Agricultural Subsidies: Cutting into Forest Conservation?*

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Abstract

We examine how agricultural subsidies may induce deforestation and interact with conservation programs by analyzing two large-scale national programs in Mexico that have existed simultaneously for more than a decade: an agricultural subsidy for livestock (PROGAN) and a program of payments for ecosystem services (PES). Looking across the entire Mexican landscape, we exploit the surprises in the timing of enrollment in PROGAN's waves, fluctuations in program payments, and the change in the value of the subsidy induced by inflation and currency fluctuations to identify the impacts of the livestock subsidy on environmental outcomes. We find that PROGAN increased municipal deforestation by 7 percent. The deforestation effects of PROGAN were smaller in municipalities with higher concentrations of PES recipients. We suggest that livestock subsidies could be better targeted to places with low deforestation risk and high livestock productivity to maximize food production and minimize negative externalities caused by deforestation.

Keywords: deforestation, agricultural subsidies, payment for environmental services, livestock, policy targeting

JEL Codes: Q15, Q56, Q28

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1 Introduction

There are $700 billion USD spent globally by governments on agricultural subsidies each year (OECD, 2020). Under certain conditions, these subsidies may have unanticipated impacts on environmental outcomes, especially native vegetation cover (Abman & Carney, 2020; Angelsen, 2010; Pfaff, 1999). While reducing deforestation has been shown to be a cost-effective way to decrease carbon emissions (Busch et al., 2019; Wunder, Engel, & Pagiola, 2008) and is promoted by international agencies through policies like payments for environmental services (PES), agricultural subsidies may increase opportunity costs of standing forest and reduce the cost-effectiveness of forest conservation. Since agriculture contributes 23% and land-cover change 13% of anthropogenic greenhouse gas emissions (IPCC, 2021), understanding the connections between agricultural policies and environmental outcomes is an essential part of climate change policy (Abman & Carney, 2020; Jaime, Coria, & Liu, 2016). It is unclear whether the conflicting goals of these programs may undermine each other, leading to inefficiencies in government expenditures. The question of whether agricultural subsidies encourage or discourage deforestation, and how they interact with conservation efforts, is central to the debate surrounding economic development and the environment.

We study these questions in Mexico, which has a history of both national agricultural subsidies and of cutting-edge conservation efforts. Between 2003 and 2014, the Mexican federal government invested on average 1% of its budget in subsidies to promote agriculture, and simultaneously in payments to mitigate deforestation. In 2020, Mexico was ranked in the top ten countries for deforestation, with about 300,000 hectares of primary forest lost, and the 67th country in terms of deforestation rate (WRI, 2021). We begin by estimating the impact of a broad-scale, per head livestock subsidy (called PROGAN) on forest loss, and examine the mechanisms that drive its effect. In a second stage, we examine whether PROGAN has enrollment effects on the Mexican PES (and vice-versa),

and if enrollment of forests in the PES program ameliorates the impacts of PROGAN on the environment.

To identify the livestock subsidy impacts, we use data from 12 years of both programs across all municipalities with measurable forest cover in Mexico. The 2,166 municipalities in our analysis include 40 million hectares of forests in 2000, which corresponds to an area larger than Germany or Japan. Our identification strategy relies on unexpected fluctuations in program payments, arbitrary program rules, surprises in the timing of enrollment, and variation in the value of the real Mexican peso.[1] We use two-way fixed effects to control for municipality and time characteristics. Our treatment measurement is continuous, so identification relies on changes across time in the intensity of enrollment within municipalities. Although it is not possible to test whether changes in enrollment intensity are uncorrelated with unobservables, comparison of pre-program trends between municipalities with high and low subsidy payment intensity suggests that this approach leverages a valid counterfactual. Our identification also relies on the assumption that there are no anticipatory effects. An estimation including the lead of the treatment variable supports this assumption.

Relative to the average municipality-level forest loss rate of 0.29%, we find that increases in subsidy intensity increase municipal forest loss by 7 percent. Focusing only on years where enrollment is fixed and payment levels vary due to program rules or currency fluctuations, this number is 11 percent. These findings suggest that the program either encourages extensification directly, or raises the marginal productivity of non-forest uses such that pasture expansion is optimal for producers. The extensification hypothesis is supported by analysis of the choice to plant fodder crops, i.e. crops that would facilitate raising more animals on the same land. We find that higher levels of PROGAN enrollment are associated with a decrease in the planting of fodder crops. Further, state-level aggregates of average cattle weight, another proxy for pro-

[1] This last source of variation is similar to the approach used by Richards, Myers, Swinton, and Walker (2012) to examine the impacts of currency fluctuations on soybean expansion and deforestation in Brazil.

ductivity, suggest that the cattle subsidy has not differentially increased productivity in states where enrollment is high. While we cannot rule out other mechanisms, we do not find evidence that the program encouraged intensification, and we do observe that it increased deforestation.

We then proceed to examine the interaction of PROGAN with the PES program. The budget of PROGAN dwarfs that of PES.[2] The two programs overlap, but producers do not appear to be substituting one program for the other – not infrequently, they enroll in both. The evidence suggests that enrollment in one program does not affect the choice to enroll in the other, and that the PES program reduces PROGAN's deforestation effect. For a municipality with average participation in PROGAN and without any participation in PES, deforestation rates increased by 11 percent. However, the increase in deforestation for municipalities with both average PROGAN and PES enrollment was 8 percent. In a supplementary analysis of land submitted to the PES program, we find that PROGAN generally increases deforestation on unenrolled land, but that the PES payments offset this effect on enrolled land.

