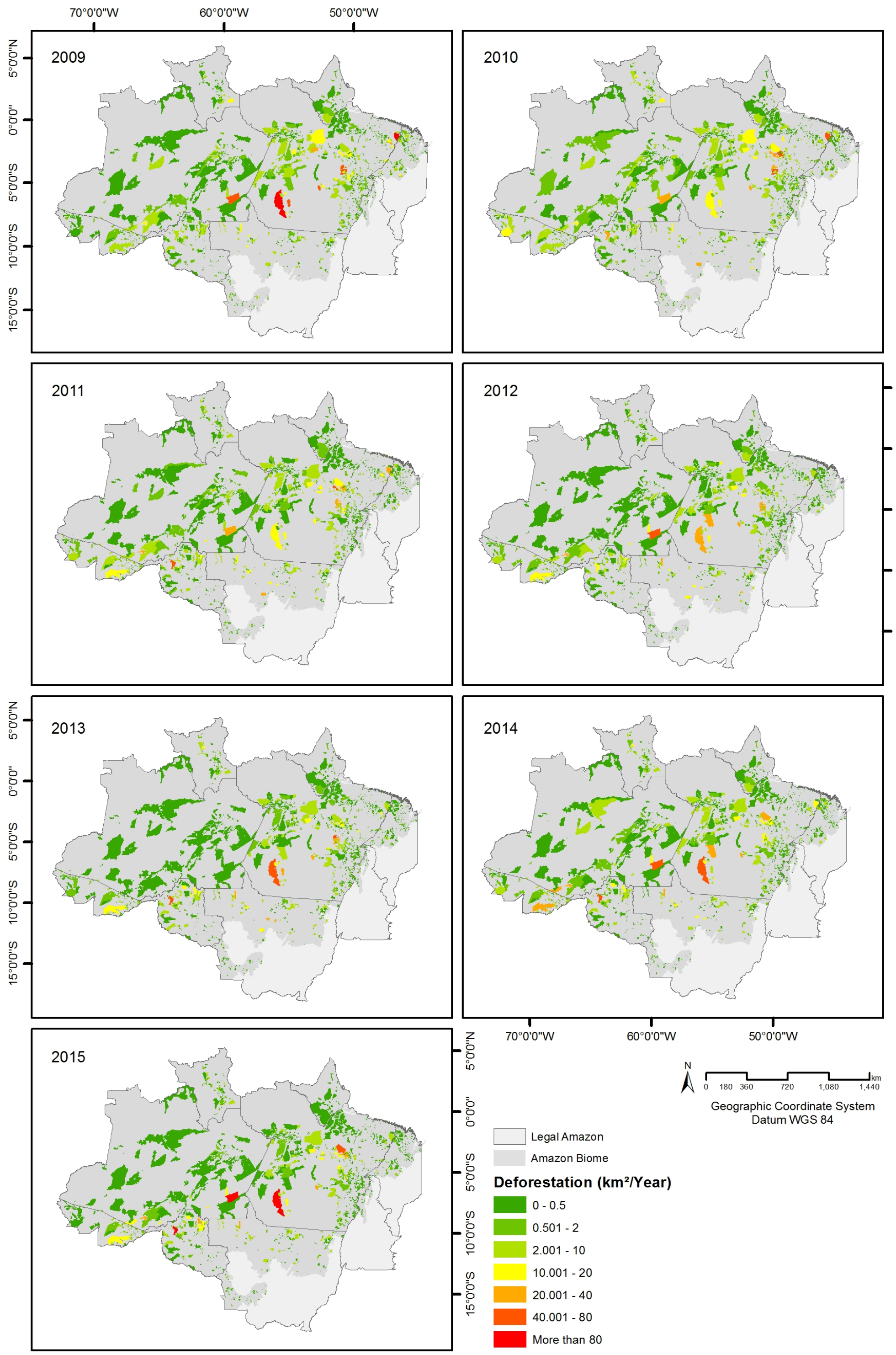

Figure 3: Annual Deforestation Rates in Areas Eligible for Bolsa Verde (2009 to 2015)

Notes: The figure plots annual area deforested in BV-eligible areas in our sample from 2009 to 2015. Deforestation levels are on average low, with a few exceptions (colored yellow, orange, and red). We observe both spatial and temporal changes in deforestation in the study region.

Table 1: Summary Statistics: Receiving and Non-Receiving Priority Areas

Administrative categories		Mean # of BV beneficiaries	Number of areas		Mean % of remaining forests in 2008		Mean Area (1000 hectare)	
		Receiving	Receiving	Non - receiving	Receiving	Non - receiving	Receiving	Non - receiving
SUC	FLONA	96.462	13	17	0.989	0.980	448.208	423.888
		(162.455)	[0.433]	[0.567]	(0.010)	(0.031)	(312.305)	(375.094)
	RESEX	218.69	29	11	0.887	0.936	304.876	167.280
		(367.860)	[0.725]	0.275	(0.238)	(0.058)	(255.943)	(93.980)
	RDS	202	1	16	0.977	0.949	57.6	584.519
		-	[0.059]	0.9412	-	(0.065)	-	(723.537)
Settlements	PA	42.269	26	1351	0.436	0.310	54.877	7.377
		(63.086)	[0.019]	0.9811	(0.380)	(0.284)	(137.726)	(14.505)
	PAE	119.689	186	59	0.894	0.862	29.176	37.860
		(208.374)	[0.759]	0.2408	(0.110)	(0.186)	(102.916)	(105.821)
	PAF	31.333	3	4	0.955	0.976	43.167	33.7
		(13.650)	[0.429]	0.5714	(0.030)	(0.027)	(53.860)	(10.079)
	PDS	76.625	8	81	0.856	0.789	31.988	26.547
		(59.678)	[0.090]	0.9101	(0.141)	(0.238)	(38.249)	(59.318)

Notes: The table presents summary statistics of all BV-eligible Priority Areas inside the PRODES mapping area in the Legal Amazon region. We exclude areas with zero remaining forests in 2009, the first year of the analysis. Only the following categories within SUC and Settlements are eligible for BV: Extractive Federal Reserves (RESEX), Sustainable Development Federal Reserves (RDS), National Forests (Flonas), Settlement Projects (PA), Agro Extractivist Settlement Project (PAE), Forest Settlement Project (PAF), and Sustainable Development Project (PDS). Percentage of areas by receiving status are in brackets. Standard deviation are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5 Empirical Strategy and Results

To quantify the total program impact on deforestation, we implement several quasi-experimental methods beginning with (1) a simple difference-in-differences (DD) analysis at the Priority Area level, which assumes a one-time change in deforestation. We also implement (2) an event study approach, which adds leads and lags to the treatment, and allows for a separate treatment effect in each year leading up to and after participating in the BV program. Identification relies on variation in forest loss over time and across Priority Areas, as well as variation in BV participation across space and over time, conditional on eligibility. We then utilize more disaggregated data to estimate (3) a triple difference (TD) model, where the third difference comes from deforestation in grid cellls that lie outside receiving and non-receiving eligible Priority Areas. We begin by comparing the full sample of Priority Areas with and without BV beneficiaries. To address concerns that Priority Areas under different administrative categories may have systematically different drivers for deforestation and may respond differently to the BV, we run the estimations on two sub-samples: eligible areas that are SUC and those that are Settlements.

5.1 Main Estimates of Program Participation on Deforestation

To capture the roll out of the BV across space and time, we use the following generalized DD framework to quantify the total program impact on deforestation:

$$Deforestation_{zt} = \alpha_0 + \beta BolsaVerde_{zt} + \alpha_1 RF_{zt-1} + \alpha_2 X_{zt} + \nu_z + \mu_t + \epsilon_{zt} \tag{1}$$

where $Deforestation_{zt}$ is the total area of deforestation in Priority Area z in year t as a fraction of remaining primary forests in 2008 (multiplied by 100). To calculate this percentage, we first add the forest loss across all 1 km^2 grid cells whose centroids lie within a Priority Area.[23] We then calculate the fraction of this total forest loss with respect to the stock of remaining forest in the Priority Area in 2008. $BolsaVerde$ is an indicator variable that equals one if the area z has residing households receiving BV payments in year t. The coefficient of interest is β, which is the difference-in-differences estimate of the average treatment effect of BV on deforestation in the treated Priority Areas.

Our specification includes RF, which denotes the stock of remaining forests in an area in the previous year. We exclude areas with zero remaining forests in 2009, the first year of the analysis. We also control for a vector of factors at the Priority Area and year levels that could impact deforestation, X_{zt}, including the proportion of clouds; as well as the interaction of lagged remaining forest with distances to the nearest paved road and city. ν_z are Priority Area fixed effects that control for differences in time-invariant unobservables across areas, and μ_t are year fixed effects to control for any year-specific unobservables affecting deforestation in all

[23] Results using the sum of forest loss are consistent with those that use the mean of deforestation across all grid cells in a Priority Area.

Priority Areas. Since the source of variation comes from differences across Priority Areas, the level of treatment assignment, we cluster standard errors at the Priority Area level to control for arbitrary spatial and serial correlation [Abadie et al., 2017].

Table 2: Impact of BV Participation on Deforestation

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.123**	-0.110*	-0.117*	-0.0734	-0.127*	-0.136*
	(0.0594)	(0.0582)	(0.0649)	(0.0446)	(0.0733)	(0.0701)
Covariate controls	No	Yes	No	Yes	No	Yes
Effect size (ha)	103.181	92.276	413.590	259.466	36.454	39.037
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.004	0.017	0.011	0.142	0.005	0.024

Notes: Dependent variable is deforestation, the total area deforested as a percentage of remaining forests in 2008. Treatment is a dummy variable that equals one if an area has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results from estimating equation (1) are reported in Table 2. Every column of the table shows the coefficient on the treatment effect of the BV from a separate regression, where the dependent variable is the annual fraction of 2008 remaining forests deforested (multiplied by 100). Columns 1 and 2 demonstrate that deforestation fell by approximately 0.11 to 0.12 percentage points more in Priority Areas receiving the BV payments than in non-receiving areas. These effects are statistically significant at the 5 to 10 percent levels. Since BV-receiving Priority Areas had 83,886 ha of remaining forests in 2008, these treatment effects translate into a 92 to 103 ha reduction in forest loss. Given the differences in management structures of conservation zones and Settlements, we explore the effects of the BV separately for each type of Priority Area.[24] Columns 3 and 4 show that we find larger effects in SUCs, where deforestation fell by 0.074 to 0.12 percentage points more in receiving areas than non-receiving areas. Since SUCs had a larger stock of remaining forests in 2008 (353,495 ha), these effects translate into 259 to 414 ha of reductions in forest loss. In Settlements, deforestation fell by approximately 0.14 percentage points more in receiving areas than non-receiving areas but these effects only translate into approximately 39 ha of reductions in forest loss. [25]

To address the potential concern that receiving and non-receiving areas are systematically different prior to the program, and that some of these differences may explain their participation in the BV, we repeat the main analysis on a matched sample of similar receiving and non-

[24] Settlements house the rural poor, who are relocated to these areas by the government without much technical support and guidance on sustainable agricultural and forest management practices (Schneider and Peres 2015).

