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Can Environmental Cash Transfers Reduce Deforestation and Improve Social Outcomes?

A Regression Discontinuity Analysis of Mexico's National Program (2011–2014)

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Abstract

Environmental conditional cash transfers, or "payments for ecosystem services" are a centerpiece of global efforts to protect biodiversity, safeguard watersheds, and mitigate climate change by reducing forest loss. This paper evaluates the impacts of Mexico's national payments for ecosystem services program, which provides five years of payments to landowners in exchange for maintaining and managing natural land cover. Using a regression discontinuity design, the paper studies impacts on environmental, socioeconomic, and social capital outcomes for the 2011–14 program cohorts. The analysis finds that treated communities increased management activities to protect land cover, such as patrolling for illegal conversion or combatting soil erosion (by 48 percent compared to controls). The program reduced the loss of tree cover in areas at high risk of deforestation (by 29 percent compared to controls), with effects being larger for those that have been in the program the longest (38 percent compared to controls). These results are similar to estimates of impact for earlier program cohorts and continue to highlight the importance of targeting the program to areas of high risk of land cover loss to increase environmental effectiveness. The program continued to reach poor communities and households, but estimated impacts on household wealth indicators are small in magnitude and not statistically significant. These results indicate that community-level conditional payments did not harm household-level socioeconomic indicators, a key safeguard requirement of conservation policies of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation. The data also show that payments for ecosystem services significantly increased community social capital—the institutions, attitudes, and values that govern human interactions—(by 9 percent compared to controls), and these externally provided incentives did not crowd out household contributions to other community work.

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1. INTRODUCTION

Deforestation is one of the leading sources of carbon emissions (Le Queré et al., 2015) as well as a major contributor to losses of biodiversity, watershed functioning and soil erosion. Environmental cash transfers, known as payments for ecosystem services (PES), are central to global efforts to reduce deforestation rates and improve environmental outcomes (e.g. Börner et al., 2017; Alix-Garcia et al., 2015). The UN Reducing Emissions from Deforestation and Forest Degradation (REDD+) is structured to financially reward developing countries that slow deforestation rates. Large-scale PES programs have been in place for at least five years in countries including Mexico, Costa Rica, the United States, China, Peru, Brazil, Vietnam and Ecuador.

PES programs support owners of environmentally valuable land by providing payments conditional on conserving land cover. The theory of change relies on the idea that landholders do not conserve forests or other vegetative cover because doing so is less profitable than converting the land to alternative uses, such as agriculture (e.g. Ferraro and Simpson, 2002; Alix-Garcia, de Janvry and Sadoulet, 2008; Alix-Garcia, Sims and Yanez-Pagans, 2015; Pagiola et al., 2015). Paying for conservation increases the profitability of maintaining forested land and thus may induce landholders at the margin to conserve. The popularity of PES stems partly from its voluntary nature, which contrasts with more traditional conservation mechanisms such as protected areas or laws prohibiting land conversion.

However, because PES is voluntary, it may attract applications by landowners who already would have conserved, limiting the additional environmental benefits it provides. PES programs also remain controversial within the global conservation community (e.g. Redford and Adams, 2009; Muradian et al., 2013; Schröter et al., 2014) because of concerns that they could make landowners worse off or could disrupt existing social structures. Although landowners accept PES voluntarily, these programs could still reduce welfare if participants do not fully understand risk-reward tradeoffs or underestimate program participation costs. In addition, while incentives to perform land management activities could support community collaboration, they might also undermine social capital by reducing intrinsic motivation for land conservation, disrupting norms of fairness within the community, or crowding-out contributions to other pro-social activities (Bowles et al., 2008; Schröter et al., 2014; Bruner and Reid, 2015).

This study contributes to these key empirical questions about the environmental and social impacts of PES by evaluating the 2011-2014 cohorts of Mexico's federal payments for environmental services program. Mexico's program provides an important global case to study because of its size, longevity, and efforts to improve program targeting. Specifically, we investigate program impacts on land-cover management and forest-cover change, household socioeconomic indicators including wealth, and community and household indicators of social capital. We estimate program impacts using a regression discontinuity (RD) design that compares accepted and rejected program applicants close to state- and year-specific cutoffs determined by the scoring system that prioritizes applicants.

Impacts on forest management, socioeconomic outcomes and social capital are based on survey data from 2016 for a representative sample of more than 800 community leaders and 8,000 households across 12 states. Impacts on forest cover change are derived from satellite-based forest cover loss data (Hansen et al. 2013; v 1.2) from 2011-2014 for all program applicants within 25 points of scoring

cutoffs (which represents 97% of applicants)[1]. For all analyses, we study "medium-term" and "short term" effects by using data on program recipients that began the five-year program in 2011-2012 (3-4 years in the program) and 2013-2014 (1-2 years in the program), respectively.

With respect to environmental impacts, we found that the program increased management activities by participant communities to protect land cover--such as patrolling for illegal conversion, building fire breaks, or combatting soil erosion. Compared to controls, we found a substantial and statistically significant increase in an index of community land cover management activities of 48% (or 0.60 standard deviation). We also found a statistically significant increase of approximately 2.7 days per year per household devoted to land management activities. This substantial increase in land-cover management activities suggests that the program is achieving its primary goal of behavior change to support ecosystem service provision.

Mexico's program has sought to overcome the inherent adverse selection problem common to PES by targeting payments to certain eligible areas of the country, prioritizing land with higher risk of deforestation, and introducing differentiated payments depending on risk level and ecosystem type. Our analysis of avoided forest cover change found suggestive evidence that the program as a whole reduced the rate of loss of tree cover, with point estimates indicating a 30-34% reduction for the early cohorts and a 20-24% reduction overall, but not being statistically significant. Due to data limitations[2] and the overall low rates of forest cover change during this time period, the minimum detectable effect sizes for the full sample were of roughly the same order of magnitude as the rate of forest loss among controls, making it difficult to detect anything less than a 70% impact of the program, which is higher than prior estimates of PES impacts in the literature, and is unlikely to occur because of remaining natural forest losses due to events such as fires or hurricane damage. However, we did find that within areas at high risk of deforestation, the program statistically significantly reduced the loss of tree cover, by approximately 30 percent, with larger effects for those who have been in the program longer (38 percent). Although imprecise, this study's estimates of the percentage change in loss rates due to PES are similar in magnitude to studies of the 2003-2010 cohorts, which found changes in the rate of expected forest loss of 20-50 percent (Alix-Garcia, Shapiro and Sims 2012, Alix-Garcia, Sims and Yanez-Pagans 2015, Sims and Alix-Garcia 2017). Unfortunately, given the limitations of the satellite data, we cannot draw conclusions about whether or not changes in targeting or more differentiated payments have increased the environmental impacts of the program compared to earlier cohorts.

With respect to socioeconomic outcomes, summary statistics show that the program continues to reach many marginalized and remote communities and is frequently used to support daily wages and community investments (see Appendix Figure A1). Analysis of the communal and household level impacts suggests the program has maintained socioeconomic indicators for program participants to be on par with non-participants. Estimated impacts were small and not statistically significant for indicators of average household assets, housing stock, food consumption and primary education. These results contrast somewhat with evidence from prior cohorts, which indicated small positive impacts of PES on household wealth (Alix-Garcia et al., 2015; Sims et al., 2017) and small positive effects on some educational opportunities and household and community-level assets for poor participant households compared to poor non-participant applicants (Alix-Garcia et al., 2015). In this

[1] Applicants with scores within 25 points of the scoring cutoffs represent 97% of the possible applicants. However, for the environmental analysis, we further restrict this group to only include individual polygons with more than 50% forest cover in 2000. We will discuss this further below in the section on the environmental analysis.

[2] The study was designed to use higher resolution land cover change data being prepared under the new MAD-MEX MRV system. Unfortunately, post-processing of that data was not completed in time to use.

case, the results are not as positive, but still provide additional evidence that community-level conditional payments did not harm household-level socioeconomic indicators, a key safeguard requirement of REDD+ conservation policies.

With respect to social capital, we found that the program supported community social capital, defined as the institutions, attitudes and values governing human interactions (Grootaert and van Bastelaer, 2002). Across all cohorts, we found a significant increase of 9% in an index of community social capital relative to controls (a magnitude of 0.41 standard deviation). Additional time spent in land management activities did not crowd out other community work devoted by households and the program did not change household-level measures of trust and participation These results indicate that the program helped to support pro-social institutions and attitudes that are likely to be crucial both for the functioning of environmental incentive programs and broader economic development.

Study Contributions to the Literature

The study makes several important contributions to the existing PES literature. First, to the best of our knowledge, this is the first study to use RD design to identify the impacts of a large-scale PES program. Although the past 10 years have seen a rapid increase in evidence about PES, all studies of large-scale programs to date have relied on matching or difference-in difference designs (Borner et al. 2017). The RD design helps to alleviate a key concern in empirically assessing the impact of PES, which is the challenge of constructing a reasonable counterfactual case on which to base estimates. The core selection issue is that landowners who choose to enroll in PES are likely to be different with respect to key characteristics such as land quality, landowner skill, or conservation preferences. In particular, landowners with the lowest risk of land cover change—those who would generate the least environmental additionality—might also have low opportunity costs of foregone production and thus be more likely to select into PES. Quasi-experimental evaluations of PES have sought to account for these selection bias concerns by controlling for landowner characteristics likely to predict enrollment and outcomes, or by using only other rejected applicants as controls. Still, these evaluations rely on estimations from differences or differences in differences, and assume that observable controls can proxy well for potential unobservable differences between participants and non-participants. In contrast, RD design relies on the less restrictive assumption that potential outcomes are continuous around the program scoring cut-offs, and thus may provide a stronger identification strategy (Wooldridge and Imbens, 2009).

Second, this study contributes new evidence to the body of work assessing the environmental effectiveness of PES. Evaluations of Mexico's PES provide evidence about a large-scale, national program that continues to serve as a key model for other global REDD+ policies. Prior studies on other national PES programs have generally also found positive but modest impacts on land cover or avoided deforestation (e.g. Costa Rica: Arriagada et al., 2012; Robalino and Pfaff, 2013; Robalino et al., 2015; Ecuador: Jones et al., 2017; Brazil: Simonet et al., 2018). A recent study by Jayachandran et al. (2017) examined a small-scale, short-term PES pilot in a high deforestation context using a well-identified strategy of random assignment to treatment, and confirmed the ability of PES to reduce deforestation. The study also illustrated that the carbon benefits of PES could outweigh costs in a setting with high risk of deforestation and valuable carbon sinks.

In addition, further evidence pertaining to the avoided deforestation impacts of Mexico's PES is worth gathering because the program has evolved considerably since its start, changing targeting priorities and introducing differentiated payments. Differentiated payments have been proposed since the early

days of the program (e.g. Alix-Garcia, de Janvry and Sadoulet, 2008) in order to reflect differences in environmental benefits due to land-use type and risk, and to reflect differences in landowner opportunity cost. They have been used by the U.S. Conservation Reserve Program (Classen et al., 2008) and could potentially be adopted by many REDD+ countries. The previous evaluation of the Mexico PES program examined cohorts from 2004-2010 (Alix-Garcia et al., 2015; Sims and Alix-Garcia, 2017), in which payments were not strongly differentiated.[3]

Growing evidence from global settings also suggests that PES complies with the spirit of REDD safeguards designed to protect local well-being, but this is far from well-established (Uchida et al. 2007, 2009; Robalino et al., 2014; Alix-Garcia and Wolff, 2014; Alix-Garcia et al. 2015, Arriagada et al., 2015, Jayachandran et al., 2017, Sims and Alix-Garcia 2017). Moreover, measuring the potential impacts of Mexico's program on socio-economic outcomes is relevant in the context of a likely reduction in the amount received by the average household compared to previous cohorts of the program. Since 2013, the new system of differentiated payments required recipients to directly reinvest almost half of program payments in forest management activities. Considering this re-direction of funds, the erosion of the real value of the payments over time, and potential adverse dynamics that this community-level intervention may have on welfare indicators for the most vulnerable households, we investigate whether effects on socio-economic outcomes found in previous cohorts persist for the 2010-2014 cohort.

Finally, our study makes a novel contribution to the literature on social capital, as it provided the first empirical test of the impacts of a large-scale PES program (results published in Alix-Garcia et al. 2018). Social capital is an important driver of development generally (Keefer and Knack, 2008; Mansuri and Rao, 2012) and contributes to the functioning of many environmental initiatives (Segerson, 2013; Kaczan et al al., 2017; Andersson et al., 2018). Mexico is an important setting to study social capital, as most of the area enrolled in the program is held as common property by *ejidos* or *comunidades*[4], so land-use decisions must be made jointly. This situation is, however, not unique to Mexico: a recent report (Rights and Resources Initiative, 2015) found that at least 18% of the world's land area is held communally or by indigenous groups, with the true number likely being much higher when accounting for informal rights.

In what follows, we explain the features of Mexico's PES program and its selection process (Section 2). We then describe the study's data (Section 3) and the evaluation design to identify the impact of the intervention (Section 4). Section 5 presents results on environmental and social outcomes; section 6 discusses study implications for policy and future research.

2. MEXICO'S ENVIRONMENTAL CONDITIONAL CASH TRANSFER PROGRAM

Between 1990 and 2010, Mexico lost 5.5 million hectares or 7.8% of its forest cover (FAO, 2010). Deforestation in Mexico is largely driven by the conversion of forested land to alternative land uses that are more profitable to landholders, such as agriculture or pasture. Although deforestation rates have declined in recent years, degradation rates remain high. Over half of Mexico's forest is classified

[3] In addition, to further explore how best to calibrate the payment scheme, the survey included a randomly-introduced referendum-style question. Analysis of those results is reported in a separate manuscript (Alix-Garcia, Phaneuf and Sims 2018). The results indicate that most participants would be willing to accept lower payments than they are currently receiving and still participate.

[4] Formally recognized units of local governance that make decisions about common-property land by assembly of members and an elected council.

as primary forest – the most biodiverse and carbon-dense form of forest – thus raising the ecological cost of deforestation far beyond the already important forest functions of carbon sequestration, erosion control, and hydrological regulation. Substantial conversion from natural lands to those with intense human use has also occurred in areas of Mexico that are ecologically critical but are not classified by the FAO as forest, such as arid zones.

To respond to deforestation and degradation,[5] as well as biodiversity losses, Mexico's National Forestry Commission (CONAFOR, for its acronym in Spanish) has implemented a national payments for environmental services program that began in 2003 and continues to the present time. The main federal program provides financial incentives to landowners with the goal of reducing loss of existing land-cover in areas important for watershed protection and biodiversity conservation. The program offers five-year contracts to either individual or common-property landowners and finances the cost of hiring technical advisors to assist in developing a management plan. The main PES program is financed by the federal government (using revenues from sources including an urban water tax) and special programs (not included in this analysis) also include co-financing by direct beneficiaries of the ecosystem services. Participants who comply with their contracts receive annual payments for each of the five years of the contract.

Enrollment in the program is dominated by land that is in collective tenure (called *ejidos* and *comunidades indigenas*), although individual households may also participate. Collective tenure existed in Mexico prior to the colonial era (Knight 1986). However, the current system was created during the 1917 Agrarian Reform, and continues to have an important presence on the landscape today – over half of the land in rural Mexico falls within this classification (de Janvry et al. 1997, Fox 2007). During the period that we analyze, 62% of recipients and 90% of area enrolled was from common properties. For this reason, we focused our household and community data collection efforts on ejidos and comunidades, although we do include private properties in the environmental analysis.

Annual payments are conditional on maintaining existing land-cover and having completed voluntary forest or biodiversity conservation management activities, which CONAFOR verifies through satellite imagery and/or field visits. In principle, a loss of forest cover or a change in land use results in either a contract cancellation (if changes were intentional) or a decrease in payments proportional to the reduction in area (if changes were due to natural causes).[6] Recipients must complete activities according to their submitted forest or land management plan and annual program rules.

Targeting and Payment Scheme, Program History

Mexico's PES program has national presence. As shown in **Figure 1**, the states with the largest numbers of program recipients across the program's history are Chiapas, Oaxaca, Veracruz, and Yucatán, each having over 400 recipients. Oaxaca dominates the area enrolled in the program over time (**Figure 2**), with over 1.3 million hectares. This is due to a combination of having high numbers of recipients and large areas of eligible forest – acceptance rates in Oaxaca are not significantly higher than those in neighboring states.

[5] The land is said to have experienced deforestation when other land uses replace forest, such as agriculture, mining, or urban development. Degradation often precedes deforestation. Degradation is a gradual process through which a forest's biomass declines, its species composition changes or its soil quality declines.

[6] Quantitative information on the number of contracts cancelled on a yearly basis is not available. Conversations with CONAFOR officials suggest that reduction and cancellation of payments occurs in only a small (but positive) number of cases.

Targeting criteria and payment levels for the program have changed over time. Over the course of the program, targeting has encompassed an increasingly complex set of criteria (see **Appendix Table A1)**. Targeting of the program to states or zones within states that experience the most deforestation has been the most common way to try to counter the potential adverse selection created by voluntary application. CONAFOR uses a combined system of eligible zones and point scores to determine priority among applicants. Past work (Sims et al., 2014) illustrates the improvement in targeting from 2003-2010 in order to reach both environmental and social objectives, as measured by the characteristics of applicants and enrolled lands in Mexico's program.

In addition, CONAFOR has used differentiated payments by type of ecosystem and deforestation risk. From 2003 to 2010, payments were differentiated only for a limited number of forest types, with a small premium for cloud forest. Initial payment amounts were based on estimates of the opportunity cost of cultivating maize. Since 2010, CONAFOR has introduced substantial payment differentiation: there are now six levels of payments determined by the type of ecosystem and deforestation risk. Thus, prices now incorporate aspects of both the potential value of the services and the opportunity costs of production. **Table 1** shows changes in the payment scheme over time for the two largest payment modalities – hydrological services and biodiversity conservation. Currently, the average payments are 525 Mexican pesos (MXN) per hectare per year (approximately 30 USD in 2016 exchange rates), while payments per hectare now range from 280 to 1,100 MXN (CONAFOR, 2010-2014) (approximately 16-80 USD depending on the exchange rate for the year). Rising incomes in Mexico and the depreciation of the peso mean that the real value of the payments has eroded by approximately 15-20% compared to earlier program cohorts.

Despite substantial heterogeneity in the amount of payments compared to the number of landowners--depending on how many people benefit from a given payment stream and how large the submitted parcel is--the total amount of the payments tends to be important in relation to income. Within the study sample, PES payments, if they were distributed to full-rights households, would represent an average of 6,138 MXN pesos ($350 USD), equivalent to approximately six weeks of the average pay for a day's agricultural labor (140 MXN pesos or US$8). In the 2011-2014 cohorts, program recipients must use a proportion of the funds for land management activities (rising to 40% in 2014). They may then use remaining funds for community purposes or distribute them to individual households. Most communities use the payments to fund supplies needed for land cover management (such as fencing), to improve community infrastructure. Some also distribute funds directly to households (see **Appendix Figure A1**). Thus, it is important to note that only a fraction of payments actually go directly to households within communal properties, and that increasing mandates to use funds specifically for forest management by definition decrease flexibility for recipients in their choices of how to spend the funds.