To illuminate how the distribution of the programs might be improved, we provide a simple analysis that focuses on the stated goals and targeting criteria of both programs. Since most of the deforestation caused by PROGAN occurred in municipalities with high underlying deforestation risk, a more narrow targeting of the livestock subsidy may reduce its negative impact on standing forests and its interactions with the forest conservation program. Because the PES program is generally targeted to areas with some level of deforestation risk and because PROGAN would generate more benefits in municipalities with greater livestock productivity, we identify the potential set of municipalities where PROGAN could maximize the benefits (i.e. livestock production) and minimize the environmental costs (i.e. deforestation).

[2]This is not unusual in developing countries. In the Brazilian Amazon and in Indonesia, the subsidies for environmental conservation are by far exceeded by those that promote agriculture (Dempsey, Martin, & Sumaila, 2020).

The literature shows that programs giving cash transfers (such as PROGAN), rather than physical inputs to increase productivity, may increase the risk of unintended consequences. This is consistent with the finding that cash transfers increase deforestation in some developing country contexts (Alix-Garcia, McIntosh, Sims, & Welch, 2013; Heß, Jaimovich, & Schündeln, 2021), although this need not always be the case (Ferraro & Simorangkir, 2020). In addition to speaking to the question of cash transfers and deforestation, this paper contributes to three other strands of literature: environmental effects of agricultural subsidies, payments for ecosystem services, and the interaction between agricultural and environmental policies.

Global policymakers are concerned about the possible effects of agricultural subsidies on the environment (Goodwin, 2011), yet there is limited empirical evidence in low and middle-income countries. Estimates of the impact of agricultural policy on environmental outcomes can be divided into two categories: first, changes in crop type or demand for inputs, such as nitrogen fertilizer, that may harm the environment (Hendricks et al., 2014; Weber, Key, & O'Donoghue, 2016), and second, increases in agricultural productivity that may affect natural resources (Abman & Carney, 2020; Assunção, Lipscomb, Mobarak, & Szerman, 2017; Cohn et al., 2014). Analyses focusing on input use and runoff externalities tend to find negative effects on water quality in high income settings, although some work shows that crop insurance can reduce chemical use (Smith & Goodwin, 1996). The Common Agricultural Policy (CAP) was found to have no effect on forest cover in Crete (Lorent, Sonnenschein, Tsiourlis, Hostert, & Lambin, 2009). The evidence on the effects of changes in agricultural policies on deforestation in low income settings is mixed. Research in Malawi demonstrates positive effects on forest conservation of an agricultural subsidy that delivers inputs to subsistence farmers (Abman & Carney, 2020; Chibwana, Jumbe, & Shively, 2012; Fisher & Shively, 2005). In this case the mechanism for conservation appears to be an increase in both agricultural productivity and income. Increases in agricultural productivity are also associated with decreased

deforestation in Brazil (Assunção et al., 2017). However, analysis of the Green Revolution demonstrate conflicting effects for forests: Stevenson, Villoria, Byerlee, Kelley, and Maredia (2013) found that it saved land from being deforested and Foster and Rosenzweig (2003) that it increased deforestation. We contribute to this work by examining the situation of livestock subsidies in Mexico, a large, middle-income country, which has labor, credit, and transport market frictions shared by many developing countries.

The literature evaluating PES targeted at forested land has generally shown positive impacts on forest conservation, with some heterogeneity. For example, estimates from Mexico show that PES reduced deforestation by 50% in enrolled parcels (Alix-Garcia, Sims, & Yanez-Pagans, 2015; Alix-Garcia, Shapiro, & Sims, 2012), in Costa Rica's, 11% to 17% (Arriagada, Ferraro, Sills, Pattanayak, & Cordero-Sancho, 2012), 50% in Brazil (Simonet, Subervie, Ezzine-De-Blas, Cromberg, & Duchelle, 2019), and results from a randomized trial of PES in Uganda estimate a reduction of 50% (Jayachandran et al., 2017). In the United States, the estimated impacts of the American Conservation Reserve Program vary widely, but generally indicate conservation (FAPRI, 2007; Parker & Thurman, 2018; Wu & Weber, 2012).[3] Current evidence suggests that PES conservation impacts are reduced by the spillovers they generate (Alix-Garcia et al., 2012; Robalino, Pfaff, & Villalobos, 2017; Roberts & Bucholtz, 2005; Wu, 2000), and that unconditional conservation payments may result in poor conservation outcomes (Wilebore, Voors, Bulte, Coomes, & Kontoleon, 2019). These studies generally do not address other policies that might be influencing outcomes, beyond trying to rule out confounding variation. For example, higher spillovers are found in areas with higher agricultural returns (Robalino et al., 2017). This implies that agricultural policies could increase spillovers by increasing the returns of land. Further, because it is rare that PES payments are indexed and that participants are compensated for the higher opportunity costs caused by agricultural subsidies (Jack, Kousky, & Sims, 2008), such subsidies may reduce PES effectiveness.

[3] Alix-Garcia and Wolff, 2014 provide a review of the literature on PES before 2014.

Consequently, environmental services may not be provided, either because contracts are not taken up or because compliance is partial (Ajayi, Jack, & Leimona, 2012). We fill a gap in this literature by estimating whether PES reduces the deforestation impact of the livestock subsidy, and if the programs have enrollment effects on each other. We show that the cattle subsidy increases deforestation, that PES partially offsets this increase in Mexico, and that there are not detectable enrollment effects in either program.

Finally, we also contribute to work that estimates interactions between environmental and agricultural policy. Although there has been much discussion of these types of dynamics in both policy circles (see DOS (2021), UNFCCC (2020)) and in theory (Angelsen, 2010; Angelsen & Rudel, 2013), less has been established empirically (Lubowski & Rose, 2013). We have identified three analyses of multiple programs related to the analysis we present here. Jaime et al., 2016 found negative interactions of a market subsidy on uptake of organic agriculture, making the adoption of sustainable practices more expensive, while Meeks, Sims, and Thompson, 2019 show how biogas subsidies supported the operation of protected areas in the hill region of Nepal. In a related line of inquiry, Moffette, Skidmore, and Gibbs, 2021 examine how two environmental policies interacted to increase cattle productivity, and subsequently reduce deforestation, in the Brazilian Amazon. Our work shows that these programs interact in important ways that are not visible in the analysis of each program individually. In particular, we show that PROGAN raises the background deforestation risk, making PES effects more visible, and that PES serves to reduce the deforestation effects of PROGAN. We also suggest ways in which more judicious targeting of livestock subsidies might reduce their impact on deforestation.