[25] At baseline, Settlements had 28,704 ha of remaining forests.

receiving areas. We carry out a coarsened exact matching procedure for non-receiving and receiving Priority Areas on a set of pre-program geophysical characteristics [Iacus et al., 2012]. Using 2009 to 2011 data, we match coarsely on the pre-BV average deforestation and remaining forests. We also divide the size of Priority Areas into ten bins and match Priority Areas across bins. Unmatched Priority Areas are dropped from the sample. Table A2 shows that results from the matched sample are consistent with the unmatched sample. We also test whether using the distance of each area from the nearest IBAMA office as a proxy for the strength of enforcement is a meaningful dimension of heterogeneity.[26] Table A3 shows that our main results are robust to controlling for these distances.

Identification in the difference-in-differences analysis draws from the variation in deforestation over time within receiving-areas versus within non-receiving areas. Thus, the validity of the estimates relies on the assumption that these two types of areas do not have systematically different trends in deforestation in absence of the BV, controlling for remaining forest, year and Priority Area fixed characteristics. Table A4 shows results of the tests for the presence of differential pre-trends by interacting future BV status with the linear time trend using data from 2009 to 2011.[27]

5.2 Impact of the BV over time

To obtain more insights into the time paths of the impacts of the BV on deforestation, we implement an event study design by repeating the main specification in Table 2 with leads and lags of the treatment:

$$Deforestation_{zt} = \sum_{k=-3}^{4} \delta_k B_{zt-k} + \psi Xzt + \tau_z + \gamma_t + u_{zt} \tag{2}$$

where B_{zt} is a binary variable that equals to 1 if area z is a BV-receiving area, and δ_k represents the average difference between receiving and non-receiving areas compared to time period -1, the period immediately before enrollment in the BV.[28] We cluster the standard errors at the area level. We depict in Figure 4 the estimated effects of the program at each point in time leading up to and after the first year of program implementation. We find suggestive evidence that the reduction in deforestation kicks in during the first year of the BV, is persistent and remains at

[26] Figure A2 shows the spatial distribution of IBAMA offices in the study area.

[27] Across the full sample as well as the SUC and Settlement sub-samples, we do not find statistically significant differences in the deforestation trends between areas that eventually will receive the BV and those that will not. Figure A3 plots the average deforestation rates across the non-receiving and receiving areas prior to the program, showing no systematically different pre-trends.

[28] This approach is also an alternative to ruling out the presence of pre-trends is the Granger Causality test. A joint significance test for the pre-enrollment coefficients to be zero and insignificant would confirm that there are no differential pre-trends in deforestation. Table A4 in the Appendix shows the estimation results and confirms the lack of pre-trends.

similar magnitude until the third year from program enrollment, with signs of mean reversion in the fourth year.

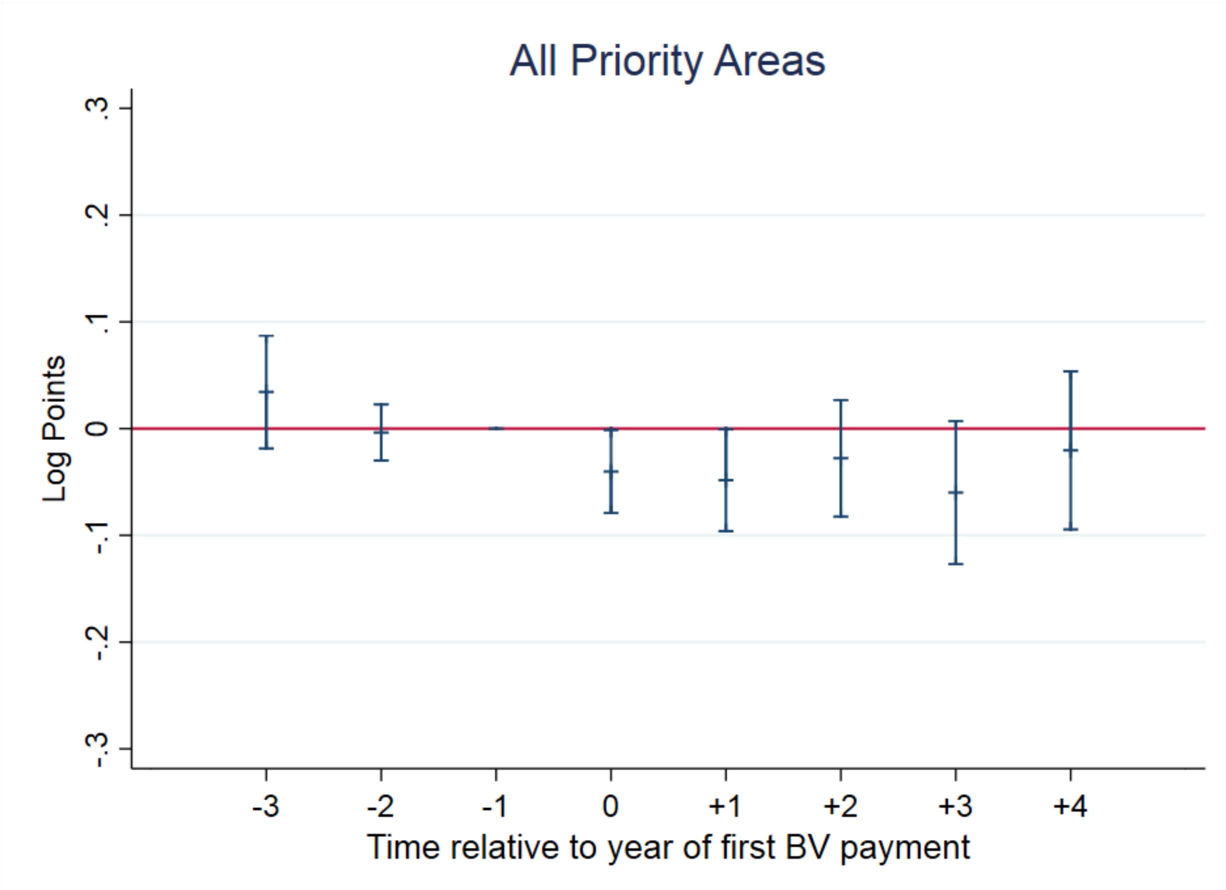

Figure 4: Estimated Changes in Deforestation around the BV Enrollment.

Notes: The figure plots the estimated coefficients and confidence intervals of the effect of the BV on log of deforestation in the years before, during, and after the first year of treatment (receiving BV payments). The time period prior to the enrollment in the BV ("-1") is the omitted category. Vertical bands represent 95 percent confidence intervals. Standard errors are clustered at the area level.

5.3 Heterogeneity

5.3.1 Program Beneficiaries

We next explore the potential sources of heterogeneity in the treatment effects of the program. First, we explore whether and how the treatment effect varies by the number of beneficiaries in a region. Our prior is that the variation could go in opposite directions. First, the effect of the BV on deforestation could be larger in areas with more recipient households. This conjecture is based on the design of the BV contract, which penalizes all beneficiaries by stopping their payments if remaining forests in their resident Priority Areas no longer comply with the Forest Code. This program design differs from typical PES schemes, where landowners commit to conserving only the pieces of land they own.[29] Under the BV program, beneficiaries are not necessarily landowners, but participation in the program for each beneficiary is vulnerable to any deforestation in the Priority Area of residence, regardless of whether the source of deforestation comes from beneficiaries themselves, non-receiving residents, or from outside the area. We therefore hypothesize that the program may reduce deforestation by encouraging beneficiaries to collectively conserve and/or to monitor the area for deforestation activities. We assume that the more beneficiaries there are in a Priority Area, the larger is the conservation and/or monitoring effort, which may translate into reductions in deforestation. Concerns of free-riding are relevant, however, and would suggest the opposite result: areas with more beneficiaries would be more prone to free-riding.

To test the validity of this concern, we repeat the estimation of equation (1) by using the log of the number of BV beneficiaries in a given Priority Area at time t as the treatment variable. Table 3 reports the estimated treatment effects. Column 2 shows the specification with covariate controls. A 10 percent increase in the number of beneficiaries is associated with a 0.24 percentage point reduction in the change in deforestation. This effect translates into an approximately 15 ha reduction in forest loss per beneficiary.[30] In SUCs, a 10 percent increase in the number of beneficiaries is associated with 0.28 percentage point more reduction in the fraction of 2008 remaining forests deforested, or an approximately 54 ha reduction in forest loss per recipient (statistically significant at the 10 percent level).[31] The effects are much smaller in magnitude among Settlements, where a 10 percent increase in the number of BV recipients is associated with 0.28 percentage point reduction in deforestation, or 7 ha of forest loss per recipient (statistically significant at the 5 percent level).[32] These results confirm our conjecture that among BV-receiving Priority Areas, those with more beneficiaries experience larger impacts of program participation on deforestation.[33]

5.3.2 Baseline Deforestation

To shed light on whether the BV has identical impacts on deforestation among Priority Areas with high and low pre-program deforestation, we construct sub-samples of receiving and

[29] In Mexico's PSAH, landowners enroll parcels of land they own and agree to conserve the forest cover on the enrolled parcels. See Alix-Garcia et al. [2015] for details of the program.

[30] The average number of beneficiaries in all Priority Areas is 132.19. The estimated impact of adding 10 percent more or 12.87 beneficiaries is 0.24 percentage points lower deforestation, or 0.0024 x 83,886 ha of remaining forests in 2008, that is a 201.32 ha reduction in forest loss, or 201.32/13.22 = 15 ha of forest.

[31] The average number of beneficiaries in SUCs is 185.81. The estimated impact of adding 10 percent more or 18.58 beneficiaries is a 0.28 percentage point lower deforestation, or 0.0028 x 353,498 ha of 2008 remaining forests, or 989.79 ha reduction in forest loss. This translates into 989.79/18.58 = 54 ha of forest.

[32] In Settlements, the average number of beneficiaries is 119.86, thus the estimated impact of adding 10 percent more or 11.99 beneficiaries is a 0.0028 X 28,704 or 80.37 ha reduction in forest loss. This reduction translates into 80.37/11.99 = 7 ha of forest loss per recipient.

[33] We also repeat the estimation on a coarsened-exact match sample. Table A6 reports the results, which are consistent with the main estimates on the unmatched sample.

