TWO-DIMENSIONAL EVALUATION: THE ENVIRONMENTAL AND SOCIOECONOMIC IMPACTS OF MEXICO'S PAYMENTS FOR HYDROLOGICAL SERVICES PROGRAM

April, 2012

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ABSTRACT

Payments for ecosystem services (PES) programs are likely to expand under international agreements to reduce carbon emissions from deforestation and forest degradation but empirical evidence on their effectiveness is limited. We investigate impacts of a federal program in Mexico that compensates landowners for forest protection on two dimensions: deforestation and household wealth. To establish counterfactual deforestation rates and growth in household assets across time, we use matched controls from the program applicant pool. We find significant evidence that deforestation was reduced by the program and suggestive evidence of positive socioeconomic benefits, particularly for landowners with full rights in common properties. Our analysis of heterogeneity in program effects indicates that most efforts to further increase avoided deforestation would have regressive wealth impacts. A possible exception is additional targeting of funds to common property recipients.

Acknowledgements: We thank the Mexican National Forestry Commission (CONAFOR) for their generous sharing of time, expertise and data (including but not limited to: Leonel Iglesias Gutiérrez, Sergio Graf Montero, Paola Bauche Petersen, Jesús Gutiérrez Cacique, Rodolfo Valdez García, Adriana Saldaña Espejel, Carmen Meneses Tovar, Efrain Abundio Ramírez, Iris Lilian Ruiz Montes, and Sofia Cortina Segovia). We thank our survey coordinator, Rodolfo Rubio Salas and all of the encuestadores for their perseverance and time in the field. We thank Pedro Camilo Alcantara for the NDVI data on Mexico. We thank Carlos Ramirez Reyes, Leah Fine, Caroline Stedman, Melissa Sullivan, Alejandro Sucre, Adam Medoff, David Ortega Flores, and Mara Munoz Quetzalli for excellent research assistance. We are especially grateful to the International Initiative for Impact Evaluation (3ie) and the National Science Foundation #1061852 for financial support. Please send comments to: alixgarcia@wisc.edu or ksims@amherst.edu.

INTRODUCTION

Payments for ecosystem services (PES) programs are expected to expand quickly under international agreements to reduce carbon emissions from deforestation and degradation ("REDD" agreements, see IUCN 2009, UNFCCC 2009, Wunder and Wertz-Kanounnikoff 2009, Angelsen 2008). The UN-REDD Program (2011) estimates that future financial flows for REDD programs, including PES, may be up to US $30 billion a year. Mexico is one of a handful of countries (Costa Rica, Ecuador and Brazil) which have already established national programs for avoided deforestation, but several countries are experimenting with such programs, including Indonesia, Bolivia, Vietnam, Columbia and Uganda (UN-REDD 2011, Wunder and Wertz-Kannounikoff 2009, Jindal et al. 2008). However, despite their increasing popularity, there are significant concerns about using PES to achieve REDD goals, including whether PES can effectively generate avoided deforestation and whether they are likely to harm the poor by restricting access to forest resources or agricultural land (Hawkins 2011, Corbera et al. 2011, Pattanayak, Wunder and Ferraro 2010, Bulte 2008, Pfaff et al. 2007, Zilberman et al. 2008). Unfortunately, current debate is limited by the small amount of rigorous retrospective empirical evidence about PES impacts in developing countries (see references in Alix-Garcia et al. 2012, Arriagada and Perrings 2011, Pattanayak, Wunder and Ferraro 2010, Uchida et al. 2009). In particular, previous analyses of avoided deforestation programs have not simultaneously evaluated impacts on both environmental and socioeconomic dimensions, despite the clear potential for tradeoffs between these goals. Although PES has been promoted as an anti-poverty tool (Lipper et al. 2009), the characteristics which are likely to drive high environmental effectiveness may or may not be correlated with those that stimulate socioeconomic gains (Pfaff and Robalino 2012, Pagiola et al. 2005, Jack et al. 2008, Zilberman et al. 2008, Alix-Garcia et al. 2008).

We evaluate avoided deforestation and wealth impacts for a federal ecosystem services program in Mexico which pays landowners to maintain forest cover under five-year renewable contracts. Between 2003 and 2011, the Mexican National Forestry Commission (CONAFOR) allocated 520 million USD to enroll more than 3.1 million hectares of land (CONAFOR 2012) in programs of payments for hydrological services (PSAH) or biodiversity services (PSACABSA). This makes Mexico's program one of the largest payments for ecosystem services programs in the world, along with the U.S. Conservation Reserve Program, China's Sloped Land Conversion Program, and Costa Rica's Payments for Ecosystem Services Program.[1]

By studying Mexico's hydrological services program, we seek to contribute to the existing literature on incentive-based conservation in two ways. First, we provide new evidence on the environmental effectiveness of a national PES program. This information may be valuable for other developing countries contemplating a similar style of promoting avoided deforestation. To date, previous research at the national level and across multiple years studies only Costa Rica's program (Pfaff et al. 2011, Robalino and Pfaff 2011, Arriagada 2008, Sánchez-Azofeifa et al. 2007). Rigorous retrospective evidence about Mexico's program is limited, covering only the earliest program cohorts (Alix-Garcia et al. 2012, Muñoz-Piña et al. 2008) and the Monarca reserve (Honey-Roses et al. 2011). Second, we simultaneously evaluate both environmental and development outcomes of PES across space. Such "two-dimensional" evaluation is difficult because of large differences in the scale and type of data needed to measure environmental versus socioeconomic impacts, but is necessary in situations where there is a high probability of tradeoffs between the two goals. Previous research on PES suggests considerable heterogeneity in both environmental effectiveness and poverty alleviation impacts across space (Pfaff and Robalino 2012, Alix-Garcia et al. 2012, Uchida et al. 2009). To date, however, the wealth impacts of avoided deforestation programs have not been evaluated directly or compared to environmental impacts.[2] More broadly, this work contributes to a small but growing number of studies which evaluate land conservation policy, including protected areas and reforestation payments, on both environmental and development dimensions (e.g. Ferraro et al. 2011, Sims 2010, Uchida et al. 2009, 2007, Xu et al. 2006, Alix-Garcia, Naughton-Treves and Chapman 2011).

To assess the avoided deforestation impacts of Mexico's program, we compare differences in forest cover, measured by mean NDVI, across time annually from 2003-2011. We estimate impacts based on panel data comparisons (including property-level fixed effects)

[1] In comparison, the United States Conservation Reserve Program had approximately 15 million hectares of land (37 million acres) enrolled at its all-time high in 2007 (Ferris and Siikamaki 2009), with an annual budget of almost $2 billion USD.

[2] Previous work on China's Sloped Land Conversion Program, which pays for reforestation, finds impacts including increases in some types of assets and in off-farm labor participation (Uchida et al. 2009, 2007).

between accepted and matched rejected applicants from the 2004-2009 cohorts. To assess socioeconomic impacts, we compare changes in household asset ownership from 2007 to 2011 between recipients and matched rejected applicants from the 2008 cohort. Household data comes from a national household survey designed and run by the authors. For both dimensions, we construct the counterfactual case--i.e. what would have happened in the absence of the program--based on the behavior of applicants rejected from the program. This allows us to control for the key unobservable issue of desire to enroll in the program, which may be correlated with land quality or other household characteristics which could otherwise bias estimates. We also control directly for other characteristics which might drive selection into the program and could influence trends in deforestation or asset ownership, including parcel location, land quality, baseline forest type and tenure type.

We find that the PSAH program has significantly reduced forest loss compared to other initially forested areas in Mexico. Back of the envelope conversions from changes in NDVI to land area deforested suggest that the expected annual loss of forest cover across Mexico is approximately 1.5% per year. Our estimates suggest the program reduces this trend by about 2%, which is approximately 30 percent of the expected 7.5% loss across 5 years. These results indicate a moderate avoided deforestation impact, with room for additional improvement in targeting of payments. We also find significant heterogeneity in avoided deforestation impacts, with larger impacts in communally held lands, near urban areas, and in less poor municipalities. Targeting on these characteristics may increase avoided deforestation but will be difficult due to the high spatial dispersion of deforestation. Finally, when we examine the year by year program impact, we find that it increases over time until the last year of enrollment, when it is not significantly different from zero. This finding, combined with standard game theoretic reasoning, suggests that lengthening contracts could improve avoided deforestation.

Our preliminary socioeconomic analysis also suggests cautious optimism with respect to poverty alleviation goals. First, we find that the PSAH program did reach many poor communities and households and that program effects within communities were broadly progressive. Second, we find suggestive evidence for small positive impacts on asset acquisition for households in communal properties, indicating improvements in wealth due to the program. We do not find significant wealth impacts for private property recipients. We interpret these results as an indication that PES is not making households worse off, but it also does not appear to be conferring large surplus rents to individual landowners which are showing up in asset growth. This may indicate that the size of the payments is relatively small compared to the total costs of participating, or that payments are being channeled to other uses. We find suggestive evidence that wealth impacts are greater further from urban localities, where opportunity costs are likely lower.

Considering the impact results from both dimensions simultaneously, our analysis indicates only limited potential for changes in targeting that could produce both more avoided deforestation and more poverty alleviation. More avoided deforestation could be produced by additional targeting to high quality lands (for instance near urban areas and in less poor municipalities) but these changes would make the program less progressive. More avoided deforestation might also be achieved by raising payments. This would increase positive wealth impacts but would simply mean higher payments to fewer individuals unless the program budget is also expanded. Our results indicate that one possibility that could represent a "win-win" on both dimensions is additional targeting of payments to communally-owned properties, which are poorer on average and also show higher avoided deforestation impacts.

The paper proceeds as follows. Section 1 describes a simple economic framework which illustrates how PES changes deforestation incentives and why we are likely to expect heterogeneity in impacts across geographic and social characteristics. Section 2 outlines the data and empirical strategy for assessing the avoided deforestation impacts of the program. Section 3 presents estimation results of program effectiveness with respect to avoided deforestation. Sections 4 and 5 describe the survey design and results on household wealth and Section 6 concludes.

1. ECONOMIC FRAMEWORK

1.1 Framework

In order to illustrate the problem faced by the program managers in designing a payments for avoided deforestation program, we discuss a simple von Thünen style model of land use (see e.g. Chomitz and Gray 1996, Samuelson et al. 1983, Pfaff 1999, Angelsen 2010, Robalino 2007, Pagiola and Zhang 2010, Pfaff et al. 2011).[3] Figure 1 shows a graphical representation. Assume that there is a set of landholders, varying in land quality (q), where quality is determined by factors such as distance to city, soil type, and altitude. This metric is decreasing across the x-axis so the highest rents are to the left (in keeping with the convention of standard von Thünen models where land quality is based on distance to city). Each landholder seeks to maximize rents and can choose to allocate his land to either agriculture or forest activities depending on the relative return to the two uses.[4] By assumption, returns to agriculture on high quality land are greater than returns to forest, while returns to forest on low quality land are higher than for agriculture. At time t=0, the initial rent curve for forest is r_f^0 and for agriculture is r_a^0. The initial equilibrium agriculture-forest boundary point is at (b^0), where agricultural rents equal forest rents. Land to the left of this point is in agricultural use and land to the right in forest use.

Deforestation between t=0 and t=1 is motivated by an increase in the rents to agriculture from r_a^0 to r_a^1 (for instance because of population growth or increasing consumption of land-intensive goods as the population grows richer). Without any policy intervention, the rent curve for agriculture shifts up and the agriculture-forest boundary point moves to b^1. Deforestation will happen on parcels between b^0 and b^1.[5]

1.2 PES payments and avoided deforestation

Now assume the regulator acts at time t=0 to combat this expected deforestation trend by offering to pay landowners who maintain forest cover. We assume that due to feasibility or political reasons, he can only offer a fixed payment amount for each hectare of land (as was the case in Mexico's PES program from 2003 to 2010). However, to target the program, the regulator may establish "eligible zones" in which the payments are available and may exclude other areas.

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[3] See Zilberman et al. 2008 for a complete general equilibrium theoretical analysis of the potential distributional effects of PES.

[4] Forest loss and degradation in Mexico are due to both human-induced change, primarily the expansion of agricultural or pastoral activities and logging, and to natural causes including fires, pests, disease, drought and storm damage (Alix-Garcia, de Janvry, and Sadoulet 2005, Alix-Garcia 2007, Bray and Klepeis 2005, Deininger and Minten 1999, 2002, Diaz-Gallegos et al. 2009.)

[5] We confirm the expected patterns using data from Mexico's Monitoreo Forestal. Probit models indicate that deforestation between 2003-2009 is indeed strongly predicted by slope, distance to the nearest locality with population greater than 5000, and elevation with the expected signs.

Looking at Figure 1, it is clear that in order to achieve full avoided deforestation[6], the regulator should choose a payment greater than or equal to the change in the agricultural rents (Δr_a). In order to minimize budget outlays, the regulator should pay as few people as possible, so the ideal eligible zone for payments is between b^0 and b^1. Assuming that there is no leakage or slippage, payments of Δr_a and eligibility from b^0 to b^1 would achieve "full" avoided deforestation at least cost--the rent curve for forest would shift up to r_f^{PESopt} and the boundary between agriculture and forest would remain at b^0.

In reality, of course, the regulator cannot perfectly predict the future. Let us consider two ways he may fail to achieve "full" avoided deforestation. First, he may set the payments too low. In this case, the forest rent curve shifts up to r_f^{PESlow} and the agriculture-forest boundary shifts to $b^{1'}$. Deforestation happens between b^0 and $b^{1'}$, and "avoided deforestation" is only between $b^{1'}$ and b^1. In general, the smaller the size of the payments, compared to the magnitude of the increase in agricultural rents, the less avoided deforestation will be achieved. Second, the regulator may not be able to perfectly target payments to the eligible zones. Suppose, for instance, the payment is set correctly, but the eligible zone is chosen to be between b^0 and b^z. If the budget is fixed and payments are allocated on a first-come, first-served basis, many of the payments will go to landowners who would not have deforested even in the absence of payments (those between b^1 and b^z). Conversely, some of the landowners between b^0 and b^1 will not get payments and will deforest. If the budget is unlimited, then full avoided deforestation is achieved with the larger eligible zones, but many payments will be made to landowners who would not have deforested. In an impact analysis, the apparent average "effectiveness" of the payments will be low.