2 Background and data

Here we provide an overview of this paper's trajectory. We begin by describing the data and providing essential programmatic background. In Section 3, we examine the

direct impacts of the PROGAN livestock subsidy on deforestation throughout Mexico, and then use the information on producer crop planting decisions to suggest a possible mechanism for the producer response. All of this analysis will be conducted at the municipal level, and the overarching strategy is to exploit variation in program take-up and payment amounts controlling for municipality and year fixed effects, with robustness checks that restrict variation to the most exogenous sources, including scheduled changes in payment levels and unanticipated currency fluctuations. In Section 4, we use this same approach to understand the interactions between PROGAN and the national PES program. In this section, we begin by providing descriptive statistics of program overlap and take-up, then we study how PROGAN has influenced take-up of PES, and finally, we estimate the joint impact of these programs on deforestation outcomes. Section 5 examines the distribution of each program and compares it with their targeting criteria to determine how PROGAN could be better targeted.

2.1 PROGAN: description and data

PROGAN is a national livestock subsidy that began accepting applications in waves, starting in 2003, with a second wave in 2008 and a third in 2014.[4] According to Álvarez-Macías and Santos-Chávez, 2019, the program was inspired by the idea of conditional cash transfers, popular in Mexico due to the rollout of Progresa (an educational conditional cash transfer program) in 1997. The goal of the initial wave (2003-2006) was to improve the productivity of extensive cattle production, and for this reason it was focused in tropical, arid and semi-arid zones where this activity generally occurs. Program managers intended to give applicants yearly payments for the entire duration of the wave after enrollment for the number of animals they owned at the moment of the application. However, payments were unexpectedly disrupted during the first wave, so producers only received payments for four out of five years between 2003 and 2007, and the timing of these varied considerably.

[4]Details on the application process are in Appendix A.

During the second and third waves of the program (2008-2013, and 2014 onwards), the focus was on expanding program coverage to include a broader set of areas and types of production beyond cattle, and on increasing the sustainability of this production. Further, the program required improving vegetation cover and increasing fodder production within their land, although the monitoring of these rules and definitions lacked clarity and guidance (more details included in Appendix A).

To broaden the program, they tried to expand the reach to smaller livestock producers by offering them larger payments starting in 2008. During the first wave, PROGAN subsidized only cattle while the second and third waves added subsidies for dairy cows, sheep, goats, and bees. The second and third waves also required commitments to environmental management activities and technical assistance to implement them. However, in practice the support for and monitoring of these commitments was extremely weak (Alvarez & Santos, 2013). In section 2.6, we examine the changing composition of enrollment over the waves included in our analysis. Table B4 summarizes the wave-specific variation in the livestock subsidy coming from changes in program rules and missed payments.

Data on PROGAN enrollment and payments from 2003 to 2015 comes from SAGARPA (Ministry of Agricultural, Livestock, Rural Development, Fish and Food). We use a GDP Deflator (World Bank, 2017) to transform monetary values in 2008 real Mexican pesos (MXN). Although the subsidy is available at the individual landowner level, we can not match them to parcels, thus we aggregate them to the municipal level.

Our analysis is focused on livestock (we exclude bee subsidies). Ranchers receive the yearly subsidy as a function of the cattle unit equivalent (referred to as "animal equivalents"), which varies according to the type of animal (e.g., one goat is equivalent to one sixth of a cow, and consequently, the subsidy amount for one goat is one sixth of the amount for a cow) and by a metric called "the pasture coefficient," which measures how many animals a hectare of land can support in a sustainable way. Subsidy amounts are

restricted by the pasture coefficient and calculated using the information provided in the National Livestock Registry. We calculate the maximum sustainable livestock for each municipality by tying the calculations for the pasture coefficient to characteristics of the land specific to each municipality (details presented in the Appendix B). Total allowed number of cattle unit equivalent subsidized are high and so large ranchers receive a significant portion of the total subsidy.[5] Beyond being given to existing livestock holders and the limitation on subsidies above the amount dictated by the pasture coefficient, PROGAN had no other targeting criteria or conditionalities. It therefore operated as a cash transfer to individuals holding livestock.

During the first wave, the subsidy per animal increased by 100 nominal pesos each year (Figure 1a). In 2007, there was not a subsidy per animal because this is the unplanned additional year of the first wave. In 2008, the subsidy per equivalent animal dropped by 50% overall, although it started to include a premium for small producers. In 2011, the subsidy represented about 5% of the average value of a cow at the slaughterhouse (SIAP, 2021). Since cattle are typically ready to slaughter after at least 24 months, the subsidy represented on average about 10% of its commercial value at the slaughterhouse (Skidmore, Sims, Rausch, & Gibbs, 2022). Figure 1c graphs the expected nominal subsidy strictly calculated according to the program rules and compares it with the aggregated payments that were received by producers. Since the first wave was originally planned to occur between 2003 and 2006, with unit payment increasing each year, there is a steep increase in the expected subsidy during those years. The comparison between the expected nominal and the real subsidy reveals two key points. First, the large variation in the real PROGAN subsidy in 2007 results from a combination of increases in payment steps and delayed payments from the beginning of the first wave that were

[5]The maximum subsidized cattle unit equivalent is 300 per producer. Starting in the third wave, the maximum was 1000 per registered group of producers. Beginning in 2008, prices were split into two categories. During the second and third wave, owners of 35 or fewer cattle unit equivalents were paid 75 and 70 MXN pesos more per unit than owners with more than 35 units. For simplicity, we excluded this detail from Figure 1a.

given in later years. Second, the greater variation in the subsidy per animal and uncertainty about timing of payments suggests that the first wave contains more exogenous variation than subsequent waves. Because of this, we implement robustness checks that use only the first wave.