Table 3: Impact of BV Beneficiaries on Deforestation

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.0275**	-0.0243**	-0.0309*	-0.0282*	-0.0271*	-0.0281**
	(0.0116)	(0.0112)	(0.0177)	(0.0148)	(0.0142)	(0.0135)
Covariate controls	No	Yes	No	Yes	No	Yes
Effect size (ha) per recipient	17.451	15.420	58.780	53.644	6.490	6.729
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.005	0.018	0.016	0.149	0.005	0.024

Notes: The dependent variable is deforestation, defined as the total area deforested as a percentage of 2008 remaining forest. The treatment is the inverse hyperbolic sine transformation of the total number of BV recipients in a given area. All specifications include Priority Area and year fixed effects. Baseline model is a fixed effects specification without controls. Covariate controls include clouds, lagged remaining forests and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

non-receiving Priority Areas based on pre-program deforestation. We assign households to either the high or low deforestation group based on two measures. The first measure is the average deforestation in the pre-program period, and the second measure is the variance of deforestation over the same period. The high deforestation group consists of households with above-median average deforestation (or variance of deforestation), and the low deforestation group consists of households with below-median averages (or variance). Table 4 reports the estimated treatment effect of program participation on deforestation by the pre-program average deforestation. We find that the established treatment effects of the BV in reducing deforestation in all type of Priority Areas are driven by those with high pre-program average deforestation. Compared to the main results using the full sample, where deforestation in receiving areas fell by 0.11 percentage points more than non-receiving areas, column 1 shows that those with high ex-ante average levels of deforestation have 0.24 percentage points higher reduction in deforestation (statistically significant at the 5 percent level) than non-receiving areas.

We obtain similar results when we construct sub-samples by the variance of pre-program deforestation. Columns 1 and 2 of Table A8 show that the treatment effects of the BV are driven by those with above-median variance of deforestation ex-ante. In SUCs, for example, deforestation in high variance receiving areas fell by 0.18 percentage point more than in non-receiving areas. This estimate is larger than the estimate of 0.07 at baseline (Table 2). Overall, the heterogeneous impact of program participation by pre-program deforestation implies that the total program impact comes from Priority Areas with initially high means and variance in deforestation. These results resonate with the finding in the energy conservation literature, which show that the economically meaningful average treatment effects of Home Energy Reports documented in the US are driven by high usage users to a large extent [Ferraro and Price, 2013].

Table 4: Heterogeneous Impacts by Pre-Program Average Deforestation

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
Average Pre-BV mean deforestation	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (Bolsa Verde participation)	-0.235**	-0.0000409	-0.170*	0.00656	-0.252*	-0.000979
	(0.108)	(0.00296)	(0.0995)	(0.00626)	(0.142)	(0.00357)
Baseline treatment effect	-0.110*		-0.0734		-0.136*	
	(0.0582)		(0.0446)		(0.0701)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,467	1,469	448	147	1,027	1,313
R^2	0.008	0.012	0.015	0.038	0.012	0.012

Notes: The dependent variable is deforestation, the total area deforested as a percentage of 2008 remaining forest. All specifications include Priority Area fixed effects and year fixed effects. Controls include cloud cover (km^2), lagged remaining forests, and interaction terms between lagged remaining forests and nearest distances to paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. We adapt the approach described in List et al. (2017) to assign Priority Areas to the binary category "High" if their average pre-BV (2009-2011) deforestation is above the median and "Low" if it is below. *** p<0.01, ** p<0.05, * p<0.1.

Our results highlight the importance of the BV in protecting areas with high risks of forest loss ex-ante.

5.3.3 Poverty

Since the BV provides financial incentives for recipients to comply with the contract and maintain forest cover in their areas of residence, we would expect BV to have a higher impact on deforestation in poorer Priority Areas than in wealthier ones. Using data on monthly per capita household income from CadUnico (the single registry), we divide Priority Areas into three poverty groups.[34] We geocode the addresses in the registry data and place households into the BV-eligible Priority Areas in our analysis sample. Due to a limited number of SUCs with information on income, we restrict our analysis here to Settlements. Figure 5 shows the distribution of average income per head in our geocoded sample. The mean income per head per month in both receiving and non-receiving Settlements in the geocoded sample is around 50 BRL. The distribution of non-receiving Settlements is slightly to the right of the distribution of receiving households, suggesting that the former group of Settlements are wealthier, on average.

Non poor Priority Areas are defined as those with the majority of BV-receiving households having per capita monthly household income at or above the 75th percentile of the 77 BRL income eligibility threshold (more than 54.2 BRL); *poor* Priority Areas are defined as those

[34]The registry is managed by Brazil's Ministry of Social Development (MDS), and is a list of all Brazilian citizens who receive any kind of social transfer. The registry has detailed demographic and socioeconomic information on all households and its members.

where the majority of BV receiving households have per capita monthly income between the 50th and 75th percentile of the 77 BRL income eligibility threshold (between 37.2 and 54.2 BRL); *extremely poor* Priority Areas are defined as those with the majority of BV receiving households having per capita monthly income below the 50th percentile of the 77 BRL income eligibility threshold (fewer than 37.2 BRL).

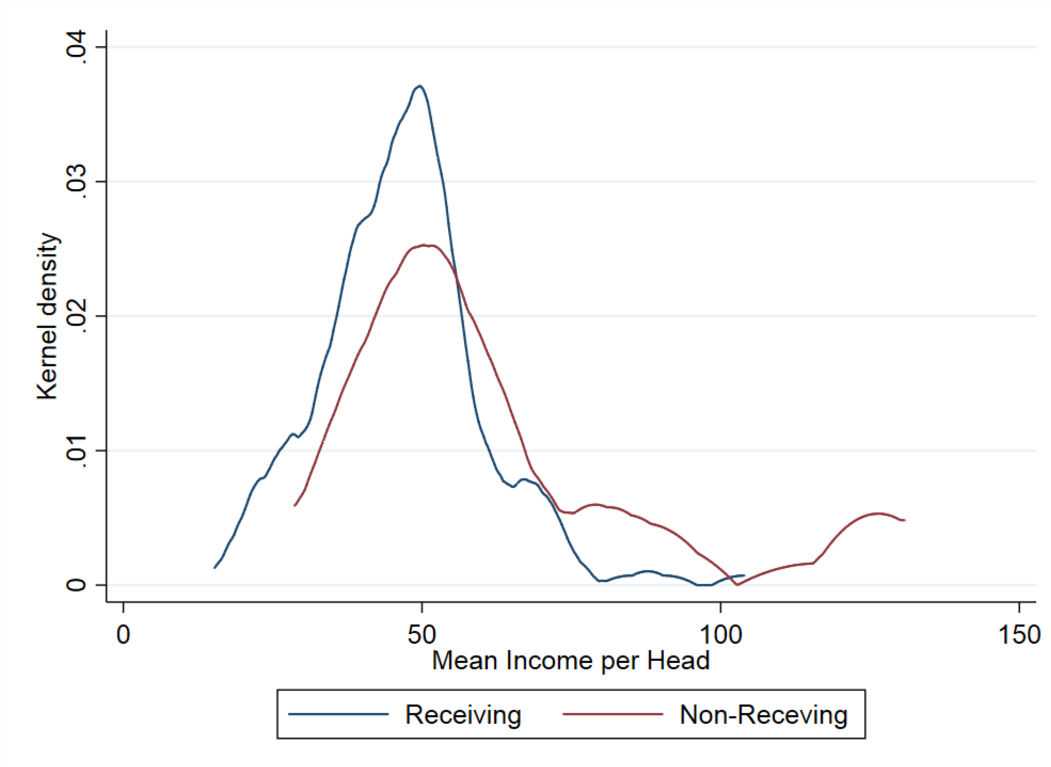

Figure 5: Distribution of Income per Head in Settlements

Notes: The figure plots the distribution of average income per head among receiving and non-receiving Settlements. We use information on income from the subgroup of households that we are able to geocode and place into BV eligible areas from the Social Registry. The assumption is that the geocoded subsample is random with respect to income and the distribution of mean income per head shown is representative of the true distribution and errors are not systematically different by BV receiving status. The mean income per head is an average over 2012 to 2015.

Table 5 reports the estimated impact of the BV on deforestation by the three categories of poverty at the priority year level. Reported coefficients are those of interactions between the log of the number of BV recipients and the poverty category dummies. Deforestation does not seem to respond to participation in the BV deferentially between extremely poor, poor and non-poor Settlements (column 2). However, we find that the number of beneficiaries in an area matters and its impact is the largest among extremely poor Settlements. Deforestation fell by approximately 14.5 percent more in receiving areas with 10 percent more beneficiaries than in non-receiving areas (column 3). This effect is statistically significant in the 10 percent level, suggesting that the BV has stronger impacts on deforestation in areas where the financial payments represent a more meaningful addition to the household budget of beneficiaries.

Table 5: Heterogeneous Impacts of Program Beneficiaries by Regional Income

Dependent variable		Log of deforetation	
Treatment		BV participation (0/1)	Log of BV beneficiaries
	(1)	(2)	(3)
	Pre-BV Mean Deforestation Rate	Estimated Impact Coefficients	Estimated Impact Coefficients
Extremely poor priority areas	0.387	-0.0637	-0.0145*
	[3.880]	(0.0445)	(0.00842)
Poor priority areas	0.754	-0.0309	-0.00945
	[2.981]	(0.0467)	(0.00900)
Nonpoor priority areas	0.115	-0.0582	-0.0144
	[0.605]	(0.0548)	(0.0112)
Covariates		Yes	Yes
	…		
Observations	…	1,590	1,590
R^2	…	0.014	0.015

Notes: Dependent variable is log of deforestation, the total area deforested as a percentage of 2008 remaining forests. All models include year fixed effects and Priority Area fixed effects. All specifications include the same set of controls as before. Robust standard errors clustered at the Priority Area level are in parentheses. Reported coefficients are interactions of the treatment with the poverty level of each Priority Area. Priority Areas are divided into poverty groups using monthly per capita household income from CadUnico (MDS). Non poor Priority Areas are defined as those with average per capita monthly income at or above the 75th percentile of the income distribution of all sampled Settlements (more than 54.2 BRL); poor Priority Areas are defined as those with mean per capita monthly income between the 50th and 75th percentile (between 37.2 and 54.2 BRL); extremely poor Priority Areas are defined as those with mean per capita monthly income below the 50th percentile (< 37.2 BRL). *** p<0.01, ** p<0.05, * p<0.10.

5.4 Triple Difference

Although participation in the BV program reduces deforestation in treated areas, the possibility that deforestation at eventually-receiving ares follows different time trends than that in areas that never receive the BV remains. If receiving areas had downward-trending deforestation, then our treatment effect overstates the program impact.To address this concern about the selection of Priority Areas int othe BV program based on unobserved characteristics, we exploit more disaggregated data to implement a triple-difference (TD) strategy at the grid cell level, with the third difference coming from deforestation rates among cells just outside non-receiving and receiving BV Priority Areas. Our assumption is that prior to the BV, the trends in deforestation in cells lying just outside the border of an eventually receiving areas should be similar to those lying just outside non-receiving areas.