1.3 PES payments and socioeconomic gains

Let us now consider the socioeconomic implications of the program. In our Figure 1, the surplus rent received by landowners equals (at most) the payments minus the opportunity cost of land use (transaction costs and maintenance costs would further lower the surplus).With the "optimal" PES policy (payments = Δr_a and an eligible zone from b_0 to b_1), the total surplus

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[6] Note that an efficient PES program would maximize environmental net benefits; these benefits might depend on land quality so full avoided deforestation might not be economically efficient. For simplicity, we assume uniform environmental benefits across land quality and we focus on the cost-effectiveness of the program.

gained by landowners is triangle s. Note that the amount of surplus gained by individual landowners increases as land quality decreases because opportunity costs are lowest on this land. This suggests that we should see greater socioeconomic impacts of the program where land quality is lower. In addition, whether or not the program is progressive will depend on the correlation between wealth and land quality. If wealth is negatively correlated with land quality, then the program should be progressive within the set of households that receive payments. However, note that for our optimal policy, the poorest landowners would be outside of the eligible zones and would not receive any benefits. As the regulator better targets the eligible zones to minimize budget expenditures, more payments go to the set of landowners in the middle of the land quality distribution, and the progressivity of the program is reduced. In addition, we would likely see lower socioeconomic impacts on average because less of the payments are surplus above opportunity costs. This implies a direct tradeoff between generating more avoided deforestation and increasing socioeconomic impacts.

This model is consistent with previous empirical and theoretical research suggesting heterogeneity in both environmental effectiveness and poverty alleviation of PES across space. For instance, Arriagada et al. (2011) find larger avoided deforestation impacts of Costa Rica's PES program in the Osa region, where threats to forest are high. Wünscher et al.'s (2008) simulation shows that the avoided deforestation benefits of PES in Costa Rica could be increased by targeting based on landowners' participation costs. Consistent with this, Pfaff et al. (2011) find that efforts to better target Costa Rica's PES payments starting in 2000 did improve avoided deforestation impacts from 2000-2005. Alix-Garcia et al. (2012) find more avoided deforestation where baseline poverty rates are lower and Honey-Roses et al. (2011) find larger impacts of PES in protecting high quality habitat in the Monarca reserve. Several previous papers have suggested theoretically that the socioeconomic impacts of PES are also likely to be heterogeneous (Zilberman et al. 2008, Pagiola et al. 2005, Jack et al. 2008, Wunder 2008) while Uchida et al. 2009 finds empirically that poorer households participating in China's SLCP had greater changes in off-farm labor participation.

1.4 Opportunities for win-win?

Land quality is a multidimensional function and may depend on several characteristics such as distance to cities, slope, soil quality, prior clearing, tenure type, forest type, and the quality of transportation networks. In most cases, we expect that factors that increase land quality will be negatively correlated with wealth: distance to city and slope are clear examples (both are positively correlated with the degree of marginalization in our data). This means that opportunities to target the program to improve both avoided deforestation and socioeconomic impacts may exist but are likely limited unless we are willing to accept low avoided deforestation per budgetary expenditure.[7]

Two possible exceptions might be increased targeting on the basis of tenure type or by region. Tenure arrangements are a complex function of historical developments (Alix-Garcia 2008) that were not driven only by geography. In our data, common properties show both a higher rate of deforestation and lower wealth than private properties on average, suggesting potential for win-win outcomes. There may also be scope for additional targeting on the basis of region. To put this in the context of our graphical model, we might imagine a second region which looks similar but in which the zone of expected deforestation starts at a lower land quality. If the relationship between poverty and land quality remains the same, then PES in this second region will go on average to poorer households.

Finally, since the correlation between threat of deforestation and poverty is not perfect, the regulator can also try to ensure that the households or communities inside the eligible zones which receive payments are poorer at baseline. This is in fact close to the system that has currently been established and gives some priority on the basis of degree of marginalization. With this simple economic framework in mind, we turn to the data on Mexico's program.

2. AVOIDED DEFORESTATION: BACKGROUND, DATA, EMPIRICAL STRATEGY

2.1 Program background

Mexico's program of Payments for Hydrological Services grants five-year renewable contracts to both individual and communal landowners. Landowners may enroll a portion of their property and must maintain existing forest cover within the enrolled parcel, but can make changes to land cover in other parts of their property. Verification of forest cover is made by

[7] Note that from an economic perspective, the true costs of the program are not measured by budgetary outlays, but by the opportunity costs of lost production or timber extraction from land that would have been cleared, the administrative and transactions costs of running and participating in the program, and any distortionary effects of raising the program revenue. The majority of the program budget therefore should be regarded as a transfer.

satellite image analysis or ground visits. Landowners are removed from the program if CONAFOR finds deforestation due to conversion to agriculture or pasture within the enrolled area. Payments are reduced if forest is lost due to natural causes such as fire or pests (Muñoz-Piña et al. 2008). Annual payment rates for the cohorts we study (2004-2009) are given in Table 1. They correspond to approximately $27 USD per hectare for general forest types and approximately $36 USD for cloud forest. The initial rates were based on estimates of the average per hectare opportunity cost of growing maize. They have since been adjusted to match inflation and are currently set as a multiple of 6.5-8.5 times the federal minimum daily wage (Shapiro and Castillo 2012).

More than half of the program participants live in communally held and governed structures, including "ejidos", which are federally recognized common property holdings with land tenure and governance rights granted to a set number of households, and "comunidades", which are indigenous lands.[8] The Mexican ejidos and comunidades resulted from a drawn-out land reform that extended from the end of the 1910 Revolution until the early 1990s. During this time, an area equivalent to half the country was redistributed to peasants organized in communities. Ejidos are composed of two different kinds of property rights over land: private parcels and commons. Private land is mostly used for agricultural activities, while the commons are mainly dedicated to pasture and forest, and are home to approximately 80% of Mexico's remaining forest. Within these same communities there also live many people who are not members of the ejido, usually descendants of the original members (ejidatarios) who were prevented from becoming members by the legal restriction on inheritance to only one child. The nonmembers do not have voting rights and are not formally given land, but in practice they often farm on ejido lands ceded by others or illegally taken from the commons.

2.2 Data on PES recipients

Using program data and GIS boundaries of program applicants from CONAFOR, we construct a spatial database of all applicants to the program from 2004-2009. Figure 2 shows the location of the participants and controls as well as the outlines of the area forested in Mexico prior to 2003 by six categories of forest. To analyze program effects from 2004-2009, we use

[8] For more detail, see references in Alix-Garcia 2008.

points as a unit of analysis; intersecting these points with the program polygons allows us to clearly code the program status of each point in each year.[9] The points are a random sample from within PSAH applicant boundaries from 2004-2009 which were classified as one of six forested categories in the INEGI Series III land use layer (circa 2002). To minimize spatial autocorrelation, we sample only at a density of 1 point per square km (~38,000 points) and cluster all standard errors by property. In order to understand deforestation behavior in lands outside of program applicants during the same time period, we also randomly select 50,000 points which were classified as forested prior to the start of the program from across all of Mexico.[10]

2.3 Measure of forest cover

To assess the environmental effectiveness of the program, we use the average dry season normalized difference vegetation index (NDVI) in each year from 2003-2011 as a measure of forest cover. NDVI is a measure of the "greenness" of vegetation based on the reflectance signatures created by leafy vegetation versus other land cover (NASA 2012). Deforestation or significant forest degradation is thus indicated by a decrease in average annual NDVI. We construct mean NDVI for each year using MODIS composites from the Aqua and Terra satellites taken between February 15 and April 15. Although the data used in this paper was newly constructed by us, similar methodology has been previously established and field-tested by the Mexican National Forestry Commission (CONAFOR 2011, Meneses-Tovar 2009a,b). Economists have also relied on NDVI decreases to measure deforestation in previous research in developing countries (Burgess et al. 2011, Foster and Rosenzweig 2003).

The key advantages of the MODIS data are its temporal density (weekly products) and wall-to-wall coverage of Mexico. Frequent passes by the satellites mean that data is complete even for areas which experience a lot of cloud cover (such as the Yucatan peninsula) and that it is thus feasible to construct a wall-to-wall dataset for all of Mexico for each year. The downside is that MODIS is spatially coarse, with resolution at 250m pixels (~ 6 ha). This does not mean

[9] This is necessary because of the complex spatial overlap of applications between years. For instance, a landowner may choose to apply with a portion of his land in one year and then if he is rejected, apply again with a different portion in the next year.

[10] We eliminate points which had 2003 NDVI values indicating they were not in forest in 2003. Specifically, we drop points where the 2003 NDVI is less than 0.3 in regions 1, 2, and 3 and less than 0.6 in region 4).

we cannot detect smaller areas of forest loss-- NDVI is a continuous measure, so clearing or degradation of smaller areas will still decrease the NDVI value. However, we are limited in that we do not know exactly where in each 250 x 250 m area this loss or degradation occurred. Given the average size of the properties enrolled between 2004-2009 is 680 ha (> 100 pixels), we believe the resolution of the data is appropriate for this analysis. However, since small areas of clearing do happen in Mexico, particularly in the south, we maintain the continuous measures of NDVI in our analysis rather than classifying each pixel as forested or non-forested. We do also check robustness of the results to several alternate definitions of forest cover.[11] Finally, we note that all measures of forest cover are sensitive to seasonal vegetative cycles ("phenology") and annual variation in rainfall. (More rainfall at the right time will increase the density of leaf cover, particularly in deciduous forests.) To control for this variability, we include measures of the average NDVI in each municipality in each year to control for geographically specific rainfall shocks.[12]

2.4 Selection of controls and regression models

Evaluation of Mexico's PSAH program involves the standard identification problem: one does not know how recipients would have behaved had they not received payments. To construct a reasonable counterfactual case, we rely on comparisons across time between accepted and rejected applicants to the PSAH program. A key advantage of using controls drawn from the applicant pool is that all owners have demonstrated their desire to enroll in the program, revealing that their expected participation costs are sufficiently low to motivate application.[13] However, even with program applicants as controls, there still may be other remaining characteristics which could be correlated with selection into the program and changes over time

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[11] Alternate measures of forest health included the log of NDVI and NDVI normalized to have a mean of zero and standard deviation of one in each year and region. We also tried classifying pixels into forest and non-forest categories based on the absolute NDVI values as well as the relative NDVI values (with respect to all other points and with respect to the non-forested points). We then constructed measures of deforestation based on the year to year difference in the mean NDVI, normalized NDVI, or classified forest categories. Results are similar across these alternate measures.

[12] Direct rainfall data may be preferable; we are currently developing the relevant measures. As a robustness check on including the mean of municipality NDVI for all points, we also use a measure of average NDVI in only non-forested points in each municipio. We select 50,000 random points in non-forested areas according to the INEGI Series III land use layer and construct municipality averages. Results are similar.

[13] The main criticism of previous research on PES programs is that results may be driven by possible selection bias due to unobservable characteristics driving lower opportunity costs of enrolled parcels compared to non-applicant controls.

in deforestation. To address this problem, we investigate the selection process, pre-match data on the basis of relevant characteristics, and estimate panel regressions including appropriate controls. Our preferred specification includes property-level fixed effects, in order to control for any unobservable fixed characteristics of the parcels.

Selection into the PSAH program is described in more detail in Shapiro and Castillo (2012). Broadly, the requirements are that the submitted parcels have a set amount of forest cover to start (> 80% in 2003-2005; > 50 in 2006-2009) and be inside designated eligible zones.[14] From 2006 onwards, priority was also given to properties with a high risk of deforestation (as measured by INE's v1 layer), in high poverty municipalities, and with other specific environmental or social criteria such as priority mountains or female leadership (Shapiro and Castillo 2012). We solicited data on the reasons for rejection in each year and find that there are four main reasons for rejection in our panel dataset: 1) having all the qualifications but being rejected for lack of funding due to program budget constraints, 2) failing to meet the minimum forest cover requirement, 3) being located outside of the eligible zones, 4) having incomplete paperwork or failing to meet other technical requirements. More than 40% of our control points are in the first group, which is the best comparison group because these applicants met all of the requirements and simply submitted an application a few days or weeks later than other applicants. Approximately 30% of the applicants in our sample were rejected for the second two reasons, which constitute selection on observables. To account for this selection, we match on or control for appropriate geographic characteristics as described below. The fourth reason for rejection is potentially more problematic: missing paperwork could reflect lower institutional capacity which is not directly observable and might be correlated with deforestation (approximately 20% of our sample). To minimize this problem, we limit our analysis to applicants which have sent in geo-referenced property boundaries and have already passed through a first round of screening, ensuring a reasonable level of institutional capacity. We also match on municipal poverty levels and tenure type, which may correlate with institutional capacity.

[14] The characteristics determining eligibility include: being in a watershed which supplies a locality with population greater than 5000, being within a watershed that is characterized as overexploited, and being in a priority mountain or protected area.

Prior to estimation, we pre-match points within accepted parcels to rejected parcels on the basis of characteristics which determined selection into the PSAH program and could drive deforestation patterns. We use 1:1 covariate matching on the Mahalanobis metric. The covariates we match on are slope, elevation, distance to the nearest locality with population greater than 5000, baseline forest type, and baseline municipal poverty. Matching is conducted within region and tenure type (common vs. other). These controls were chosen on the basis of the reasons for rejection and the economic drivers of deforestation in Mexico (Alix-Garcia 2007, Alix-Garcia et al. 2005, Muñoz-Piña et al. 2008, Bray and Klepeis 2005, Deininger and Minten 1999).

Our preferred specification ("property fixed effects") is as follows:

$$(1) \quad MNDVI_{ipmvst} = \beta(beneficiary_{it}) + \sum_{v=2}^{6} \gamma_v (foresttype_v * munNDVI_{mt}) + \alpha_{st} + \alpha_p + \varepsilon_{ipt}$$

where *MNDVI* is the mean dry season NDVI value for point *i* in parcel *p*, municipality *m*, forest type *v*, state *s,* and year *t*. The variable *beneficiary* is an indicator equal to 1 if the point was enrolled in the program in the previous year's cohort; β is the coefficient of interest (average program impact).[15] $MunNDVI_{mt}$ is the average NDVI for each municipality and year and provides a control for rainfall shocks; it is interacted with the forest type to account for the different NDVI signatures of different forest types. We also include state-year fixed effects (α_{st}) to control for possible economic shocks to states in each year. Finally, we include property level fixed effects (α_p) to control for possible unobservable fixed characteristics. Standard errors are clustered at the property level to account for spatial and serial correlation.