Variation over time in the amount of PROGAN subsidies comes from four sources: changes in (1) the subsidy per animal determined by the program, which varies within enrollment waves; (2) the timing of payments, some of which were unexpected; (3) animals enrolled in 2003, 2008, and 2014 (which varies according to the type of animals eligible and maximum allowed), and (4) the real value of the peso. While the variation from (1), (2), and (4) is arguably exogenous to individual farmer actions, (3) presents identification challenges which we will discuss further below. Figure 1 shows these sources of variation in the livestock subsidy: Figure 1a presents (1) and (4); Figure 1b presents (3), and Figure 1c presents the aggregated subsidy which includes all four sources of variation. The treatment variable we use throughout this analysis is depicted by the thick line in Figure 1c.

The number of equivalent animals enrolled in PROGAN is about 5.7 million during the first wave (Figure 1b). This initial enrollment occurred in nearly 68% of the municipalities in our sample. Equivalent animals increased by almost 88% for the second wave, with 22% of municipalities enrolling for the first time, and a large part of the increase was due to increases in livestock number in the first wave municipalities (Figure B6). In 2014, the number of equivalent animals decreased by 17%, with new enrollment in only 3% of municipalities. According to conversations with program managers, this is most likely due to a stronger enforcement of the maximum capacity of the land as dictated by the pasture coefficient. Seven percent of municipalities never had any enrollment in PROGAN.

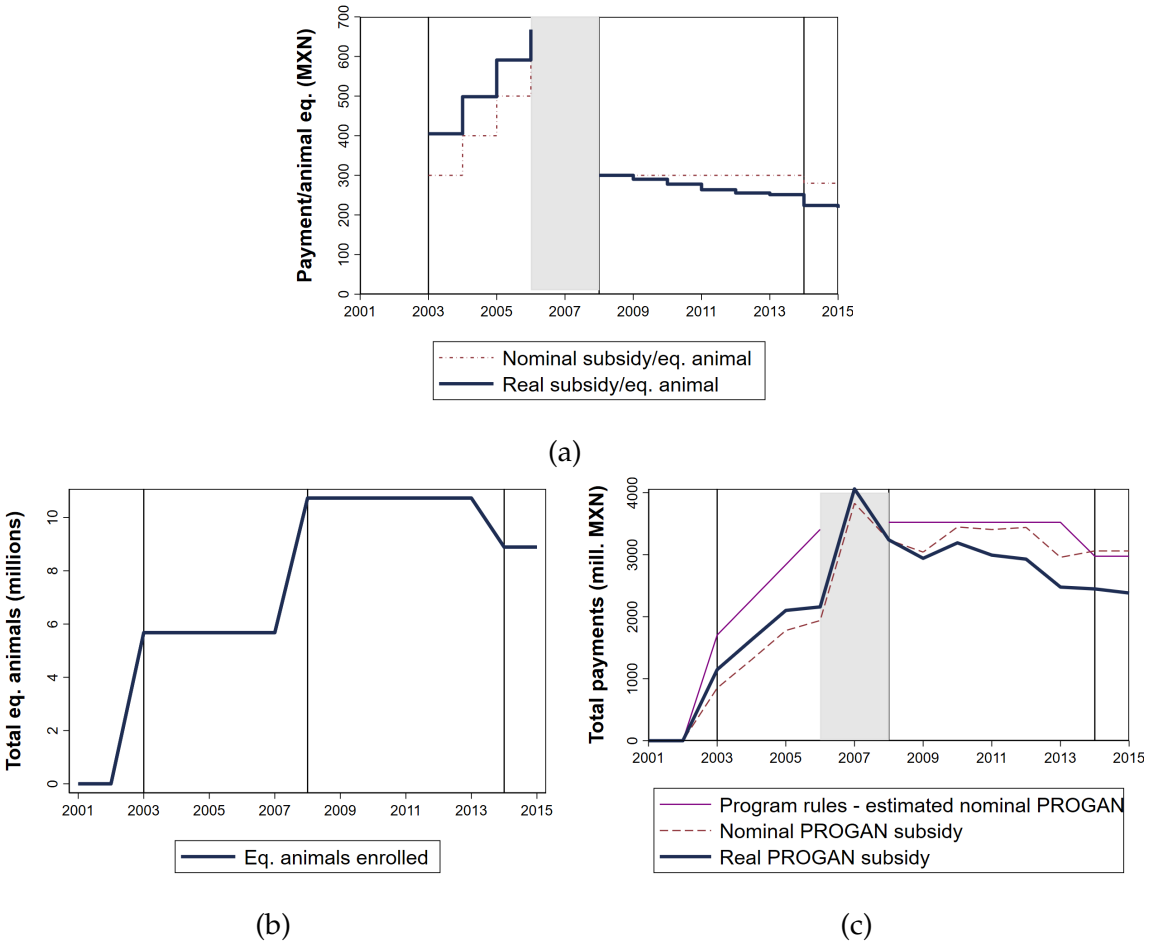


Figure 1: Nominal and real subsidy per equivalent animal (a), variation in equivalent animals enrolled (b) and PROGAN subsidies (c). Vertical lines represent application years for PROGAN (i.e., 2003, 2008, 2014). The grey shadowed area represents the unplanned additional year of the first wave.