The DD estimate from the baseline model represents the combined effect of the treatment effect and the border effect (the confounder), while the TD estimate from the new comparison group represents the estimate of the effect of the time-varying confounder (border) on deforestation. By subtracting one estimate from another, and forming a triple difference, we could remove the bias from the time-varying confounder and isolate the treatment effect. Formally, we estimate the TD model of the following form:

$$\begin{aligned} Deforestation_{zht} = \beta_0 + \beta_1 Inside * Post * Receiving + \beta_2 Inside * Receiving + \beta_3 Post * Receiving + \\ + \beta_4 Inside * Post + \beta_5 Inside + \beta_6 Post + \beta_7 Receiving + \epsilon_{zt} \end{aligned} \quad (3)$$

where $Deforestation_{zht}$ is the total area of deforestation in grid cell z in year t as a fraction of remaining primary forests in 2008 (multiplied by 100). *Inside* is an indicator variables that equals one if the cell is inside of the Priority area, and zero if outside; *post* is an indicator variable that equals to one if the cell was ever "treated"; *Receiving* is an indicator variable that equals to one if the cell is observation from BV-receiving areas and zero, if the cell is observation from BV-non-receiving areas.

The estimation sample includes all inside and outside cells of both receiving and non-receiving (placebo) areas. The main parameter of interest is β_1 (triple-difference estimate), and β_2 through β_7 are the estimates of the double interaction terms and linear terms, respectively. Table 6 reports the triple difference estimates, showing that overall, BV-receiving areas experience more reduction in deforestation compared to non-receiving areas (approximately 37.67 percent of pre-BV average). When distinguishing between SUCs and Settlements, column 2 shows that the treatment effect is larger in the former (47.41 percent of pre-program mean) than in the latter areas (30.16 percent), consistent with our DD estimates that the BV is more effective in SUCs.

6 Mechanisms: Actors of Deforestation

6.1 CAR Properties

On average, we do not find that the BV reduces deforestation on private properties registered on the CAR Registry. If anything, we find that deforestation on mini properties in receiving areas

Table 6: Triple Difference Estimates of Program Impact on Deforestation

	y = % deforested			
	(1)		(2)	
Dinside = 1 X Dreceiv = 1 X Dpost = 1	-0.0545***	37.67%		
	(0.0180)			
Dinside = 1 X Dreceiv_UC = 1 X Dpost = 1			-0.0643***	47.41%
			(0.0181)	
Dinside = 1 X Dreceiv_SET = 1 X Dpost = 1			-0.0377*	30.16%
			(0.226)	
Year FE	Yes		Yes	
Observations	18,137,646		18,137,646	

Notes: Dependent variable is the percentage of deforestation in each 1 km^2 grid cell. Each column reports triple difference estimates from separate specifications. The magnitude of the coefficients in terms of the pre-BV mean deforestation is expressed to the right of the coefficient estimates. Robust standard errors clustered at the Priority Area level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

to have increased (Table 7, column 2). We do not find the BV to have impacted deforestation on properties of other sizes in neither SUCs nor Settlements. Consistent with the baseline TD estimates, we find that non-CAR deforestation decreased in both receiving SUCs and Settlements. Our interpretation is that the BV program is not about reporting on your neighbors. Rather, these results suggest that the program induces reporting against deforestation that happen on non-CAR properties.

Table 7: Impacts of Program on Deforestation in CAR and Non-CAR Properties

	All CAR Properties	Mini Properties	Small Properties	Medium Properties	Large Properties	Non Car Land
	(1)	(2)	(3)	(4)	(5)	(6)
Dinside x Dreceiv x Dpost	-0.00975	0.00175	-0.00140	0.00999	-0.140	-0.0518***
	(0.0138)	(0.00122)	(0.00505)	(0.0109)	(0.140)	(0.0177)
Dinside x Dreceiv_SUC x Dpost	-0.0170	0.00266*	-0.00516	-0.000720	-0.154	-0.0597***
	(0.0141)	(0.00146)	(0.00442)	(0.0100)	(0.144)	(0.0177)
Dinside x Dreceiv_SET x Dpost	-0.00683	0.00174	0.000406	0.0174	-0.128	-0.0383*
	(0.0138)	(0.00122)	(0.00540)	(0.0121)	(0.139)	(0.0208)
Year and Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,084,272	442,328	344,312	135,664	76,384	17,053,774

Notes: Dependent variable is the average deforestation at the property level (in squared kilometers). Column 6 uses deforestation at the cell level as the dependent variable. The table reports triple difference estimates on separate specifications. Robust standard errors clustered at the Priority Area level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

6.2 Monitoring and Fines

We explore plausible channels through which the BV is effective in maintaining the regional forest cover. First, beneficiaries sign a two-year contract to commit to using natural resources in sustainable ways. Since all BV recipients will lose their payments if the regional forest cover no longer complies with the Forest Code, they may have stronger incentives after enrollment into the program to monitor and report illegal deforestation to the authorities.[35] Higher levels of monitoring by poor and threat of being reported,- the expectation channel, may drive up the costs and lower the incidence of deforestation.

This plausible mechanism can be tested empirically. To formalize these arguments and to guide the empirical strategy, we begin by outlining a conceptual framework, which emphasizes several channels through which the BV program could affect the prevalence of environmental offenses, including illegal deforestation. Our conventional framework draws on the models and ideas developed in the literature on crime, specifically in Becker [1968] and Dustmann et al. [2011].

6.2.1 A simple model

Consider the scenario in which a potential offender lives in an area with a concentration of BV recipients, π. Suppose that his attitude towards illegal deforestation is captured by a function $A(\psi, \pi)$, which depends negatively on π, through higher concentration of BV beneficiaries and thus higher monitoring efforts, and positively on his innate ability, ψ, to engage in illegal activities. Similarly to Becker [1968], suppose that the individual chooses to engage in illegal activities if the perceived gain from doing so, denoted by $B[A(\psi, \pi), \pi]$, which is an increasing function of his attitude towards offense and possibly also varies negatively with π, exceeds the cost, denoted by $K(\pi)$, which depends positively on π through the possibility of higher monitoring.

To the extent that the decision to illegally deforest by potential offenders is driven by the characteristics of the area in terms of the concentration of BV beneficiaries, as well as other area characteristics (forest cover, intensity, size of the areas and so forth), the innate attitude towards illegal deforestation, ψ, will differ in areas with different concentrations of BV beneficiaries. Thus, the probability that a potential offender decides to commit an offense will be the conditional probability that ψ is great enough so that the perceived benefits exceed the costs:

$$Pr\left(B[A(\psi, \pi), \pi] > K(\pi) | \pi\right) \tag{4}$$

Next, we need to specify the probability of an offense being detected. This probability depends on the levels of monitoring by poor and thus on the concentration of BV beneficiaries π and also the overall level of enforcement E, denoted as $\mu(\pi, E)$. Because of the peer monitoring channel, $\mu(\pi, E)$ is an increasing function of π. Also, $\mu(\pi, E)$ is positively related to overall enforcement by government authorities in the area, E.

[35] In the Legal Amazon, two agencies have the authority to issue fines against illegal environmental acts, IBAMA and ICMBio.

Putting the above considerations together, we arrive at a model which defines the probability of issuing deforestation-related fines for illegal deforestation in an area:

$$\lambda^{df}(\pi) = \mu(\pi, E) Pr\left(B[A(\psi, \pi), \pi] > K(\pi)|\pi\right) \tag{5}$$

The dependence of $\lambda^{df}(\pi)$ on π is ambiguous. Higher efforts of monitoring by poor reflected in higher π should decrease $A(\psi, \pi)$ and consequently $B[A(\psi, \pi)]$. The values of ψ also should decrease with π , we should expect stricter enforcement in the areas with higher concentration of BV beneficiaries. Furthermore, $K(\pi)$ should increase with higher π, so that the conditional probability is likely to fall, while the probability of detection $\mu(\pi)$ increases with π.

Therefore the ambiguity of the relationship between deforestation-related fines and the BV derived in equation (5) hinges on our conjecture that deforesters likely internalize the threat of being reported by the monitoring agents (so that Pr falls). If this was the case, then we might see the indirect effects of stricter enforcement on fines issued for other environmental offenses and expect a positive relationship between fines issued for other environmental offenses and the concentration of the BV beneficiaries. To illustrate these arguments, we use the same model as above, with now considering a problem faced by a potential offender who considers whether to commit other than illegal deforestation environmental crime. Suppose that $C(\psi, \pi)$ denotes his attitude towards committing an offense, which depends negatively on π, and positively on his innate ability to engage in criminal activities. Suppose further that the individual decides to commit an offense, if the perceived gain from doing so, $D[C(\psi, \pi)]$ exceeds the costs, $N(\pi)$, which depend negatively on π. As before, if we denote $\omega(\pi)$ the probability of detection, then we arrive at the model which defines probability of issuing fines for other environmental offences in an area:

$$\lambda^{o}(\pi) = \omega(\pi, E) Pr\left(D[C(\psi, \pi), \pi] > N(\pi)|\pi\right) \tag{6}$$

The dependence of λ^{o} on π is positive. Because of the positive spillover effects of stricter enforcement on detection of other environmental offenses, ω should increase with π. Furthermore, as $D[C(\psi, \pi)]$ should increase and $N(\pi)$ should fall with an increase in π, the conditional probability increases too.

There is also no reason to expect $\lambda^{i}(\pi)$, $i = df, o$ to be necessary monotonic. In the empirical implementation below, we therefore experiment with linear and quadratic forms for the dependence of $\ln \lambda^{i}(\pi)$ on π.

6.2.2 Empirical Strategy

Let the number of fines issued, which corresponds to the expression we derived in equations (5) and (6) be given by:

$$\ln \lambda^{i}_{zt} = \gamma \pi_z + \alpha X_z \tag{7}$$

where π_z is the BV receipts concentration in area z, X_z includes indicators of other observed relevant characteristics of the area. Our key parameter of interest is γ, which measures the association between peer monitoring and fines.

A typical source of information for the location of illegal deforestation is the DETER or the Real Time System for Detection of Deforestation, a monitoring system developed by the Brazilian government to identify deforestation hot spots in near real time using satellite images. Figure 6 shows the spatial distribution of DETER alarms and fines issued for illegal deforestation in the Legal Amazon in 2015. While there is much spatial overlap between DETER alarms and fines, we observe fines that are far away from alarms, suggesting that enforcement officials also detect illegal deforestation activities from other sources, for example, reports from locals.