3. AVOIDED DEFORESTATION: RESULTS

3.1 Summary stats

Table 2 shows summary statistics for the unmatched and matched treated and comparison groups and the normalized difference in means (Imbens and Wooldridge 2007). For comparison, we also include summary statistics and normalized differences for a random sample of initially forested points outside of program applicants. We see that beneficiary lands are somewhat closer

[15] Equal to 1 if the point was enrolled in the program in the previous year's cohort (including receiving "elaboration" support to develop a proposal.) The lag is to take into account the timing of the applications versus the timing of the NDVI measurements. Applications are submitted in the spring and notifications are made in late summer, while NDVI is measured Feb-April.

to localities than the non-beneficiaries and all other forest points (-.14 standard deviations closer) but have higher slope and elevation than the non-beneficiaries and the random sample of forest points. The beneficiaries are in municipalities with slightly higher poverty index values (.27 vs .26 and .24) but these differences are quite small (0.009 and 0.021) when normalized by standard deviations. The program clearly enrolled more land in common properties (88% in the accepted points vs. 80% in the rejected applicant points and 60% in other forested points) and these differences are fairly large in standard deviation terms: .15 and .48 standard deviations greater, respectively. The mean risk of deforestation among beneficiaries, according to Mexico's Instituto Nacional Ecología (INE),[16] is slightly higher among the accepted applicants vs. rejected applicants (.04 standard deviations) and somewhat lower (-.22 standard deviations) than all randomly selected forest points. Compared to all forest in the country, the beneficiaries over-represent bosque mesofilo (cloud forest) and bosque coniferas (coniferous forest), and under represent selva baja (low-lying rainforest).

Taken together, these statistics suggest CONAFOR was moderately successful in targeting the program to areas with both a reasonable risk of deforestation and more poverty. A major concern about PES programs has been that it will enroll only those areas with a very low risk of deforestation. These statistics indicate that this is not the case for Mexico's program. Within the available applicants, CONAFOR appears to have selected those which are closer to urban areas, have a higher risk of deforestation on INE's layer and have higher poverty. However, the beneficiaries do have higher slope and elevation and a somewhat lower risk of deforestation when compared to all other forested points-- this may indicate that the payments are currently too low to attract applicants with the highest risk of deforestation. Figure 2b indicates the same summary statistics for the sample of matched beneficiary and non-beneficiary applicant points. Matching substantially improves the balance across distance to urban areas, baseline poverty and forest type, although we note that the matched non-beneficiaries have higher slope and elevation and somewhat lower risk of deforestation. Post-matching, none of the normalized differences are greater than .25 standard deviations, which is the rule of thumb suggested by Imbens and Wooldridge (2007).

[16] INE's 5 point scale."Index of Economic Pressure to Deforest / Risk of Deforestation" version 1. Methodology at http://www.ine.gob.mx/irdef-eng.

3.2 Average impacts

Table 3 gives our main estimates of program impacts on mean NDVI, using the estimating equation described above with property-level fixed effects. Column 1 shows average program impact while columns 2-5 test for heterogeneity in impacts. The coefficient in column 1 indicates that the average impact of receiving the program is an increase of 0.0041 in mean annual NDVI. To roughly convert this statistic to land area with avoided deforestation, consider that the mean NDVI value across all of our forested points is 0.60. The overall mean NDVI value of non-forested points over the same time period was 0.20.[17] This means that if we started with 100 forested pixels, and one of them were deforested while the others remained the same, this would change the average NDVI across those 100 pixels from .60 to .598 (so 1% deforestation is approximately equal to a loss of .002 in NDVI); 2 pixels deforested would change the average NDVI from .60 to .596 (so 2% deforestation is approximately equal to loss of .004). Our coefficients can thus be interpreted as indicating an average avoided deforestation effect of approximately 2%--in other words, 2 out of 100 pixels that would have been deforested are not, due to the program. On matched non-beneficiary properties, the average annual loss of NDVI is -0.003 for one year or -0.015 across 5 years (~7.5%). This suggests that the program reduces deforestation by nearly 30 percent compared to what would have been expected. Interestingly, these results are quite similar to estimates from Costa Rica, which indicate that less than 0.4% of parcels enrolled in the program would have been deforested each year (Pfaff et al. 2011), although it is worth noting that Costa Rica's payments are significantly larger (USD 45-163 per ha per year, see Wunder et al. 2008).

One pattern which is evident looking at our GIS data but is difficult to discern from the regression analysis is that deforestation is highly dispersed spatially. Rather than a frontier situation, where we might expect lots of clearing in a few areas, deforestation in Mexico is generally scattered in small amounts over vast land areas. This means that most individual landowners are clearing small amounts in percentage terms. While this adds up to large areas

[17] This is calculated from the mean NDVI for a sample of 50,000 points which were classified by INEGI as agriculture or pasture in 2002.

deforested in total[18], it means that it is very difficult for policymakers to offer payments only for the "marginal hectares" that would be cleared in the absence of the program. Whether or not there are opportunities for mangers to increase the cost-effectiveness of the program depends on whether there is systematic heterogeneity in avoided deforestation impacts that can be better exploited.

3.3 Heterogeneity in impacts across space

Motivated by the simple economic framework discussed in section 1, we test for heterogeneity in effectiveness across region, distance to the nearest urban locality, baseline municipal poverty and tenure type. We find (column 2) that effects across the four regions are not significantly different from each other, although there may be somewhat higher avoided deforestation in region 2 (0.0061 increase in NDVI). We do see significant heterogeneity by distance to urban area. As expected by our von Thünen model, we see less avoided deforestation as we move away from cities. We also see less avoided deforestation at higher levels of baseline municipal poverty, unfortunately suggesting that there is no easy win-win strategy to increase avoided deforestation and make the program more progressive. However, when we break recipients down into common property beneficiaries (ejidos and communidades) versus private and other types of beneficiaries, the program is most effective in the common properties. This suggests possible win-win targeting if more payments were given to common property beneficiaries.

3.4 Heterogeneity in time and robustness checks

A question which consistently comes up in debates about PES is what happens when recipients stop receiving payments? To get at this question we coded points according to the number of years they had been in the program. The first column of Table 4 shows regression results when we allow a separate effect for each year of being in the program, including the year of application ("beneficiary yr0 - beneficiary yr5"). To interpret these, recall that the coefficients on each year will indicate the difference between the level of mean NDVI between beneficiary and non-beneficiaries. In other word, the near zero coefficient (0.0006) on Beneficiary year zero

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[18] Consider for instance an annual degradation rate of 0.5%. This seems small in percentage but equals more than 680,000 hectares lost each year (Land area of Mexico =1943950 sq km) (100 ha / sq km) (~.70 forest)*(0.005 cleared) = 680,382 ha.

indicates that beneficiary and non-beneficiary properties were very similar in the year they applied to the program. The positive and significant coefficients on years 1-4 indicate divergence in the trends between beneficiaries and non-beneficiaries for the first four years of receiving payments. Roughly speaking, this is consistent with a total of approximately 1.5 % avoided deforestation after the first year, 1.7 % after the second year, 2.3 % after the third and 3.1% after the fourth year. However, after the 5th year of receiving payments, we see that the difference is reduced to approximately 1% and is not statistically significant. This is consistent with the standard game theory prediction that landowners would simply deforest in the last round of the game if they expect to stop receiving payments. Although this bolsters the argument that our results do represent true avoided deforestation effects, it also reinforces the concern that avoided deforestation will stop when the payments stop. The remaining positive coefficient on the 5th year does indicate that there is some lasting program effect which might be due to transitions to other livelihoods or the expectation of future enrollment. Column 2 indicates similar results when we only include variables for years 1-5.

Columns 3-5 show the results of additional robustness checks. Column 3 changes the recipient variable to be defined in the same calendar year as the landowner received payments and finds smaller but still significant results. Column 4 uses as a control group the random sample of all forest outside of program applicants, rather than rejected applicants. This suggests that the program has attracted active land users, since it appears slightly less effective when compared to matched forested points outside of program applicants. Column 5 uses the same main specification but includes as controls only those points inside properties which met all the requirements but did not receive payments due to lack of funding ("aprobados sin recurso"). We see that the coefficient is again somewhat smaller (0.0029 vs. 0.0041) but remains strongly significant. The smaller magnitude may be explained by the fact that landowners in this control group would receive notification that they met all the requirements and would be encouraged to reapply in future years, so they may delay planned deforestation in anticipation of applying again. Finally, a separate analysis (results not shown) of the 2008 cohort alone indicates similar average avoided deforestation impacts for the 2008 cohort.[19]

[19] To analyze the 2008 cohort we calculate the total average NDVI within the boundaries of accepted and rejected control properties. We match rejected applicants from 2008 on the basis of poverty grade and forest type, with exact matching within region and tenure type.

4. SOCIOECONOMIC IMPACTS: DATA AND EMPIRICAL STRATEGY

4.1 Survey design

To assess the socioeconomic impacts of Mexico's program, we conducted a national field survey between June and August of 2011. The surveyed covered beneficiary and non-beneficiary applicants from the 2008 PSAH cohort. A stratified random sampling strategy was applied by region. The four regions (north, central, southwest and southeast) were determined by dominant ecosystem type and socioeconomic groupings and are shown in Figure 3). Within each region, we then randomly selected Landsat footprints (areas 180x180 sq km) from within the set that contained sufficient good quality past images to monitor deforestation over time.[20] We then identified all 2008 cohort applicants within each footprint and matched them to controls from the applicant pool which did not subsequently become beneficiaries in 2009 or 2010 using nearest-neighbor covariate matching. Matching was conducted applying the Mahalanobis metric within region and tenure type (common property vs. private property) and on the basis of the following covariates: distance to the nearest locality with population greater than 5000, elevation, slope, the area of the property submitted to be enrolled, the density of roads within a 50 km buffer, the average locality poverty level in 2005, and the percentage of submitted forest in coniferous forest, oak forest, cloud forest, upland tropical forest and lowland tropical forest. Matches with high distance measures between covariates were eliminated from the possible sample (i.e. because there was no good match available). Within region and tenure type, priority then was given to possible survey properties which had multiple good matches among the controls and vice versa. Some last minute adjustments in the sample were made due to security concerns--this resulted in the swapping of two Landsat footprints for nearby ones and the addition of two footprints in order to increase sampling possibilities among the non-beneficiaries.

Surveyors further stratified the sample within common property communities by land-use rights. Based on lists provided by program officers or community leaders, surveyors randomly selected 5 households with full land-use rights and voting power ("ejidatarios") and 5 without ("non-ejidatarios"). The final sample is composed of 117 private households (61 beneficiaries and 56 non beneficiaries) and 1125 households (596 beneficiaries) and (529 non-beneficiaries)

[20] Analysis of the more detailed Landsat data (30m x 30 m pixels) is currently in process.

distributed over 116 common property communities. Table 5 indicates the breakdown of surveyed households in each region and Figure 3 shows the locations of the beneficiary and non-beneficiary properties (here shown as points rather than polygons). The reasons for rejection in our surveyed sample are similar to the overall rejected pool. 35% were approved but rejected due to lack of funding, 50% were rejected due to having less than the required percentage of forest cover on the submitted property, 6% were outside of the eligible zones and the remaining 9% had incomplete documentation or did not meet other technical criteria.

4.2 Household assets section

Ennumerators applied surveys to the head of the household. The questionnaires contained sections on household demographics, assets, land use, production and participation in forest management activities. To establish baseline measurements, surveys included recall questions about assets, land use, etc. in 2007, which is the year prior to program implementation. Entry and analysis of much of the survey data is still in progress; here we use information from the section covering household assets and characteristics only.

To identify program impacts at the household level, we compare differences over time in household asset ownership between beneficiaries and non-beneficiaries. We first estimate the presence or absence of each asset using a household fixed effects model.

(2) $A_{iet} = \beta_1 benef_{et} + \gamma_i + t + u_{iet}$

Where A_{iet} indicates the presence of an asset for household *i* in property *e* at time *t* (2007 vs. 2011). The variable *benef* is equal to zero for all properties in 2007 and to one in 2011 if the property was a beneficiary starting in 2008. Standard errors are robust and clustered at the community level. For private households, the errors are simply heteroskedastic robust, and the *e* subscript is superfluous.[21]

4.3 Assets indices

The vector A_{iet} has many dimensions – we record a variety of assets ranging in size from a cell phone to a car. The demand for specific assets may vary depending on geographic factors

[21] For simplicity, we use a linear probability model, but we check robustness using first differences in assets and an ordered probit model and results are similar.

such as access to electricity or cell phone service, or the quality of transportation infrastructure. We report average effects on individual assets, but in order to reduce the dimensionality we also report results which aggregate assets into an index (full details given in the appendix). We report average impacts and heterogeneity in impacts for three types of index common in the development literature, which use different weighting schemes.

The first index is created using principal components analysis (PCA) on ordered data, which constitutes an improvement over the traditional Filmer and Pritchett (2001) method based on binary data (Kolenikov and Angeles 2009). Principal components analysis considers the correlations between variables and gives more weight to those which provide more information about the variation in the data. The second index, the inverse proportion index, applies weights to the assets which are the inverse of the proportion of households which hold a particular asset in 2007. This gives greater weight to assets which are relatively rare – like cars and computers– and less to more common assets, like televisions. Finally, we construct a price index based on data from consumer agencies in Mexico on the prices of consumer goods and estimates of the values of housing characteristics (see appendix for details). In order to measure changes in wealth over time, the baseline weights or prices are used to construct the indices for 2011 in all cases.

5. SOCIOECONOMIC IMPACTS: RESULTS

5.1 Summary statistics

Table 6 shows summary statistics of the covariates for beneficiary and non-beneficiary households. We separately analyze households living in common property communities and private landowner households. This is because, as can be seen from the summary statistics, common property households differ substantially from private property households, particularly along the wealth dimension. The last column in Table 6 shows the normalized difference between non-beneficiaries and beneficiaries. For the households in common property communities, we see that the beneficiaries are slightly farther from localities greater than 5000 people, are at higher elevation, and have higher initial poverty within their locality. However, none of the normalized differences is greater than .25 standard deviations, suggesting reasonable balance in the sample between beneficiaries and non-beneficiaries. This rule of thumb (Imbens and Wooldridge 2007) is also met for the private landowners but the balance is somewhat less convincing. In particular, we note that the private beneficiaries are more than .1 standard deviations better off in 2007 according to each of our indices.

5.2 Average impacts

Figure 4 shows kernel density distributions of assets according to our price index for each of the three groups. The blue lines show assets in 2007 while red shows assets in 2011. Graphs on the left indicate beneficiary households while graphs on the right indicate non-beneficiary households. Figure 5 shows the same graphs for the PCA index. From this we can see several key insights. First we see that the overall distributions of beneficiaries and non-beneficiary households are fairly similar at baseline for each of the three sample groups, indicating reasonable balance across the distribution of wealth at baseline. Second, we see that all households have gained assets over this time period, i.e. there is no evidence that participation in the program has made households worse off in an absolute sense. Third, we see that the pattern of gains for beneficiaries and non-beneficiaries is not dramatically different at any levels of wealth; thus we do not expect to find dramatic wealth impacts of the program in our regression analysis.[22] Both Figure 4 and Figure 5 indicate that the ejidatario beneficiaries may have increased assets by more than non-beneficiaries, particularly in the middle and at the upper end of the distribution. The non-ejido beneficiaries have similar changes to the control group on the PCA index but possibly smaller gains at the upper end of the distribution according to the price index. For the private properties, we notice first that they have significantly more assets than common property households, and that the changes over time in assets are smaller. Changes appear similar for both groups according to both indices.