The program accepts applicants every year; **Figure 2** shows the total area enrolled by state between 2004 and 2015. Many program participants re-apply to the program after the contract ends, as do rejected applicants. While it is impossible to ascertain how many applications are repeated among the private properties, by matching the common property application polygons with RAN's (National Agrarian Registry) ejido database, we are able to approximate how many applications are repeated among the common properties. In particular, we find that between 2004 and 2015, 4,676 unique *ejidos* and *comunidades* applied to the program. Among these, the average number of applications over all years was 2.5, with a maximum of 10 applications. However, the average number of times an applicant ejido benefitted from the program was 0.83. Forty-two percent of applicants never receive benefits from the program. Those who do ever receive benefits do so on average 1.4 times. The state

with the highest average number of application attempts is Durango, followed by Nuevo León, San Luís Potosí, and Aguascalientes (**Figure 3**), where the average number is just above 3, and for most states the average is 2-3.[7] These statistics illustrate that there is more demand for the program than the budget can allow, which is the basis for the regression discontinuity approach.

Selection Process of Applicants

Applicant point scores are assigned by the national office of CONAFOR and used to prioritize the limited funds for the program. Applicants send in information about the property they wish to submit, and about their household or community. This is then combined with information from multiple geographic layers produced by different government agencies that reflect national conservation and social priorities. Because point scores are based on observable characteristics and are clearly defined, they are unlikely to be manipulated or influenced by subjective judgement.[8] After assigning point scores, CONAFOR admits properties into the PES program in the order of their total score until the available state budget for each sub-program has been allocated. This means that the score cutoff determining who receives payments differs by state, year, and program modality and is unlikely to be systematically correlated with characteristics that could influence outcomes. **Appendix Table A1** shows in detail the criteria used to award points for 2011-2014, including both land and applicant characteristics. **Appendix Figure A2** shows the percent contribution of the different elements of CONAFOR's point system across time. In 2015, environmental value contributed approximately 40 percent, social elements 25 percent and deforestation risk 5 percent. Implementation capacity contributed the remaining 30 percent.

3. DATA

This study uses two data sources: interpreted satellite data and survey data. Satellite-based data are used to study program impacts on land-cover change or avoided deforestation. For the land-cover analysis, we compiled data for the entire population of both private and common property applicants to the program in all 32 states between 2011 and 2014. We include applicants from each of these four individual years, but combine them into two groups for purposes of analysis – we suggest that those who applied in 2011 or 2012 represent "medium term" effects, while those more recent applicants (2013-2014) represent "short term" effects. The survey data are used to measure program impacts on land-cover management activities, as well as community-level social capital and household welfare indicators. The survey, which took place in 12 states, focused on common property communities, which currently receive the majority of the program's budget. These states include 60% of the common property applicants to the program between 2011 and 2014, and our sample represents approximately 30% of the total applicants to the program during these years. Communal governance structures own more than 45% of land with forest or vegetative cover in Mexico (Registro Agrario Nacional, 2012) and are crucial to the maintenance of Mexico's forests and biodiversity.

[7] It bears mentioning that in terms of sustainability of conservation, re-enrolling the same properties over time is likely to be the correct approach, since it may guarantee sustained conservation of lands at high risk of conversion.

[8] Approximately two-thirds of the points assigned in each year are based on geographic covariates, such as location within an overexploited aquifer or being a majority indigenous municipality. The remaining points are based on observable applicant characteristics or documented certifications, such as whether the applicant has a property management plan or whether the applicant has a registered agroforestry program.

3.1 LAND-COVER DATA

To analyze land cover change, we used the Hansen et al. global analysis data (2013), version 1.2 (accessed in 2016).[9] The data set provides forest cover in 2000 and loss of forest cover from 2000-2014. The Hansen data are the only available data source with annual variation in land-cover during our period of study. The data set is based on a combination of Landsat (30m resolution) and MODIS (250m resolution) satellite images. We use the reported annual changes from Hansen's data, summing reported deforestation for each polygon after application to the program. This means that for those polygons that enter in 2011, we are summing deforestation from 2011 to 2014, while for those entering in 2012, we sum from 2012 to 2014, etc. To calculate percent changes, we take the total forest cover loss divided by the area of forest in the data set baseline year of 2000. Given that our land cover data are measured across different time periods for each cohort, they are not comparable to the government official rates. Furthermore, they are not easily comparable across cohorts, since for the earliest cohorts we sum deforestation across four years and for the later ones only across two.

The Hansen et al. data set has important limitations. It was intended for global/regional change analysis, not change analysis at the small parcel-level, as is necessary to evaluate the PES program. It has been shown that the accuracy of the classification algorithm varies across different countries and ecosystem types (Hansen et al., 2014; Bellot et al., 2014; Burivalova et al., 2015). For example, assessments by the CONAFOR remote sensing team suggest that the Hansen product offers better results in Mexico when the percentages of forest cover are below 30 or above 60 percent. The data are likely to understate loss of natural forest because they may classify plantations and agroforestry crops as forested areas, and they may also understate selective logging--an important source of forest degradation --or very small areas of deforestation. Furthermore, the data do not not capture degradation (and no forest cover change data set captures other important ecosystem services such as conservation of biodiversity, soil conservation, or watershed functions). For these reasons, our estimates are likely to be conservative with respect to forest cover change and do not measure multiple other potential environmental impacts. Most importantly, all conclusions are limited by the lack of power in the analysis. Although pre-analysis power calculation estimates suggested that we could detect medium sized effects, the actual power based on the Hansen data from the study years and the entire universe of applicants reveals substantial power limitations (further discussed below).

For the analysis of land-cover impacts, the unit of analysis for the environmental estimates is the parcel (polygon). These polygons were created by dividing applicant parcels into smaller units so that they have unique application histories and we avoid any possible issues of double-counting areas. For example, if a landowner submitted a parcel in 2011 and was rejected, and the following year submitted an imperfectly overlapping parcel that was accepted, these two applications would generate three polygons: one rejected in 2011, one rejected in 2011 and accepted in 2012, and one accepted in 2012.[10] We cluster the standard errors by common property to account for the spatial clustering of these units. **Figure 4** shows a visual representation of these units within various communities with repeated applications.

[9] The high-resolution MAD-Mex system being developed by CONAFOR was originally the preferred option, but post-processing of this layer was not completed by the time of analysis.

[10] A preliminary analysis of changes in submissions within the same ejido over time indicates that landowners are responding to the point system (e.g. higher points for higher risk land) when they resubmit applications. A full analysis is outside the scope of this project.

3.2 LAND-COVER MANAGEMENT AND SOCIAL OUTCOMES DATA

Sampling Framework

Land-cover management and social outcomes were obtained through a survey designed specifically for this study and implemented in 2016. As noted above, the survey focused on common property communities. Two types of surveys were administered in each study community: one to the community leader (defined as a person holding one of four key governance positions in the *ejido* or *comunidad*) and one to household heads or substitute household members.

The sample for the survey consisted of 862 communities - 493 program participants and 369 non-participants. In each community, we surveyed the community leader and a randomly selected set of 10 households, for a total of 8,413 households. Our sampling strategy initially divided the country into four zones (North, Centre, South and Yucatan Peninsula), corresponding to major regions of Mexico. Within these zones, we selected the 12 states with high numbers of applications.

We then took all treatments and controls as close as possible to the cutoff for each cohort and state until arriving at a sample size that represented the proportion of program applicants for that state and cohort and a total sample size in accordance with pre-study power calculations (described in detail in the Appendix). The sample size for land management activities, socio-economic and social capital outcomes assumed larger minimum detectable effects (MDE) for the earlier cohorts. The survey sample was powered to detect effects in the range of 0.16-0.30 standard deviation for the early cohorts and 0.13 to 0.25 for the later ones. The survey interviewed only households with full land rights (*ejidatarios/comuneros*) as these are the households who formally participate in decisions about whether to enroll in the program, how to participate, and how to use the payments received. Non-*ejidatario* households (*avecindados*) were excluded due to budgetary constraints and past work suggesting minimal impacts on those households.[11]

Measures and Indices

Outcome indicators were developed by drawing on instruments from previous evaluations of the Mexico PES program (Alix-Garcia et al., 2012, 2015) and CONAFOR's Annual Participant Surveys, as well as field testing of new questions. The community leader provided information on land-cover management activities such as the construction of fire breaks, fences and boreholes, firefighting, pest control, nurseries, reforestation, pruning, post-harvest cleaning, patrolling for illegal logging and soil conservation. We created the index of land management by summing up the number of these activities practiced by each ejido. The household survey collected data on paid and unpaid forest management and community work by household members, household assets, consumption, educational attainment, credit constraints, attitudes and participation in community activities. Household wealth measures were constructed from questions related to housing characteristics, asset ownership and food consumption. We also collected other socio-economic indicators, such as livestock ownership and emigration patterns, as well as educational indicators (the fraction of children

[11] This is of policy concern as the latter do not formally participate in key decisions related to the program, such as what parcels to submit and how to use the PES payments. Prior work in Mexico (Alix-Garcia et al. 2015), suggests that the program did not have negative impacts on households without full rights. Our community-leader survey indicates that non-ejidatario households represented approximately 30 percent of the total number of households.

attending school). **Appendix Figure A3** describes the composition of the different household wealth measures used.

As described in Alix-Garcia et al. (2018), our social capital measures included elements generally considered to be relevant both globally (Grootaert, 2004) and locally (Merino and Martinez, 2014). We included actions that indicate cooperation (participation), investments that benefit the whole community (infrastructure), and attitudes demonstrating the foundations of social capital (trust or functions). We also measured institutional structures that support social capital, including the range of decisions made by the community assembly (governance), and whether a wide variety of community members participated in decisions (inclusion). **Appendix Figure A4** describes the composition of the social capital indices. The full survey instruments are published as part of the supplemental information in Alix-Garcia et al. (2018).

To reduce dimensionality and multiple-hypothesis testing concerns due to the large number of outcomes, we aggregated into indices the land-cover management activities, the household-level socio-economic measures, and the community-level social capital measures. We used a variety of methods, including simple summation of the presence or absence of particular characteristics, principal components, polychoric principal components (which takes into account categorical variables), and inverse proportion weighting (which applies higher weight to rare items). The results were similar across different aggregating methods. We report the results of simple aggregation, but other results are available upon request.

This paper also explores impact heterogeneity for a series of time-invariant covariates where theory suggests there may be differential impacts. In particular, we expect greater program impact where there is higher deforestation risk. Risk may also be (but is not necessarily) indicative of higher participation costs and hence lower economic gains. We also test for differential impacts across regions for similar reasons.

Comparison between Study Samples and Universe of Applicants

A key concern for external validity is the extent to which the studied samples are representative of the population from which they were drawn. In the environmental analysis, we analyzed the universe of polygons within 25 points of the cutoff, which includes 97% of the applicants. However, to examine deforestation, we begin with applicant polygons that include more than 50% forest cover in 2000, which eliminates 43% of the area submitted for consideration during our study period. Therefore, our results cannot shed light on program impacts in areas without land that is easily classified as forest, which includes many types of vegetation important for the biodiversity program, such as the low shrubs and cacti characteristic of arid regions. This is a fundamental limitation of having to fall back on the Hansen et al. data set.

With regards to the survey data, survey participant characteristics indicate they are very similar to the universe of eligible applicants to the program for the years studied. **Table 2** compares environmental and social characteristics of the communities that were surveyed with the rest of the population of properties that applied in 2011-2014. Our survey sample of 862 properties represents 30% of the available universe of 2,839 *ejidos* and *communidades* that met the minimum program requirements in these years (after dropping repeat applications and 52 properties without a matching code for the *Sistema Padrón e Historial de Núcleos Agrarios-PHINA*). To assess differences between our survey

sample and all applicants, we use normalized differences in means,[12] which is a scale-free measure of the difference in distributions (e.g. Imbens and Wooldridge, 2009). Normalized differences greater than 0.25 standard deviation should be considered substantial (Imbens and Rubin, 2015). By this measure, our sample is close to representative of the universe of applicants (**Table 2**). We also analyzed potential differences between communities we interviewed and communities that we did not due to security issues or inaccessibility and those that refused to participate. While we do not observe substantial imbalances, this potential source of bias is unlikely to affect our results as only 8 communities or 1% of the total of sampled communities refused to participate.[13]

4. EMPIRICAL STRATEGY

Our empirical design uses regression discontinuity (RD) to identify causal impacts of the program. RD estimates program effects through a comparison of participants and rejected applicants who just passed or just missed the eligibility cutoffs. This cutoff is established by the point score calculated by CONAFOR during its selection process and is different for each state, cohort and sub-program, depending on the availability of funds. For ease of interpretation, we re-center the original CONAFOR scores around zero for the purposes of regressions and figures. The essence of the RD strategy is that rejected communities below the cutoff score for selection (the threshold score) can serve as a valid counterfactual (control group) for communities that were accepted. We note that the reason for using other program applicants as a control group is to ensure that they are similar with respect to key unobservable characteristics driving the decision to apply for the program (see e.g. Alix-Garcia et al., 2012, 2015).

In addition to standard causal inference assumptions of excludability and no interference, the key assumption required for a valid RD design is that potential outcomes are continuous around the cutoff. The continuity of potential outcomes requires that applicants cannot precisely manipulate their place in relation to the cutoff and that no key determinants of the outcomes change discontinuously at the cutoff (Lee and Lemieux, 2010). If these assumptions hold, we can interpret cross-sectional differences in outcomes close to the discontinuity threshold as causal estimates of program effects.

Estimation Strategy for Land-Cover Impacts

We examine the total impact of the program from the year of application through 2014, the last year for which we have loss of forest cover data. Since treatment extends over multiple years, the outcome variable for polygon p from community i, cohort c, and state s, or Y_{pjcs}, varies with the year of application. For the 2011 cohort, for example, we examine aggregated loss of forest cover from 2011 to 2014, for the 2012 cohort, loss of forest cover from 2012 to 2014, etc. We limit the sample to those with over 50 percent of the polygon in forest in 2000, and greater than 5 hectares in area, in order to focus on changes in existing land cover and to reduce possible errors from classification of very small

[12] Normalized differences in means are equal to $\frac{Mean_{Treatment}-Mean_{Control}}{\sqrt{Variance_{Treatment}+Variance_{Control}}}$.

[13] Communities that could not be reached during the sampling period tended to be larger in land area, have fewer non-members, be farther from cities, and with higher slope and lower deforestation risk. Nearly all these communities were located in three nearby municipalities in northern Durango state. However, these communities were also relatively balanced across participant status (58 percent were participants, compared to 56 percent in the full sample). Those who refused to participate tended to have been rejected from the program, have higher deforestation risk, be from more indigenous municipalities, and have smaller area. The results of the attrition from the survey sample are reported as Supplementary Information in Alix-Garcia et al. (2018).

areas. We conduct two separate estimations, one for the early cohorts that started the program in 2011-12, and another for the more recent 2013-14 cohorts.

To address the issue that applicants frequently re-apply after they have been rejected, these two estimations are implemented over non-overlapping samples. Applicants who submitted a polygon in a later year after having been rejected in an earlier year are a part of the control group in the first year they apply. Program recipients are a part of the treatment group in the first year that they become enrollees, and are never part of the control group.

The basic estimation equation for the environmental analysis is:

$$Y_{pics} = \beta_1 E_{pics} + \beta_2 Pts_{pics} + \beta_3 E_{pics} \times Pts_{pics} + \beta_4 Pts_{pics}^2 + \beta_5 E_{pics} \times Pts_{pics}^2 + X_p\theta + \rho_c + \alpha_s + \varepsilon_{pic} \quad (1)$$

Following a strict RD design, E_{pics} is a dummy variable indicating whether or not an applicant exceeded the eligibility cutoff in the state, program, and year in which it applied. Pts_{pics} is the point score re-centered around zero, i.e. equal to the original point score minus the cutoff value for that state (*s*), program and year (*c*). We allowed for a flexible, quadratic relationship between the point score and the outcome on either side of the discontinuity. The matrix X_p includes polygon level characteristics, including size, ecoregion type, an *ejido* indicator variable, percent forested in 2000, log-transformed elevation, and standard deviation of slope. These additional covariates are not usually required for the RD design but are included here to reduce noise in the land cover classifications due to land cover type and parcel location. We also include dummy variables for the application cohort for each parcel, denoted ρ_c, and state dummies for state-level fixed effects, α_s. Standard errors, ε are clustered at the community level for *ejido/comunidad* applicants, and at the municipal level for private property applications. Because there are a small number of properties that do not receive payments even though they are above the threshold, we check the robustness of our estimation to a fuzzy discontinuity design that uses the E_p threshold to predict enrollee status. Finally, in order to account for the fact that polygons of larger area are likely to have more precise measurements of forest cover loss, the regressions are weighted by the area of the polygon.

Estimation Strategy for Land-Cover Management and Social Outcomes

We use the same type of regression discontinuity strategy to estimate impacts on land-cover management activities, social capital, and household socio-economic outcomes collected in our survey. To calculate medium and short-term effects, we estimated results separately for each of two cohorts - 2011-12 and 2013-14. Specifically, we estimated the treatment effect β_1 for community/household i of cohort *c*={2011-2012, 2013-2014} in state s, using the following functional form:

$$Y_{ics} = \beta_1 E_{ics} + \beta_2 Pts_{ics} + \beta_3 E_{ics} \times Pts_{ics} + \beta_4 Pts_{ics}^2 + \beta_5 E_{ics} \times Pts_{ics}^2 + \alpha_s + \varepsilon_{ijs} \quad (2)$$

where E_{ics}, Pts_{ics} and α_s have the same interpretation as in equation 1. Standard errors are clustered at the community level for the household level analysis. Communities are weighted equally in the regression. As with the specification for estimating land-cover impacts, we allowed for a flexible, quadratic relationship between the point score and the outcome on either side of the discontinuity. The main text shows results from a quadratic form of the score, though they are robust to linear and cubic transformations as well; consistent with the recommendations given by Lee and Lemieux (2008). For robustness checks, we include for comparison a variation without state fixed effects and a robustness check including a set of control variables (see discussion in the Results section).

Within our community sample, more than 97% of communities above the cutoff received the program as intended, while no communities having point totals below the cutoff received the program. Although our analysis is based on an intent-to-treat analysis, the high levels of compliance with the program cutoffs for both treatment and control groups means that our ITT estimates are similar to (local) average treatment effects.

Tests for Discontinuities of Covariates

To assess the covariate discontinuity and therefore validity of the RD design, this section presents a series of visual and parametric tests using the satellite and survey data. While the assumption that no determinants of the outcomes jump discontinuously at the threshold is untestable for unobservable characteristics, **Figures 5** and **6** show kernel regressions of several observable characteristics, re-centered by subtracting their year and state mean, on the point scores. **Figure 5** shows these graphs for the survey data, while **Figure 6** contains those for the environmental data. In neither case do we observe substantial visual discontinuities in key observable environmental and social characteristics. Parametric tests of discontinuity for these same covariates generally confirm the visual inspection. These tests are presented in **Tables 3a and 3b** for the environmental polygon data set and the survey data set respectively. We do reject the null of no discontinuity for some indicators, but we do not think that these differences drive our results for two reasons. First, most of the differences are small in magnitude with respect to the control means.[14] Second, when we include poverty and the other controls in our final regressions, we find that the results are unaffected, even when we allow for differential slopes on either side of the discontinuity. Furthermore, the correlation between the poverty index and our social capital outcomes, controlling for state effects, is 0.005-0.009 across the cohorts and is not statistically significant.