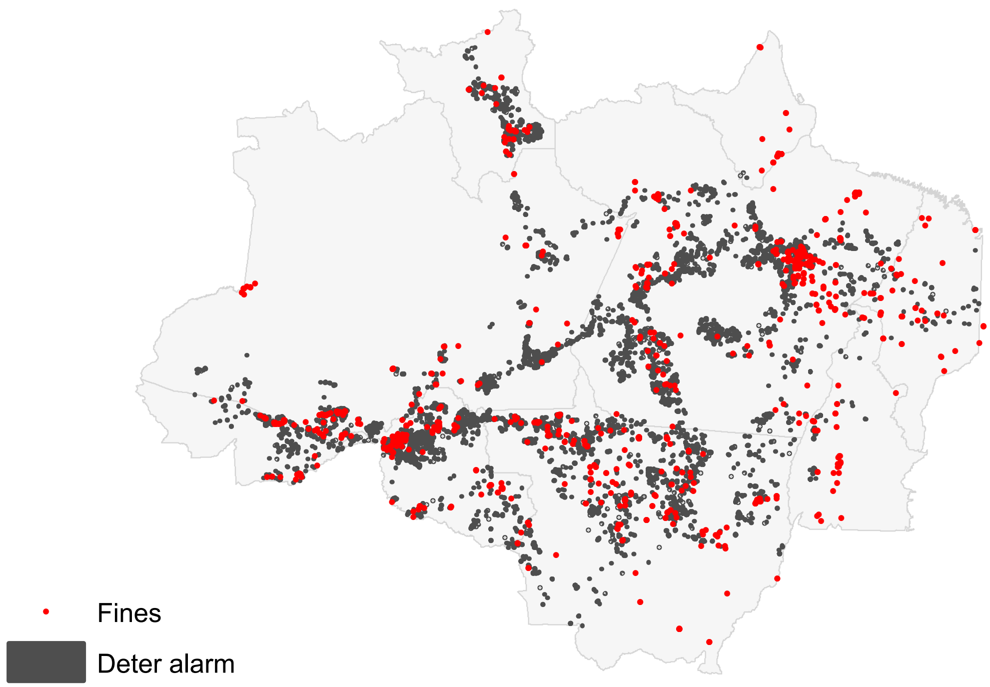

Figure 6: Distribution of fines and DETER Alarms in 2015

Notes: The map plots the location of fines issued by either IBAMA or ICMBio, as well as DETER alarms in the Legal Amazon in 2015. When fines and DETER alarm locations overlap, it is suggestive that the fines are due to the alarm. However, in regions where a fine was issued but no alarm was set off, then we have reasons to believe that the fine was issued due to intelligence from other sources, such as the reports by locals.

To test for the presence of peer monitoring by BV recipients, we use time-series data on fines to examine the relationship between fines and participation in the BV. First, we calculate the total number of fines that lie inside the administrative boundaries of each BV-eligible Priority Area in a given year. Second, we distinguish between fines issued for illegal deforestation, I^{df}, and those that are issued for other illegal environmental acts, I^o. We consider the number of fines issued, I_{zt}, in a given area z and year t. Using the expression derived in equation (7) and discussions earlier, for our empirical analysis we write $I_{zt} = \ln \lambda_{zt}$ and test whether the BV reduces deforestation by encouraging peer-monitoring via the following specification:

$$I^i_{zt} = \alpha_0 + \gamma BolsaVerde_{zt} + \alpha_1 Deforestation_{zt} + \alpha_2 X_{zt} + \nu_z + \mu_t + \epsilon_{zt} \tag{8}$$

where $I^i_{zt}, i = df, o$ denote fines issued for illegal deforestation or other environmental offences respectively; and the other variables are defined in the same way as in equation (1). We control for deforestation in the specification because we want to control for the conservation channel. Our key parameter of interest is γ, which measures the association between peer monitoring and fines. As our discussion in the previous sub-section suggests, the sign of this parameter is not clear-cut if the outcome is fines for illegal deforestation, but it is positive if outcome is fines for other environmental offences and if the BV increases the monitoring by recipients.

Table 8 reports the estimated coefficients of equation (8). Columns 1, 3 and 5 include areas with no fines while columns 2, 4, and 6 report the effect of the BV on fines, conditional on having at least one fine in a given year. Panel A shows that BV-receiving areas do not have statistically higher numbers of deforestation-related fines. However, we find weak evidence that these areas do have more fines issued for other illegal environmental offenses (Panel B). Conditional on having some fines, we find that the BV-receiving areas have 48.4 percent more fines. These estimates are conditional on contemporaneous deforestation, which may decrease due to higher conservation efforts by recipients. The finding that there is an increase in fines against other illegal environmental offenses but not fines related to illegal deforestation is only present in SUCs, not Settlements, suggesting that capacity for coordination is a necessary condition for peer monitoring.[36] Overall, these results confirm our conjecture that the BV is a pay for performance scheme that encourages peer-monitoring, with indirect effects on non-deforestation related fines. Table 8 shows that if we do not distinguish between fines due to illegal deforestation or other environmental offenses, we would find a positive effect of the BV on the number of fines, masking the meaningful heterogeneity that allows us to demonstrate the indirect effects of peer monitoring.

[36]Examples of SUCs include national parks and extractive reserves, which are organized by the Chico Mendes Institute for Biodiversity Conservation (ICMBio). Each area has a manager and there are regular council meetings among residents. In contrast, Settlements are established by the National Institute of Colonization and Agrarian Reform but the management in many areas are met with obstacles Ezzine-de Blas et al. [2011].

Table 8: Impact of BV Participation on Fines

	All		SUC		Settlements	
	y	log(y)	y	log(y)	y	log(y)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: y = I^{df}						
Treatment effect	0.127	0.137	-0.128	0.197	0.208	-0.0275
	(0.132)	(0.196)	(0.401)	(0.275)	(0.130)	(0.258)
Deforestation (%)	0.216*	0.0482	-1.229***	-0.0183	0.295***	0.0475
	(0.116)	(0.0318)	(0.288)	(0.0676)	(0.0935)	(0.0403)
Pre-BV mean y	0.299 [1.251]		1.181 [2.413]		0.119 [0.715]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	368	602	184	2,359	184
R^2	0.320	0.148	0.412	0.122	0.236	0.360
Panel B: y = I^{o}						
Treatment effect	0.130	0.484**	0.679	0.516**	0.00663	0.294
	(0.0843)	(0.214)	(0.412)	(0.220)	(0.0232)	(0.210)
Deforestation (%)	-0.0127	-0.0770	-0.107	-0.0236	0.00520	0.135*
	(0.0182)	(0.0505)	(0.220)	(0.0358)	(0.00560)	(0.0720)
Pre-BV mean y	0.256 [1.367]		1.343 [3.057]		0.033 [0.252]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	278	602	224	2,359	54
R^2	0.075	0.163	0.099	0.190	0.087	0.734

Notes: The dependent variable is total number of fines or log of fines (conditional on some fines). The treatment is a dummy variable that equals one if an area has BV-receiving households, and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include cloud cover, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses Standard deviation of the number of fines are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.

To further confirm the peer monitoring channel, we investigate whether the increase in fines due to the BV varies by the number of beneficiaries. Results are reported in Table A12. Overall, a 10 percent increase in the number of recipients (about 13 households) is associated with a 0.32 unit increase in fines, or 87.7 percent in areas with at least one fine (columns 1 and 2). This effect is statistically zero in Settlements, indicating that the peer monitoring channel generates indirect effects to other illegal environmental offenses only in SUCs .

Table 9 reports triple difference estimates on fines at the grid cell level. Here, we restrict the sample to include cells with non-zero deforestation in a given year, and we calculate the average distance to alarms among fines issued in a cell. We use the count of fines as the dependent variable, and we distinguish between fines that overlap and do not overlap with alarms. The former may be a result of the alarm but we believe that the latter is more likely to be due to reporting. Across all specifications, we find an increase in fines among BV-receiving SUCs and Settlements. We find both stronger statistical significance and larger coefficients in SUCs, consistent with the result at the Priority Area level that the monitoring channel is more effective in SUCs, where the actors of deforestation are likely to be outsiders instead of the BV beneficiaries or their neighbors.

Table 9: Triple difference: Impact of BV Participation on Fines

	(1)	(2)	(3)	(4)	(5)	(6)
	all	no alarm	no alarm 5k	all	no alarm	no alarm 5k
Dpost=1	19.03***	19.64***	19.08***	19.01***	19.24***	18.23***
	(0.135)	(0.295)	(0.333)	(0.173)	(0.222)	(0.296)
Dinside=1 × Dpost=1	-0.635**	-1.204***	-1.295***	-0.567*	-1.043***	-1.115**
	(0.293)	(0.350)	(0.468)	(0.296)	(0.372)	(0.475)
Dreceiv_UC=1 × Dpost=1	-1.379***	-2.320***	-2.426***	-1.372***	-2.286***	-2.306***
	(0.385)	(0.607)	(0.824)	(0.384)	(0.600)	(0.813)
Dinside=1 × Dreceiv_UC=1 × Dpost=1	19.02***	20.48***	20.98***	18.42***	19.22***	19.33***
	(0.847)	(0.946)	(1.141)	(0.955)	(1.060)	(1.237)
Dreceiv_SET=1 × Dpost=1	-1.799***	-1.874***	-1.148**	-1.810***	-1.856***	-1.056*
	(0.467)	(0.503)	(0.540)	(0.496)	(0.535)	(0.576)
Dinside=1 × Dreceiv_SET=1 × Dpost=1	1.391*	1.777**	1.222	1.326*	1.606*	1.027
	(0.778)	(0.844)	(1.098)	(0.797)	(0.871)	(1.119)
Observations	6179	3036	1301	5986	2925	1249
Cells	1871	874	406	1810	843	389

Notes: The dependent variable is the count of fines in the cell in a given year. Estimated with Poisson, cell and time fixed effects included. Robust standard errors clustered at cell-level. Based on cells with non-zero deforestation. Columns 1-3 based on all fines, columns 4-6 based on fines related to deforestation only. Columns 1 and 4 include all cells, columns 2 and 5 exclude cell-years with DETER alarms and column 3 and 6 exclude cell-years with DETER-alarms within a radius of 5 km.