Table 7 shows estimates of program impact on ownership for each asset following equation (2) above. The first set of estimates is for households of ejido members with full voting status and land rights (ejidatarios) while the second set is for non-ejidatarios. (Note that all members of communidades have full rights and are grouped with the ejidatarios.) The third set combines these two groups and weights households by the share of each type of household in the community (weights are the ratio of the number of ejidatarios and the number of non-ejidtarios

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[22] Proper statistical tests forthcoming.

relative to the total in the community). We interpret these results as the impact of the program on the entire community. The fourth set shows impacts for the private landowner households.

For households in common properties, we find that the program has had marginally significant positive impacts. In particular, among ejidatarios, we find marginally significant increases in the probability of owning computers (0.034), cars (0.051) and number of rooms in the house (0.076). Given that the average baseline probabilities of ownership are .03 and .25 for computers and cars, and the average number of rooms is 2, these impacts constitute increases of approximately 100 percent, 20 percent, and 4 percent, respectively. For non-ejidatarios, we see a significant increase in cell phone ownership (0.117 – a 50 percent increase). We do not find any negative and significant or marginally significant impacts.

Although it is difficult to conclude too much with certainty based on these results, we note that it seems the ejidatarios make more significant investments in capital goods and home improvements while the non-ejidatarios are able to make smaller purchases. This is in keeping with the likely distribution of more substantial payments to the ejidatarios versus the non-ejidatarios within community. (Preliminary analysis of our community survey data indicates that among communities that provided lump sum transfers, approximately 80% of the amount transferred went to households with full land rights).

We do not find significant positive or negative impacts for the private households, although the coefficients imply an increase of 0.063 in cars (~9% change) as well as upgrades to walls and flooring materials. We find marginally significant results that the beneficiaries were less likely to acquire a cell phone than non-beneficiaries. It is possible that this may be explained by the greater presence of cell phones in the beneficiary group at baseline (49 percent of beneficiaries had cell phones in 2007, compared to 42 percent of non-beneficiaries) or by differential changes in access to coverage across this period. (We are seeking geographic information on changes in coverage.) Table 8 substitutes the amount of per capita payments for the binary treatment variable. This continuous treatment variable indicates similar results. In addition, a robustness check where we use only households in communities where the per capita total payment is greater than 1000 pesos (results available from authors) indicates statistically significant average impacts on car purchases and wall upgrades for households in communal properties and no significant or marginally significant impacts on private households.

Table 9 gives results for each of the three household wealth indices which aggregate assets. For households in common properties, we find that being a beneficiary has on average a positive but not statistically significant effect. Considering the weighted sample results, we find that the estimated magnitudes are a 0.170 increase for the PCA index, a 0.060 increase for the inverse proportion index and a 0.101 increase in the price index. The price index is measured in 10,000's of pesos so a coefficient of .10 indicates that the program resulted in an additional 1010 pesos more of assets. Compared to the average baseline value among the beneficiaries of 11.3, this represents an approximately 0.9 % change. For the private landowners, the estimated effect is larger, at 0.241, but the baseline value is also higher, at 20.4, so in percentage terms, this implies a change of approximately 1.1 %. However, among private households, the results are negative for the PCA index and inverse proportion index, which place more weight on the consumer goods. In general, the inconsistency in signs leads us to conclude that there is no significant detectable effect on private households' assets.

We interpret these results as an indication that PES is not making households worse off, but it also does not appear to be conferring large surplus rents to individual landowners which are showing up in asset growth. This may indicate that the size of the payments is relatively small compared to the sum of opportunity costs, transaction costs and forest maintenance costs of participating, or that payments are being channeled to other uses. Preliminary analysis of the common property leader surveys indicates that only 40% of communities provided the payments directly to households as lump-sum transfers. Of these, approximately 75% of the funds were transferred directly. This suggests significant potential spending by the communities rather than individual households. For the private households, an alternate explanation for small apparent changes in assets is that many already had these assets at baseline, making it difficult to detect improvements.

5.3 Heterogeneity in impacts

In Table 10, we test for heterogeneity in impacts of the program using the price and PCA indices. Considering the weighted sample, we find positive coefficients in the north, center and southeast, and negative impacts in the southwest, although none are significantly different from zero. Among just the ejidatarios, the regional interactions indicate significant and positive impacts in the southeast region (Yucatan, Campeche, and Quintana Roo), but a negative and significant impact in the southeast region (Chiapas, Guerrero and Oaxaca). According to the price index, private landowners also gain in three out of four regions and lose in the southeast, but results are not significant. When we test by distance to the nearest locality with population greater than 5000, we do find the expected pattern for all four groups. Although again the results are not statistically significant, estimated gains in wealth are increasing as we move away from large localities, which is consistent with the notion that the economic surplus gained by landowners is greater when the opportunity cost of enrolling in the program is lower. The third set of results and Figure 6 indicates heterogeneity in the program impact by 2005 municipality poverty level. For the households living in communities, we find that the program leads to more asset acquisition by those in lower poverty communities. Figure 6 indicates positive asset acquisition for those with a marginality index of -1.3 to -.1, which corresponds to municipalities with low to medium poverty. For poorer municipalities, which constitute the majority of our sample, the asset impacts are insignificant. Note that for the private households, we see the opposite direction of heterogeneity with respect to municipal poverty: households with higher municipal poverty gain show stronger positive effects. These patterns may be due to the fact that the assets we measure are more likely to be acquired by those in the middle of the wealth distribution.

Finally, in Table 11, we investigate within ejido outcomes by including ejido-level fixed effects in order to analyze the extent to which relative wealth within the ejido determines program impacts. The ejido-level fixed effect controls for the average level of impact within the ejido, and the interaction with the baseline household wealth index identifies differential impact across this dimension. In contrast to the municipal poverty interactions, the within-community estimates suggest a generally progressive effect of the program. Beneficiary households with greater initial wealth are generally less likely to acquire assets, with the exception of computers.

6. CONCLUSION

Considering simultaneously the evidence on avoided deforestation impacts and socioeconomic impacts, we suggest three possible insights about targeting. First, the avoided deforestation benefits of Mexico's PSAH program might be increased by targeting more payments to areas closer to cities or at lower municipal poverty levels, but this would likely be regressive overall. Although we do not find evidence of larger benefits for poor households across communities, we do find suggestive evidence of larger socioeconomic benefits for poor households within communities and as we move away from cities. Second, we find similar avoided deforestation benefits across regions. Although there is some indication that impacts on household wealth are different across region, these are not conclusive enough to motivate changes in targeting by region. Third, the results do suggest that there is a possible win-win opportunity to target more of the funds to ejidos and communidades. This would be consistent with our findings of larger avoided deforestation in common properties as well as possible positive wealth impacts. Future work should continue to explore how the duration of the contract matters, whether there are significant non-linearities in the heterogeneity of impacts and whether there is slippage or leakage of avoided deforestation. Previous work (Alix-Garcia et al. 2012) suggests significant slippage effects for an early cohort of PSAH, possibly due to the relaxation of credit constraints in more poor communities. Such effects would amplify the tradeoff between targeting based on avoided deforestation versus poverty.

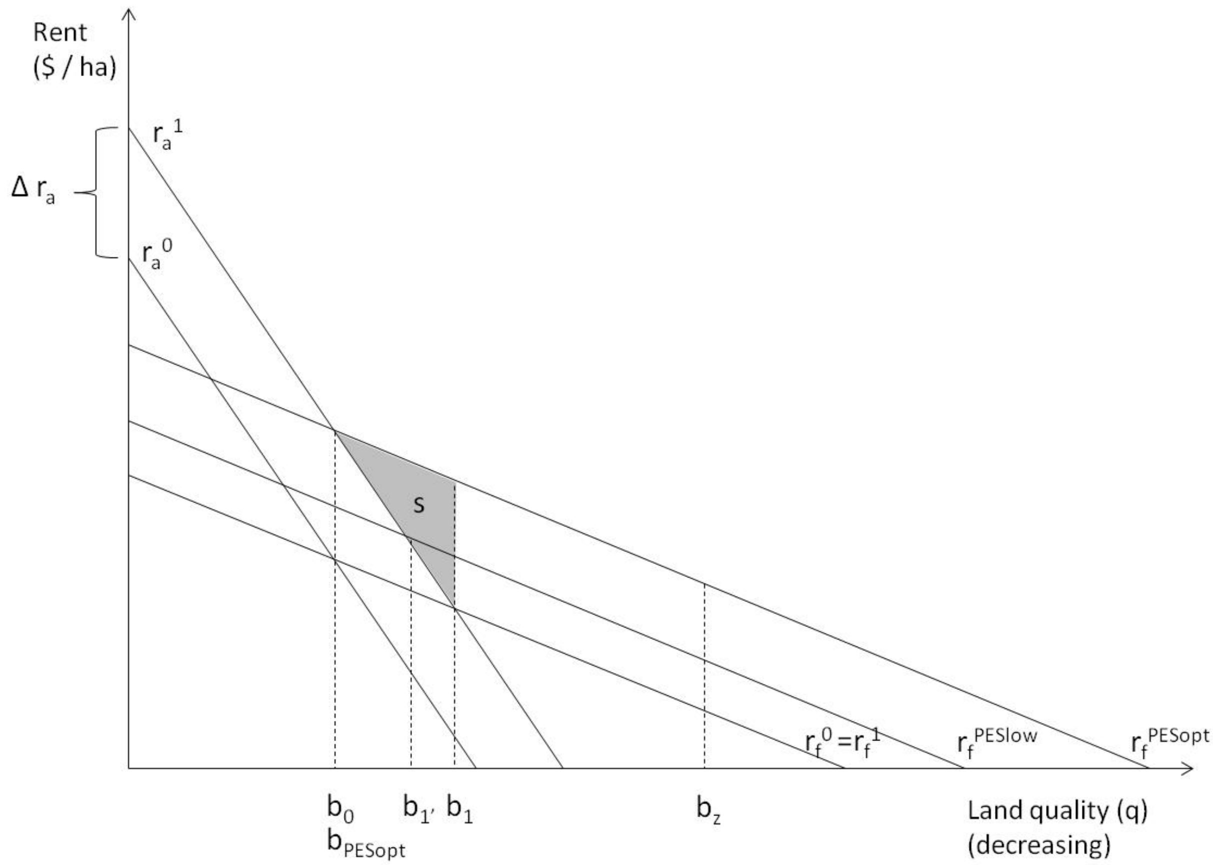
One puzzle that emerges when we consider the two sets of results together is that the program appears to be transferring significant amounts of funds which are not directly generating avoided deforestation, suggesting a low opportunity cost of enrolling much of the forest in the program. In theory, that should then imply that much of the payments are gained as surplus to the landowners--yet these transfers are not showing up as large asset increases. There are several possible explanations for this puzzle. One is that the other costs of participating, including the transaction costs of enrolling and communicating with CONAFOR and the costs of enforcement or maintenance (preventing illegal deforestation/ fire / pest outbreaks) are quite high compared to the total payments received.[23] The implication of this is that the program payments perfectly compensate landowners for the total costs of enrollment, and hence there is no net gain to households for enrolling. A second possibility is that program payments have gone into other uses by the community as a whole or by individual households. Future work will explore these questions in more detail using the other sections of the household surveys as well as the surveys conducted with community leaders.

[23] In particular, CONAFOR has been concerned about high payments to consultants who prepare the applications and has made concerted efforts to make the application as simple as possible and to ensure as much of the payments as possible go directly to landowners.

Better understanding of other possible changes due to the payments is also important in order to understand the overall welfare implications of the program. If the difficulty of targeting perfectly means that PES programs end up giving a substantial number of payments which are not generating avoided deforestation, is this actually a problem from a welfare perspective? Maybe and maybe not. Small avoided deforestation also implies small opportunity costs, which means that most of the funds are transfers and not true economic costs. Possible deadweight loss would then be in the distortions caused by raising the funds or the administrative costs of the program. In Mexico's case, the funds are generated by a Pigouvian-style tax on water use, so this may actually have a positive environmental benefit in and of itself by internalizing the externalities of water use. Since the tax effectively transfers funds from generally wealthier urban citizens to rural areas in compensation for ecosystem services, it also has the potential to increase social welfare depending on the social welfare function. Finally, administrative costs are small in Mexico's case (mandated to be less than 4 %, see Wunder et al. 2008) and would likely increase if the program tried to use more sophisticated contracts to elicit only the "marginal hectares" from every landowner.