Table 4a shows summary statistics for participant and non-participant groups for a series of geographic characteristics for the sample of polygons submitted in each cohort. The first two columns show means and the third column of the table shows normalized differences of means (Imbens and Wooldridge 2009) between treatment and control polygons. It is important to note that in a regression discontinuity design, differences in average covariates across groups above and below the cutoff threshold are to be expected if it is the case that the running variable used for prioritization is correlated with these characteristics. The normalized differences were above the 0.25 standard deviation threshold (Imbens and Rubin, 2015) for only two of the 36 indicator-cohort comparisons. Enrollees tend to be located in higher elevations and to be ejidos for the 2011-2012 cohorts (normal differences of 0.342 and 0.334 respectively), with differences persisting for the 2013-2014 cohorts (0.186-0.196). The higher prevalence of ejidos is a direct result of the targeting criterion, and elevation in Mexico tends to be correlated with forest cover, another targeting criteria of the program.

Tables 4b and **4c** present summary statistics of community and household level characteristics, as reported in the leader and household surveys respectively. Similarly, we find that enrollees and rejected applicants have generally small normalized differences in means.

[14] For the polygon environmental data (Appendix Table A2a), we run OLS of the covariates on the treatment threshold, a quadratic of the running variable with slopes that vary on either side of the threshold, polygon size, an ejido dummy variable, ecosystem indicator variables, and state and year fixed effects. For the community and household-level survey data (Appendix Table A2b), we run regressions that include the threshold dummy variable, the first and second order polynomials of the de-meaned point score and their interactions with the threshold dummy, as well as state fixed effects.

Heaping

Because we study four program cohorts, we must account for the fact that several beneficiaries who are rejected in early years re-apply in future years. For the analysis, we count any properties who applied and were accepted between 2011 and 2014 as treated, and remove them from the set of potential controls. For this reason, **Appendix Figure A5** has a high density of observations just to the right of the RD cutoff. High density near the cutoff ordinarily could suggest "heaping", which could threaten RD validity because it could imply manipulation close to the cutoff. However, we do not see any evidence that this pattern is due to manipulation for the following three reasons. First, if there were manipulation close to the cutoff, there should also be heaping in the histograms of applicants for each cohort. **Appendix Figure A6** shows the distribution of point scores for all applicants to each individual cohort. These individual histograms for each year do not show heaping at the cutoff. Second, we note that re-application is unlikely to lead to violations of the continuity of potential outcomes assumption because the cutoff varies from state to state and year to year and is unpredictable. This means that a set of re-applicants who were close to the cutoff in one year might be very far over or very far under the cutoff in the following year. In other words, it is very unlikely that systematic sorting around the cutoff is possible, even allowing for reapplication. Third, our main results are robust to excluding those properties just over the threshold (see discussion about robustness checks in the Results section below).

5. RESULTS

5.1 AVOIDED DEFORESTATION

To study program impacts on the primary outcome of avoided deforestation, we begin by showing visual results for forest cover change as a percentage of forest in the year 2000 for the two cohorts combined. Tables then show results for this measure as well as a binary measure of land cover change that is equal to one in the case where the area of change is greater than two hectares.

Figure 7 shows forest cover change on either side of the acceptance threshold, combining all the years of data and estimating a quadratic fit regression across the normalized point scores for the state-demeaned data. The outcome is the percent forest cover loss. The figure shows a decrease in forest cover change to the right of the acceptance threshold – indicating that the program likely reduced forest cover change. This difference is, however, not statistically significant.

Table 5 shows the point estimates for the same outcomes based on our regressions described in equation 1. The table shows two outcomes – percent forest cover loss and a binary variable indicating loss greater than 2 hectares. We show estimations for all cohorts together (full), and medium (2011-12) versus short term (2013-14) subgroups. The point estimates for all samples indicate avoided forest cover loss – but the magnitudes are not statistically significant. As seen in Panel A, compared to the control rate of cover loss for the full sample between -25 and 25 points (0.619), the point estimate of -0.125 implies a reduction in cover loss of about 20% (0.125/0.619). The corresponding impacts in percentage terms are 30% (0.285/0.956) for the 2011-12 cohort and 5% (0.016/0.319) for the 2013-14 cohort. It is important to note that for the 2013-14 group, the measurement of forest loss includes only 2013 and 2014, a very limited window of time given the overall low rates of deforestation in the country at this time. The magnitudes of the effects for the earlier group of participants are larger than

those for the more recent group, as we might expect, given that the total measured forest cover loss for this group is higher.

Using the narrower discontinuity within 10 points of the cutoff (Panel B), we lose around 3,000 observations, but the results are broadly similar for the rate of cover loss indicator: all point estimates indicate greater conservation of forest in participant parcels than non-participant parcels. The magnitudes range from 24% (0.151/0.634) for the full sample, 35% (0.324/0.934) for 2011-12, and 8% (0.025/0.329) for 2013-14. For the binary variable indicating cover loss greater than 2 hectares, the linear probability model indicates similar trends. For both bandwidth windows, the point-estimates for all the combined and individual cohorts also indicated avoided forest cover loss. Moreover, for the whole sample we find a marginally significant impact of 7.2 percentage points.

Heterogeneous Effects

Knowing for what subgroups an intervention works for is particularly relevant for program design and program targeting. We tested for heterogeneous effects across category of deforestation risk and regions. **Table 6** shows heterogeneity in results by the risk of forest cover loss and **Appendix Figure A7** shows the coefficients of interest. With regards to deforestation risk (where high is defined as above the median level of risk in the sample), we observe a significant impact in areas of high deforestation risk. **Table 6** shows the estimates for the combined and individual cohorts. For the combined sample (2011-2014), the deforestation rate in the rejected group with high risk of deforestation is 0.865 percent, and the sum of the main effect with the interaction term is -0.256, so the total reduction in forest cover lost for this type of land overall is 29.6% (0.256/0.865). For the cohorts that have been enrolled for longer in the program (2011-2012), this effect is 38.1% (0.491/1.294). For the combined and the 2011-2012 cohorts, the impact on avoided deforestation is statistically significant at the 1 and 5 percent level respectively. We also observe a smaller (but not significant) effect in the expected direction for program recipients that have only been in the program a short period of time (2013-2014). We believe that the larger and statistically significant impacts in high risk areas can be ascribed to the fact that there is more scope for behavioral change in an area with high risk of deforestation – in other words, it is easier to have an impact when there is greater possibility for change.

In addition, the program has differential impacts across regions (see **Appendix Figure A8)**. While effects on percent of avoided deforestation were not detected in the north, center and southwest regions, the program's effectiveness was high in the Yucatan peninsula, which is an area of high risk of deforestation.

Robustness Checks

The above results are consistent across a series of robustness checks. Results for the fuzzy design (i.e., the instrumental variables approach where the discontinuity is used as an instrument while controlling for the point score) are shown in **Appendix Table A3**. The point estimates for the different outcomes and for the different windows are very similar to our intent to treat estimates. We conducted two further robustness checks. First, we ran a placebo test using deforestation outcomes from the years 2007-2010. These estimates are shown in the **Appendix Table A4**. As expected, this effect shows no pattern of program impacts in the years prior to enrollment. Second, our results are robust to excluding those properties just over the threshold, i.e. with point scores between 0 and .5 (see **Appendix Table A5**).

Power Limitations

Our analysis of forest cover loss is unfortunately limited by low statistical power. The minimum detectable effect sizes (shown in the row above the number of observations in **Table 5**) are very large relative to the variation in the data. For example, the MDE in the Hansen data for the percent deforested (column 1) is 0.304. The mean value of percent forest cover loss for the non-beneficiaries is 0.619, with a standard deviation of 3.38. The MDE of 0.30 suggests that the impact of the program would have to be larger than 49% in order to be detected (0.304/0.619). In order to detect impacts in the 25-point window sample with the 2011-2012 cohort, the impact would have had to have exceeded 67% (0.644/0.956), and the corresponding minimum detectable effectiveness for the 2013-2014 cohort would have had to exceed 50% (0.151/0.319).

Results from previous studies suggest that power limitations, rather than null effects, could explain the lack of statistically significant results. The estimated changes as a percentage of expected loss are similar to those from previous research, which suggest that the 2003-2010 cohorts lowered loss of forest cover by 25-50 percent depending on methodology and unit of analysis (Alix-Garcia et al. 2013, Alix-Garcia et al. 2015, Sims and Alix-Garcia 2017). This previous work, which finds statistically significant effects, used longer time frames and/or measures that included the Normalized Difference Vegetation Index (NDVI), the latter making the environmental analysis more sensitive to degradation. These differences helped to improve power of prior studies.

5.2 Land-Cover Management Activities

In this section, we describe results for the land-cover management impacts, which provide an alternate measure of the environmental impacts of the program.[15] **Table 7** presents results for land-cover management activities using our preferred specification, which is described in equation 2. We find evidence that the PES program substantially increased an index of forest management activities at the community level (Panel A). Compared to the control means, enrolled communities have an aggregate index that is 72.0% higher for the earlier 2011-12 cohorts (equivalent to 0.80 standard deviation) and 40.0% higher for the later cohorts (0.40 standard deviation). These effect sizes correspond to large and medium effects, respectively (Cohen 1988; Sawilowsky 2009). Although the magnitude of the difference between these two effects is large, there is no statistical difference between the impacts for the two cohorts (z statistic = 0.867). When combining both cohorts, the effect was an increase of 47.6% or 0.60 standard deviation. These effects are statistically significant at the 1 percent level.

Figure 8 shows impacts for specific community-level land management activities. While we find no statistically significant effects for specific indicators in the 2013-14 cohorts, we find that PES payments had statistically significant effects for many indicators for the 2011-12 cohorts - the construction or support for fire breaks, post control, nurseries, reforestation, patrolling and soil conservation. This may suggest having more time to organize this type of community work is important. The apparent larger magnitude for the earlier cohort could also be partly explained by the fact that earlier controls started with lower overall land cover management activities when compared to more recent controls.

[15] These results are also published in Alix-Garcia et al. 2018.

In addition, drawing on responses from the household-level survey, we find that individual households increased their participation in land-cover maintenance activities. Panel B of **Table 7** presents program effects on work days.[16] For the full sample, we find statistically significant impacts ($p<0.01$) on total land-cover work, which includes both work that is paid for through wages and work that is not financially compensated. Transforming the estimated impact into days, land-cover work in treated communities increased by approximately 4.2 days for the earlier cohorts and 2.3 days for the later cohorts (about 2.7 days for the combined sample). These are large percentage changes compared to the means among controls of (2.4 and 3.8 days per household).

Heterogeneous Effects

For the heterogeneous effects analysis, the research team re-classified the survey zones to better group states that had similar communities on the basis of characteristics measured by the surveys. These five regions were: North (Chihuahua and Durango states), North-east (Nuevo Leon and San Luis Potosi states), Center (Jalisco, Michoacan, and Puebla states), South (Chiapas and Oaxaca states), and Yucatan Peninsula (Campeche, Quintana Roo and Yucatan). We investigated possible impact heterogeneity by region (**Appendix Table A6**) and found that enrolled communities in the northeast states of Nuevo Leon and San Luis Potosi increased their land-cover management activities with the greatest magnitude. However, this region is also the one with the lowest baseline level among controls, suggesting perhaps higher effectiveness where activities were low to start. We also estimated impacts for communities whose parcels were at high risk of deforestation and did not find any significant differences in land-cover management activities (**Appendix Table A7**).

Robustness checks

Our impact estimates for the land management index analysis are consistent across a series of robustness checks. Point estimates are robust to excluding state fixed-effects, and to the inclusion of a series of controls (see Table S4 in the Supplementary information for Alix-Garcia et al., 2018). Following Barreca et al. (2016), we restricted the analysis to communities whose point scores were within certain bandwidths of the threshold (-5 to 5, -4 to 4, -3 to 3). Our point estimates on land management are robust to these changes (see columns 1-5 in Table S13 of the Supplementary information for Alix-Garcia et al., 2018). Our results are also consistent when dropping any properties just over the cutoff (point scores that are positive but less than 0.05) and using a fuzzy RD regression (columns 5 and 6 in the same table).

5.3 Household Socio-Economic Indicators

Because PES is voluntary, we would generally expect that communities would not agree to participate unless it made them better off. However, there are several reasons to be concerned about whether payments given to communities will necessarily improve household-level indicators. One reason is that households may need to devote substantial labor time in order to fulfill the management plan submitted to CONAFOR. Previous research suggests that program participation costs are high (Alix-

[16] The values of work days are log transformed according to $Y = \ln(workdays + \sqrt{workdays^2 + 1})$, which is equivalent to the inverse hyperbolic sine with a shift parameter of 1.

Garcia et al 2015),[17] so there may be little surplus wealth available to individual households. At the same time, estimates based on a referendum-style question conducted in the study's 2016 survey (see Alix-Garcia, Phaneuf and Sims 2018) suggest that most participants would be willing to accept lower payments than they are currently receiving and still participate. Prior evaluations of PES in Mexico found that it likely had a small positive effect on assets of the 2003-2009 cohorts of the hydrological services program (with non-differentiated payments) and may have increased educational opportunities for some households (Alix-Garcia et al. 2015). Changes in program rules starting with the 2013 cohort mandated that more of the funds be spent directly on land management equipment or activities.

How this mandate affects household-level outcomes is theoretically ambiguous. This is because money does not necessarily flow directly to households from the pool of payment money. Ejido authorities, usually after discussion with the assembly, make decisions about how the money will be invested – this sometimes occurs through direct transfers to households, but more often it is through investment in public goods or by paying wages for forest work. If households receive wages for this work, as was the case in 65% of the ejidos surveyed in 2011 (Yañez-Pagans, 2015), then they may directly gain additional income compared to prior cohorts. However, if this compensation is less than their opportunity cost of labor, they could be worse off. In addition, the real value of the payments has eroded over time by 15-20%.

Table 8 presents our results on multiple indicators of wealth. We observe no effects on household wealth, as measured by indices of housing characteristics, asset ownership and food consumption (Panel A). Regarding the detectable effects for these three wealth indices, they ranged between 0.10 and 0.12 (equivalent to 14-30% increases). Given the variation in the data, the sample would not have been able to detect these small effects. In addition to the household wealth indices, we analyzed other social variables that are meaningful on their own: migration, children's education, ownership of livestock and whether the household was credit constrained. We do not observe statistically significant changes ($p < .05$) in any outcomes. The point estimates indicate treated households were 54.9% less likely to report a household member to have migrated (3.9 percentage points with respect to a control of 7.1 percent) which is a substantial change, but only marginally statistically significant ($p < .10$). The 2013-2014 cohort was also more likely to report having a household member enrolled in secondary school (18.6% increase with respect to a control of 59 percent) and enrolled in high-school (28.8% with respect to a control of 40.0 percent). Again, these are substantial changes in magnitudes but only marginally statistically significant. The point estimates for most of these social outcomes were similar for the 2011-2012 cohorts, though these were not statistically significant.

Heterogeneous Effects

We tested for impact heterogeneity for our welfare indices across regions, deforestation risk and payment magnitude. There were smaller effects on the housing index in the Yucatan Peninsula in both cohorts and in the same region in the later cohort (see **Appendix Table A8**). There were also consistently more positive effects for the housing and asset indices in the central region of the country, although the total effect (the sum of the threshold and the differential impacts) indicates very small

[17] Previous work based on the survey of applicants from the 2008 cohort found that the program induced significant increases in the time dedicated to the forest and that the ratio of the cost of additional labor (i.e., increases in forest management in beneficiaries relative to non-beneficiaries) to the payment amounts was 0.84.

and not statistically significant positive effects. There were no differential impacts by deforestation risk (**Appendix Table A9**).

Finally, because the distribution of payments is often not directly to *ejido* or *comunidad* members but rather through community investments, we tested whether households that directly received payments experienced differential increases in wealth (see **Appendix Table A10**). Generally, we did not find positive and significant impacts for those households. This is most likely because the decision of whether or not to distribute payments in this way is highly likely to be endogenous to community wealth levels – in other words, poorer communities may be more likely to distribute cash payments directly, which results in biased estimates of the effect of such payments on wealth.

5.4 SOCIAL CAPITAL

Table 9 presents impacts on social outcomes at the community-level (Panel A) and household-level (panel B).[18] The first row shows that PES payments increased the community-level social capital index for those cohorts with longer exposure to PES (a 15.3% increase compared to the mean value for the controls); as well as for the 2013-14 cohorts (6.7%). The effect on the social capital index is 8.6% when combining both cohorts. Results are consistent across the different specifications. Although in percentage terms these changes are relatively small, they are large relative to the variation in the data. The effect sizes are 0.65, 0.35 and 0.40 standard deviation for the earlier, later cohorts and both combined, respectively.

Panel A shows program impacts on the sub-indices that make up the community-level index. We find suggestive evidence that the intervention increased both the trust and the infrastructure sub-indices (each by 22%) for the 2011-12 cohorts; and the infrastructure sub-index for the 2013-14 cohorts (24.1%). For both cohorts combined, the intervention increased communal infrastructure by 19.8%.

Panel B of **Table 9** indicates that there were no significant changes in household-level measures of social capital. We find no significant effects for the sub-indices of Trust and Participation, nor for the aggregate index across all samples. In addition, we find no evidence that the increased participation in land-cover work crowded out unpaid contributions to other pro-social community work, such as building roads or maintaining communal infrastructure (see Panel B of **Table 7**). For the social capital indexes and its sub-indices, we ran similar robustness checks to those we ran for the forest management index; results do not substantially change (see Tables S4 and S13 in the Supplementary information for Alix-Garcia et al., 2018).

One possible concern with the social capital analysis is that the process of applying for and being rejected by the program might impact the controls (e.g., the application process could bring the community together or lead to disharmony lowering social capital among the control communities), which could violate the excludability assumption While we cannot fully test this possible threat to validity as we do not have true pre-treatment measures of social capital, we did examine social capital measures among the control group for those who were rejected once versus multiple times. We found no statistically significant differences or substantial normalized differences among social capital measures for those rejected multiple times (see Table S14 in the Supplementary Information for Alix-Garcia et al., 2018). This suggests that the process of applying is not related to underlying social capital.

[18] These results are also published in Alix-Garcia et al. 2018.

6. DISCUSSION

Our research evaluates the environmental, socioeconomic, and social capital effects of Mexico's payments for ecosystem services program, for the 2011-2014 cohorts. This study is the first to use a regression discontinuity design to identify the impacts of a PES program globally. In contrast to prior studies that may focus on specific regions or small-scale programs, we study a national-level government program and the sample greatly resembles the average program applicant. In addition, our results are robust to a series of specification checks.

We find evidence that the program achieved its primary goals of reducing rates of land cover change and promoting land management activities. Our analysis suggests the program reduced the loss of tree cover, although we detect statistically significant effects only for areas at high risk of deforestation. The magnitudes of the estimated impacts are consistent with prior work (Alix-Garcia, Shapiro and Sims 2012, Alix-Garcia, Sims and Yanez-Pagans 2015, Sims and Alix-Garcia 2017). We note that as measured in the Hansen et al. data set, deforestation rates in Mexico were quite low during this period, making it difficult to detect impacts but possibly reflecting the overall success of national efforts to reduce deforestation. Given the serious limitations of the environmental indicators provided by the Hansen et al. data, we do not recommend using these estimates to perform cost-benefit analysis as they would likely understate potential benefits by an unknown multiple.[19]

We found that the PES program had medium to large effects on land-cover management activities that support the provision of ecosystem services. Participant communities increased management activities by an estimated 48% or 0.60 standard deviation relative to controls, with effects being larger for the 2011-2012 cohort (0.80 standard deviation).

We did not find statistically significant or substantial changes in housing, assets and food consumption of households in participant communities. We found suggestive evidence that the intervention reduced emigration and increased enrollment rates for secondary education in treated households. These results are similar to prior results on Mexico's program (Alix-Garcia et al. 2015; Sims et al. 2017) but are not as positive, possibly due to the erosion in the real value of payments over time and increased mandates for the communities to spend the funds on land-management activities. Future research should consider whether these mandates translate into additional ecosystem services and whether they may effectively increase the participation or implementation costs of the program.