7 Conclusion

This paper evaluates a cash transfer program that pays extremely poor families for forest conservation. Exploiting the aggregate conditionality of Brazil's Bolsa Verde program, we show that deforestation in treated areas fell by 44-53 percent of the counterfactual deforestation. Using difference-in-differences and event study approaches, we show that these effects kick in immediately and remain in the fourth year. Additionally, we uncover important heterogeneity in program impact, with the poorest areas exhibiting the largest reductions in forest loss. We show that these results can be explained by the incentives for beneficiaries to monitor illegal deforestation in their areas of residence by in two ways. First, data from CAR show that deforestation reductions occur on non-private properties, suggesting that the BV recipients either do no deforest themselves or do not report on their neighbors. Moreover, we exploit data on fines issued illegal deforestation to show that reporting does happen, especially in SUCs. Overall, our study suggests that paying the poor to monitor rather than paying resource owners to conserve may be effective in maintaining forest cover as long as they are not the main actors of deforestation. [37] Our results also speak to the debate on whether social programs should tar-

[37] Our study also highlights a unique policy example among Brazil's basket of anti-deforestation policies that can simultaneously achieve both environmental and development objectives. Many of these policies target deforestation

get the poor, by providing an estimate of paying poor individuals on promoting an aggregate outcome, which has benefits that flow to others in society.

To compare the program's costs with benefits, we conduct a back-of-the-envelope calculation to evaluate the treatment effect on forest loss in terms of averted CO_2 emissions. In Table 2, we estimate that the reduction in deforestation is 0.07 percentage points or 259 ha more in BV-receiving SUCs than non-receiving areas. To convert these effects into reduction in CO_2 emissions, we use the existing estimate of 125 MT of carbon stock per ha of forest in the Brazilian Amazon. [38] We translate our results into (259 ha x 125 MT) = 32,375 MT of carbon sequestered per Priority Area. This amount of carbon sequestered translates into (32,375 MT x 3.67) = 118,816 MT of averted CO_2 emissions. Taking the U.S. Environmental Protection Agency's estimated Social Cost of Carbon (SCC) at USD39 per ton of averted CO_2 (in 2012 U.S. dollars), program benefits in SUCs are approximately USD 4.6 million per area or USD 199 million for all SUCs in our sample.[39] A similar calculation for Settlements yields program benefits at approximately USD 0.7 million per area or USD 136 million in total.[40]

The program costs 300 BRL (USD154) per recipient household per quarter, or USD616 per year. Since our analysis sample has 31,621 beneficiaries, the cost of the program between 2011 and 2015 is USD 97.5 million.[41] The estimated program benefits (USD 335 million) are approximately 3 times the program costs. The costs calculated in this way only take into account the quarterly cash payment to each beneficiary household and is likely a lower bound estimate. Given the large estimated benefits, however, we are confident that the benefits of the BV program outweigh the costs.[42]

Importantly, our study highlights the importance of providing incentives to the appropriate group in situations where the principal agent problem is characterized by a principal who is concerned only about the aggregate payoff and not effort of individual agents. More under-

at the potential expense of economic development. Supply chain interventions against deforestation, for example, the Soy Moratorium and zero-deforestation cattle agreements, have been shown to have no average impact on forest cover Alix-Garcia and Gibbs [2017]. Policies that penalize violators, such as the blacklisting of heavily-deforesting municipalities, have been shown to reduce deforestation by 35 percent but limited evidence exists on the economic costs of the policy Assunção and Rocha [2014].

[38] We average the existing estimates of 150 metric tons (MT) per ha Andersen et al. [2012] and 100 MT per ha Margulis [2016].

[39] In 2010, the EPA estimates the SCC to be USD33 in 2007 U.S. dollars. In 2015, the value is updated to be USD38 in 2007 U.S. dollars. In our calculations of program benefits of BV, we follow [Jayachandran et al., 2017] to use the SCC value of USD39 for 2012 in 2012 U.S. dollars. There are 43 receiving SUCs in our analysis sample, so the benefits are 118,816 X 39 X 43 = 199 million.

[40] There are 195 receiving Settlements in our analysis sample.

[41] This cost measure abstracts away from administrative cost of the program that are unobserved by us. Therefore, the actual costs associated with implementing the program are likely higher than only the payment to each beneficiary.

[42] Even if we conduct a conservative calculation of the benefits by assuming that not all but only half of the carbon stock per ha of forest is lost when trees are cut down, the total benefits would be 99.5 million for SUCs and 68 million for Settlements, more than 1.5 times the program costs. Alternatively, if we adopt the the recent SCC estimations at the country-level by Ricke et al. [2018], and use Brazil's SCC of USD24, then the total benefits of the BV would be 122 million for SUCs and 84 million for Settlements, approximately twice the program costs.

standing on how beneficiaries interact with non-recipients and the extent to which the effectiveness of community-level monitoring depends on this interaction remains an important topic for future research.

A Appendix

Table A1: Estimated Impact of the BV on Log of Deforestation

Dependent variable	Log of deforetation					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.0489**	-0.0413*	-0.0562*	-0.0385*	-0.0470*	-0.0466*
	(0.0225)	(0.0219)	(0.0283)	(0.0196)	(0.0274)	(0.0265)
Covariate controls	No	Yes	No	Yes	No	Yes
Pre-BV mean deforestation in receiving areas (%)	0.116		0.205		0.098	
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.007	0.021	0.018	0.216	0.007	0.028

Notes: Dependent variable is the log of deforestation, the percentage of 2008 remaining forests deforested in a given year. Treatment is a dummy variable that equals one if an area has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: Impact of BV Participation on Deforestation using a Matchted Sample

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.124**	-0.117**	-0.0766	-0.0936*	-0.138*	-0.124*
	(0.0594)	(0.0588)	(0.0519)	(0.0548)	(0.0750)	(0.0696)
Covariate controls	No	Yes	No	Yes	No	Yes
Effect size (ha)	89.616	84.557	235.628	287.922	39.592	35.575
Observations	2,849	2,849	532	532	2,317	2,317
R^2	0.005	0.013	0.012	0.049	0.007	0.027

Notes: The sample result from a coarsened exact matching procedure based on pre-2011 data. The dependent variable is deforestation, the total area deforested as a percentage of remaining forests in 2008. Treatment is a dummy variable that equals one if an area has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Estimated Impact of BV on Deforestation by Distance to IBAMA Offices

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.150**	-0.111	-0.213	-0.148	-0.147*	-0.143*
	(0.0699)	(0.0691)	(0.144)	(0.130)	(0.0842)	(0.0797)
Treatment X Distance to IBAMA	0.000182	0.0000048	0.000438	0.000337	0.000163	0.0000534
	(0.000147)	(0.000164)	(0.000438)	(0.000432)	(0.000169)	(0.000151)
Pre-BV deforestation in receving areas (%)	0.116		0.205		0.098	
Controls	No	Yes	No	Yes	No	Yes
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.004	0.017	0.015	0.144	0.005	0.024

Notes: Dependent variable is deforestation, the total area deforested in a given year as a percentage of 2008 remaining forests. Treatment is a dummy variable that equals one if an area has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. We calculate the average distance of all cells inside a Priority Area to the nearest IBAMA office. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. R^2 of baseline specification in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Estimated Impact of the BV on Deforestation with Leads and Lags

Dependent variable	Deforestation (%)			Log of deforestation		
	All	SUC	Settlements	All	SUC	Settlements
	(1)	(2)	(3)	(4)	(5)	(6)
$BV_{\_t+3}$	0.0924	0.411	0.0173	0.0343	0.126	0.0117
	(0.0799)	(0.328)	(0.0529)	(0.0269)	(0.0814)	(0.0279)
$BV_{\_t+2}$	-0.0209	-0.0299	-0.0181	-0.00367	0.00783	-0.00692
	(0.0309)	(0.0510)	(0.0381)	(0.0134)	(0.0172)	(0.0172)
$BV_{\_t0}$	-0.0954	0.0477	-0.139*	-0.0402**	0.00140	-0.0508**
	(0.0611)	(0.0536)	(0.0777)	(0.0198)	(0.0106)	(0.0257)
$BV_{\_t-1}$	-0.137**	-0.157	-0.147**	-0.0483**	-0.0568	-0.0551*
	(0.0651)	(0.145)	(0.0728)	(0.0243)	(0.0458)	(0.0289)
$BV_{\_t-2}$	-0.114	-0.0831	-0.134	-0.0278	-0.0252	-0.0282
	(0.0719)	(0.0709)	(0.0894)	(0.0278)	(0.0268)	(0.0350)
$BV_{\_t-3}$	-0.140*	-0.0209	-0.198*	-0.0599*	-0.0162	-0.0868*
	(0.0801)	(0.0438)	(0.104)	(0.0341)	(0.0270)	(0.0442)
$BV_{\_t-4}$	-0.0824	-0.127*	-0.106	-0.0204	-0.0598	-0.0199
	(0.0864)	(0.0668)	(0.107)	(0.0377)	(0.0378)	(0.0471)
F Test: all leads jointly 0	0.70(0.497)	1.34(0.268)	0.13(0.874)	0.91(0.405)	1.24(0.296)	0.17(0.842)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	602	2,359	2,961	602	2,359
R^2	0.018	0.177	0.024	0.023	0.242	0.030

Notes: Deforestation is the total area deforested in a given year as a percentage of 2008 remaining forests. Treatment is a dummy variable that equals one if an area eventually has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects, as well as leads and lags of participation in the BV. The period prior to the BV enrollment is the omitted category. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Impact of BV Beneficiaries on Deforestation using a Matched Sample

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.0277**	-0.0262**	-0.0246	-0.0325*	-0.0295**	-0.0262*
	(0.0116)	(0.0114)	(0.0172)	(0.0181)	(0.0145)	(0.0135)
Covariate controls	No	Yes	No	Yes	No	Yes
Effect size (ha) per recipient	15.555	14.712	43.987	58.114	7.061	6.271
Observations	2,849	2,849	532	532	2,317	2,317
R^2	0.006	0.013	0.017	0.057	0.007	0.027

Notes: The sample result from a coarsened exact matching procedure based on pre-2011 data. The dependent variable is deforestation, the total area deforested as a percentage of 2008 remaining forest. The treatment is the inverse hyperbolic sine transformation of the total number of BV recipients in a given area. All specifications include Priority Area and year fixed effects. Baseline model is a fixed effects specification without controls. Covariate controls include clouds, lagged remaining forests and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: Estimated Impact of the BV Intensity on Log of Deforestation

Dependent variable	Log of deforetation					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	-0.0120***	-0.0104**	-0.0138**	-0.0129**	-0.0115**	-0.0112**
	(0.00448)	(0.00431)	(0.00638)	(0.00527)	(0.00550)	(0.00527)
Covariate controls	No	Yes	No	Yes	No	Yes
Pre-BV mean deforestation in receiving areas (%)	0.116		0.205		0.098	
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.008	0.022	0.025	0.226	0.008	0.029

Notes: Dependent variable is the log of deforestation, the percentage of 2008 remaining forests deforested in a given year. The treatment is the inverse hyperbolic sine transformation of the total number of BV recipients in a given area. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: Estimated Impact of BV on Log of Deforestation by Distance to IBAMA Offices

Dependent variable	Log of deforestation					
	All		SUC		Settlements	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0564**	-0.0395	-0.0787*	-0.0535	-0.0554*	-0.0500
	(0.0266)	(0.0263)	(0.0453)	(0.0381)	(0.0321)	(0.0316)
Treatment X Distance to IBAMA	0.0000523	-0.0000123	0.000102	0.0000674	0.0000656	0.0000266
	-0.0000633	-0.0000709	(0.000116)	(0.000122)	(0.0000837)	(0.0000842)
		(0.0305)		(0.126)		(0.0310)
Pre-BV deforestation in receving areas (%)	0.116		0.205		0.098	
Controls	No	Yes	No	Yes	No	Yes
Observations	2,961	2,961	602	602	2,359	2,359
R^2	0.007	0.021	0.020	0.217	0.008	0.028

Notes: Dependent variable is deforestation, the total area deforested in a given year as a percentage of 2008 remaining forests. Treatment is a dummy variable that equals one if an area has BV-receiving households and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. We calculate the average distance of all cells inside a Priority Area to the nearest IBAMA office. Covariate controls include clouds, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. R^2 of baseline specification in brackets.
*** p<0.01, ** p<0.05, * p<0.1.