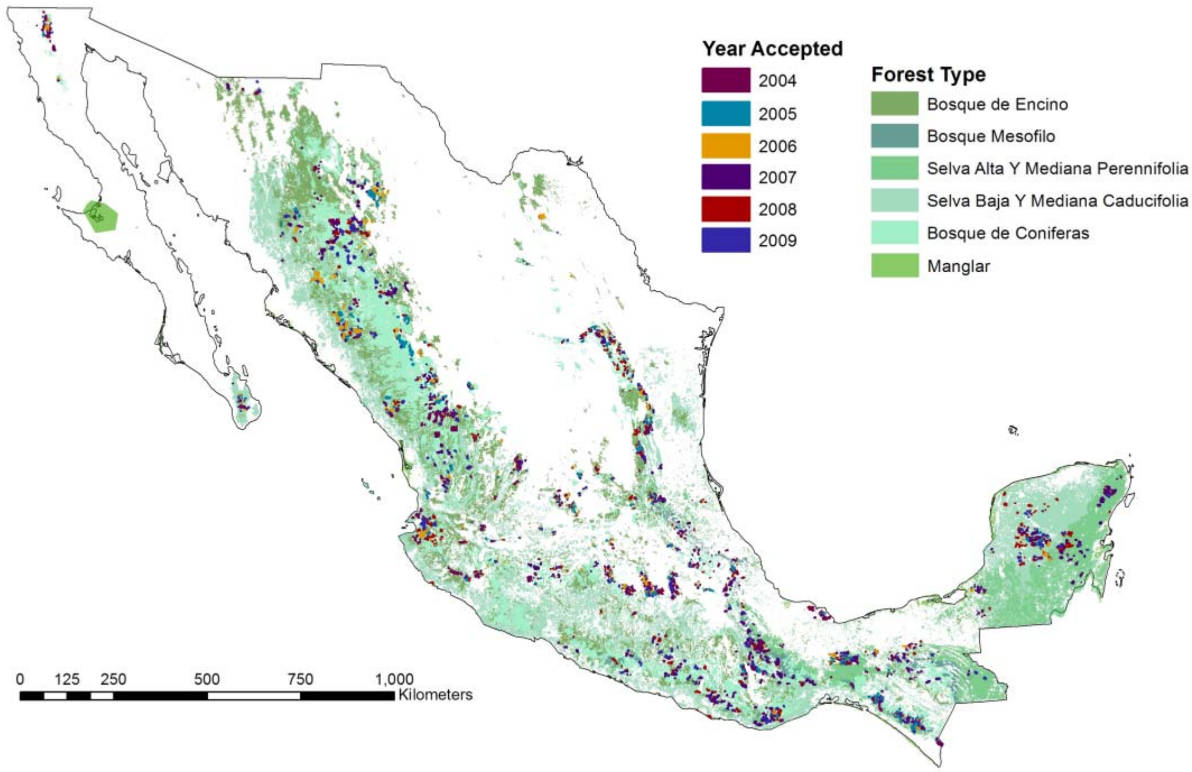
In general, our data indicates that CONAFOR has already made substantial efforts to improve the targeting of the program and has succeeded in enrolling lands from among the potential applicants with both higher rates of expected deforestation and higher poverty. We conclude that Mexico's experience so far justifies optimism about the potential of payments for ecosystem services to maintain existing forest cover and to establish compensation for services provided in the case of missing markets. The analysis does suggest caution in terms of expecting significantly larger avoided deforestation gains without either higher payments or more regressive targeting. There is likely some scope to improve on both environmental and socioeconomic dimensions in Mexico by targeting more payments to common properties and extending the length of contracts.

Fig 1: Economic framework: von Thünen model of PES



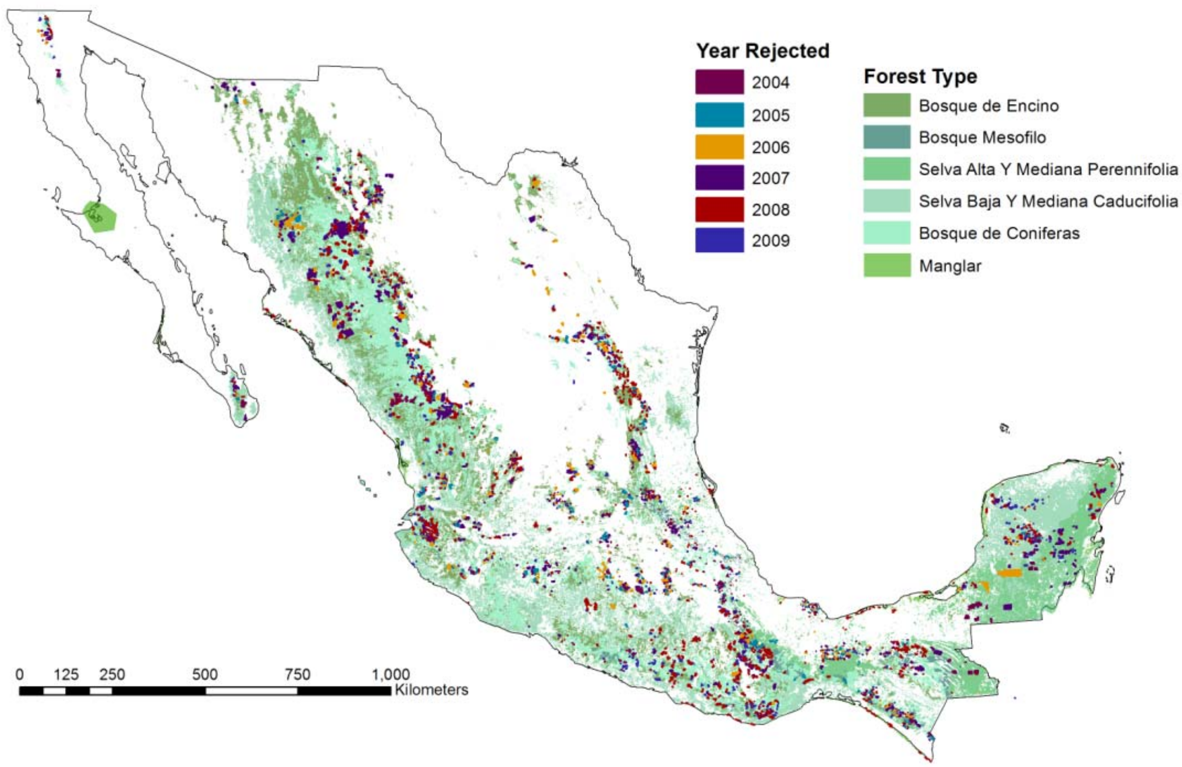
Graphical von Thünen model. X-axis indicates quality of land parcels (decreasing). Y-axis indicates rents from agricultural or forest land use. See text in Section 1 for full explanation.

Fig 2a: Recipients of PSAH 2004-2009



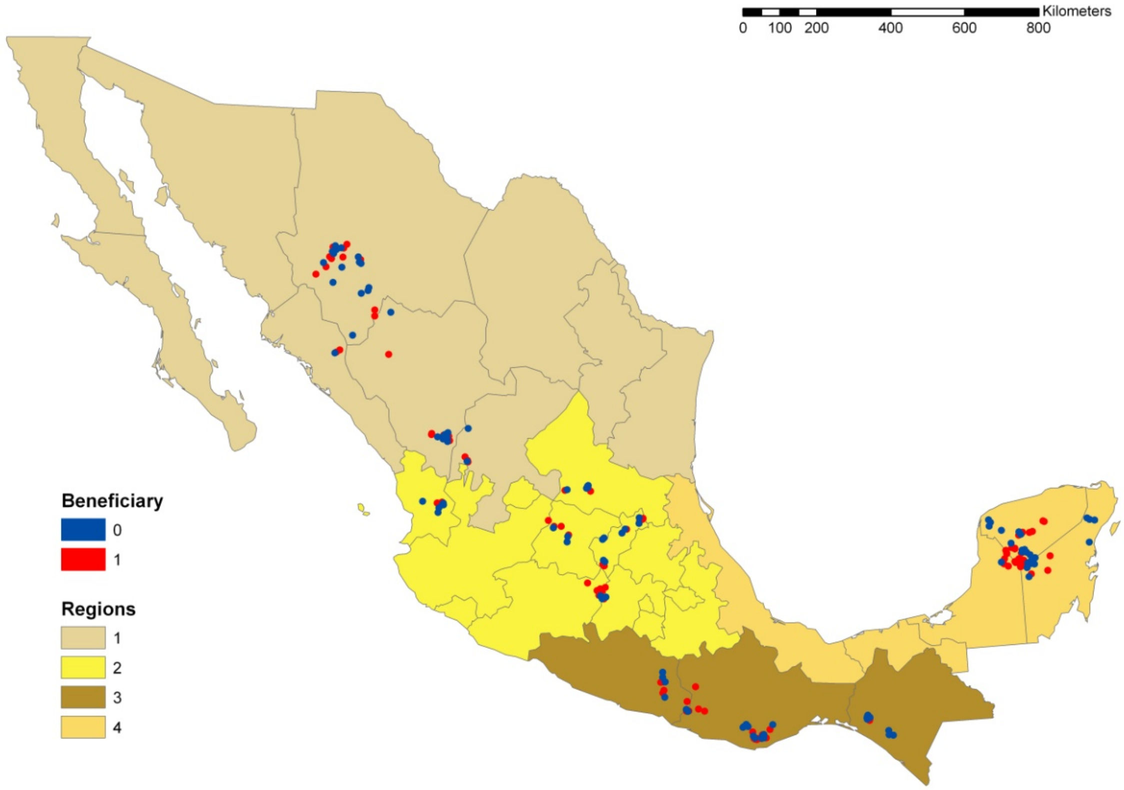
Data on program recipients from CONAFOR. Forest types from the INEGI Series III land use layer (circa 2002).

Fig 2b: Rejected applicants to PSAH 2004-2009



Data on program applicants from CONAFOR. Forest types from the INEGI Series III land use layer (circa 2002).

Figure 3: Survey sample and survey regions

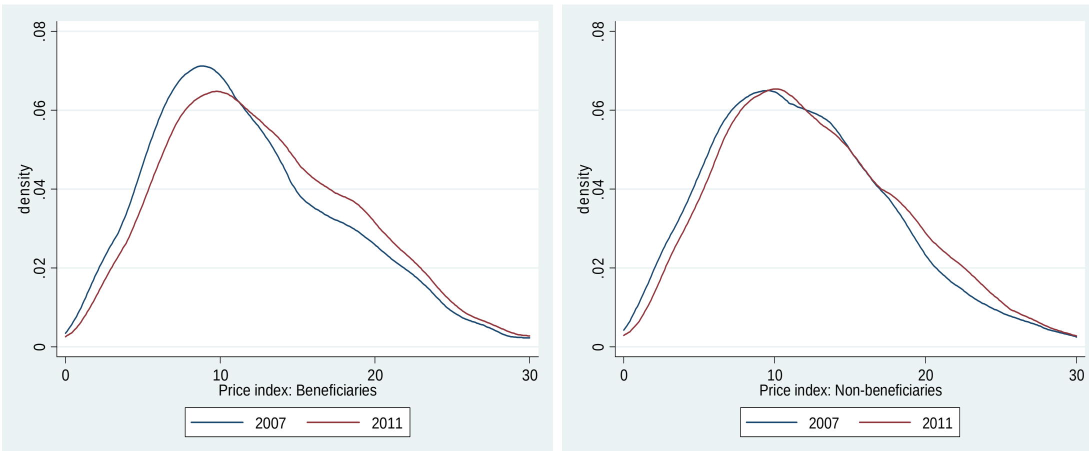


Centroid points of properties surveyed (summer 2011). Total number of properties surveyed = 233.

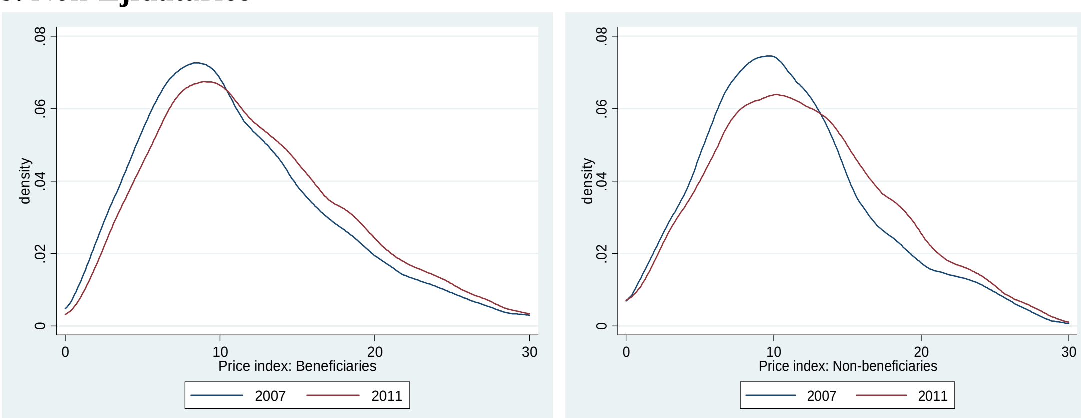
Figure 4: Distributions of assets over time (price index)

Graphs show the density of the price index in 2007 (blue) and 2011 (red) for beneficiaries (left) and non-beneficiaries (right). Kernel density graphs with bandwidth = 2.5.

a. Ejidatarios



b. Non-Ejidatarios



c. Private properties

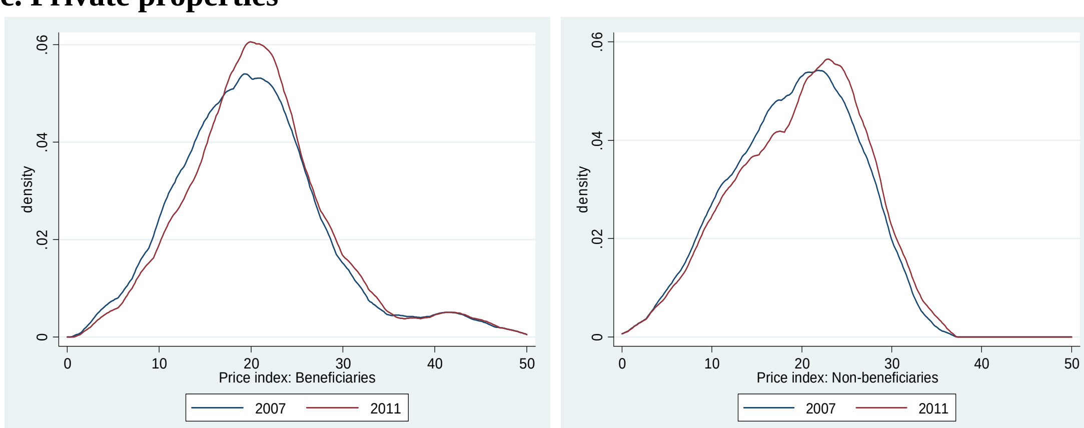
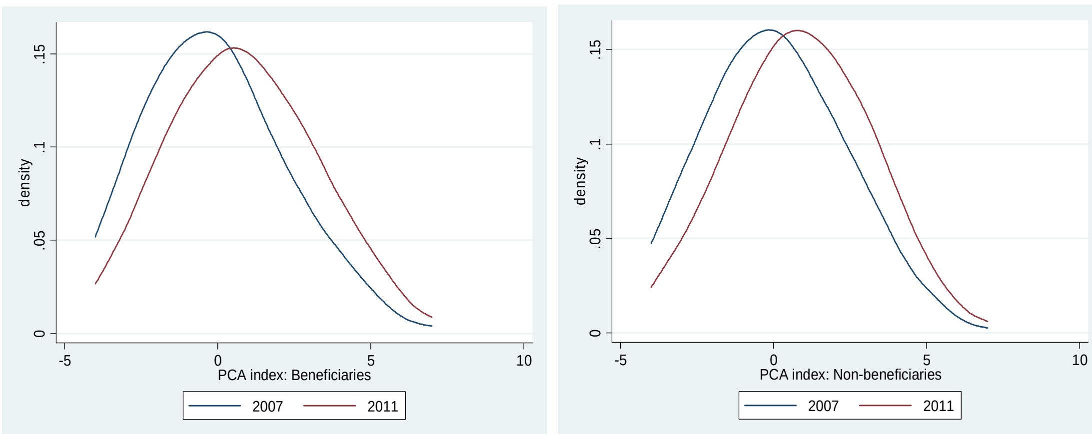