2.2 PES: description and data

Mexico's PES program, like PROGAN, began in 2003 with a program of payments for hydrological services. Application is voluntary, and payments are only awarded to applicants within eligible zones defined by the government. Eligible zones are determined by geographic characteristics chosen by the federal government and vary year to year. The amount of the subsidy depends on forest type and the government estimates of deforestation risk, and has evolved over time (see Table A2), with decreases in its real value driven by inflation. We examine the arms of the PES program that focus on hydrological services and biodiversity, which are the largest and most durable.[6] Initially, targeting was based almost entirely on eligible zones and existence of forest cover, with properties having higher forest cover receiving priority. Starting in 2006, a point system was implemented to allocate the subsidies to the applicants. Scores are calculated according to a number of criteria that have also evolved over time, such as deforestation risk; surface water scarcity; indicators about whether the property falls in an over-exploited aquifer, a Natural Protected Area, or a municipality with majority indigenous population or with high poverty; and other factors. Applicants with the highest scores are approved until the state budget limit is reached. This means that the threshold of points for acceptance into the program varies by state-year, and by sub-program within state-year. Participants sign a five-year contract, during which payments are conditional upon forest preservation and improvements in forest management (e.g., building fire breaks). Monitoring is done via satellite imagery and follow-up live inspection in the case of suspected violations. Payments are revoked or reduced in the event of contract violations. The evolution of program targeting is discussed in detail in Sims et al., 2014 and Alix-Garcia, Sims, and Phaneuf, 2019.

Data for the federal PES comes from the agency managing the program, the Mex-

[6]Through the years, there have also been programs for agroforestry, carbon capture, and natural regeneration of the forest. However, the number of properties enrolled in these has been quite small and these programs often did not follow the same rules of operation for the larger programs.

ican National Forestry Commission (CONAFOR by its Spanish acronym). CONAFOR provided digital maps of the parcels, which detail the location and boundaries for all land submitted to the program from 2003 to 2015. For our main analysis, this data is aggregated to the municipality level. An analysis at the parcel level is provided in Appendix F.

Our main treatment variable for the PES program is ratio of recipient hectares per municipal area. We use this rather than the monetary value of payments per municipality hectare because this measure is a more direct proxy for the contract that producers make regarding their deforestation behavior. However, this measure, unlike the treatment variable for PROGAN, does not change with the rate of inflation or the exchange rate. Any effects of the relative value of payments will already be realized in our enrollment levels measure. Figure B5 shows the delineation of the eligible zones over time for the PES program and the geographic distribution of the applicants accepted (in black) and rejected (in red). Accepted and rejected parcels tend to be near each other, and they are distributed evenly throughout the country and the eligible zones. Over time, the eligible zones have expanded considerably, so there is significant variation in the number of years in which specific land has been eligible.

The ratio of PES applicant hectares at the municipality level per eligible zone is an outcome of interest to measure whether PROGAN affected the willingness to apply in PES. To control for characteristics of eligible zones land that could confound the willingness to enroll in PES and PROGAN, we calculate the following for each municipality and year: percent in common property, in natural pasture in 2002, in pasture associated with livestock production, as well as road density and the area of the zones. The National Institute of Statistics and Geography provides data on the baseline pasture (INEGI a) and the road network (INEGI b). The percentage within communal land is from the National Agrarian Registry (PHINA). Because the zones change from year to year, these aggregates vary across time.

2.3 Sample

In all of our analysis, we restrict ourselves to municipalities that had at least 50 ha of measured forest cover in 2000 (the baseline year of our forest data). The reason for this is that our measure of environmental impact is deforestation, which cannot be detected if there is not measurable forest. We also restrict ourselves to municipalities that had at least 50 ha of eligible zones for the PES program on average over the sample period, although the Appendix shows results with a sample unrestricted by eligible zones. This is because we intend to measure the extent of the competition between agricultural and environmental subsidies. Although the PES program does pay for the conservation of arid ecosystems, many of these may not have forest as measured by our remotely sensed outcome. Because we cannot assess environmental impacts in these areas, we exclude them from our analysis. This restriction limits us to 2,166 municipalities out of the 2,457 total municipalities in Mexico. Despite the continuous expansion of the eligible zones across the country, PES payments were ever allocated in 887 municipalities during our study-period.

2.4 Deforestation

To analyze the impact of the livestock subsidy on deforestation, we use tree cover loss information from 2001-2014 and forest cover metrics for 2000 from Hansen et al., 2013 at the level of the PES parcels and the municipality.[7] An area is defined as forested in 2000 if its canopy cover was greater than 50%, and deforestation is conditional on the area being forested in 2000.

To examine heterogeneity as well as to conduct program targeting analyses, we create a deforestation risk measure at the municipal level. We use a sample of nearly 80,000 5 km x 5 km grid cells created by the authors to predict the probability of deforestation

[7]The dataset has a spatial resolution of 1 arc-second per pixel, or approximately 30 meters per pixel at the equator. In Mexico, this is an average of 710 m^2 per pixel. Forest cover loss is defined as a stand-replacement disturbance.

using pre-program data (i.e. 2001-2002). Rather than choosing a set of variables to predict deforestation, we use machine learning. Specifically, we apply a probit lasso estimator, which relies on both regularized estimation and data-driven choices of the regularization parameter. It has an advantage over OLS for prediction in that it helps to minimize overfitting (Ahrens, Hansen, & Schaffer, 2018). The choice of a probit also ensures that the predicted value remains between 0 and 1, which is useful when the user is interested in the predicted probability, rather than the marginal effects of particular covariates. Covariates included are baseline forest cover, distance to city, road density, distance to nearest urban area, average and standard deviation of elevation, average and standard deviation of slope, biome indicators, and state indicators (estimation equation and results are presented in Table B3). The deforestation risk measure is equal to the municipal average of the predicted probability of deforestation of each grid cell included in the municipality.