Table A8: Heterogeneous Impacts by the Variance of Pre-Program Deforestation

Dependent variable	Deforetation (%)					
	All		SUC		Settlements	
Variance of Pre-BV deforestation	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect (Bolsa Verde participation)	-0.238**	-0.000268	-0.180*	0.00393	-0.252*	-0.000965
	(0.110)	(0.00292)	(0.105)	(0.00508)	(0.142)	(0.00359)
Baseline treatment effect	-0.110*		-0.0734		-0.136*	
	(0.0582)		(0.0446)		(0.0701)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,468	1,467	448	147	1,020	1,320
R^2	0.041	0.007	0.040	0.067	0.058	0.005

Notes: The dependent variable is deforestation, the total area deforested in a given year as a percentage of 2008 remaining forest. All specifications include Priority Area fixed effects and year fixed effects. Controls include cloud cover ((km^2), lagged remaining forests, and interaction terms between lagged remaining forests and nearest distances to paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. We adopt the approach described in List et al. (2017) to assign Priority Areas to the binary category "High" if the variance of pre-BV (2009-2011) deforestation is above the median and "Low" if it is below. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Descriptive Statistics of Geocoded Sample in Settlements

	Receiving				Non-Receiving			
	2012	2013	2014	20015	2012	2013	2014	20015
Average income per head	37.960	40.193	47.037	61.334	45.714	54.065	66.085	85.386
	(13.246)	(13.938)	(15.970)	(18.412)	(24.663)	(31.817)	(33.477)	(43.711)
Number of geocoded households in Social Registry	174.782	186.553	190.371	190.721	48.265	49.559	49.559	47.412
	(308.132)	(325.488)	(341.190)	(340.519)	(48.042)	(48.421)	(48.545)	(46.519)
25 percentile of income per head	19.759	18.467	18.322	19.249	19.926	17.382	21.426	31.162
	(13.128)	(12.405)	(11.886)	(12.226)	(18.574)	(13.345)	(16.253)	(41.69)
Share of households receiving Bolsa Verde	0.660	0.647	0.641	0.643	-	-	-	-
	(0.217)	(0.215)	(0.214)	(0.215)	-	-	-	-
Share of households under Bolsa Verde thresehold	0.779	0.863	0.869	0.818	0.777	0.807	0.757	0.666
	(0.163)	(0.120)	(0.087)	(0.095)	(0.206)	(0.171)	(0.170)	(0.212)
% of remaining forests deforested	1.110	0.069	0.129	0.070	2.160	1.840	1.781	1.248
	(7.527)	(0.332)	(0.611)	(0.434)	(6.375)	(2.863)	(2.470)	(2.352)
Observations (number of priority areas)	197				34			

Notes: The table reports averages per year per type of Priority Area. Standard deviations are in parentheses.

Table A10: Fines and BV Participation

	All		SUC		Settlements	
Dependent variable: All Infractions	y	log(y)	y	log(y)	y	log(y)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	0.258	0.332**	0.551	0.422**	0.215*	0.153
	(0.161)	(0.155)	(0.554)	(0.195)	(0.127)	(0.240)
Deforestation (%)	0.203*	0.0439	-1.337***	0.0513	0.300***	0.0479
	(0.120)	(0.0295)	(0.390)	(0.0809)	(0.0960)	(0.0353)
Pre-BV mean y	0.555 [2.059]		2.524 [4.151]		0.152 [0.808]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	496	602	289	2,359	207
R^2	0.300	0.132	0.348	0.132	0.245	0.310

Notes: The dependent variable is total number of fines or log of fines (conditional on some fines). The treatment is a dummy variable that equals one if an area has BV-receiving households, and zero otherwise. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include cloud cover, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. Standard deviation of the number of fines are in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A11: Fines and BV Intensity

	All		SUC		Settlements	
Dependent variable: All Infractions	y	log(y)	y	log(y)	y	log(y)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	0.0525*	0.0503*	0.119	0.0663*	0.0361	0.0202
	(0.0309)	(0.0296)	(0.124)	(0.0386)	(0.0238)	(0.0474)
Deforestation (%)	0.203*	0.0419	-1.315***	0.0552	0.299***	0.0466
	(0.120)	(0.0296)	(0.393)	(0.0846)	(0.0959)	(0.0354)
Pre-BV mean y	0.555 [2.059]		2.524 [4.151]		0.152 [0.808]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	496	602	289	2,359	207
R^2	0.300	0.128	0.348	0.126	0.245	0.309

Notes: The dependent variable is total number of fines or log of fines (conditional on some fines). The treatment is log of number BV beneficiaries. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include cloud cover, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. Standard deviation of the number of fines are in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A12: Impact of the Number of BV Beneficiaries on Fines

	All		SUC		Settlements	
	y	log(y)	y	log(y)	y	log(y)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: $y = I^{df}$						
Treatment effect	0.0209	0.0274	-0.0384	0.0361	0.0335	-0.00737
	(0.0262)	(0.0370)	(0.0977)	(0.0510)	(0.0242)	(0.0477)
Deforestation (%)	0.216*	0.0484	-1.238***	-0.0168	0.294***	0.0473
	(0.115)	(0.0319)	(0.300)	(0.0702)	(0.0934)	(0.0404)
Pre-BV mean y	0.299 [1.251]		1.181 [2.413]		0.119 [0.715]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	368	602	184	2,359	184
R^2	0.320	0.148	0.412	0.122	0.236	0.360
Panel B: $y = I^{o}$						
Treatment effect	0.0316**	0.0877**	0.157**	0.0978***	0.00254	0.0731
	(0.0160)	(0.0352)	(0.0737)	(0.0357)	(0.00484)	(0.0480)
Deforestation (%)	-0.0121	-0.0710	-0.0771	-0.0120	0.00530	0.135*
	(0.0182)	(0.0496)	(0.212)	(0.0369)	(0.00560)	(0.0715)
Pre-BV mean y	0.256 [1.367]		1.343 [3.057]		0.033 [0.252]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,961	278	602	224	2,359	54
R^2	0.076	0.159	0.101	0.188	0.087	0.736

Notes: In Panel A, the dependent variable is total number (or log) of deforestation-related fines (conditional on some fines). In Panel B, the dependent variable is total number (or log) of non-deforestation-related fines (conditional on some fines). The treatment is log of number of beneficiaries. All specifications include Priority Area fixed effects and year fixed effects. Covariate controls include cloud cover, lagged remaining forests, and interaction terms between lagged remaining forests and distances to the nearest paved roads and cities. Robust standard errors clustered at the Priority Area level in parentheses. Standard deviation of the number of fines are in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

BOLSA VERDE

TERMO DE ADESÃO - PROGRAMA BOLSA VERDE
Dados do(a) Beneficiário(a)

Nome:____

CPF:____________________ Nº NIS:____________________

Unidade de Conservação/Assentamento:____________________

Compromissos com a Conservação Ambiental e Uso Sustentável dos Recursos Naturais

a - As atividades de conservação a serem desenvolvidas deverão atender ao previsto nos instrumentos de gestão das Unidades de Conservação (Plano de Utilização ou Uso e/ou Planos de Manejo) ou dos Projetos de Assentamentos (Planos de Utilização ou Planos de Desenvolvimento dos Assentamentos), conforme o caso;

b - Na inexistência dos instrumentos acima referidos, as atividades de conservação a serem desenvolvidas serão regidas pelos Contrato de Concessão de Direito Real de Uso – CCDRU ou Contrato de Concessão de Uso – CCU.

c - Além dos instrumentos acima referidos a família deve, sempre que cabível, se integrar a outros planos ou acordos, que façam referência à conservação e uso sustentável dos recursos naturais, quando estabelecidos na unidade a qual a família se vincula, a exemplo dos acordos de pesca, caça ou de queima controlada.

Informações Gerais

Dos objetivos do Bolsa Verde:

a - Incentivar a conservação dos ecossistemas, entendida como sua manutenção e uso sustentável; e

b - Promover a cidadania, a melhoria das condições de vida e a elevação da renda da população em situação de extrema pobreza que exerça atividades de conservação dos recursos naturais no meio rural;

c - Incentivar a participação de seus beneficiários em ações de capacitação ambiental, social, educacional, técnica e profissional.

Do funcionamento do Bolsa Verde:

a - A transferência de recursos financeiros do Programa de Apoio à Conservação Ambiental será realizada a famílias em situação de extrema pobreza, inscritas no Cadastro Único para Programas Sociais do Governo Federal e que exerçam atividades de conservação;

b - Serão realizados repasses trimestrais no valor de R$ 300,00 (trezentos reais);

c - A Caixa Econômica Federal exercerá a função de Agente Operador do Programa de Apoio à Conservação Ambiental, realizando os repasses trimestrais;

d - O recebimento destes recursos tem caráter temporário e não gera direito adquirido, sendo que a transferência destes recursos será realizada por um prazo de até dois anos, podendo ser prorrogada;

e - A transferência de recursos de que trata este Termo de Adesão cessará se a família beneficiária: 1. Não cumprir as condições estabelecidas neste Termo de Adesão; 2. Estiver ou for habilitada em outros programas ou ações federais de incentivo à conservação ambiental.condições estabelecidas neste Termo de Adesão; 2. Estiver ou for habilitada em outro programa federal de incentivo à conservação ambiental.

É compromisso e responsabilidade desta família zelar pelo cumprimento de todas as regras estabelecidas por este Termo de Adesão, bem como na Lei nº 12.521, de 14 de outubro de 2011 e em seu regulamento.

Declaro que li e concordo com as condições do Termo de Adesão.