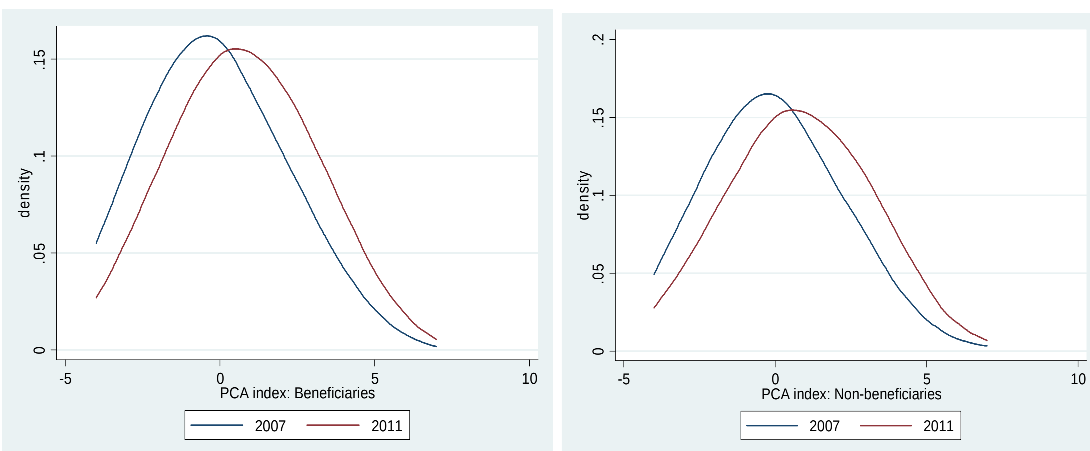
Figure 5: Distributions of assets over time (PCA index)

Graphs show the density of the PCA index in 2007 (blue) and 2011 (red) for beneficiaries (left) and non-beneficiaries (right). Kernel density graphs with bandwidth = 1.5

a. Ejidatarios



b. Non-Ejidatarios



c. Private properties

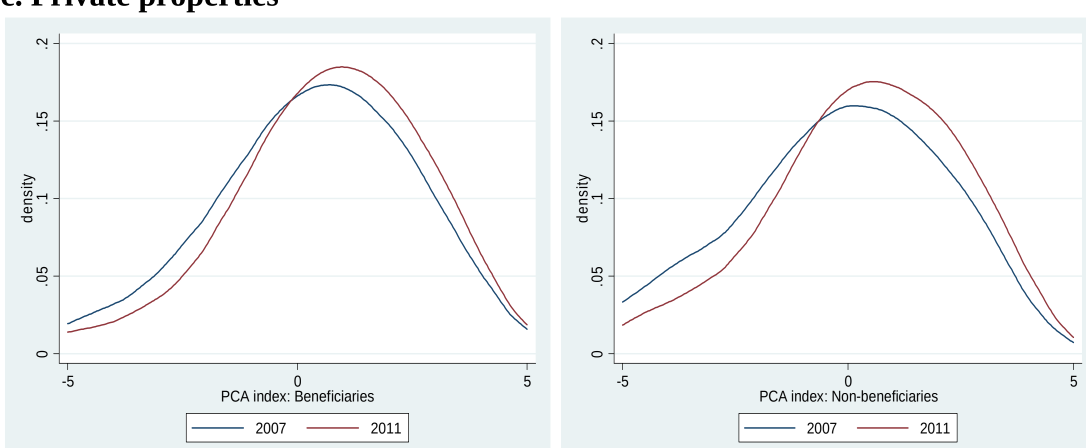
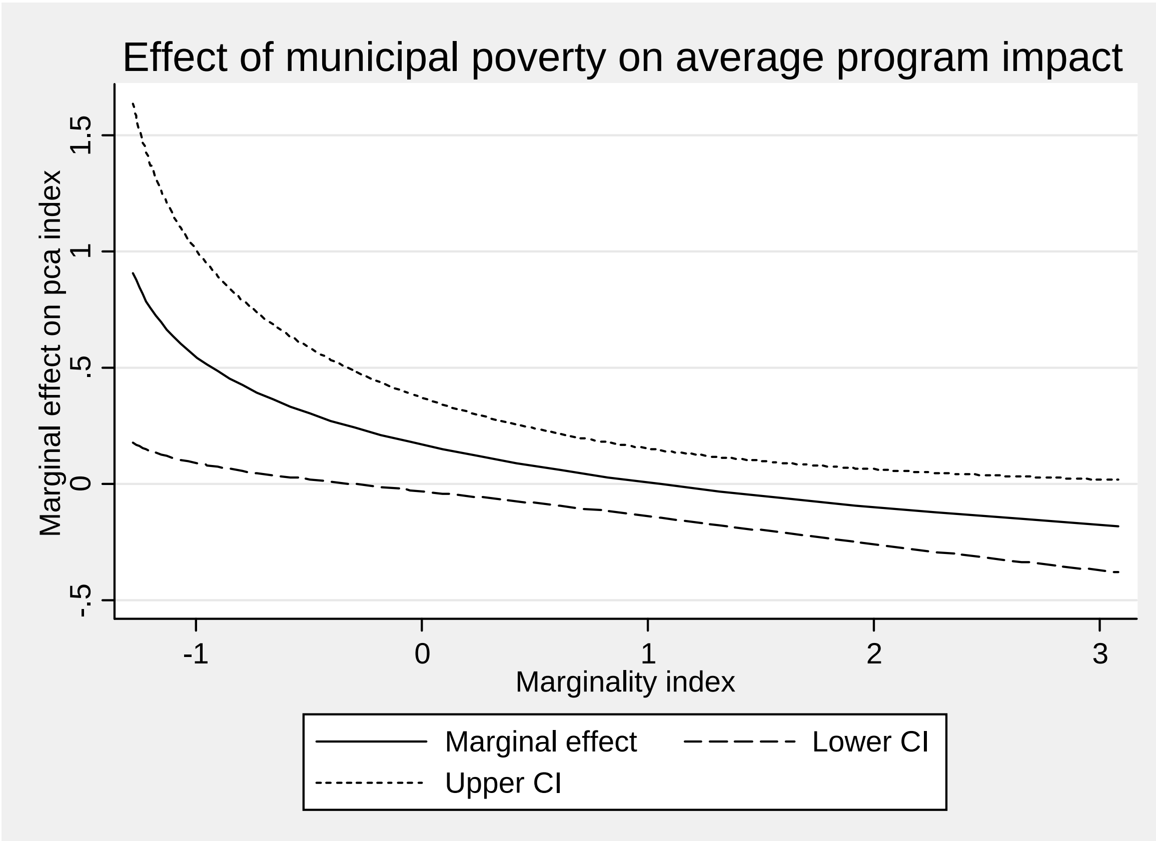


Figure 6: Heterogeneity in program impact across poverty index



Marginal effects for households in communities by 2005 municipality marginality index (CONAPO 2005, Anexo C). Numbers correspond to poverty grades as follows: very low (<-1.2), low (-1.2 to -.65), medium (-.65 to -.08), high(-.08 to 1.1), very high(> 1.1).

Table 1: PSAH Payment Rates per hectare 2004-2009 (in Mexican pesos)

Payment Rates	2004	2005	2006	2007	2008	2009
Rate per hectare for bosquemesófilo (cloud forest)	400	400	413.70	429.85	447.02	465.80
Rate per hectare for other forest types	300	300	316.35	328.71	341.84 394.43 for oak forest	356.20 411.00 for oak forest
Daily minimum wage in the Federal District	45.24	46.80	48.67	50.57	52.59	54.80

PSAH rates from 2006 onward are set using multiples of the minimum wage in the Federal District, at the rate of 8.5* min wage for cloud forest, 7.5*min wage for oak forest and 6.5*min wage for other forest.

Table 2: Summary statistics: points within applicant boundaries and other forested points

a. Unmatched

Variable	**Beneficiaries**		**Non-beneficiaries**		**Norm diff**	**Other forest points**		**Norm diff**
	mean	sd	mean	sd		mean	sd	
Slope (deg)	12.307	9.922	11.400	9.675	0.066	10.145	9.468	0.158
Elevation (m)	1540.1	979.7	1437.9	924.7	0.076	1135.6	874.73	0.308
Distance to loc > 5000 (km)	33.253	22.17	38.230	26.81	-0.143	38.367	27.519	-0.145
Municipal poverty index	0.274	1.114	0.259	1.133	0.009	0.242	1.008	0.021
Common property	0.878	0.327	0.803	0.398	0.146	0.596	0.491	0.479
Manglar	0.006	0.076	0.020	0.142	-0.091	0.009	0.097	-0.030
Bosque encino	0.212	0.408	0.266	0.442	-0.090	0.223	0.416	-0.019
Bosque mesófilo	0.090	0.287	0.044	0.205	0.132	0.029	0.169	0.183
Selva alta	0.141	0.348	0.151	0.358	-0.019	0.155	0.362	-0.027
Selva baja	0.142	0.350	0.179	0.384	-0.071	0.323	0.467	-0.309
Bosque coniferas	0.409	0.492	0.340	0.474	0.101	0.261	0.439	0.224
Risk of defor	2.464	1.332	2.395	1.301	0.037	2.880	1.389	-0.216
Mean ndvi	0.624	0.154	0.577	0.162	0.209	0.553	0.162	0.316
Δ mean ndvi	-0.0030	0.063	-0.0031	0.065	0.001	-0.0032	0.072	0.002
N	17033		19304			41282		

b. Matched

Variable	**Beneficiaries**		**Non-beneficiaries**		**Normalized difference**
	mean	sd	mean	sd	
Slope (deg)	12.239	9.859	13.388	9.554	-0.084
Elevation (m)	1541.804	980.409	1672.384	888.981	-0.099
Distance to loc > 5000 (km)	33.305	22.158	32.397	21.532	0.029
Municipal poverty index	0.272	1.114	0.220	1.111	0.033
Common property	0.878	0.327	0.863	0.344	0.033
Manglar	0.006	0.076	0.006	0.079	-0.004
Bosque encino	0.213	0.409	0.259	0.438	-0.078
Bosque mesófilo	0.089	0.285	0.074	0.261	0.040
Selva alta	0.139	0.346	0.099	0.299	0.087
Selva baja	0.143	0.350	0.118	0.322	0.053
Bosque coniferas	0.410	0.492	0.444	0.497	-0.048
Risk of defor	2.466	1.332	2.365	1.254	0.055
N	16917		6243		

Matches are found using 1:1 covariate matching with replacement and calipers of 2 on the Mahalanobis metric. Matching is conducted within region and tenure type on the basis of slope, elevation, poverty index, distance to nearest locality with population greater than 5000, and forest type. Normalized difference is the difference in average covariate values, normalized by the standard deviation (Imbens and Wooldridge 2007).

Table 3. Impacts of PSAH 2004-2009 on forest cover: property fixed effects

Dependent variable: mean NDVI	(1)	(2)	(3)	(4)	(5)
Beneficiary	0.0041***		0.0061***	0.0047***	-0.0014
	(0.0008)		(0.0014)	(0.0008)	(0.0016)
Benef x north		0.0037***			
		(0.0009)			
Benef x center		0.0061***			
		(0.0020)			
Benef x southwest		0.0029**			
		(0.0013)			
Benef x southeast		0.0035			
		(0.0031)			
Benef x km to large locality			-0.0001**		
			(0.0000)		
Benef x municipal poverty index				-0.0026***	
				(0.0005)	
Benef x common property					0.0063***
					(0.0018)
N properties	3785	3785	3785	3785	3785
N total	208440	208440	208440	208440	208440
R2 overall	.6299	0.6326	.5492	0.6245	0.6059

* p< .10 ** p < .05 *** p < .01

Property-level fixed effects model (equation 1). Robust standard errors clustered at the property level in parentheses. Dependent variable is mean ndvi (ranges from 0 to 1). All regressions include state*year fixed effects, and controls for the municipal average ndvi in each year*forest type. Matching as described in Table 1. Regressions use only data from program applicants (beneficiaries and rejected applicants).

Table 4. Impacts of PSAH 2004-2009 on forest cover: robustness checks

Dependent variable: mean NDVI	(1) by years (incl. zero)	(2) by years	(3) no lag	(4) outside forest points	(5) approved w/o funds
Beneficiary yr0	0.0007				
	(0.0010)				
Beneficiary yr1	0.0031***	0.0029***			
	(0.0010)	(0.0009)			
Beneficiary yr2	0.0035***	0.0033***			
	(0.0010)	(0.0009)			
Beneficiary yr3	0.0046***	0.0044***			
	(0.0013)	(0.0011)			
Beneficiary yr4	0.0063***	0.0061***			
	(0.0014)	(0.0013)			
Beneficiary yr5	0.0023	0.0021			
	(0.0022)	(0.0021)			
Beneficiary (no lag)			.0028***		
			(0.0008)		
Beneficiary				0.0018***	0.0029***
				(0.0006)	(0.0007)
N properties	3785	3785	3785	5385	2969
N	208440	208440	208440	211689	174384
R2 overall	.4982	.4961	.5002	.5867	.4210

* p< .10 ** p < .05 *** p < .01

Property-level fixed effects model (equation 1). Robust standard errors clustered at the property level in parentheses. Dependent variable is mean ndvi (ranges from 0 to 1). All regressions include state*year fixed effects, and controls for the municipal average ndvi in each year*forest type. Matching is as described in Table 1. Columns 1-3 use data from all program applicants (beneficiaries and rejected applicants). Column 4 uses data from beneficiaries and other matched non-applicant points which were forested in 2003. Column 5 uses data from beneficiaries and applicants which met all the criteria but were rejected due to lack of funds.

Table 5. Sample size of survey and distribution by region

Regions	Households in common property			Private landowners		
	Non-beneficiaries	Beneficiaries	Total	Non-beneficiaries	Beneficiaries	Total
North	140	138	278	14	15	29
Center	137	161	298	15	15	30
Southwest	133	150	283	14	16	30
Southeast	119	147	266	13	15	28
Total	**529**	**596**	**1,125**	**56**	**61**	**117**

Regions as shown in Figure 3.