Our results also show that PES significantly increased community social capital (by 8-9% or 0.40 standard deviation) and had no statistically significant or large impacts on household-level measures of trust and participation. In addition, PES did not crowd out other freely contributed community work devoted by households.

Policy Lessons

These findings suggest several policy lessons regarding the potential scale-up of PES programs. First, the finding of impact on land-cover management activities, one of the program's primary goals, suggests that the program effectively generated behavioral changes at the community and household

[19] The remote sensing data do not capture forest degradation or reforestation, do not measure impacts in areas with important types of cover that are not classified as forests (e.g. arid zones), and represent only one indicator of a broad range of ecosystem services supported by the program.

levels. These changes may increase the provision of key ecosystem services, including watershed functioning, biodiversity, fire prevention, and soil conservation.

Second, reductions of land-cover change in areas with high risk of loss indicate that the program is more effective where land cover is most threatened. This suggests important scope to re-target the program to achieve more avoided land cover change in the most ecologically important zones. This could be achieved by putting more weight on the point scores for the risk of vegetative loss, by increasing payments in areas with high risk of cover change and high participation costs, or by re-allocating funding across regions. Currently, risk of deforestation is a fairly small portion of the overall priority points system although CONAFOR has already placed additional priority on high risk-of-loss zones in the most recent cohorts. Future evaluations should assess the effectiveness of this adjustment.

Third, the evidence from indicators of household assets and consumption indicate that PES can meet the safeguard standards of REDD+ which are designed to prevent ancillary harm. The lack of large positive impacts is not surprising given that the potential amount of the cash transfer that reaches the household is likely to be modest, as most program funds are devoted to equipment needed for land management or community infrastructure. Still, comparison with prior work suggests that larger payments would be needed to achieve poverty reduction as a co-benefit of PES.

In addition, greater emphasis on environmental additionality may involve a trade-off between environmental goals and livelihood support. As shown in Alix-Garcia et al. (2015), higher risk land is sometimes but not always owned by the poor, so targeting to higher risk areas may reduce payments going to poorer communities and households. As reported in Alix-Garcia, Phaneuf and Sims (2018), changes to targeting and payment levels based on predicted willingness to accept measures could lead to important cost savings, which could be used to enroll more land and increase the environmental effectiveness of the program. However, by definition, maximizing the impact of the available budget on ecosystem services would require paying as little above costs as possible for every hectare enrolled, so participants would be barely better off than without the program. Improving the well-being of poor participants requires transferring net resources to them, which necessarily reduces resources available for conservation.

Finally, the finding that PES improves social capital supports the conclusion that paying for conservation under REDD+ schemes can support pro-social behavior. This is an important finding given global debates over the possible impacts on communities of using externally provided incentives to motivate conservation behavior.

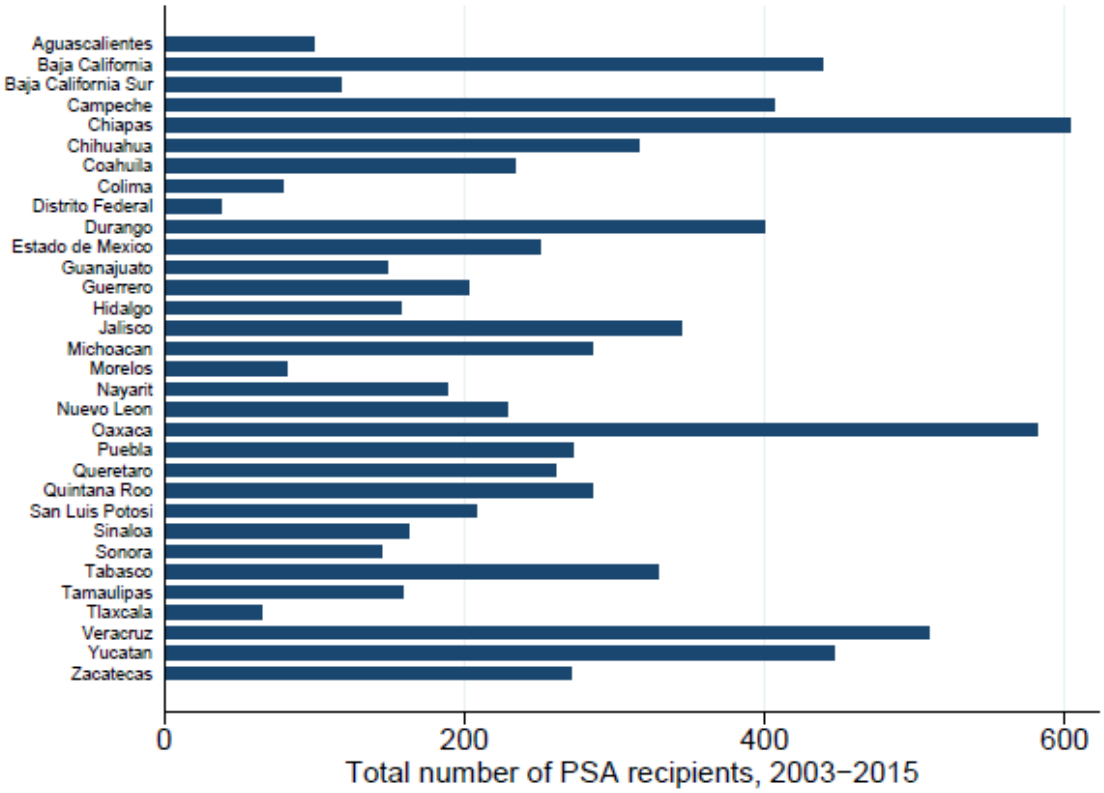
Data for Development

This study also suggests three policy lessons regarding the continued evaluation of PES programs in Mexico and around the world. First, given the high costs of collecting large, representative household data sets for continued evaluation, we suggest that future evaluations of PES in Mexico and globally make use of household indicators already being collected where possible. This may require additional data sharing agreements between agencies to access micro data not publicly available. Second, our study provided the chance to construct and use novel measures of social capital. These measures are not included in standard secondary data and yet our results indicate that they may be an important aspect of environmental conditional cash transfer impacts. Future studies of environmental policy impacts might use similar measures productively. Third, greater investment in remote sensing-based

analysis of land-cover change would have important policy and research benefits. Accurate analysis of avoided deforestation and forest degradation impacts, improved targeting, or meaningful cost-benefit analysis would all require improved cover-change data. The Mexican government is working toward this objective through its MAD-Mex system. Investments in strengthening this type of system will also support much needed new research efforts to better understand under-researched areas, such as the long-term impacts of PES and its relative effectiveness and cost-effectiveness compared to other land conservation initiatives.

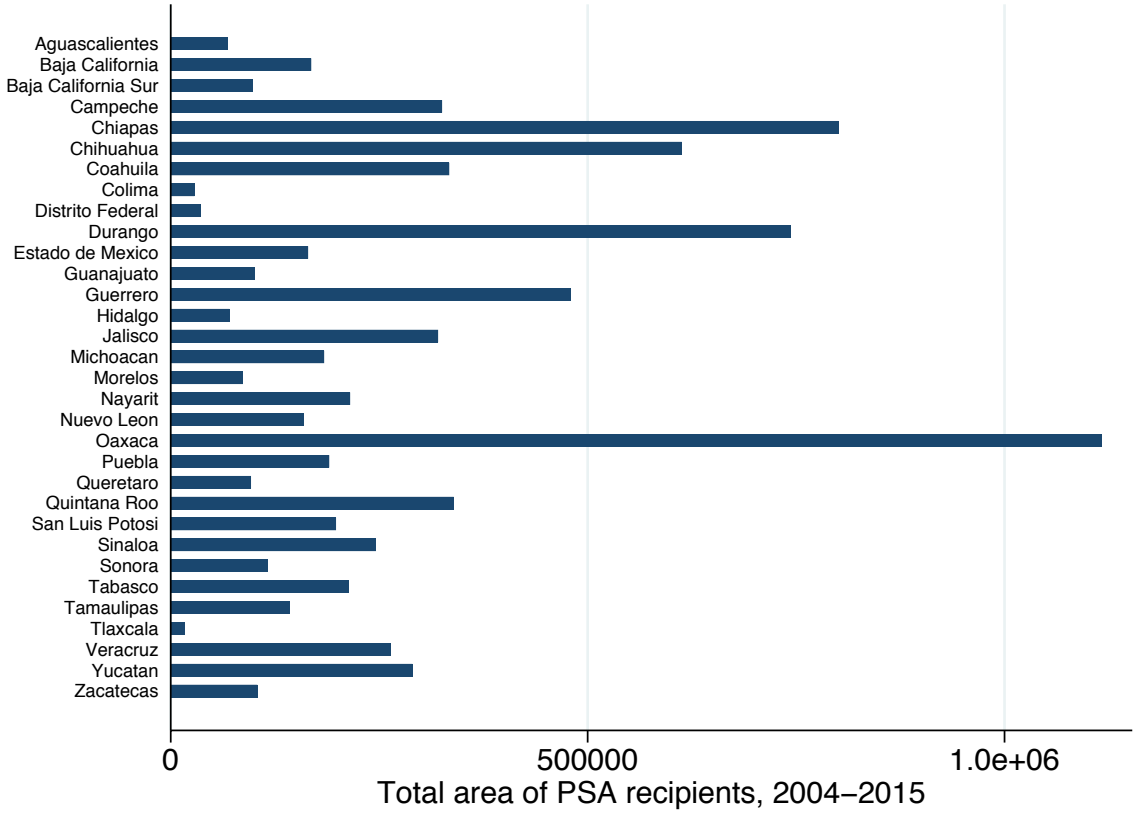
Figures and Tables

Figure 1: Total recipients across all years of the PES program by state (common and private properties)



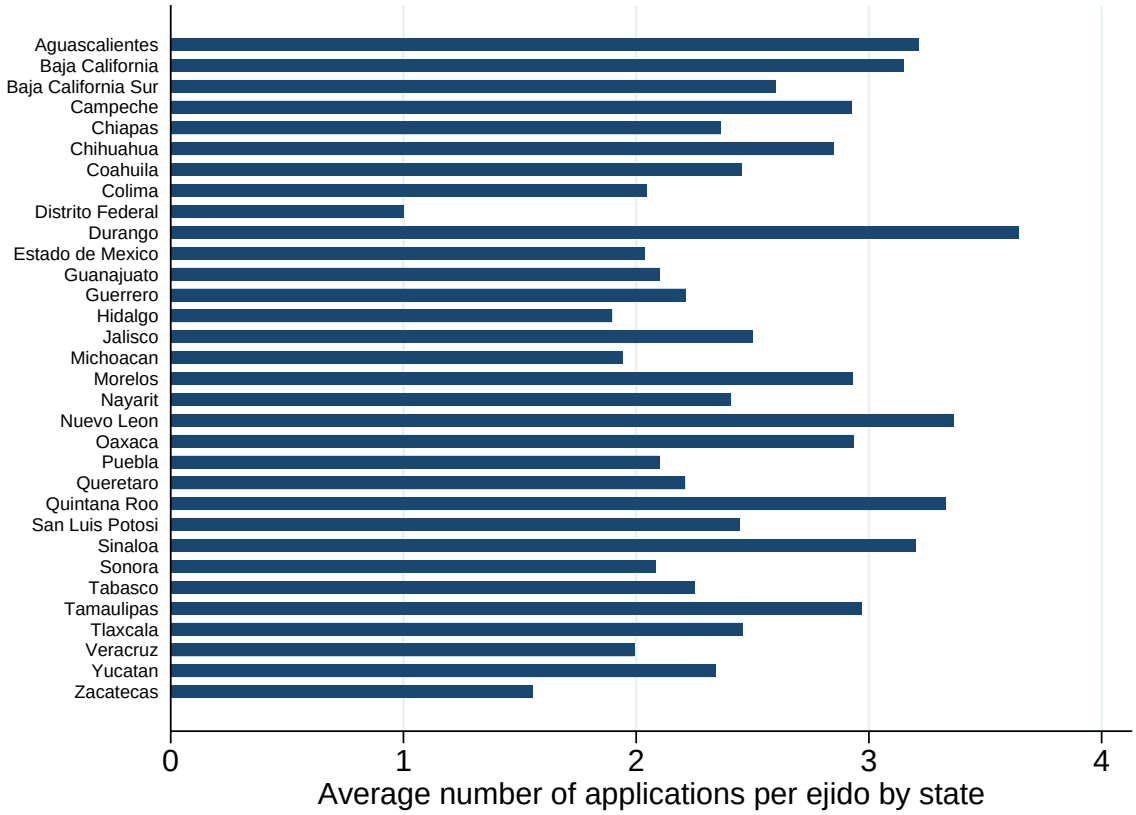
[1] Source: authors calculations from CONAFOR program data.

Figure 2: Total area enrolled across all years of the PES program by state (in hectares, both common and private properties)



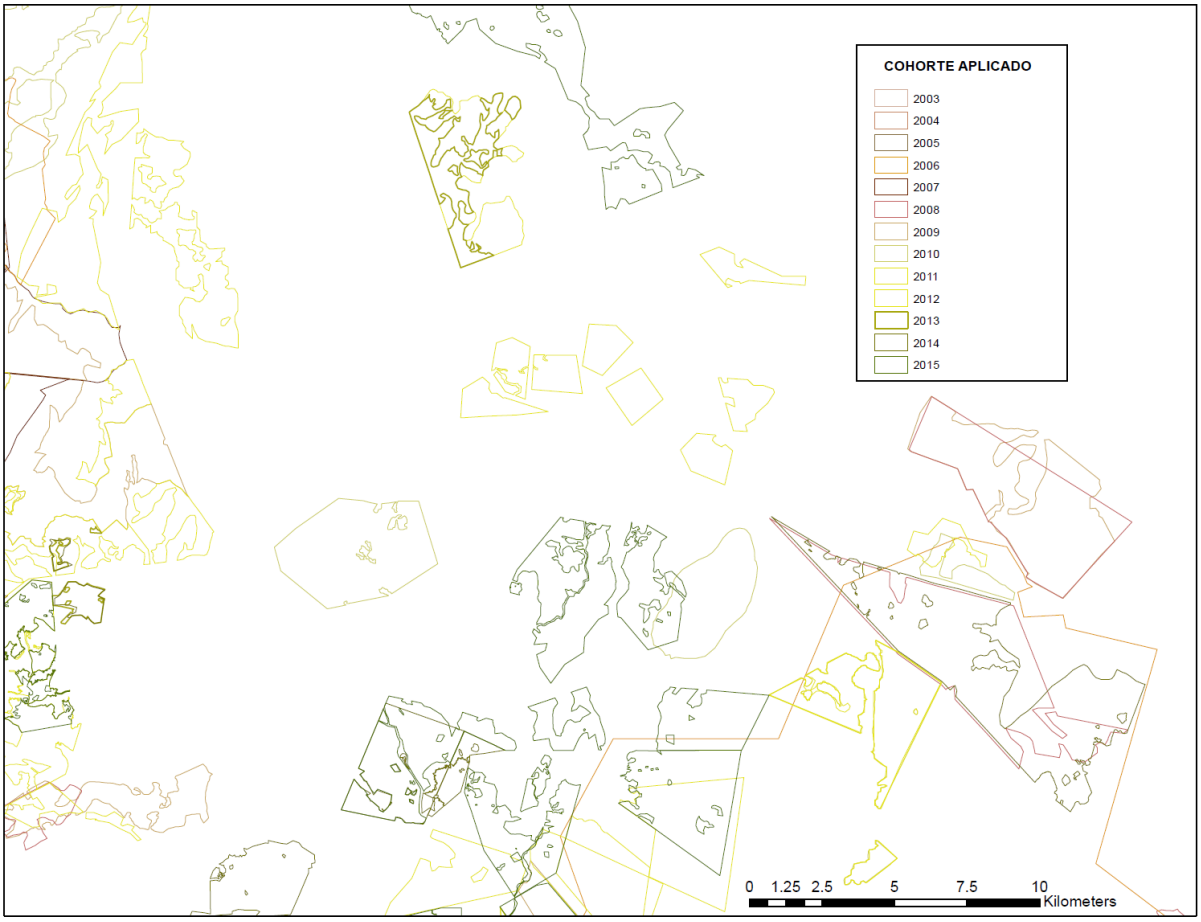
[1] Source: authors calculations from CONAFOR program data.

Figure 3: Average number of ejido applications by state



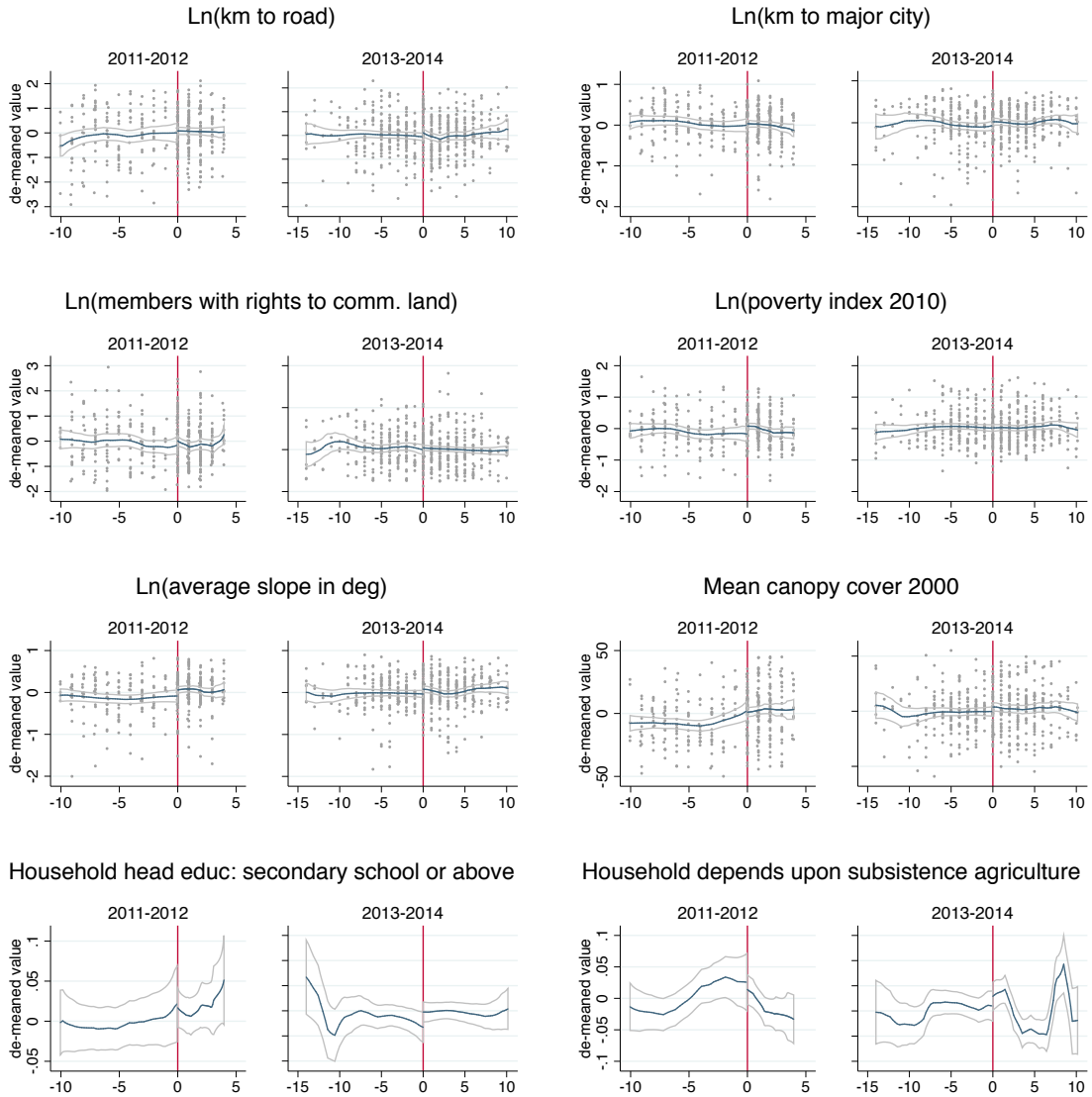
[1] Source: authors calculations from CONAFOR program data.