__________, ___/_______ de ____ ____________________

Local Data Assinatura do(a) Beneficiário(a)

Ministério do Planejamento, Orçamento e Gestão | Ministério do Desenvolvimento Agrário | Ministério do Desenvolvimento Social e Combate à Fome | Ministério do Meio Ambiente | GOVERNO FEDERAL BRASIL PAÍS RICO É PAÍS SEM POBREZA

Figure A1: Terms of Adhesion Signed by Bolsa Verde Beneficiaries

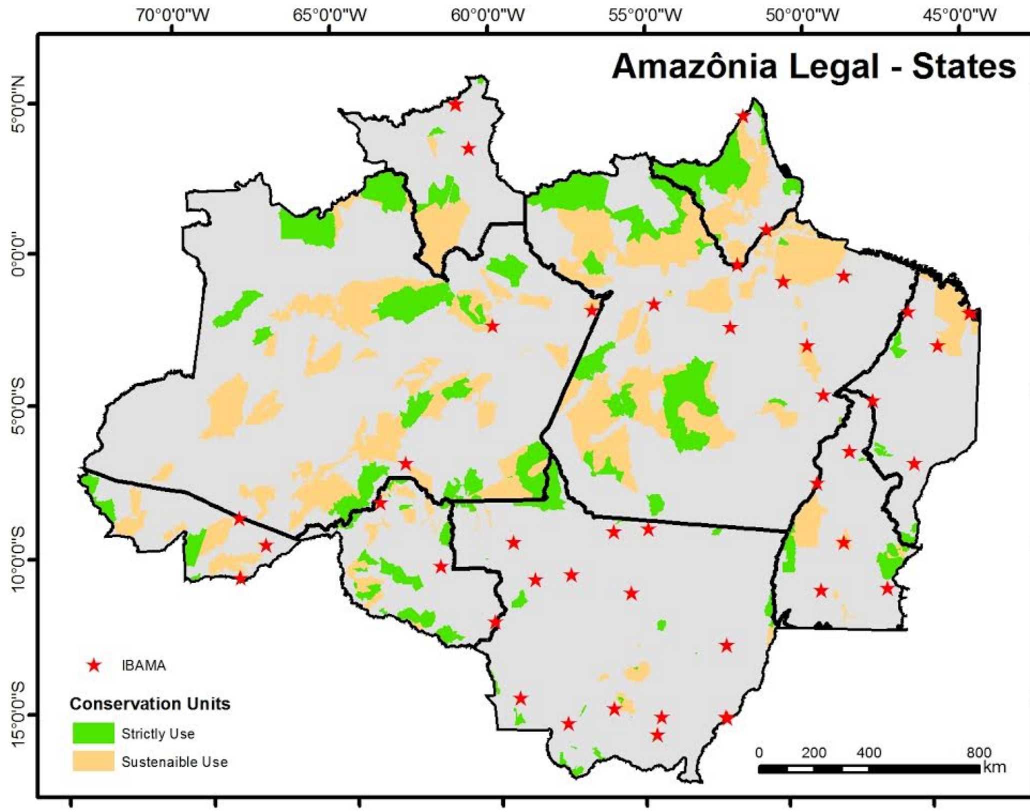

Figure A2: Location of IBAMA offices in the Legal Amazon

Notes: The figure plots the locations of IBAMA offices in the Legal Amazon.

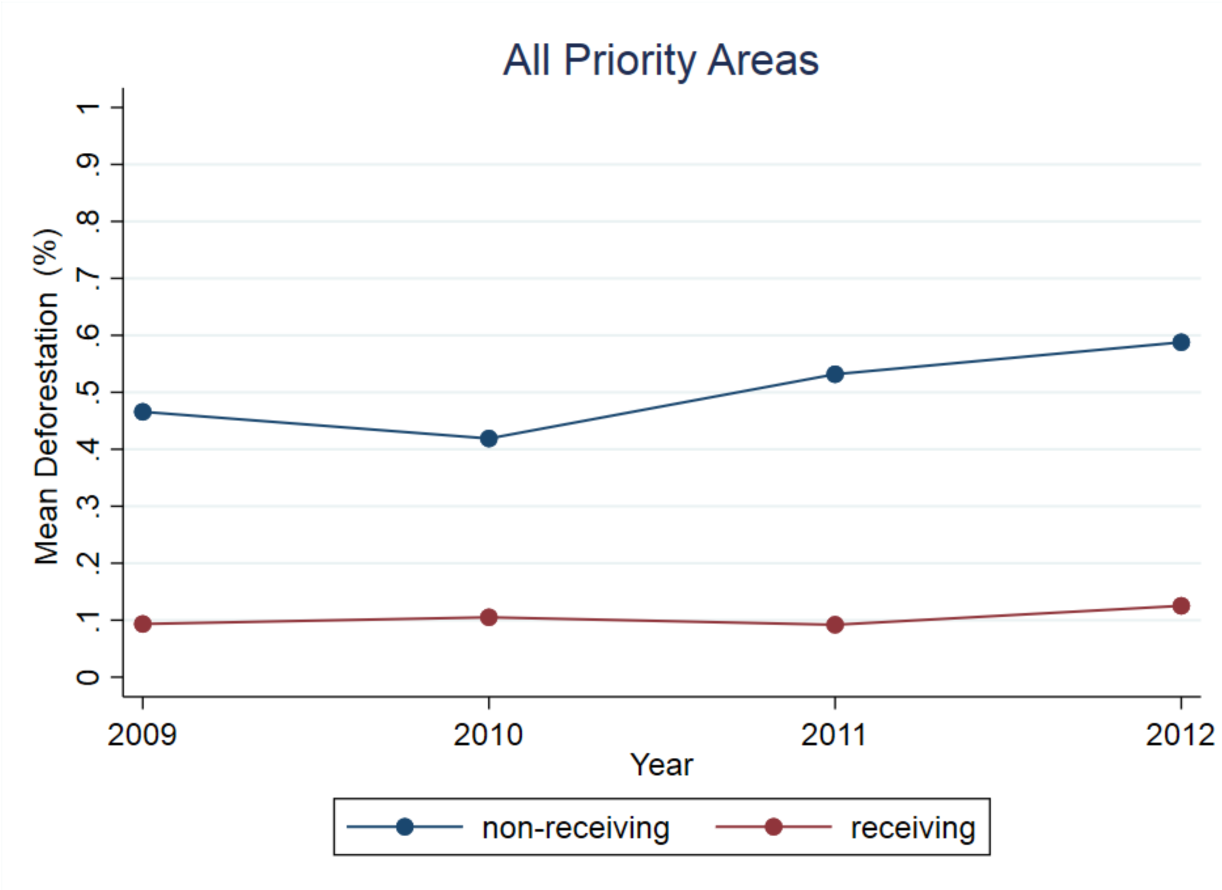

Figure A3: Mean Deforestation by BV Status, 2009 - 2012

Notes: The figure plots the average deforestation, expressed as the percentage of 2008 remaining forests deforested in a given year, in BV-receiving and non-receiving Priority Areas from 2009 to 2012. Non-receiving areas always have higher deforestation on average, than the receiving areas. The trends over time are parallel.

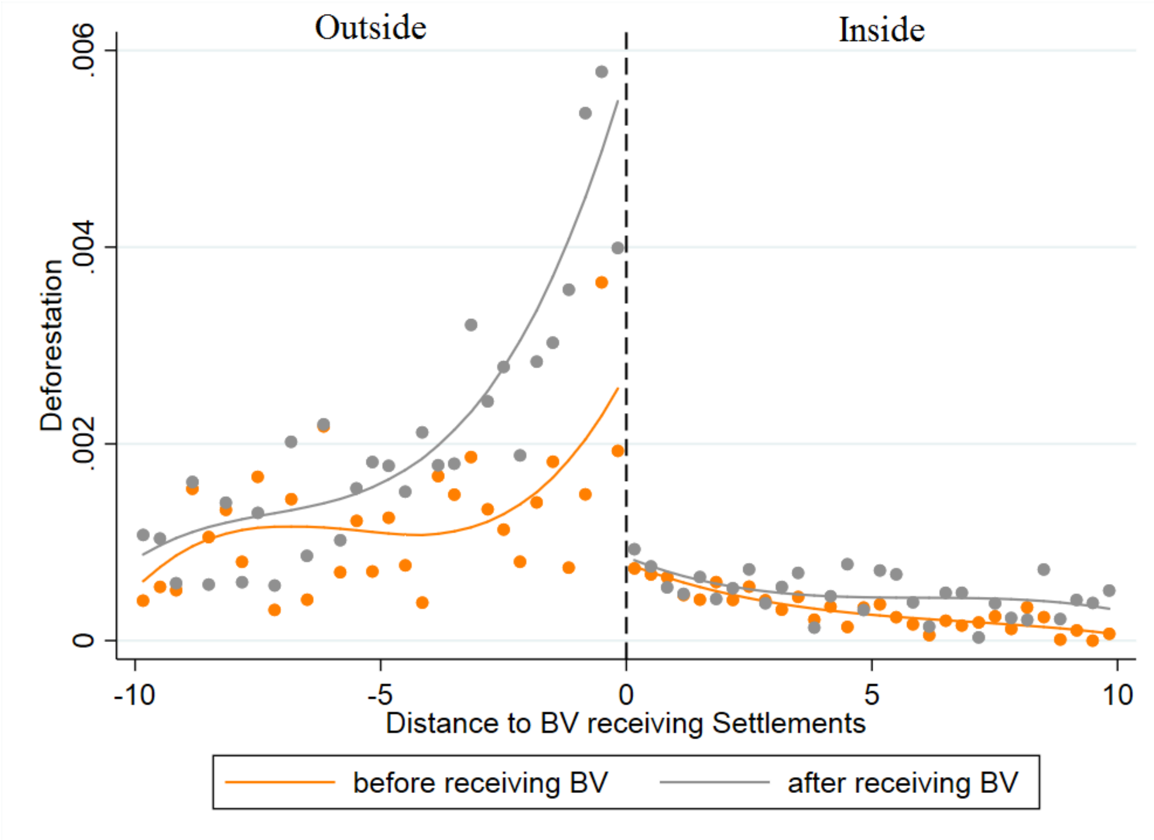

Figure A4: Deforestation Inside and Outside BV-Receiving Settlements

Notes: The figure plots local averages of deforestation in a given grid cell using data from 2009 to 2015. The x-axis shows the distance (in km) of grid cells to the borders of Settlements that eventually receive BV. The orange line is a second degree polynomial fit for averages over periods before the Settlements receive BV; the grey line is the equivalent over periods after the Settlements have started receiving BV payments. The necessary assumption for RD to be valid, the continuity assumption across the running variable (in this case, distance), is clearly violated. Before the Settlements receive BV, we observe a sharp reduction in the level of deforestation at the border. Therefore, we cannot attribute the similar reduction at the border after the realization of BV payments to the program.

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