Table 6: Summary statistics: beneficiary and non-beneficiary households

a. Households living in common property communities

Variables	Non-beneficiaries		Beneficiaries		Normalized
	mean	sd	mean	sd	difference
Inverse proportion wealth index 2007	1.905	1.032	1.915	1.078	0.006
Inverse proportion wealth index 2011	2.298	0.975	2.357	1.024	0.041
Price wealth index 2007	11.750	5.518	11.798	5.984	0.006
Price wealth index 2011	12.583	5.705	12.803	6.071	0.026
PCA wealth index 2011	0.090	1.868	-0.079	1.883	-0.064
PCA wealth index 2007	0.922	1.886	0.832	1.954	-0.033
Log (Elevation)	6.581	1.706	6.795	1.396	0.097
Log (Distance locality>=5000 people)	3.276	0.547	3.366	0.548	0.116
Minutes to nearest town (reported by households)	68.899	65.299	71.586	70.033	0.028
Locality poverty 2005	0.512	0.952	0.675	0.855	0.127
Municipal poverty 2005	0.752	1.091	0.724	0.881	-0.020
Log (Area)	6.710	0.991	6.436	1.135	-0.182
Household size	4.578	2.289	4.876	2.337	0.091

b. Private landowners

Variables	Non-beneficiaries		Beneficiaries		Normalized
	mean	sd	mean	sd	difference
Inverse proportion wealth index 2007	2.221	0.561	2.345	0.474	0.170
Inverse proportion wealth index 2011	2.399	0.463	2.478	0.371	0.134
Price wealth index 2007	19.186	6.515	21.477	12.852	0.159
Price wealth index 2011	19.902	6.677	22.219	12.633	0.162
PCA wealth index 2011	-0.284	2.007	0.251	1.841	0.196
PCA wealth index 2007	0.305	1.772	0.653	1.645	0.144
Log (Elevation)	6.603	1.458	6.472	1.553	-0.062
Log (Distance locality>=5000 people)	3.269	0.612	3.137	0.634	-0.150
Minutes to nearest town (reported by households)	56.240	63.343	61.386	61.302	0.058
Locality poverty 2005	0.637	1.119	0.463	0.876	-0.123
Municipal poverty 2005	0.678	1.084	0.908	1.008	0.155
Log (Area)	4.334	0.989	4.373	0.838	0.030
Household size	3.875	2.166	4.328	1.947	0.155

The price index is measured in 10,000's of pesos. The PCA index ranges from -3.07 to 6.40 and the inverse proportion index ranges from 0 to 4.28

Table 7. Impacts of PSAH on individual assets: household fixed effects, linear model, binary treatment

	TV	Refrigerator	Computer	Car	Stove	Phone	Cell phone	Wall	Floor	# rooms
Ejidatarios sample										
Beneficiary	-0.056	0.004	0.034*	0.051*	-0.019	0.026	0.033	-0.006	0.003	0.076*
	(0.037)	(0.033)	(0.020)	(0.028)	(0.030)	(0.021)	(0.041)	(0.079)	(0.048)	(0.043)
N	1423	1425	1426	1426	1425	1426	1426	1416	1424	1424
Baseline mean	0.499	0.369	0.031	0.254	0.350	0.135	0.191	4.337	1.64	1.963
Non-ejidatarios sample										
Beneficiary	-0.032	-0.034	0.004	-0.033	0.056	-0.005	0.117**	0.070	0.033	-0.029
	(0.049)	(0.048)	(0.023)	(0.033)	(0.037)	(0.029)	(0.058)	(0.092)	(0.068)	(0.070)
N	762	761	762	762	762	762	762	761	760	759
Baseline mean	0.501	0.346	0.045	0.215	0.394	0.097	0.228	4.291	1.642	1.81
Weighted sample										
Beneficiary	-0.045	-0.022	0.028	-0.000	0.047	0.002	0.144***	0.104	0.042	0.016
	(0.054)	(0.043)	(0.017)	(0.025)	(0.030)	(0.028)	(0.048)	(0.091)	(0.065)	(0.057)
N	2035	2036	2038	2038	2037	2038	2038	2027	2035	2034
Baseline mean	0.461	0.349	0.053	0.227	0.363	0.122	0.21	4.235	1.648	1.862
Private landowners										
Beneficiary	-0.022	-0.055	-0.030	0.063	-0.021	-0.021	-0.143*	0.033	0.063	-0.100
	(0.044)	(0.037)	(0.066)	(0.053)	(0.038)	(0.051)	(0.080)	(0.081)	(0.047)	(0.090)
N	234	234	234	234	234	234	233	234	234	232
Baseline mean	0.863	0.829	0.308	0.675	0.812	0.547	0.457	5.12	2.197	3.44

* p< .10 ** p < .05 *** p < .01

Coefficients and standard errors in parentheses for household fixed effects model as described in equation (2). Mean at baseline gives the mean proportion of the asset owned among all households in 2007.

Table 8. Impacts of PSAH on individual assets: household fixed effects, linear model, continuous treatment

	TV	Refrigerator	Computer	Car	Stove	Phone	Cell phone	Wall	Floor	# rooms
Ejidatarios sample										
Log (per capita payment)	-0.007	-0.001	0.006	0.006	-0.004	0.002	0.004	-0.004	0.002	0.011*
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.009)	(0.006)	(0.006)
N	1390	1392	1393	1393	1392	1393	1393	1383	1391	1391
Non-ejidatarios sample										
Log (per capita payment)	-0.004	-0.008	-0.002	-0.006	0.003	-0.003	0.014*	0.009	0.012	-0.007
	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)	(0.008)	(0.012)	(0.009)	(0.009)
N	750	749	750	750	750	750	750	749	748	747
Weighted sample										
Log (per capita payment)	-0.006	-0.004	0.003	0.001	0.003	0.000	0.015**	0.017	0.011	0.003
	(0.006)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.013)	(0.008)	(0.007)
N	2030	2031	2033	2033	2032	2033	2033	2022	2030	2029
Private landowners										
Log (Payment)	-0.002	-0.005	-0.002	0.005	-0.002	-0.002	-0.011*	0.003	0.005	-0.008
	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.006)	(0.007)	(0.004)	(0.007)
N	233	233	233	233	233	233	232	233	233	231

* p< .10 ** p < .05 *** p < .01

Coefficients and standard errors in parentheses for household fixed effects model. As described in equation (2); benef is measured as the log of (1+per capita payment).

Table 9: Impacts of PSAH on asset indices: household fixed effects, linear model, binary treatment

Dependent variable:	Index (PCA)	Index (Inverse proportion)	Index (Prices)
Ejidatarios sample			
Beneficiary	0.076	0.052	0.230
	(0.098)	(0.052)	(0.156)
N	1410	1412	1410
Baseline mean	-0.008	1.886	11.97
Non-ejidatarios sample			
Beneficiary	0.099	0.046	-0.098
	(0.134)	(0.075)	(0.187)
N	754	759	758
Baseline mean	-0.089	1.912	11.184
Weighted sample			
Beneficiary	0.170	0.060	0.101
	(0.123)	(0.072)	(0.154)
N	2016	2021	2019
Baseline mean	-0.122	1.875	11.308
Private landowners			
Beneficiary	-0.168	-0.041	0.241
	(0.145)	(0.045)	(0.265)
N	231	233	231
Baseline mean	0	2.286	20.401

* p< .10 ** p < .05 *** p < .01

Coefficients and standard errors in parentheses for household fixed effects model as described in equation (2). Mean at baseline gives the mean of the relevant index among all households in 2007.

Table 10. Heterogeneous effects across region, distance, and poverty

	Dependent variable: PCA index				Dependent variable: Price index			
	Ejidatarios	Non-ejidatarios	Weighted sample	Private landowners	Ejidatarios	Non-ejidatarios	Weighted sample	Private landowners
Interaction with region								
Benef x north	-0.077	0.209	0.288*	-0.053	0.200	-0.024	0.246	0.638
	(0.124)	(0.199)	(0.167)	(0.227)	(0.269)	(0.217)	(0.202)	(0.416)
Benef x center	0.140	0.185	0.184	0.011	0.244	-0.070	0.130	0.165
	(0.164)	(0.172)	(0.196)	(0.227)	(0.280)	(0.320)	(0.292)	(0.416)
Benef x southwest	-0.130	-0.241	-0.034	-0.215	-0.283**	-0.385	-0.186	0.227
	(0.093)	(0.165)	(0.183)	(0.222)	(0.130)	(0.242)	(0.177)	(0.406)
Benef x southeast	0.312*	0.184	0.300	-0.410*	0.701**	0.122	0.307	-0.064
	(0.175)	(0.276)	(0.213)	(0.227)	(0.286)	(0.379)	(0.294)	(0.416)
Interaction with distance to locality with >= 5000 people								
Beneficiary	-0.054	-0.167	-0.323	-0.383	-0.936	-0.366	-0.353	-0.306
	(0.479)	(0.508)	(0.570)	(0.520)	(0.912)	(0.594)	(0.627)	(0.948)
Benef x distance	0.039	0.080	0.147	0.069	0.345	0.080	0.135	0.174
	(0.142)	(0.153)	(0.164)	(0.159)	(0.266)	(0.161)	(0.177)	(0.290)
Interaction with ln(|min municipal poverty in sample| + municipal poverty 2005)								
Beneficiary	0.246	0.164	0.196	-0.040	0.511*	0.063	0.146	0.189
	(0.150)	(0.193)	(0.209)	(0.169)	(0.266)	(0.313)	(0.256)	(0.364)
Benef x muni poverty index	-0.286**	-0.097	-0.037	-0.010	-0.472*	-0.241	-0.066	0.170
	(0.138)	(0.224)	(0.229)	(0.183)	(0.278)	(0.308)	(0.264)	(0.394)
N	1410	754	2016	221	1410	758	2019	221

* p< .10 ** p < .05 *** p < .01
Coefficients and standard errors in parentheses for household fixed effects model as described in equation (2) with interactions.

Table 11: Within community heterogeneity in impact

	TV	Refrigerator	Computer	Car	Stove	Phone	Cell phone	Wall	Floor	# of rooms
Interaction with PCA index										
Beneficiary	-0.045	-0.007	0.021	0.021	0.007	0.011	0.072**	0.006	0.010	0.062
	(0.031)	(0.029)	(0.016)	(0.022)	(0.024)	(0.019)	(0.036)	(0.064)	(0.040)	(0.043)
Benef x index	-0.030***	-0.024**	0.019***	-0.013	-0.022***	-0.005	0.011	-0.051*	-0.068***	-0.045*
	(0.009)	(0.010)	(0.007)	(0.009)	(0.008)	(0.008)	(0.011)	(0.030)	(0.013)	(0.025)
Interaction with price index										
Beneficiary	0.043	0.020	-0.034	-0.111**	0.063*	0.007	0.061	0.070	0.109	-1.207***
	(0.044)	(0.048)	(0.025)	(0.044)	(0.038)	(0.037)	(0.062)	(0.140)	(0.066)	(0.116)
Benef x index	-0.007***	-0.002	0.005**	0.011***	-0.005*	0.000	0.001	-0.005	-0.008**	0.108***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)	(0.004)	(0.008)
N	2210	2209	2210	2209	2210	2210	2210	2209	2209	2210

* p< .10 ** p < .05 *** p < .01
Coefficients and standard errors in parentheses. Regressions include ejido-level fixed effects and interaction with baseline household wealth index.

APPENDIX: CONSTRUCTION OF WEALTH INDICES

We construct different wealth indices to summarize the socioeconomic status of households based on a set of variables about household ownership of several assets and characteristics of household's dwelling (floors, wall, number of rooms). As Moser and Felton (2007) indicate, there are two advantages of using an asset index in comparison to using traditional consumption expenditure data to measure household's welfare. First, there is less possibility of recall or measurement problems. Second, assets can provide a better picture of long-term living standards. Despite these benefits, the construction of wealth indices involves several challenges. In particular, we need to take decisions about how to aggregate and weight each asset. In general, an index takes following form:

$$A_i = \hat{\gamma}_1 a_{i1} + ... + \hat{\gamma}_2 a_{i2}$$

where A_i is the asset index for household i, a_{ik} are the individual assets k that household i owns and $\hat{\gamma}_k$ are the weights given to asset k, which we must estimate. There are several approaches to constructing these weights and each of them has it own limitations and benefits. In this paper, we adopted three different methods, trying to find an adequate balance between the limitations and how intuitive or easy to understand the measure is. We explain them in detail in this appendix.

A.1 Inverse proportion index

This is probably one of the most simple and intuitive approaches. It is based on a method originally suggested by Townsend (1979) and constructs the weights as the inverse of the proportion of households that owned each asset. The underlying assumption is that assets owned by a smaller proportion of households are indicative of higher household wealth and, therefore, are assigned a higher weight. This method can only be applied to binary variables and the index takes the following form:

$$A_i = \frac{1}{\sum_{i=1}^{N} a_{i1} / N} a_{i1} + ... + \frac{1}{\sum_{i=1}^{N} a_{ik} / N} a_{ik}$$

where a_{ik} is a binary variable taking the value of 1 when household i owns asset k, and N is the total number of households in the sample. We can see that the weight for asset k in this case is given by $\hat{\gamma}_k = N / \sum_{i=1}^{N} a_{ik}$. One limitation with this method is that not all assets show a linear relationship with living standards, for example, ownership of a motorbike may tend to increase up to a certain income and subsequently decrease in richer households (Howe et al. 2008). Also, for categorical data, such as walls' material, we are using binary variables representing the best categories; therefore, any order implicit in these categorical variables is lost.

A.2 Price index

This method uses prices to weight assets, this means $\hat{\gamma}_k = p_k$. The index then represents the total monetary value of the household's asset wealth and it is expressed as follows[24]:

$$A_i = p_1 a_{i1} + ... + p_k a_{ik}$$

Although this approach is very intuitive it has also some limitations. First, price data can be difficult to obtain, even more, local price information. Ideally, an accurate monetary valuation of households' assets will require detailed information about the date of purchase, the market or area where the asset was purchased, and the current condition of the asset (Howe et al. 2008). Second, it is difficult to impute prices for non-market commodities. As Ravallion (2011) suggests, missing prices need to be assigned on a priori grounds or estimations.[25]

A.3 Principal Components Analysis (PCA) Index

Principal Components Analysis (PCA) was recommended as a method for determining weights for variables in a wealth index by Filmer and Pritchett (2001). PCA is a data reduction procedure, closely related to factor analysis. Intuitively, it involves extracting from a large number of variables those few orthogonal linear combinations ("principal components") of the variables that best capture the common information. The first principal component explains the largest proportion of the total variance. Weights are derived from the correlation matrix of the data and assets that are more unequally distributed across the sample will have a higher weight in the first principal component. The index is constructed in the following way:

$$Index_j = f_1 \frac{(a_{j1} - a_1)}{s_1} + ... + f_N \frac{(a_{jN} - a_N)}{s_N}$$

where, f_1 is the scoring factor for the first asset which is determined by the PCA procedure, a_{j1} is the j th household's value for the first asset and a_1 and s_1 are the mean and standard deviation of the first asset over all households in the sample. The main assumption in this method is that household long-run wealth is what causes the most common variation in asset variables.