2.5 Livestock intensification outcome

To proxy for intensification of livestock production, we examine a measure of transition from non-fodder crops into fodder production. The planting of fodder crops allows producers to raise more animals on less land, and with proper choice of fodders can improve animal and pasture health, as well as reducing the carbon footprint of raising livestock (Ates et al., 2018). The increase of fodder use and productivity of livestock production was a major focus for PROGAN throughout its various waves (Álvarez-Macías & Santos-Chávez, 2019). The information on fodder crops comes from a government program called PROCAMPO, which began in 1994 as a reaction to the NAFTA agreement (Sadoulet, Davis, & de Janvry, 2001).[8] This program subsidizes continuous agricultural production for around 3 million producers, or approximately 14 million hectares per year. Because additional enrollment in the program was forbidden after 1993 and subsidies do not vary by crop type, producer choice is limited to which crop to produce.

[8]Program background is available in Appendix A.

If they cease planting, they lose the subsidy. To obtain data on replacement of crop with fodder for each municipality and year, we aggregate the area cultivated in alfalfa, fodders, yellow corn, fodder corn, annual pasture, and forage sorghum, and divide by the total subsidized hectares of the municipality in 1999, the first year of our data. PROCAMPO covered almost all of the agricultural area in 1994 and 58% of the total agricultural area in 2002 (OECD, 2005). Although it is not a census, it does cover a large part of the agricultural activity in the country. Further, it provides a detailed panel on agricultural production that includes producers of all sizes and for all crops.

2.6 Descriptive statistics

Table B5 summarizes a number of key variables according to whether PROGAN enrollment was, on average, above or below the median across all municipalities. Total submitted hectares of PES are lower in areas with high PROGAN, and given the relatively similar percent hectares submitted within eligible zones in both types of municipalities, it would appear that the eligible zones are smaller in areas with high PROGAN. We also observe higher deforestation in high PROGAN municipalities, a smaller drop in deforestation over time in areas where PROGAN is more prevalent, and a greater deforestation risk in high PROGAN municipalities. Municipalities with low and high PROGAN intensity have similar baseline forest per municipal hectare. PROGAN tends to be higher in municipalities that have less dense population, lower slope and elevation, and also have greater replacement of crop with fodders.

Since the first wave provides a key robustness check to our analysis, we provide additional details about the randomness in payments occurring during this period. Table B6 shows when each of the four payments were provided over the five years. Only 40% of total payments were allocated in the first year of the first wave as expected, with some producers even receiving their first payment in 2007. Overall, 5.1% of the planned payments did not occur in the first wave, 7.6% did not occur in the second wave, and 2.9% additional payments occurred in the third wave (Table B4). When examining the

spatial distribution of payments during the first wave (Table B7), we show that no region benefited disproportionately from earlier payments. In sum, Tables B6 and B7 show that the shifts in the timing of payments during the first wave are beyond control of producers and occur without any particular spatial pattern.

Municipalities that enrolled in the first two waves had more potential for livestock production as measured by the average municipal pasture coefficient. This potential decreased substantially for the few municipalities that started enrollment in the third wave, and those that never received PROGAN also have relatively lower livestock potential (Figures B7 and B8). Underlying deforestation risk is highest in municipalities that enrolled first, and drops significantly for those beginning in the second wave, increasing slightly for third wave and never enrolled municipalities. We test statistically how characteristics change by cohort and intensity of enrollment (Table B8). Overall, municipalities with higher PROGAN enrollment are larger, at lower slope and elevation, with higher deforestation risk and greater potential for animal production. As enrollment progressed, smaller municipalities with somewhat lower deforestation risk and less livestock potential began to enroll.

These wave-specific summary statistics imply that comparisons that exploit the enrollment choice after the first wave may be biased upwards. However, when we limit analysis to the first wave, we observe similar results to the analysis using the entire sample, suggesting that this bias is unlikely to drive our results.

3 Deforestation effects of PROGAN

This section examines the deforestation impact of PROGAN. We begin by briefly discussing our expectations. We then describe the empirical strategy, examine the assumptions that underlie the validity of the strategy, and present the results on deforestation followed by results on intensification.

What is our expectation? A standard land rent framework with higher transport

costs for agricultural goods (Angelsen, 2010) yields a familiar set of predictions. Under the simplest assumption of three land uses (forest, pasture, and agriculture), this type of model suggests that landowners would choose to hold forests in areas where the rents to pasture are less than rents to forest, and livestock production would occur in other places. A per head livestock payment increases capital as a function of livestock that is already owned. This effectively lowers the cost of having livestock, and possibly releases producer credit constraints, which we assume to exist in our setting. Because there are no enforced conditionalities, producers might use this income for investment, consumption, or savings.

For credit-constrained producers, releasing the constraint may allow for investments that would have otherwise been impossible, including purchasing more livestock, productivity-increasing technology, or some other investment or consumption good. Even if producers are not credit-constrained, they may believe that enrollment will open up again in the future, and may purchase more livestock in the hopes of receiving greater future payments. This would be a risky choice, given that program renewal was not announced until very close to the next wave. Further, if there is a wealth effect from the transfer that increases the consumption of land-intensive goods, then this could lead to spillover deforestation effects. Increased demand through a wealth effect could also lead to local price increases if markets are not fully integrated, thus intensifying the spillover effect.

Given this set of relationships, if the program induces productivity-increasing investments in livestock by releasing credit constraints, it is possible that PROGAN will leave forests unaffected, since it could increase output on existing pasture. However, if this investment greatly increases the marginal productivity of land in pasture, deforestation is likely to ensue. Deforestation increases might also occur through wealth effects, but would depend upon the income elasticities of consumption of land-intensive versus other goods, and upon the degree of market integration. In a scenario where PROGAN induces additional purchase of animals using the same production techniques or

increased consumption of land-intensive goods, deforestation is also likely to increase.