Figure 4: Overlapping parcels submitted to PES program in different years



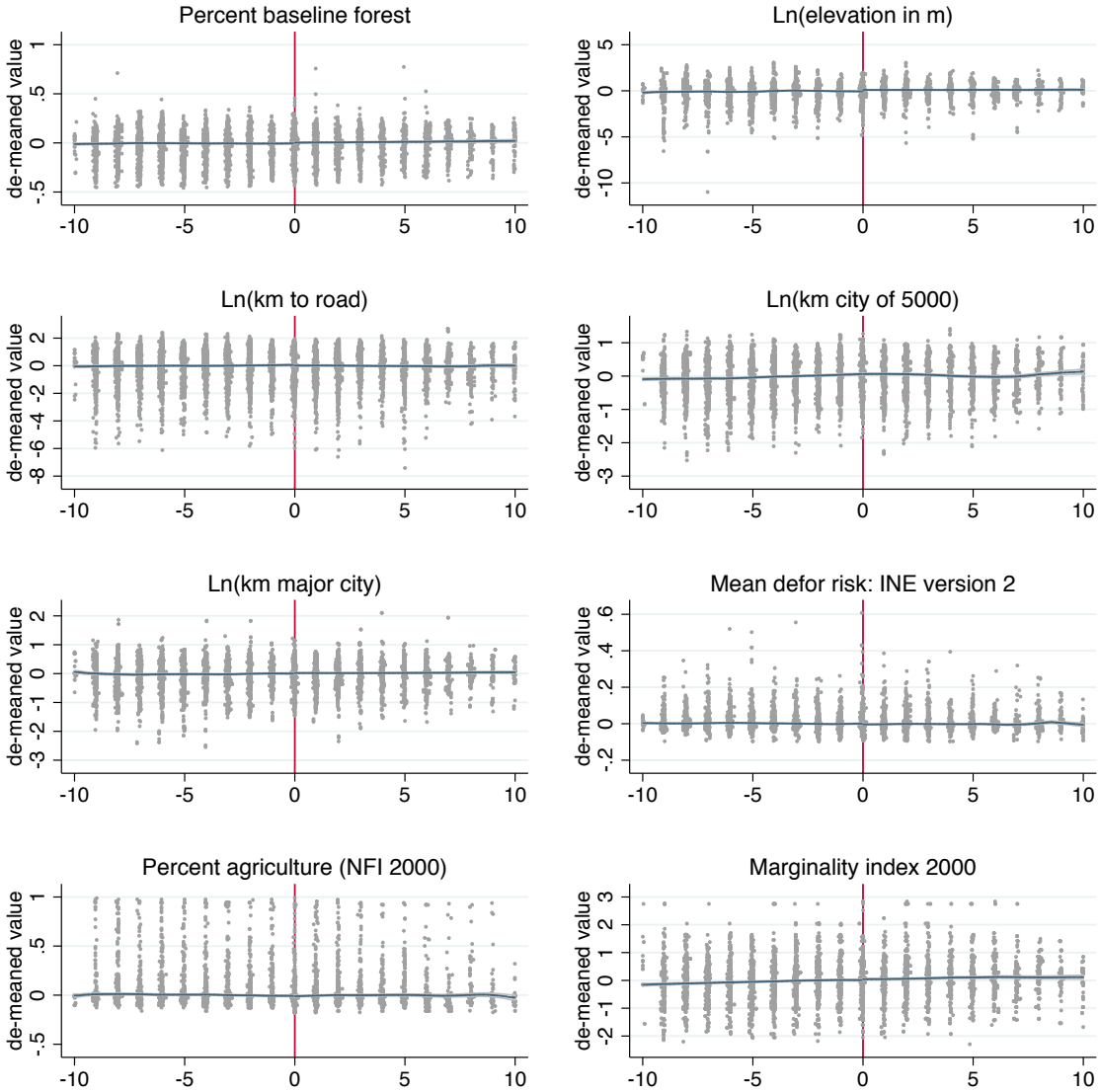
[1] Source: authors calculations from CONAFOR program data.

Figure 5: Test for discontinuity of selected covariates: survey data



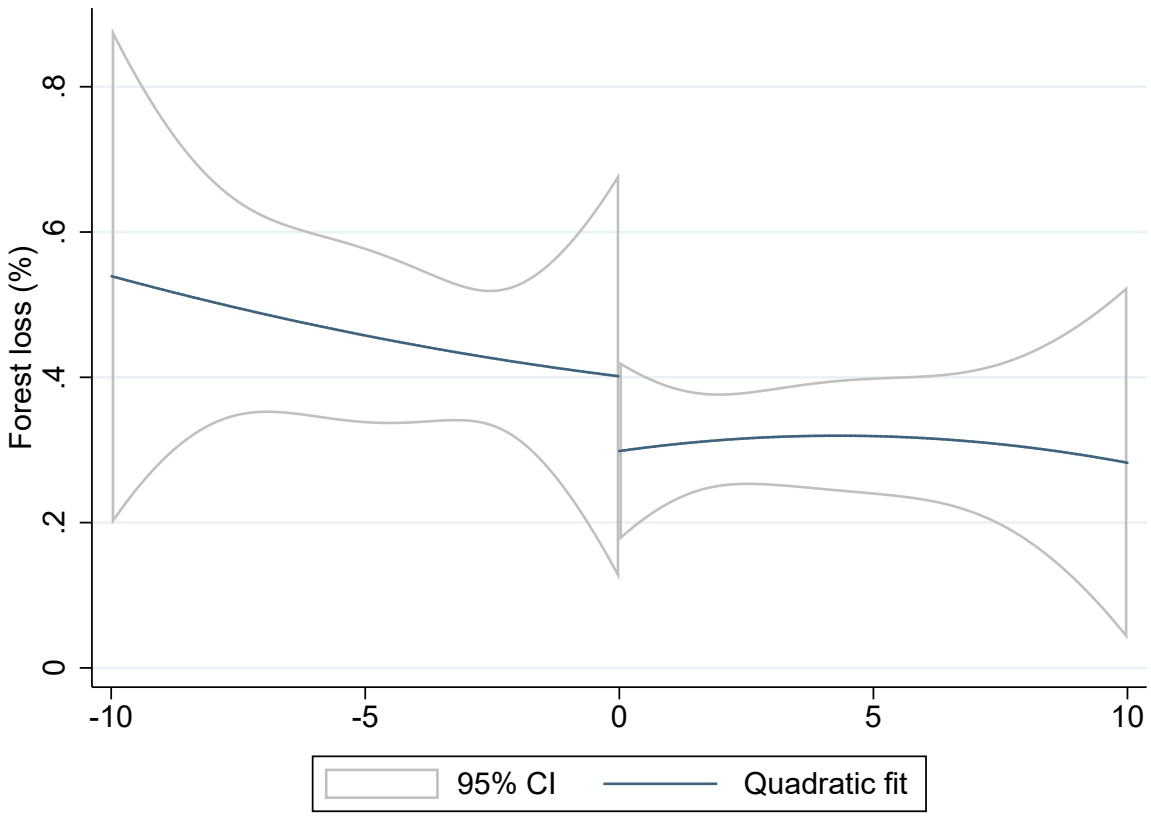
[1] Figures plot the variables of interest from which we subtracted their state-level means, against the re-centered applicant point scores.

Figure 6: Test for discontinuity of selected covariates: environmental data



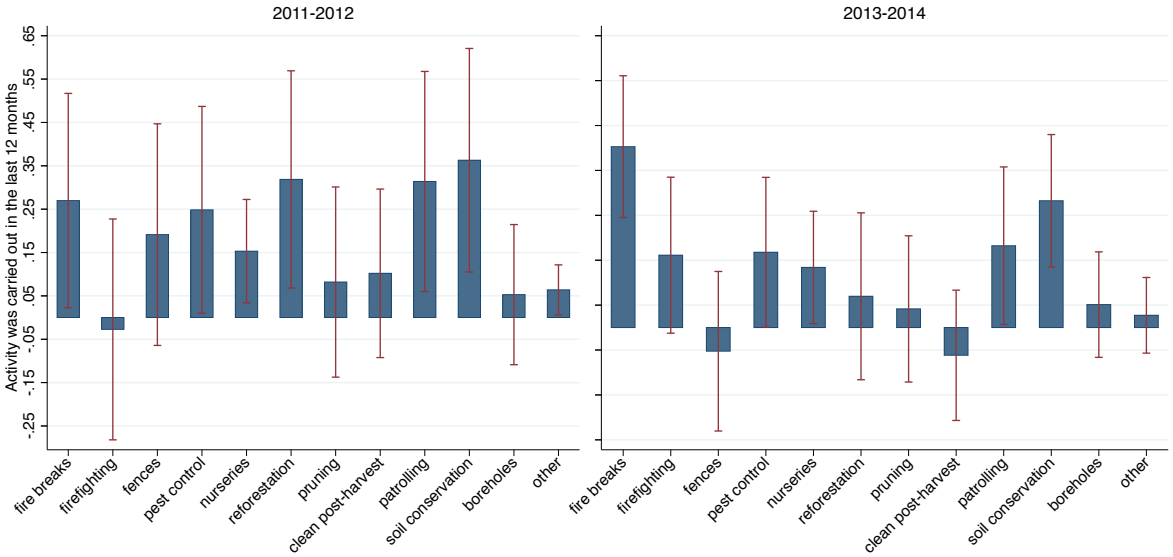
[1] Figures plot the variables of interest from which we subtracted their state-level means, against the re-centered applicant point scores.

Figure 7: Visual representation of discontinuity estimate for percent cover loss



[1] The figure shows a quadratic fit of the percent forest cover loss from a regression weighted by polygon size and with standard errors clustered at the level of the ejido (for common properties) or municipality (for private properties).

Figure 8: Impacts on specific land management activities



[1] Bars show impacts on land cover maintenance activity types as measured in the community survey. Estimates are produced using regressions that include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, as well as state fixed effects.
[2] Sample sizes for the 2011-2012 cohort are: above threshold 206, below threshold 151, total 357; for the 2013-2014 cohort: above threshold 287, below threshold, total 505.

Table 1: Evolution of PSA payment scheme

Modality	**Sub group**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**Sub group**	**2010**	**2011**	**2012**	**2013**	**2014**
Hydrological													
	Cloud forest	400	400	410	430	450	470	Area 1	1100	1100	1100	1100	1100
	Oak forest				380	390	410	Area 2	700	700	700	700	700
	Rain forest	300	300	320	330	340	360	Area 3	382	382	382	382	382
Biodiversity													
	All				330	390	410	Area 4	550	550	550	550	550
								Area 5	382	382	382	382	382
								Area 6	280	280	280	280	280

[1] All payments are expressed in Mexican pesos.

Table 2: Sampled versus non-sampled communities in 2011-2014 cohorts

	(1) **Not sampled**	(2) **Sampled**	(3) **Normalized Differences**
Ln(community area, ha)	8.269	8.211	-0.037
Ln(common property area, ha)	7.759	7.809	0.020
Ln(members with rights to comm. land)	4.602	4.599	-0.003
Ln(members without rights to comm. land)	1.416	1.354	-0.027
Ln(area submitted, ha)	6.682	6.697	0.012
Ln(average slope in deg)	2.384	2.217	-0.153
Ln(average elevation in deg)	6.681	6.507	-0.079
Ln(km to any road)	7.772	7.643	-0.089
Ln(km to major city)	4.430	4.597	0.195
Ln(km to city > 5,000)	3.229	3.227	-0.002
Mean canopy cover 2000	42.433	50.909	0.200
Percent indigenous in municipality	0.161	0.328	0.289
Deforestation risk (INE)	0.057	0.055	-0.025
Obs	1977	862	2839

[1] Table shows mean values in columns (1) and (2), and the normalized differences between these means in columns (3).

Table 3a: Tests for discontinuities in covariates: environmental data

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Panel A: Community survey	
% baseline forest	0.011	0.019*	0.007
	(0.007)	(0.010)	(0.010)
Control Mean	0.893	0.880	0.907
Observations	11035	5859	5197
Ln(elevation)	0.121**	0.260***	-0.028
	(0.059)	(0.068)	(0.087)
Control Mean	6.250	6.293	6.208
Observations	11031	5856	5196
Ln(km to any road)	-0.012	-0.034	-0.060
	(0.077)	(0.098)	(0.120)
Control Mean	7.922	7.886	7.956
Observations	11035	5859	5197
Ln(km to city>5000 people)	0.024	0.030	-0.027
	(0.039)	(0.046)	(0.063)
Control Mean	3.268	3.212	3.326
Observations	11035	5859	5197
Ln(km to major city)	0.028	0.013	0.052
	(0.034)	(0.036)	(0.057)
Control Mean	4.530	4.537	4.523
Observations	11035	5859	5197
Deforestation risk	-0.002	-0.005	0.001
	(0.003)	(0.005)	(0.005)
Control Mean	0.042	0.047	0.038
Observations	10708	5669	5060
% agricultural land (NFI 2000)	-0.002	-0	0.001
	(0.007)	(0.011)	(0.009)
Control Mean	0.043	0.053	0.033
Observations	11035	5859	5197
Marginality 2000	0.015	0.082	-0.023
	(0.050)	(0.054)	(0.083)
Control Mean	0.238	0.198	0.280
Observations	11035	5859	5197

[1] To test for the same discontinuity statistically, we run OLS of the covariates on the treatment threshold, a quadratic of the running variable with slopes that vary on either side of the threshold, polygon size, a ejido dummy variable, ecosystem indicator variables, and state and year fixed effects. Standard errors are clustered at the ejido level for ejidal polygons, and at the municipal level for private properties.

Table 3b: Tests for discontinuity on selected covariates: survey data

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
	Panel A: Community survey		
Ln(km to any road)	0.228*	0.322	0.305*
	(0.138)	(0.250)	(0.171)
Control Mean	7.613	7.648	7.588
Ln(km to major city)	0.154**	0.085	0.181**
	(0.070)	(0.126)	(0.085)
Control Mean	4.601	4.664	4.557
Ln(members with rights to comm. land)	0.138	0.201	0.253
	(0.137)	(0.263)	(0.166)
Control Mean	4.641	4.616	4.659
Ln(poverty index 2010)	0.148*	0.340**	0.057
	(0.081)	(0.161)	(0.102)
Control Mean	0.079	0.015	0.124
Ln(average slope in degrees)	0.133**	0.092	0.124
	(0.060)	(0.110)	(0.076)
Control Mean	2.222	2.360	2.126
Mean canopy cover 2000	-0.498	-3.768	1.436
	(3.076)	(5.743)	(3.911)
Control Mean	47.318	40.318	52.166
Observations	862	357	505
	Panel B: Household survey		
Household head educ: sec school or above	0.015	0.001	0.019
	(0.019)	(0.037)	(0.024)
Control Mean	0.160	0.172	0.152
Observations	8350	3442	4908
Household depends upon subsistence agric	0.001	-0.058	0.047*
	(0.021)	(0.038)	(0.027)
Control Mean	0.197	0.185	0.205
Observations	8413	3466	4947

[1] Regressions include the threshold dummy, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, as well as state fixed effects. For the community level analysis, robust standard errors are presented in parentheses. For the household level analysis, standard errors were clustered at the community level.

[2] In Panel B, the number of obs for the household being dependent upon subsistence agriculture matches the full number of observations, while the number of observations for the household head education has some missing data.

Table 4a: Summary statistics: environmental polygons 2011-2014

	2011-2012			2013-2014		
	(1) Mean enrollees	(2) Mean non-enrollees	(3) Normalized difference	(4) Mean enrollees	(5) Mean non enrollees	(6) Normalized difference
% baseline forest (Hansen)	0.891	0.883	0.036	0.904	0.897	0.032
% forest 2000 (NFI)	0.918	0.876	0.126	0.908	0.900	0.025
% agricultural land (NFI 2000)	0.046	0.055	-0.037	0.055	0.038	0.081
Area of Tiny polygon	393	257	0.193	284	193	0.161
Average Elevation (in meters)	1455	991	0.342	1385	1123	0.186
Average Slope (in degrees)	15	13	0.136	14	13	0.010
Km to major city	94	106	-0.182	96	108	-0.157
Km to city > 5000 people	29	29	-0.004	28	31	-0.102
Meters to any road	3918	4420	-0.088	3859	4872	-0.170
Meters to highway with speed > 60 km/h	7096	7253	-0.018	6638	8293	-0.184
Meters to highway with speed > 80 km/h	19468	17369	0.098	18798	17868	0.044
Deforestation risk	0.040	0.050	-0.124	0.044	0.039	0.077
Marginality 2000	0.173	0.138	0.029	0.238	0.166	0.059
Applied as ejido	0.819	0.611	0.334	0.785	0.662	0.196
Obs	2456	5028	.	2110	5070	.

[1] The table shows means for enrolled and non-enrolled polygons and normalized differences in means.

Table 4b: Summary statistics: household characteristics

	2011-2012			2013-2014		
	(1) Mean enrolees	(2) Mean non-enrolees	(3) Normalized difference	(4) Mean enrolees	(5) Mean non enrolees	(6) Normalized difference
Household (HH) head is female	0.086	0.088	-0.004	0.097	0.091	0.016
HH head age	57.003	58.170	-0.059	57.154	57.011	0.007
HH head can read and write	0.800	0.855	-0.103	0.806	0.782	0.041
HH head went to sec. school or above	0.178	0.171	0.013	0.161	0.150	0.022
# hh members	3.896	3.737	0.057	3.945	3.819	0.044
Indigeneous language spoken in hh	0.371	0.275	0.146	0.402	0.380	0.033
Receives PROCAMPO support (gov prog. for agric)	0.614	0.626	-0.018	0.618	0.594	0.035
Receives PROGAN support (gov prog. for livestock)	0.164	0.183	-0.035	0.175	0.144	0.059
Experienced a shock to husbandry prod (last 12m)	0.673	0.676	-0.004	0.674	0.707	-0.050
HH member ill and unable to work >1w (last 12m)	0.427	0.402	0.036	0.430	0.385	0.064
HH member had a large medical expense (last 12m)	0.468	0.446	0.031	0.487	0.458	0.041
Observations	2038	1428	.	2828	2119	.

[1] The table shows means for households in enrolled and non-enrolled communities and normalized differences in means.