PCA is designed for use with continuous and normally-distributed data; therefore, its application to discrete data, as proposed by Filmer and Pritchett, can be problematic. For example, for household dwelling characteristics, such as the type of floors, which can be recorded in a scale with n categories, Filmer and Pritchett propose splitting them into n binary

[24] The following values were used for each good (Mexican pesos): tv 4805 , refrigerator 3969, computer 7660, car 46462, stove 3269, phone 384, cell phone 3605, room 36000, dirt floor 6000, cement floor 12000, wood/tile floor 24000, bamboo or other walls 6000, adobe or wood walls 12000, concrete or brick walls 24000. Consumer goods were priced based on reports from Mexico's "Procuraduría Federal del Consumador" (PROFECO).

[25] Consumer goods prices were assigned by a research assistant who did not have knowledge of the survey results.

variables. This procedure introduces distortion in the correlation matrix as variables are perfectly negatively correlated with each other. Moreover, if there is any particular order this is lost since PCA treats every binary variable in the same way (Moser and Felton, 2007). More recently, some authors have suggested the use of polychoric PCA (Kolenikov and Angeles, 2009), which improves on PCA and it is also designed for categorical data. The weighs in this case come from polychoric or polyserial correlations which are maximum likelihood estimates of the correlation between unobserved normally distributed continuous variables underlying their discretized versions.

Kolenikov and Angeles (2004) argue that the gain from using polychoric correlations, which are computationally more intensive than PCA applied on ordinal data, is only related to more accurate estimation of the proportion of explained variance that PCA tends to underestimate. In spite of this, the misclassification rates, as well as rank correlations of indices constructed with these two methods seem to be not substantially different. For this reason, we construct the third index in this paper using PCA on ordered data. It is important to mention some limitations related to this method. First, it requires assumptions about how to rank different categories of the data. Second, it assumes that categories are equally spaced from each other in terms of their relationship with a household's socioeconomic status. Finally, PCA is a fairly complex method and it is likely to be difficult to understand by less technical readers. This is the reason why we also construct the price and inverse proportion index, which seem to be more intuitive.

REFERENCES

Alix-Garcia, J. (2007). "A spatial analysis of common property deforestation." *Journal of Environmental Economics and Management* 53(2): 141-157.

Alix-Garcia, J. (2008). "An exploration of the positive effect of inequality on common property forests." *Journal of Development Economics* 87(1): 92-105.

Alix-Garcia, J., A. De Janvry and E. Sadoulet (2008). "The role of deforestation risk and calibrated compensation in designing payments for environmental services." *Environment and Development Economics* 13(3): 375-394.

Alix-Garcia, J., A. de Janvry, E. Sadoulet, J. Torres, J. Varela and M. Ramos (2005). "An Assessment of Mexico's Payment for Environmental Services Program." UC Berkeley, The Centre for Research and Teaching of Economics, Mexico.

Alix-Garcia, J., E. N. Shapiro and K. R. E. Sims (2012). "Forest Conservation and Slippage: Evidence from Mexico's National Payments for Ecosystem Services Program." *Land Economics*, forthcoming.

Angelsen, A. (2008). *Moving Ahead with REDD: Issues, Options, and Implications*. Bogor, Indonesia, CIFOR.

Angelsen, A. (2010). "Policies for reduced deforestation and their impact on agricultural production." *Proceedings of the National Academy of Sciences* 107(46): 19639-19644.

Arriagada, R., P. J. Ferraro, S. Pattanayak, E. O. Sills and S. Cordero (2011). "Do payments for environmental services reduce deforestation? A farm-level evaluation from Costa Rica." Working Paper, Georgia State University.

Arriagada, R. and C. Perrings (2011). "Paying for International Environmental Public Goods." *AMBIO: A Journal of the Human Environment* 40(7): 798-806.

Arriagada, R. A. (2008). "Private provision of public goods: applying matching methods to evaluate payments for ecosystem services in Costa Rica." Doctoral Thesis, Latin American and Caribbean Environmental Economics Program, North Carolina State University.

Bray, D. B. and P. Klepeis (2005). "Deforestation, Forest Transitions, and Institutions for Sustainability in Southeastern Mexico, 1900-2000." *Environment and History* 11(2): 195-223.

Bulte, E. H., L. Lipper, R. Stringer and D. Zilberman (2008). "Payments for ecosystem services and poverty reduction: concepts, issues, and empirical perspectives." *Environment and Development Economics* 13(03): 245-254.

Burgess, R., B. Olken, M. Hansen, P. Potapov and S. Sieber (2011). "The Political Economy of Deforestation in the Tropics." Working paper, MIT, LSE, World Bank and SDSU.

Chomitz, K. M. and D. A. Gray (1996). "Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize." *World Bank Economic Review* 10(3): 487-512.

CONAFOR (2011). "Sistema Nacional de Información Forestal - Monitoreo Forestal de México:

Aspectos Metodologicos ", Online documentation, accessed March 18. (http://148.223.105.188:2222/gif/snif_portal/index.php?option=com_content&task=view&id=2&Itemid=3#5).

CONAFOR (2012). "National Forestry Commission and the Payments for Ecosystem Services in Mexico." Presentation at University of Wisconsin-Madison, January 2012.

Corbera, E., M. Estrada, P. May, G. Navarro and P. Pacheco (2011). "Rights to Land, Forests and Carbon in REDD+: Insights from Mexico, Brazil and Costa Rica." *Forests* 2(1): 301-342.

Deininger, K. W. and B. Minten (1999). "Poverty, Policies and Deforestation: The Case of Mexico." *Economic Development and Cultural Change* 47(2): 313-344.

Deininger, K. W. and B. Minten (2002). "Determinants of Deforestation and the Economics of Protection: An Application to Mexico." *American Journal of Agricultural Economics* 84(4): 943-960.

Díaz-Gallegos, J. R., J.-F. Mas and A. Velázquez (2009). "Trends of tropical deforestation in Southeast Mexico." *Singapore Journal of Tropical Geography* 31(2): 180-196.

Ferraro, P. J., M. M. Hanauer and K. R. E. Sims (2011). "Conditions associated with protected area success in conservation and poverty reduction." *Proceedings of the National Academy of Sciences* 108(34): 13913-13918.

Ferris, J. and J. V. Siikamaki (2009). "Conservation Reserve Program and Wetland Reserve Program: Primary Land Retirement Programs for Promoting Farmland Conservation." RFF Backgrounder, Resources for the Future.

Filmer, D. and L. Pritchett (2001). "Estimating Wealth Effects Without Expenditure Data—Or Tears: An Application To Educational Enrollments In States Of India." *Demography* 38(1): 115-132.

Foster, A. D. and M. R. Rosenzweig (2003). "Economic Growth and the Rise of Forests." *The Quarterly Journal of Economics* 118(2): 601-637.

Hawkins, S. (2011). "An Analytical Tool for Assessing Legal and Institutional Readiness for PES." Washington, D.C., Forest Trends Report.

Honey-Roses, J., K. Baylis and M. I. Ramirez (2011). "A Spatially Explicit Estimate of Avoided Forest Loss." *Conservation Biology* 25(5): 1032-1043.

Howe, L., J. Hargreaves and S. Huttly (2008). "Issues in the construction of wealth indices for the measurement of socioeconomic position in low income countries." *Emerging Themes in Epidemiology* 5(3).

Imbens, G. and J. Wooldridge (2007). "What's New in Econometrics." NBER Summer Institute Lecture Series.

International Union for Conservation of Nature (2009). "Reducing emissions from deforestation and forest degradation (REDD) in developing countries." *UNFCCC Climate Change Talks*. Bonn.

Jack, B. K., C. Kousky and K. R. E. Sims (2008). "Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms." *Proceedings of the*

National Academy of Sciences 105(28): 9465-9470.

Jindal, R., B. Swallow and J. Kerr (2008). "Forestry-based carbon sequestration projects in Africa: Potential benefits and challenges." *Natural Resources Forum* 32(2): 116-130.

Kolenikov, S. and G. Angeles (2009). "Socioeconomic Status Measurement with Discrete Proxy Variables: Is Principal Component Analysis a Reliable Answer?" *Review of Income and Wealth* 55(1): 128-165.

Lipper, L. (2009). "Payment for environmental services in agricultural landscapes: Economic policies and poverty reduction in developing countries." Rome: Food and Agriculture Organization of the United Nations FAO.

Meneses Tovar, C. L. (2009a). "Analysis of the normalized differential vegetation index (NDVI) for the detection of degradation of forest coverage in Mexico 2008-2009." Working Paper 173, Food and Agriculture Organization Forest Resources Assessment

Meneses Tovar, C. L. (2009b). "Analysis of the normalized differential vegetation index (NDVI) for the detection of degradation of forest coverage in Mexico 2008-2009." Presentation for the Technical Meeting of Forest Degradation. Rome. Sept. 8-10. , Food and Agriculture Organization Forest Resources Assessment

Moser, C. and A. Felton (2007). "The Construction of an Asset Index Measuring Asset Accumulation in Ecuador." CPRC Working Paper 87, The Brookings Institution.

Muñoz-Piña, C., A. Guevara, J. Torres and J. Braña (2008). "Paying for the hydrological services of Mexico's forests: Analysis, negotiations and results." *Ecological Economics* 65(4): 725-736.

NASA (2012). "Measuring Vegetation: Normalized Difference Vegetation Index (NDVI)." Online article, accessed Feb 20, 2012, http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php.

Naughton-Treves, L., J. Alix-Garcia and C. A. Chapman (2011). "Lessons about parks and poverty from a decade of forest loss and economic growth around Kibale National Park, Uganda." *Proceedings of the National Academy of Sciences* 108(34): 13919-13924.

Pagiola, S., A. Arcenas and G. Platais (2005). "Can payments for environmental services help reduce poverty? An exploration of the issues and the evidence to date from Latin America." *World Development* 33(2): 237-253.

Pagiola, S. and W. Zhang (2010). "Using PES to implement REDD." *4th World Congress of Environmental Economists*. Montreal, Canada.

Pattanayak, S. K., S. Wunder and P. J. Ferraro (2010). "Show Me the Money: Do Payments Supply Environmental Services in Developing Countries?" *Review of Environmental Economics and Policy* 4(2): 254-274.

Pfaff, A. (2007). "Will buying tropical forest carbon benefit the poor? Evidence from Costa Rica." *Land Use Policy* 24(3): 600-610.

Pfaff, A. and J. Robalino (2012). "Protecting Forests, Biodiversity and the Climate: Explaining Observed Spatial Variation in Policy Impacts." Duke University, working paper.

Pfaff, A., J. Robalino and G. A. Sanchez-Azofeifa (2011). "Changing the deforestation impacts of Ecopayments: Evolutions (2000-2005) in Costa Rica's PSA." Duke University, working paper.

Pfaff, A., J. Robalino, G. A. Sanchez-Azofeifa, K. S. Andam and P. Ferraro (2009). "Park Location Affects Forest Protection: Land Characteristics Cause Differences in Park Impacts across Costa Rica." *B.E. Journal of Economic Analysis and Policy* 9(2).

Pfaff, A. S. P. (1999). "What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic Data." *Journal of Environmental Economics and Management* 37: 26-43.

Ravallion, M. (2011). "On multidimensional indices of poverty " Policy Research Working Paper 5580, The World Bank.

Robalino, J. and A. Pfaff (2011). "Eco-payments and Forest Loss in Costa Rica: all dressed up but nowhere to avoid deforestation." CATIE and Duke University, Manuscript.

Robalino, J. A. (2007). "Land Conservation Policies and Income Distribution: Who Bears the Burden of our Environmental Efforts?" *Environment and Development Economics* 12(4): 521-533.

Samuelson, P. A. (1983). "Thünen at Two Hundred." *Journal of Economic Literature* 21(4): 1468-1488.

Sánchez-Azofeifa, G. A. (2007). "Costa Rica's Payment for Environmental Services Program: Intention, Implementation, and Impact." *Conservation Biology* 21(5): 1165-1173.

Shapiro, E. N. and S. Castillo (2012). "Evolution of Mexico's Payments for Ecosystem Services Program." Working paper, Duke University.

Sims, K.R.E. (2010). "Conservation and development: Evidence from Thai protected areas." *Journal of Environmental Economics and Management* 60: 94-114.

Townsend, P. (1979). *Poverty in the United Kingdom: Survey of household resources and standards of living* England, Penguin Books Ltd.

Uchida, E., S. Rozelle and J. Xu (2009). "Conservation Payments, Liquidity Constraints, and Off-Farm Labor: Impact of the Grain-for-Green Program on Rural Households in China." *American Journal of Agricultural Economics* 91(1): 70-86.

Uchida, E., J. Xu, Z. Xu and S. Rozelle (2007). "Are the poor benefiting from China's land conservation program?" *Environment and Development Economics* 12(04): 593-620.

United Nations Framework Convention on Climate Change (2009). "Copenhagen Accord." *Conference of the Parties Fifteenth Session*. Copenhagen.

United Nations REDD Programme (UN-REDD) (2011). "About REDD+." Accessed January 13, 2012. (http://www.un-redd.org/AboutREDD/tabid/582/Default.aspx).

Wunder, S. (2008). "Payments for environmental services and the poor: concepts and preliminary evidence." *Environment and Development Economics* 13(03): 279-297.

Wunder, S., S. Engel and S. Pagiola (2008). "Taking stock: A comparative analysis of payments for environmental services programs in developed and developing countries." *Ecological Economics* 65(4): 834-852.

Wunder, S. and S. Wertz-Kanounnikoff (2009). "Payments for Ecosystem Services: A New Way of Conserving Biodiversity in Forests." *Journal of Sustainable Forestry* 28(3-5): 576-596.

Wünscher, T., S. Engel and S. Wunder (2008). "Spatial targeting of payments for environmental services: A tool for boosting conservation benefits." *Ecological Economics* 65(4): 822-833.

Xu, Z., J. Xu, X. Deng, J. Huang, E. Uchida and S. Rozelle (2006). "Grain for green versus grain: conflict between food security and conservation set-aside in China." *World Development* 34(1): 130-148.

Zilberman, D., L. Lipper and N. McCarthy (2008). "When could payments for environmental services benefit the poor?" *Environment and Development Economics* 13(03): 255-278.