3.1 Empirical strategy

Because agricultural and forest productivity both depend on underlying characteristics of the land, identifying the effect of PROGAN on deforestation is challenging. However, under the assumptions that 1.1) the programmatic adjustments in payment levels, 1.2) the unexpected change in payment timing, and 1.3) fluctuations in the real value of the peso are all exogenous to characteristics of the land; and that 2) producers did not change their behavior in anticipation of enrollment years, we can approach the causal effect of the impact of changes in the value of the livestock subsidy on deforestation. The baseline estimation equation is:

$$Y_{mt} = \beta PROGAN_{mt} + M_m + \theta_t + u_{mt}, \tag{3.1}$$

where Y_{mt} is the percent deforestation over baseline forest cover for municipality m and $PROGAN_{mt}$ is the municipal livestock subsidy per hectare. We prefer this measure to the direct measure of PROGAN-funded animals per hectare because the claim for exogeneity is stronger. This amount changes annually, which allows us to examine subsets of the data where no enrollment decisions are being made, and where identification of changes over time comes only from the changes beyond the control of the individual producers. In Tables C9 and C10 we show estimations using only PROGAN-funded livestock per hectare as the treatment metric.

Depending on the specification, M_m is a state or a municipal fixed effect. The first controls for geographic variation across states and the second for time-invariant characteristics of the municipalities. θ_t are year fixed effects and standard errors u_{mt} are clustered at the municipal level. In the fourth specification, we restrict the sample to municipalities that ever had PES enrollment; this sample supports comparability with the parcel level PES analysis, discussed in Section 4. In the last specification, we apply the baseline forest area as a weight because these areas vary substantially from munici-

pality to municipality.

The identification of β comes from variation in PROGAN intensity within municipalities across time.[9] The implicit comparison is between municipalities with higher and lower PROGAN intensity. To examine the assumption that trends might be different in places where there was eventually high program enrollment in PROGAN, we apply two tests of differences in trends before 2003. First, we create categories based on the median level of payments over the full duration of the program. Second, we calculate the average of subsidy payments across all years. We interact these with the year trend for the two pre-program years. We observe no differential trends after conditioning on municipality and year fixed effects (Table C1). Figure C1 shows these pretrends visually.

In the results section, we also discuss several robustness checks intended to probe these underlying assumptions, including whether the result is robust to using only the variation in payments caused by adjustments in program rules and changes in the value of the currency during the first wave (2003-2007), a test of anticipatory behavior using leaders, a falsification exercise based on randomizing the treatment multiple times, and analyses of robustness to additional controls.

3.2 Results

Table 1 shows the results of Equation 3.1. Columns (1)-(4) present unweighted regressions and column (5) adds probability weights corresponding to the baseline forest cover area. The estimations show that the livestock subsidy increased deforestation at the municipal level. All coefficients on the livestock subsidy intensity are positive and statistically significant at the 1% level. Results are robust to different specifications including unweighted (column (3)), limiting the sample only to those municipalities that ever had PES enrollment (column (4)), and weighted regression (column (5)). Using specification from column (3), we calculate that the magnitude of the average municipal intensity of

[9]The continuous nature of the treatment variables means that we cannot exploit the recent advances in difference in differences estimators (e.g., Callaway and Sant'Anna, 2021).

PROGAN resulted in a 10% increase in the rate of municipal deforestation. Using the specification from column (5), the effect is 7%.[10]

Table 1: Regressions of deforestation on PROGAN subsidy

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	6.3578***	5.6952***	1.8383***	1.2148**	1.2660***
	(0.3347)	(0.3636)	(0.5706)	(0.4851)	(0.4792)
Adjusted R2	0.027	0.144	0.361	0.249	0.501
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

The results of the impact of PROGAN on deforestation are robust to examining only the years between 2003 and 2007, when variation from number of animals enrolled is excluded (Table C2). Since the presence of never treated municipalities affords the possibility of finding estimators centered around the average true coefficient (Sun & Shapiro, 2022), we compare these municipalities to those that enrolled in the first wave. Results are robust for all waves (Table C3) and for the first wave exclusively (Table C4). The similar results for the first wave and all waves together implies that treatment effects may be relatively constant across cohorts, which supports the underlying assumptions for identification. We also test whether leads of the treatment variable indicate anticipatory effects of changes in the subsidy (Table C5) and find none. Further, we restrict the sample to municipalities that had eligible zones for the PES program (Table C6) and run the estimation on all municipalities (Table C7). Finally, we conduct a falsification exercise, where we randomize the existing distribution of PROGAN "treatments" – the vector of PROGAN subsidies associated with a municipality – across all municipalities

[10]The average subsidy per ha is .01546 kMXN/ha (or 15.46 MXN/ha). We multiply the estimated coefficient from column (3) per the average subsidy, and divide by the pre-mean deforestation of 2002 (i.e. (1.838 x .01546)/0.29% = 10%). For column (5), we do the same steps but use the weighted PROGAN treatment and the weighted deforestation pre-mean (i.e. (1.266 x .01912)/0.34% = 7%).

1,000 times. This is similar to the process of randomization inference (Athey & Imbens, 2017). Using this method, we find that our estimated coefficient falls very far outside the distribution that would have been expected had PROGAN enrollments been randomly allocated across municipalities (see Figure C2).

Our results may suffer from estimation bias due to different municipality trends that affect deforestation rates and are correlated with enrollment in PROGAN. Table C8 shows the stability of the results to variables that may affect deforestation rates and be correlated with PROGAN enrollment. We proxy for violence with a panel dataset on murders by municipality, for credit access by the number of bank branches in the municipality, and for migration with flexible state trends since patterns of migration in Mexico are known to be driven by historical persistence (i.e., following old railroad lines and Bracero program recruitment as in Woodruff and Zenteno, 2007) and change very slowly over time (e.g., the recent increase in migration from more southern parts of the country (Riosmena & Massey, 2012)). The state-by-year interactions address not just migration, but also any other year-to-year variation within states that might be related to the capacity of state governments. None of these additional controls change the results.