Table 4c: Summary statistics: community characteristics

	2011-2012			2013-2014		
	(1) Mean enrolees	(2) Mean non-enrolees	(3) Normalized differences	(4) Mean enrolees	(5) Mean enrolees	(6) Normalized difference
Type of land cover: forest	0.568	0.576	-0.012	0.533	0.555	-0.031
Type of land cover: rainforest	0.369	0.298	0.106	0.366	0.349	0.025
Type of land cover: bush/shrubs	0.063	0.126	-0.152	0.101	0.078	0.057
Community leader age	51.646	53.305	-0.103	51.711	51.472	0.016
Community leader is a man	0.961	0.954	0.026	0.965	0.968	-0.011
Community leader can read and write	0.927	0.967	-0.126	0.976	0.963	0.050
Community leader completed sec. school or above	0.252	0.384	-0.201	0.383	0.335	0.071
Community is connected to public electr. grid	0.898	0.887	0.024	0.944	0.908	0.097
# comm. members with rights to comm. land	150.456	178.026	-0.084	165.906	185.280	-0.052
# comm. members without rights to comm. land	209.568	168.861	0.049	298.606	202.294	0.077
1st/2nd livelihood: income gen. agric	0.471	0.510	-0.055	0.526	0.431	0.135
1st/2nd livelihood: subsistence agric	0.456	0.430	0.037	0.408	0.500	-0.131
1st/2nd livelihood: income gen. livestock rearing	0.471	0.523	-0.074	0.477	0.413	0.092
1st/2nd livelihood: labor in husbandry/forestry	0.199	0.132	0.127	0.157	0.138	0.038
Daily wage (pesos)	140.413	141.464	-0.015	138.868	131.367	0.116
PES payment per capita	6685.073	5365.926	0.118	5591.061	6030.615	-0.045
Obs	206	151	.	287	218	.

[1] The table shows means for enrolled and non-enrolled communities and normalized differences in means.

[2] For control communities in the 2011-2012 cohort, payments per capita are those that would have been awarded had they been successful. For control communiites in the 2013-2014 cohort, CONAFOR did not calculate these payments, so we inputed the median payment per hectare for that state, year and modality, and multiplied it by the area they submitted.

Table 5: Impacts of program on forest cover loss, 25-point and 10-point windows

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**,	(4) **Full**	(5) **2011-2012**	(6) **2013-2014**
	Perc. deforested			**Defor >2 ha**		
			Panel A: 25-point window			
Above threshold	-0.125	-0.285	-0.016	-0.029	-0.042	-0.028
	(0.109)	(0.230)	(0.054)	(0.032)	(0.049)	(0.038)
Control Mean	0.619	0.956	0.319	0.062	0.093	0.033
Control SD	3.385	4.138	2.495	0.240	0.291	0.179
MDE	0.304	0.644	0.151	0.089	0.138	0.106
Observations	14119	7019	7127	14119	7019	7127
			Panel B: 10-point window			
Above threshold	-0.151	-0.324	-0.025	-0.072*	-0.070	-0.062
	(0.160)	(0.336)	(0.059)	(0.039)	(0.060)	(0.049)
Control Mean	0.634	0.934	0.329	0.060	0.084	0.036
Control SD	3.507	4.158	2.654	0.238	0.277	0.186
MDE	0.448	0.940	0.164	0.109	0.168	0.136
Observations	11030	5856	5195	11030	5856	5195

[1] Covariates include: point score, threshold x point score, ejido indicator, ln(polygon ha) percent forest in 2000, cohort indicators, ecosystem indicators, and state dummy variables. Standard errors are clustered at the ejido level for ejidos, and at the level of the municipality for private properties. Sample is limited to polygons greater than 5 ha and with more than 50% forest in 2000. *** p < .01; ** p < .05; * p < .10

Table 6: Heterogeneity by level of deforestation risk (% Forest Cover Loss)

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
Threshold	0.006	-0.002	-0.002
	(0.103)	(0.220)	(0.050)
Threshold x high defor risk	-0.256***	-0.491**	-0.049
	(0.091)	(0.028)	(0.028)
Control mean (high risk)	0.865	1.294	0.421
Observations	14119	7019	7127

[1] Covariates include: point score, threshold x point score, ejido indicator, ln(polygon ha) percent forest in 2000, cohort indicators, ecosystem indicators, and state dummy variables. Standard errors are clustered at the ejido level for ejidos, and at the level of the municipality for private properties. Sample is limited to polygons greater than 5 ha and with more than 50% forest in 2000. Deforestation risk indicates that the level of risk using the INECC layer is higher than the median in the sample. *** p < .01; ** p < .05; * p < .10

Table 7: Impacts on community land cover management index and on household participation in land cover maintenance activities and community work (log no. days)

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Panel A: Community survey	
Land management index	0.130***	0.178***	0.117***
	(0.029)	(0.061)	(0.035)
Control Mean	0.273	0.247	0.292
Control SD	0.217	0.223	0.211
Observations	862	357	505
		Panel B: Household survey	
Land cover work	0.613***	0.963***	0.474***
	(0.140)	(0.220)	(0.179)
Control Mean	1.869	1.628	2.034
Paid land cover work	0.461***	0.553***	0.481***
	(0.104)	(0.169)	(0.142)
Control Mean	0.418	0.302	0.498
Unpaid land cover work	0.260**	0.586***	0.092
	(0.127)	(0.199)	(0.169)
Control Mean	1.558	1.401	1.666
Community work	0.183	0.250	0.042
	(0.113)	(0.179)	(0.148)
Control Mean	1.968	1.882	2.028
Obs	8050	3342	4708

[1] Regressions include the threshold dummy, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy and state fixed effects. For the community level analysis, robust standard errors are presented in parentheses. For the household level analysis, standard errors were clustered at the community level. *** $p < .01$; ** $p < .05$; * $p < .10$

[2] The sample for the household level analysis includes only observations for which all four variables had non-missing values. This was done to ensure results were fully comparable.

Table 8: Impacts on household wealth indices

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Panel A: Wealth indices	
Housing index	-0.015	-0.029	-0.009
	(0.017)	(0.037)	(0.019)
Control Mean	0.654	0.679	0.638
Assets index	0.003	0.003	0.004
	(0.019)	(0.044)	(0.022)
Control Mean	0.366	0.393	0.347
Food index	-0.008	-0.029	-0.003
	(0.022)	(0.040)	(0.029)
Control Mean	0.535	0.562	0.517
Observations	8413	3466	4947
		Panel B: Other wealth components	
Had livestock last 12m	-0.029	-0.018	-0.039
	(0.040)	(0.072)	(0.052)
Control Mean	0.418	0.461	0.389
Household member migrated	-0.035*	-0.031	-0.039*
	(0.019)	(0.045)	(0.022)
Control Mean	0.080	0.094	0.071
Credit constrained	0.001	0.009	0.027
	(0.031)	(0.056)	(0.040)
Control Mean	0.531	0.505	0.549
Sold smth to cover unexpected cost	0.016	-0.001	0.013
	(0.030)	(0.051)	(0.040)
Control Mean	0.378	0.386	0.373
Observations	8413	3466	4947
		Panel C: Education	
Fraction 6-11 year olds in pri. sch.	0.005	-0.032	0.052
	(0.031)	(0.050)	(0.041)
Control Mean	0.837	0.837	0.837
Observations	2152	875	1277
Fraction 12-15 year olds in sec. sch.	0.059	-0.069	0.110*
	(0.053)	(0.095)	(0.063)
Control Mean	0.606	0.632	0.590
Observations	1978	798	1180
Fraction 16-18 year olds in high-sch.	0.090	0.148	0.115*
	(0.055)	(0.113)	(0.069)
Control Mean	0.385	0.361	0.400
Observations	1766	691	1075
Fraction 19-25 year olds in univ.	0.002	-0.043	0.039
	(0.033)	(0.065)	(0.040)
Control Mean	0.136	0.137	0.135
Observations	2514	1043	1471

[1] Regressions include the threshold dummy variable, the first and second order polynomials of the de-meaned point score and their interactions with the threshold dummy, as well as state fixed effects. Standard errors clustered at the community level are presented in parentheses. *** p < .01; ** p < .05; * p < .10

Table 9: Impacts on social capital indices

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Panel A: Community survey	
Total	0.048***	0.084***	0.038*
	(0.016)	(0.030)	(0.020)
Control Mean	0.559	0.548	0.567
Trust	0.050	0.120*	0.037
	(0.033)	(0.061)	(0.041)
Control Mean	0.562	0.547	0.572
Inclusion	-0.007	0.091	-0.077*
	(0.033)	(0.059)	(0.043)
Control Mean	0.590	0.610	0.576
Governance	0.022	0.065	0.014
	(0.018)	(0.041)	(0.021)
Control Mean	0.532	0.535	0.530
Participation	0.058	0.025	0.072
	(0.042)	(0.072)	(0.052)
Control Mean	0.533	0.502	0.554
Infrastructure	0.115***	0.118*	0.146***
	(0.035)	(0.065)	(0.043)
Control Mean	0.581	0.547	0.604
Obs	862	357	505
		Panel B: Household survey	
Total	0.018	0.029	0.004
	(0.018)	(0.030)	(0.023)
Control Mean	0.377	0.360	0.389
Trust	0.022	0.032	0.020
	(0.015)	(0.024)	(0.019)
Control Mean	0.287	0.280	0.291
Participation	0.014	0.026	-0.011
	(0.030)	(0.052)	(0.038)
Control Mean	0.468	0.440	0.487
Obs	8413	3466	4947

[1] Regressions include the threshold dummy, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy and state fixed effects. For the community level analysis, robust standard errors are presented in parentheses. For the household level analysis, standard errors were clustered at the community level. *** $p < .01$; ** $p < .05$; * $p < .10$

[2] The inclusion index contained two questions related to the participation in assemblies of members without rights to communal land. In communities where there were no such individuals, these questions were skipped. To avoid working on a restricted dataset due to those missing values, we imputed them to the mean.

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APPENDIX: Sample calculations and additional Figures and Tables

Sample Size

Power calculations for our land cover analysis followed the formula for calculating minimum detectable effect (MDE) in cluster randomized designs proposed by Bloom (2005) and relied on the average yearly forest loss from the Hansen et al. (2013) dataset, summarized at the level of locality polygons. In that dataset, the average yearly forest loss in polygons sized between 50 and 3,000 hectares with more than 10 percent baseline forest cover was 0.270 (sd=0.421). To detect a program impact of 40 percent, slightly less than the impact found in Alix-Garcia et al. (2015), we calculated we would require a sample size of 943 controls and 332 treatments from 425 municipalities to study effects for both 2011-12 and 2013-14 cohorts. However, preliminary analysis of our land cover data suggested important power limitations when using the Hansen (2013) data. Only 6.3 percent of polygons in the sample exhibited any deforestation over 2 hectares in area; and only seven or a fifth of the states in our sample had at most one polygon experiencing deforestation of over 2 hectares. As a result, and as noted in Section 5, the overall rate of forest cover loss that is reliably measured by the Hansen data is quite small, making it potentially difficult to detect program effects on avoided deforestation.

Power calculations for social outcomes followed Duflo et al. (2008) and use individual components of a social capital index proposed by Merino and Martinez (2014), drawn from data collected through CONAFOR's 2011 and 2013 Beneficiary surveys. Power calculations for socio-economic impacts followed Bloom (2005) and were based on household level data collected for the 2011 Mexico PES study (Alix-Garcia et al., 2015) for indices of assets (mean 2.41, s.d. 2.51) and housing (mean 10.11, s.d. 4.41) with intra-cluster correlations at the community level of 0.20 and 0.21 respectively. Power calculations for social capital and socio-economic outcomes suggested we needed to interview 864 community leaders and 8,640 households. The effective survey sample was 862 community leaders and 8,413 households; which represented 99.8 and 97.4 percent of our target sample respectively.

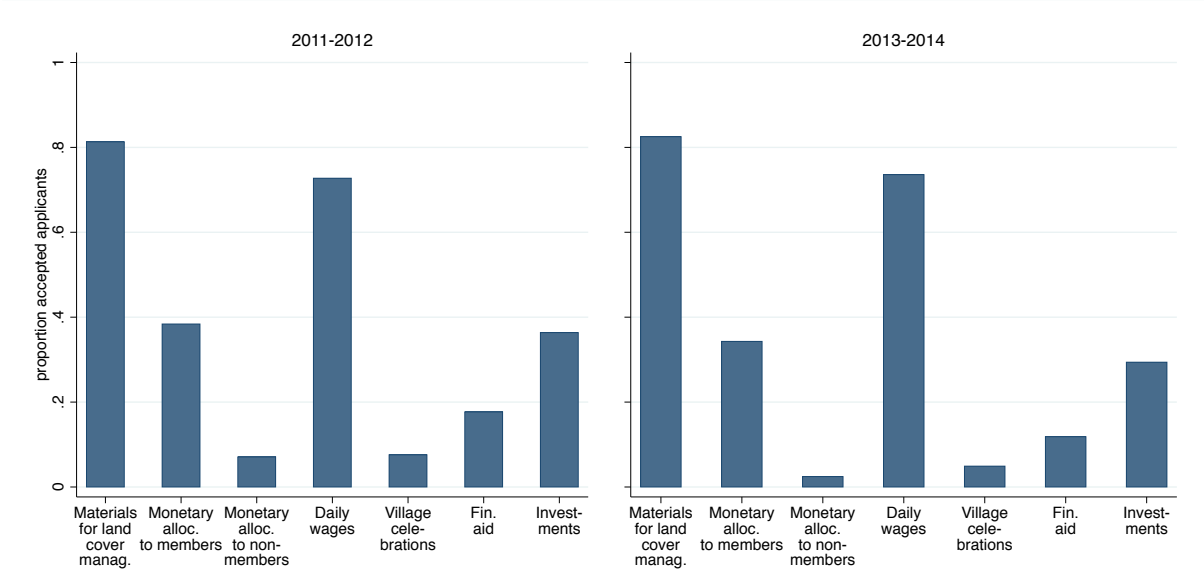
Because for all outcomes we assumed effects would grow stronger over time, we assumed larger MDEs for the earlier cohorts (and therefore smaller sample sizes for them)[1]. The sample size was determined by our power calculations for social capital impacts, which required the largest samples. The sample size for social capital impacts assumed MDEs of 0.3 standard deviations and 0.25 standard deviations for the 2013-14 and 2011-12 cohorts respectively; and of 0.13 and 0.16 standard deviations for the socio-economic outcomes[2]. These effect sizes are considered "small to medium" in the literature on sample design.

[1] However, this meant that for the 2013-14 cohorts, where the required sample size was larger, the controls were further from the threshold; thus, these cohorts have a broader range of point scores than the earlier cohorts.

[2] Power calculations for social outcomes followed Duflo et al. (2008) and use individual components of a social capital index proposed by Merino and Martinez (2014), drawn from data collected through CONAFOR's 2011 and 2013 Participant surveys. Power calculations for socio-economic impacts followed Bloom (2005) and were based on household level data collected for the 2011 Mexico PES study (Alix-Garcia et al., 2015) for indices of assets (mean 2.41, s.d. 2.51) and housing (mean 10.11, s.d. 4.41) with intra-cluster correlations at the community level of 0.20 and 0.21 respectively.

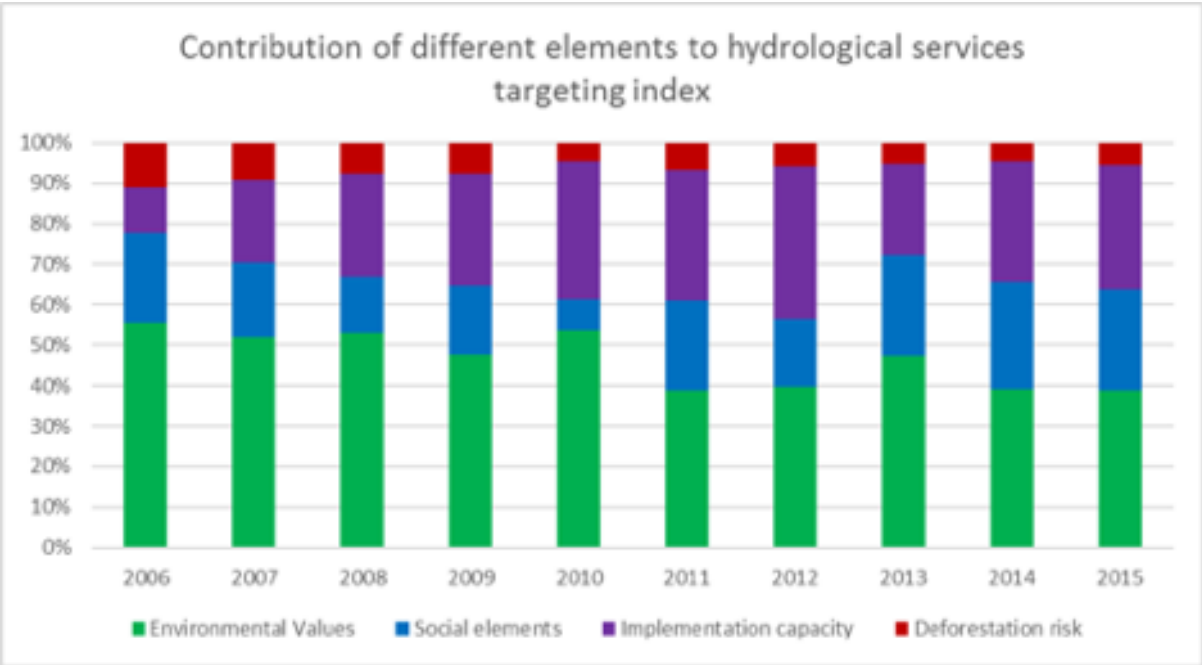
Additional tables and figures

Figure A1: Use of PES funds by accepted applicants



[1] The bars indicate the proportion of accepted applicants that used PES funds for a particular activity. Data is based on surveys of community leaders who said they were aware of the existence of the PES program (N=198 for 2011-2012 cohorts, N=245 for 2013-2014 cohorts).

Figure A2: Composition of the CONAFOR Eligibility Score



[1] Source: authors' own calculations. Percentages are determined by attributing the maximum possible point category to each targeting criterion, and then dividing by the maximum total points available.

Figure A3: Household socio-economic measures - components

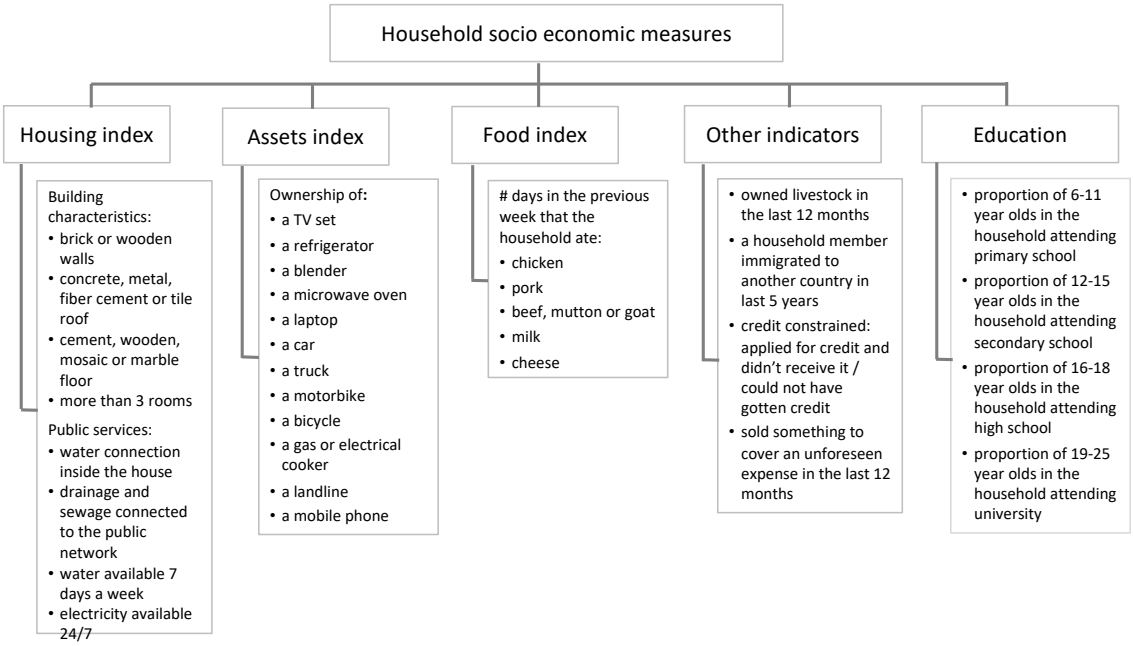


Figure A4: Social capital indices - components

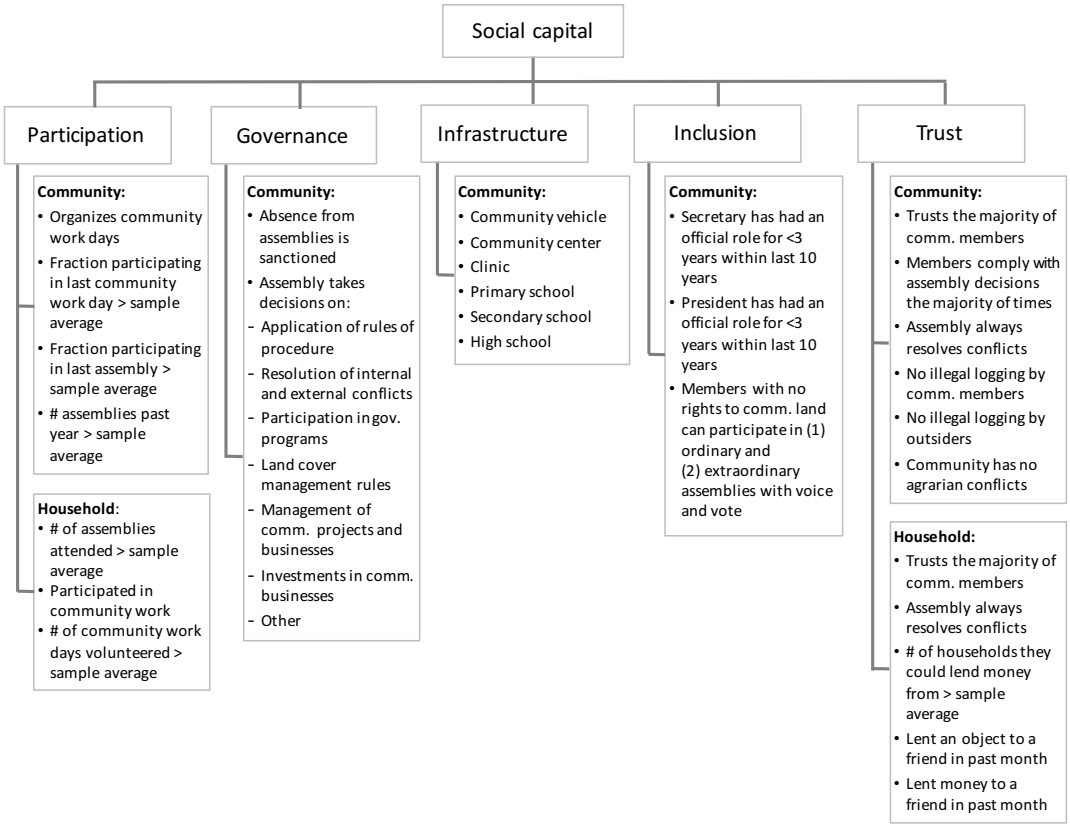
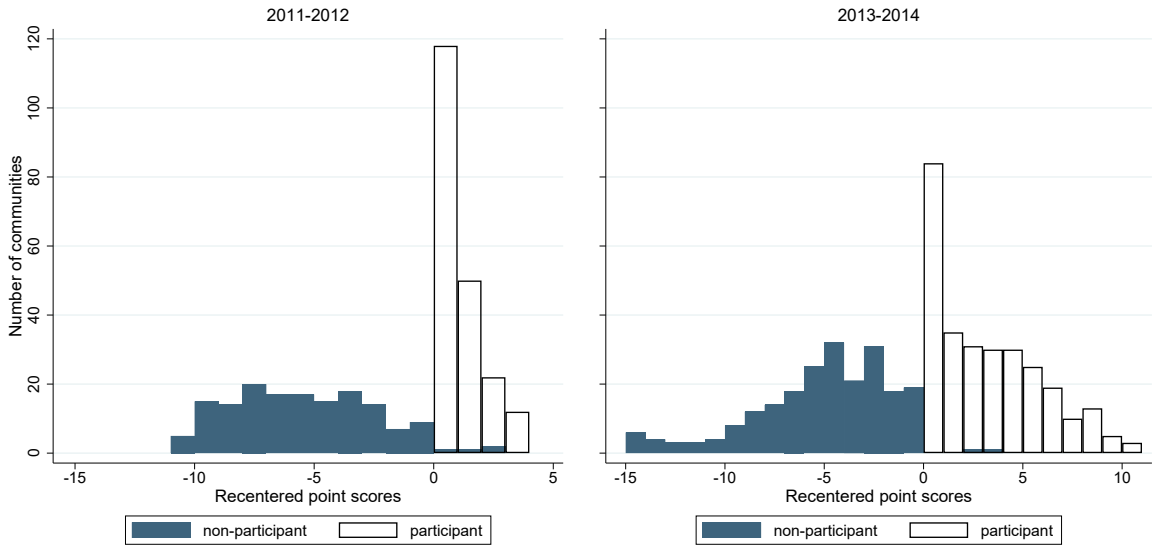


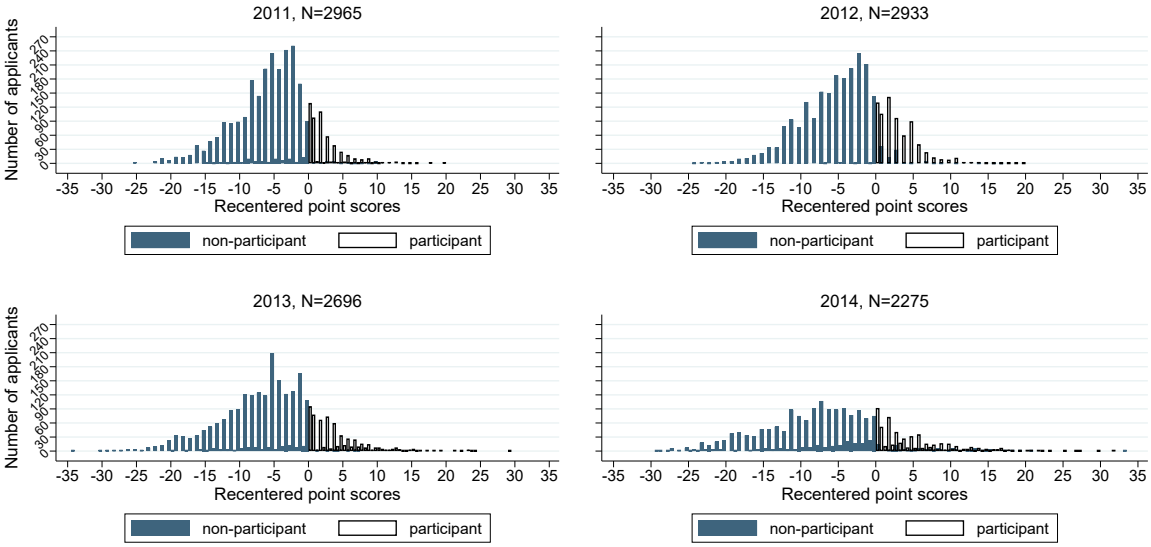
Figure A5: Distribution of point scores among surveyed communities



[1]Applicant scores were assigned by the central CONAFOR office based on pre-set formulas published in annual calls for applicants. Applicants with the highest scores within each state and sub-program received funding until the nationally-determined budgets for each state and program were exhausted. This process created multiple exogenous assignment cutoffs at different point scores. We re-centered these state and sub-program cutoffs around zero, so communities with original scores above the cutoff have positive re-centered scores ("treated" units) while communities below the cutoff have negative re-centuered scores ("control" units).

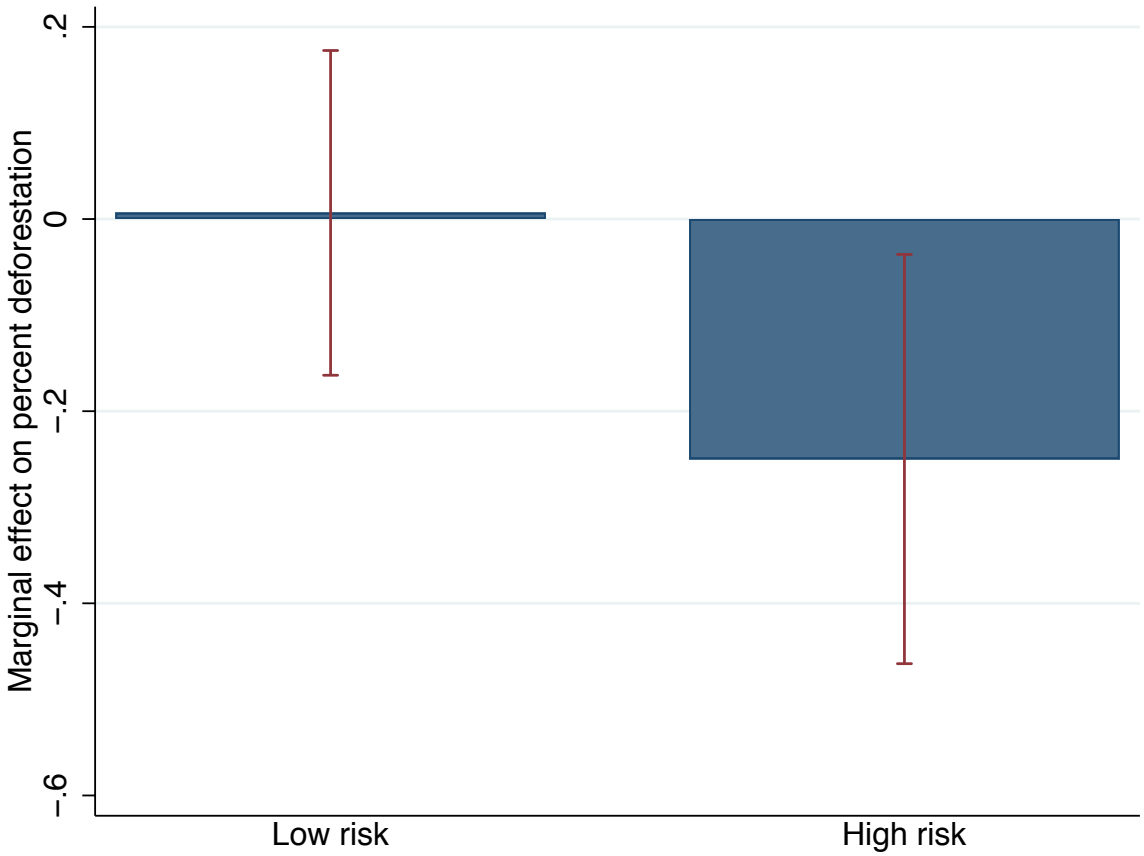
[2] Sample sizes for the 2011-2012 cohort are: above threshold 206, below threshold 151, total 357; for the 2013-2014 cohort: above threshold 287, below threshold, total 505.

Figure A6: Distribution of point scores by year - all applicants



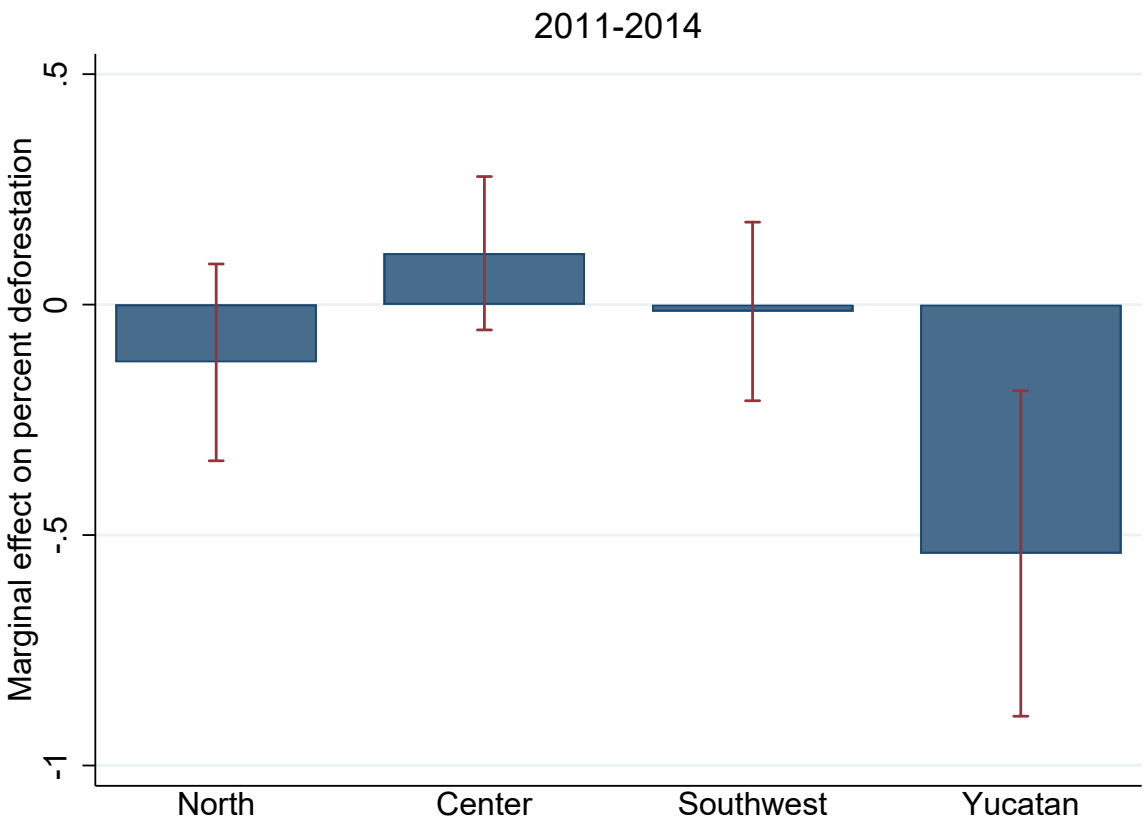
[1] The figure shows the re-centered point score for all applicants, i.e. both private and common properties, for each year of application.

Figure A7: Heterogeneity in forest cover loss impacts by deforestation risk (all cohorts)



[1]The blue columns show the estimated coefficients on the treatment for parcels with low and high deforestation risk. These are total effects. The red lines are 95% confidence intervals..

Figure A8: Heterogeneity in forest cover loss impacts across regions



[1] The blue columns show the estimated coefficients on the interaction between program treatment and region. The red lines are 95% confidence intervals.

Table A1: Point allocation by year

Type of criteria	Criteria	Points awarded by year 2011	2012	2013	2014
Required	Land area: hydrological	100-200 ha per individual 200-3000 ha (areas 1,2) and 200-6000 ha (area 3) per community	100-200 ha per individual 200-3000 ha (areas 1,2) and 200-6000 ha (area 3) per community	100-200 ha per individual 200-3000 ha per community	100-200 ha per individual 200-3000 ha per community
Required	Land area: biodiversity	100-200 ha per individual 200-3000 ha (area 4) and 200-2000 ha (areas 5,6) per community	100-200 ha per individual 200-3000 ha (area 4) and 200-2000 ha (areas 5,6) per community	100-200 ha per individual 200-3000 ha (area 4) and 200-3000 ha (areas 5,6)	100-200 ha per individual 200-3000 (area 4) and 200-2000 ha (areas 5,6)
Required	Forest Cover	50%	50%	70% North-Central 50% South-Central	70% North-Central 50% South-Central
Shared: social	Applicant has never received support from CONAFOR	7	7	7	7
Shared: social	Applicant is P-PREDIAL approved	*	*	*	10
Shared: social	Located in a municipality with 100x100 strategy	5	*	*	*
Shared: social	Applicants from marginalized areas defined by CONAPO	3	5	5	*
Shared: social	Applicants in municipality with majority indigenous population	3	3	*	*
Shared: social	Located within an Indigenous Region of Mexico and indigenous municipalities	*	*	5: All or partially located in a Type A municipality (>70% indigenous population) 3: All or partially located in a Type B municipality (40-69% indigenous population)	5: All or partially located in a Type A municipality (>70% indigenous population) 3: All or partially located in a Type B municipality (40-69% indigenous population)
Shared: social	Located within a municipality with National Crusade against Hunger program	*	*	*	10
Shared: social	Agrarian population center or indigenous population	*	*	4	4
Shared: social	Applicant is a woman	2	2	4	4
Shared: social	Applicant is a young adult (18-25 years of age)	*	*	4	4
Shared: social	Applicant presents a forest management plan at time of application	3	3	5	5
Shared: social	Audit or forest management certification in progress	2	1	2	2
Shared: social	Forestry certification	*	*	3: Environmental services component 10: Forest development, commercial forest plantations, conservation and restoration components	3: Environmental services 10: Projects and studies; Capacity building; Production and productivity; Restoration and restructing; Chain of production
Shared: social	Awards or recognition in environmental and forestry matters	*	*	*	2
Shared: social	Applicant responds quickly to the program call	10: Type I and II producers 5: Type III and IV producers	5	5	

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Type of criteria	Criteria	Points awarded by year 2011	2012	2013	2014
Shared: environment	Within a Protected Natural Area	5: Within biosphere reserve 4: Within federal ANP 2: Within municipal, state, or private ANP 1: Outside of ANP	5: Within biosphere reserve 4: Within federal ANP 2: Within municipal, state, or private ANP 1: Outside of ANP	5: Within biosphere reserve 4: Within federal ANP 2: Within municipal, state, or private ANP 1: Outside of ANP	5: Within biosphere reserve 4: Within federal ANP 2: Within municipal, state, or private ANP 1: Outside of ANP
Shared: environment	In a watershed where there are others with local payments for environmental services	5: Yes 1: No	5: Yes 1: No	5: Yes 1: No	5: Yes 1: No
Shared: environment	Environmental Watch Network (red viga) created in ejido or community	3: Yes 1: No	3: Yes 1: No	3: Yes 1: No	3: Yes 1: No
Shared: environment	In an area with an initiative for the development of a local PES mechanism	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No
Shared: environment	Land has an associated property management plan	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No
Shared: environment	Within area of high risk of deforestation as classified by INE	6: Very high 4: High 2: Medium	6: Very high 4: High 2: Medium	6: Very high 4: High 2: Medium	6 Very high 4: High 2 Medium
Shared: environment	In an area with a high risk of natural disasters	6: High risk 4: Medium 2: Low	6: High risk 4: Medium 2: Low	6 High risk 4: Medium 2: Low	6: High risk 4: Medium 2: Low
Shared: environment	Applicant provides georeferenced polygon	4: Yes 1: No	4: Yes 1: No	*	*
Shared: environment	Refrendos	4	6	*	*
Shared: environment	Applicant is prepared to assume responsibility for additional land area	*	3: 200% larger than area requested 2: 100% larger than area requested 1: 50% larger than area requested	3: 200% larger than area requested 2: 100% larger than area requested 1: 50% larger than area requested	3: 200% larger than area requested 2: 100% larger than area requested 1: 50% larger than area requested

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		Points awarded by year			
Type of criteria	Criteria	2011	2012	2013	2014
Hydrological	Priority to applicants with land of highest % forest cover	5: More than 70% 3: 61-70% 1: 50-60%	5: More than 70% 3: 61-70% 1: 50-60%	5: Greater than 70% in North-Central region or greater than 90% in the South-Central region 3: 61-70% in North-Central region or 81-90% in South-Central region 1: 50-60% in North-Central region or 70-80% in South-Central region	5: $>$ 70% in North-Central region or $>$ 90% in the South-Central region 3: 61-70% in North-Central region or 81-90% in South-Central region 1: 50-60% in North-Central region or 70-80% in South-Central region
Hydrological	Located in an overexploited aquifer	6: Overexploitation equal or greater than 100% 3: Overexploitation $<$ 100%	6: Overexploitation $\geq$ 100% 3: Overexploitation $<$ 100%	6: Overexploitation $\geq$ 100% 3: Overexploitation $<$ 100%	6: Overexploitation $\geq$ 100% 3: Overexploitation $<$ 100%
Hydrological	Within an area of high surface water scarcity	7: Availability less than 4 in the upper basin OR between 4 and 7 in the upper basin 5: Availability less than 4 in the middle of the basin or greater than 7 in the upper basin 3: Availability less than 4 in the lower basin or between 4 and 7 in the middle 2: Availability between 4 and 7 in the lower basin or greater than 7 in the middle 1: Availability greater than 7 in the lower basin	7: Availability less than 4 in the upper basin OR between 4 and 7 in the upper basin 5: Availability less than 4 in the middle of the basin or greater than 7 in the upper basin 3: Availability less than 4 in the lower basin or between 4 and 7 in the middle 2: Availability between 4 and 7 in the lower basin or greater than 7 in the middle 1: Availability greater than 7 in the lower basin	7: Availability less than 4 in the upper basin OR between 4 and 7 in the upper basin 5: Availability less than 4 in the middle of the basin or greater than 7 in the upper basin 3: Availability less than 4 in the lower basin or between 4 and 7 in the middle 2: Availability between 4 and 7 in the lower basin or greater than 7 in the middle 1: Availability greater than 7 in the lower basin	7: Availability less than 4 in the upper basin OR between 4 and 7 in the upper basin 5: Availability less than 4 in the middle of the basin or greater than 7 in the upper basin 3: Availability less than 4 in the lower basin or between 4 and 7 in the middle 2: Availability between 4 and 7 in the lower basin or greater than 7 in the middle 1: Availability greater than 7 in the lower basin
Hydrological	Area has low rate of anthropogenic soil degradation	3: Low degradation 2: Medium degradation 1: High degradation	3: Low degradation 2: Medium degradation 1: High degradation	3: Low degradation 2: Medium degradation 1: High degradation	3: Low degradation 2: Medium degradation 1: High degradation
Hydrological	Within a strategic restoration zone as determined by CONAFOR	3: Yes 1: No	3: Yes 1: No	3: Yes 1: No	3: Yes 1: No
Hydrological	Area contains high biomass density determined by ECOSUR	5: High 3: Medium 1: Low	5: High 3: Medium 1: Low	5 High 3: Medium 1: Low	5 High 3: Medium 1: Low
Biodiversity	Within a Bird Conservation Area (AICA) or a Ramsar site	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No
Biodiversity	Within a hydrological priority region (RHP) or terrestrial priority region (RTP)	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No
Biodiversity	Located within the habitat of endangered or threatened species (NOM-59-SEMARNAT-2001)	7: Probably extinct in natural environment or endangered 4: Threatened or protected 1: Outside of habitat area			
Biodiversity	Priority site for biodiversity conservation as determined by CONABIO, CONANP, The Nature Conservancy, and Pronatura	7: Extreme priority 4: High Priority 1: Medium Priority	7 Extreme priority 4: High Priority 1: Medium Priority	7 Extreme priority 4: High Priority 1: Medium Priority	7 Extreme priority 4: High Priority 1: Medium Priority
Biodiversity	Located within biological corridors	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No	4: Yes 1: No
Biodiversity	Proposed property has a shade grown agroforestry system registered with ASERCA	3: Yes 1: No	3: Yes 1: No		
Biodiversity	Applicant has an assessment regarding the establishment of community conservation areas approved by CONAFOR	*	*	4: Yes 1: No	4: Yes 1: No

Table A2a: Tests for discontinuities in covariates: environmental data

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Panel A: Community survey	
% baseline forest	0.011	0.019*	0.007
	(0.007)	(0.010)	(0.010)
Control Mean	0.893	0.880	0.907
Observations	11035	5859	5197
Ln(elevation)	0.121**	0.260***	-0.028
	(0.059)	(0.068)	(0.087)
Control Mean	6.250	6.293	6.208
Observations	11031	5856	5196
Ln(km to any road)	-0.012	-0.034	-0.060
	(0.077)	(0.098)	(0.120)
Control Mean	7.922	7.886	7.956
Observations	11035	5859	5197
Ln(km to city>5000 people)	0.024	0.030	-0.027
	(0.039)	(0.046)	(0.063)
Control Mean	3.268	3.212	3.326
Observations	11035	5859	5197
Ln(km to major city)	0.028	0.013	0.052
	(0.034)	(0.036)	(0.057)
Control Mean	4.530	4.537	4.523
Observations	11035	5859	5197
Deforestation risk	-0.002	-0.005	0.001
	(0.003)	(0.005)	(0.005)
Control Mean	0.042	0.047	0.038
Observations	10708	5669	5060
% agricultural land (NFI 2000)	-0.002	-0	0.001
	(0.007)	(0.011)	(0.009)
Control Mean	0.043	0.053	0.033
Observations	11035	5859	5197
Marginality 2000	0.015	0.082	-0.023
	(0.050)	(0.054)	(0.083)
Control Mean	0.238	0.198	0.280
Observations	11035	5859	5197

[1] To test for the same discontinuity statistically, we run OLS of the covariates on the treatment threshold, a quadratic of the running variable with slopes that vary on either side of the threshold, polygon size, a ejido dummy variable, ecosystem indicator variables, and state and year fixed effects. Standard errors are clustered at the ejido level for ejidal polygons, and at the municipal level for private properties.

Table A2b: Tests for discontinuity on selected covariates: survey data

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
	Panel A: Community survey		
Ln(km to any road)	0.228*	0.322	0.305*
	(0.138)	(0.250)	(0.171)
Control Mean	7.613	7.648	7.588
Ln(km to major city)	0.154**	0.085	0.181**
	(0.070)	(0.126)	(0.085)
Control Mean	4.601	4.664	4.557
Ln(members with rights to comm. land)	0.138	0.201	0.253
	(0.137)	(0.263)	(0.166)
Control Mean	4.641	4.616	4.659
Ln(poverty index 2010)	0.148*	0.340**	0.057
	(0.081)	(0.161)	(0.102)
Control Mean	0.079	0.015	0.124
Ln(average slope in degrees)	0.133**	0.092	0.124
	(0.060)	(0.110)	(0.076)
Control Mean	2.222	2.360	2.126
Mean canopy cover 2000	-0.498	-3.768	1.436
	(3.076)	(5.743)	(3.911)
Control Mean	47.318	40.318	52.166
Observations	862	357	505
	Panel B: Household survey		
Household head educ: sec school or above	0.015	0.001	0.019
	(0.019)	(0.037)	(0.024)
Control Mean	0.160	0.172	0.152
Observations	8350	3442	4908
Household depends upon subsistence agric	0.001	-0.058	0.047*
	(0.021)	(0.038)	(0.027)
Control Mean	0.197	0.185	0.205
Observations	8413	3466	4947

[1] Regressions include the threshold dummy, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, as well as state fixed effects. For the community level analysis, robust standard errors are presented in parentheses. For the household level analysis, standard errors were clustered at the community level.

[2] In Panel B, the number of obs for the household being dependent upon subsistence agriculture matches the full number of observations, while the number of observations for the household head education has some missing data.

Table A3: Impacts of program on forest cover loss, 25-point and 10-point windows: robustness check using a fuzzy design (IV)

	(1) **OLS**	(2) **IV**	(3) **OLS**	(4) **IV**
	Perc. deforested		**Defor >2 ha**	
		Panel A: 25-point window		
		2011-2012		
Threshold	-0.285		-0.042	
	(0.230)		(0.049)	
Enrollee		-0.295		-0.044
		(0.240)		(0.051)
Control Mean	0.956	0.939	0.093	0.092
MDE	0.644	0.672	0.138	0.143
Observations	7019	7019	7019	7019
		2013-2014		
Threshold	-0.016		-0.028	
	(0.054)		(0.038)	
Enrollee		-0.016		-0.028
		(0.054)		(0.038)
Control Mean	0.319	0.317	0.033	0.033
MDE	0.151	0.152	0.106	0.107
Observations	7127	7127	7127	7127
		Panel A: 10-point window		
		2011-2012		
Threshold	-0.324		-0.070	
	(0.336)		(0.060)	
Enrollee		-0.340		-0.073
		(0.355)		(0.063)
Control Mean	0.934	0.916	0.084	0.083
MDE	0.940	0.993	0.168	0.176
Observations	5856	5856	5856	5856
		2013-2014		
Threshold	-0.025		-0.062	
	(0.059)		(0.049)	
Enrollee		-0.025		-0.062
		(0.059)		(0.049)
Control Mean	0.329	0.326	0.036	0.036
MDE	0.164	0.165	0.136	0.137
Observations	5195	5195	5195	5195

[1] Covariates include: point score, threshold x point score, ejido indicator, ln(polygon ha) percent forest in 2000, cohort indicators, ecosystem indicators, and state dummy variables. Standard errors are clustered at the ejido level for ejidos, and at the level of the municipality for private properties. Sample is limited to polygons greater than 5 ha and with more than 50% forest in 2000. *** $p < .01$; ** $p < .05$; * $p < .10$

Table A4: Impacts of program on forest cover loss: robustness check - placebo test (dependent variable measured in 2007-2010 Hansen)

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**,	(4) **Full**	(5) **2011-2012**	(6) **2013-2014**
		Perc. deforested			**Defor >2 ha**	
Threshold	-0.056	-0.170	0.103	0.027	0.019	0.027
	(0.086)	(0.144)	(0.164)	(0.030)	(0.046)	(0.039)
MDE	0.241	0.404	0.459	0.083	0.129	0.108
Observations	14119	7019	7127	14119	7019	7127

[1] Covariates include: point score, threshold x point score, ejido indicator, ln(polygon ha) percent forest in 2000, cohort indicators, ecosystem indicators, and state dummy variables. Standard errors are clustered at the ejido level for ejidos, and at the level of the municipality for private properties. Sample is limited to polygons greater than 5 ha and with more than 50% forest in 2000. *** $p < .01$; ** $p < .05$; * $p < .10$

Table A5: Impacts of program on forest cover loss: robustness check - dropping observations with points between 0 and .5

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**	(4) **Full**	(5) **2011-2012**	(6) **2013-2014**
		Perc. deforested			**Defor >2 ha**	
Threshold	-0.132	-0.310	-0.014	-0.023	-0.030	-0.027
	(0.108)	(0.230)	(0.055)	(0.032)	(0.051)	(0.039)
MDE	0.302	0.644	0.155	0.090	0.142	0.108
Observations	14034	6975	7084	14034	6975	7084

[1] Covariates include: point score, threshold x point score, ejido indicator, ln(polygon ha) percent forest in 2000, cohort indicators, ecosystem indicators, and state dummy variables. Standard errors are clustered at the ejido level for ejidos, and at the level of the municipality for private properties. Sample is limited to polygons greater than 5 ha and with more than 50% forest in 2000. *** $p < .01$; ** $p < .05$; * $p < .10$

Table A6: Impacts on land management index: heterogeneous effects by region

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
		Impact estimates	
Threshold	0.069**	0.116*	0.073*
	(0.033)	(0.070)	(0.041)
Threshold * Chih+Dgo	0.096	0.079	0.046
	(0.044)	(0.062)	(0.069)
Threshold * NL+SLP	0.138	0.212***	0.097**
	(0.033)	(0.058)	(0.041)
Threshold * Mich+Pue+Jal	0.026	0.047	0.010
	(0.036)	(0.068)	(0.040)
Threshold * Oax+Chi	0.050	0.030	0.047
	(0.032)	(0.051)	(0.045)
Control Mean	0.273	0.247	0.292
Obs	862	357	505
		Means in control communities by region	
Chih+Dgo	0.337	0.280	0.433
NL+SLP	0.151	0.078	0.179
Mich+Pue+Jal	0.393	0.349	0.418
Oax+Chi	0.263	0.245	0.285
Camp+Yuc+Q.Roo	0.198	0.143	0.211

[1] Regressions include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, region dummies and their interactions with the threshold dummy, as well as state fixed effects. Robust standard errors are presented in parentheses. *** p < .01; ** p < .05; * p < .10

[1] The interaction term between the threshold variable and the regional dummy for the Yucatan Peninsula (Campeche, Yucatan and Quintana Roo) was omitted.

Table A7: Impacts on land management index: heterogeneous effects by deforestation risk

	(1) **Full**	(2) **2011-2012**	(3) **2013-2014**
Threshold	0.156***	0.229***	0.117***
	(0.033)	(0.065)	(0.039)
Threshold x high defor risk	-0.060	-0.131	0.005
	(0.026)	(0.041)	(0.032)
Control mean (high risk)	0.272	0.268	0.267
Obs	817	340	477

[1] Regressions include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, a dummy for high deforestation risk and its interactions with the threshold dummy, as well as state fixed effects. Robust standard errors are presented in parentheses. *** p < .01; ** p < .05; * p < .10

Table A8: Impacts on household wealth indices: heterogeneous effects by region

	(1)	(2)	(3)	(4)	(5)	(6)
	Housing index		**Assets index**		**Food index**	
	2011-2012	2013-2014	2011-2012	2013-2014	2011-2012	2013-2014
			Impact estimates			
Threshold	-0.048**	-0.027**	0.016	-0.026*	0.016	-0.005
	(0.024)	(0.013)	(0.027)	(0.015)	(0.034)	(0.023)
Threshold * Chih+Dgo	-0.016	0.019	-0.066***	0.042**	-0.091***	0.010
	(0.023)	(0.020)	(0.024)	(0.021)	(0.032)	(0.030)
Threshold * NL+SLP	0.009	0.029**	-0.009	0.049***	-0.036	0.024
	(0.024)	(0.014)	(0.026)	(0.015)	(0.036)	(0.023)
Threshold * Mich+Pue+Jal	0.077***	0	0.037	0.032**	0.013	0.014
	(0.022)	(0.012)	(0.025)	(0.014)	(0.033)	(0.021)
Threshold * Oax+Chi	0.023	0.031**	-0.011	0.030*	-0.054*	-0.023
	(0.020)	(0.014)	(0.022)	(0.016)	(0.029)	(0.025)
Control Mean	0.679	0.638	0.393	0.347	0.562	0.517
Obs	3466	4947	3466	4947	3466	4947
			Means in control communities by region			
Chih+Dgo	0.728	0.666	0.452	0.300	0.576	0.472
NL+SLP	0.639	0.630	0.368	0.344	0.563	0.512
Mich+Pue+Jal	0.666	0.693	0.478	0.461	0.678	0.623
Oax+Chi	0.679	0.647	0.326	0.264	0.503	0.441
Camp+Yuc+Q.Roo	0.611	0.582	0.326	0.337	0.507	0.509

[1] Regressions include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, region dummies and their interactions with the threshold dummy, as well as state fixed effects. Standard errors were clustered at the community level. *** $p < .01$; ** $p < .05$; * $p < .10$

[1] The interaction term between the threshold variable and the regional dummy for the Yucatan Peninsula (Campeche, Yucatan and Quintana Roo) was omitted.

Table A9: Impacts on household wealth indices: heterogeneous effects by deforestation risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Housing index		**Assets index**		**Food index**	
	2011-2012	2013-2014	2011-2012	2013-2014	2011-2012	2013-2014
Threshold	-0.020	0.003	-0	0.010	-0.033	-0.008
	(0.039)	(0.022)	(0.048)	(0.026)	(0.044)	(0.033)
Threshold * high defor risk	-0.017	-0.025	0.007	-0.027	-0.008	-0.007
	(0.027)	(0.019)	(0.031)	(0.021)	(0.033)	(0.026)
Control Mean high risk	0.682	0.638	0.379	0.363	0.553	0.523
Observations	3302	4669	3302	4669	3302	4669

[1] Regressions include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, a dummy for high deforestation risk and its interactions with the threshold dummy, as well as state fixed effects. Standard errors were clustered at the community level. *** p < .01; ** p < .05; * p < .10

Table A10: Impacts on household wealth indices: heterogeneous effects by whether the household received PES payments

	(1)	(2)	(3)	(4)	(5)	(6)
	Housing index		**Assets index**		**Food index**	
	2011-2012	2013-2014	2011-2012	2013-2014	2011-2012	2013-2014
Threshold	-0.023	-0.005	-0.001	0.009	-0.036	-0.003
	(0.038)	(0.020)	(0.044)	(0.023)	(0.040)	(0.030)
Threshold * received PES payments	-0.022	-0.017	0.013	-0.022*	0.024	0.003
	(0.015)	(0.012)	(0.020)	(0.013)	(0.020)	(0.017)
Control Mean	0.679	0.638	0.393	0.347	0.562	0.517
Observations	3466	4947	3466	4947	3466	4947

[1] [1] Regressions include the threshold dummy variable, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy, region dummies and their interactions with the threshold dummy, as well as state fixed effects. Standard errors were clustered at the community level. *** p < .01; ** p < .05; * p < .10

Table A11: Impacts on household wealth indices - robustness check: excluding State fixed effects and including a set of controls

	(1) No covariates	(2) State FE	(3) State FE, controls	(4) No covariates	(5) State FE	(6) State FE, controls
		2011-2012			**2013-2014**	
Housing index	-0.054	-0.029	0.011	0.001	-0.009	-0.012
	(0.041)	(0.037)	(0.029)	(0.021)	(0.019)	(0.018)
Control Mean	0.679	0.679	0.679	0.638	0.638	0.638
Assets index	0.012	0.003	0.046	0.032	0.004	0.001
	(0.052)	(0.044)	(0.033)	(0.027)	(0.022)	(0.020)
Control Mean	0.393	0.393	0.393	0.347	0.347	0.347
Food index	-0.023	-0.029	-0.003	0.027	-0.003	-0.011
	(0.047)	(0.040)	(0.036)	(0.032)	(0.029)	(0.028)
Control Mean	0.562	0.562	0.562	0.517	0.517	0.517
Obs	3466	3466	3466	4947	4947	4947

[1] [1] Specs (1) and (4) are basic regressions with the threshold dummy, the first and second order polynomials of the re-centered point score and their interactions with the threshold dummy. Specs (2) and (5), in addition, include state fixed effects. Specs (3) and (6) include state fixed effects and a set of control variables. Standard errors were clustered at the community level. *** $p < .01$; ** $p < .05$; * $p < .10$

[2] Controls include the following variables: the log transformation of the number of community members with and without rights to communal land, of the number of hectares of land (private and communal) the community had, of the distance to the nearest market (in minutes) and of the poverty index in 2010, a dummy indicating whether the community is an ejido or a comunidad, dummies for the type of land cover (primal forest, rainforest, shrub vegetation), mean canopy cover, distance to the nearest city with at least 5000 inhabitants (in km).