Pre-program trends and results for the simple measure of animal equivalents enrolled per ha are presented in Tables C9 and C10 respectively. While animals enrolled is a measure of livestock pressure at the time of enrollment, the subsidy measure includes both this initial livestock intensity and variation in the value of the subsidy.

3.3 Intensification of livestock production

These estimations demonstrate that the livestock subsidy increased deforestation when the amount of the payments increased. One possible mechanism to explain this effect is extensification. To examine this dynamic, we consider how the introduction of the livestock subsidy modified the crop choices within the long-standing PROCAMPO program. Specifically, we measure the impact of PROGAN on the percent fodder cultivated on program land between 1999 and 2014. The logic is that planting fodder may allow

more livestock to be supported on less land because fodder is of higher nutritional value than extensive pasture. We use a similar specification to Equation 3.1, replacing the deforestation outcome with percent fodder on PROCAMPO land. As above, the identifying assumption is that changes in PROGAN enrollment are uncorrelated with other factors driving crop choice within PROCAMPO. This is untestable, but we do not find any statistical difference in crop choices during pre-PROGAN years (1999-2002) (Table D1).

Table 2, specifications (1)-(3), show that PROGAN actually *decreased* the share of fodder on PROCAMPO land. Since there is large variation in PROCAMPO baseline area across municipalities, our preferred specification is in column (4), which contains area weights. We estimate a negative effect significant at the 10% level associated with the subsidy. These findings are similar to the analysis restricted to the impact of PROGAN for 2003-2007 (Table D2).

Further descriptive evidence that intensification did not occur as intended can be found in Appendix B. These figures show trends in average cattle weight over time using aggregated state data from the Service of Agri-food and Fishery Information (SIAP, 2021), in states with above versus below median levels of PROGAN enrollment. Cattle weight is a proxy for productivity, since increases in weight are associated with better feed and genetics (Terry, Basarab, Guan, & McAllister, 2021, 1). The data show flat cattle weight in both high and low PROGAN states, with a simultaneous increase in 2014. We also do not observe differential trends across states in heads slaughtered, cattle price, or production. Trends for pork, a potential placebo, also show no differences across high and low PROGAN states, and exhibit similar time trends to cattle.

We therefore find no evidence that PROGAN increased intensification. There are two caveats to this. First, producers might be planting fodder on their own PROCAMPO plots and selling it to neighboring municipalities, so spillover effects might undermine identification. Second, producers may be intensifying in other ways, for example, by importing feed, improving livestock rotations, or planting fodder on non-PROCAMPO

Table 2: Regressions of PROCAMPO fodder (%) on PROGAN intensity

	Fodder (%)			
	(1)	(2)	(3)	(4)
Subsidy/ha (kMXN)	-20.7149***	-2.3503**	-7.8311***	-2.2047*
	(1.3155)	(0.9466)	(1.5647)	(1.3254)
Adjusted R2	0.008	0.370	0.747	0.713
Observations	34,153	34,153	34,153	34,153
Year FE	X	X	X	X
State FE		X		
Municipality FE			X	X
PROCAMPO weights (1999)				X

Note: Years 1999-2014. Pre-mean of dependent variable is 1.3%. Robust standard errors are clustered by municipality. The fourth column includes weights for the municipal area of PROCAMPO in 1999. * p< 0.10, ** p<0.05, *** p<0.01.

land. There are also other potential mechanisms that might drive the observed increase in deforestation. First, higher rents per hectare as a result of the program could induce land use change. A complementary dynamic might occur if the cash payments allowed producers to engage in production for which they did not have capital prior to the program. Finally, increases in income resulting from the program could result in deforestation via increased consumption of land-intensive goods. We thus take this evidence as suggestive.

4 Agricultural subsidies and PES

This section examines the interaction of PROGAN with Mexico's national PES program. We begin with a brief discussion of how the programs might affect each other. Then we use data to describe the actual spatial interaction of both programs, and we confirm that each is not measurably affecting enrollment in the other. Finally, we examine the interactions of the two programs on deforestation.

We established above that inreases in the PROGAN subsidy values increase deforestation. This suggests that producers are using the subsidies either to augment the number of their livestock or that they are making other investments that favor pasture

and agriculture over forest. It is also possible that there is a wealth effect that is driving increased demand for non-forest uses of land. The subsidy does not appear to finance fodder that would allow for the production of more livestock on the same amount of land. So, what happens in the presence of the PES incentive?

PES gives payments that are conditional on preserving forest, and therefore raise the value of standing forest. By themselves, they should help conserve forest in places where it otherwise might have been replaced by other uses. Whether or not this incentive interacts directly with PROGAN depends upon producers' land holdings. There are three possibilities for program interactions for those that hold forested property. Producers with small amounts of forest might have to make a choice about whether or not to enroll in the PES (or PROGAN) program at all. If it is simply more profitable to engage in their agricultural or livestock investment activities on forested land than to enroll it in the PES, they may do so, thus decreasing enrollment in PES. The process could also work in reverse, resulting in lower PROGAN enrollment in areas with high PES potential.

For producers with larger amounts of forest than the PES program minimums, PROGAN could increase the appeal of deforestation on land that is not already enrolled in the PES program, provided that land can support livestock. In this case, the additional deforestation would not take place on land submitted to the PES program but this activity would still undermine conservation by increasing deforestation in general. If producers already have land enrolled in the PES, they may break the program rules and deforest it. This would directly undermine the goals of the PES, and is the third potential outcome (analyzed in Appendix F).

To summarize, the interaction of the programs may change enrollment in the PES program, increase deforestation on non-PES land, or induce deforestation on enrolled PES land. Since PES is also a cash transfer program, if the main available investment activities involve deforestation, then the additional capital from PES may, perversely, support future deforestation. The next section describes the distribution and overlap of

the land enrolled in the two programs.

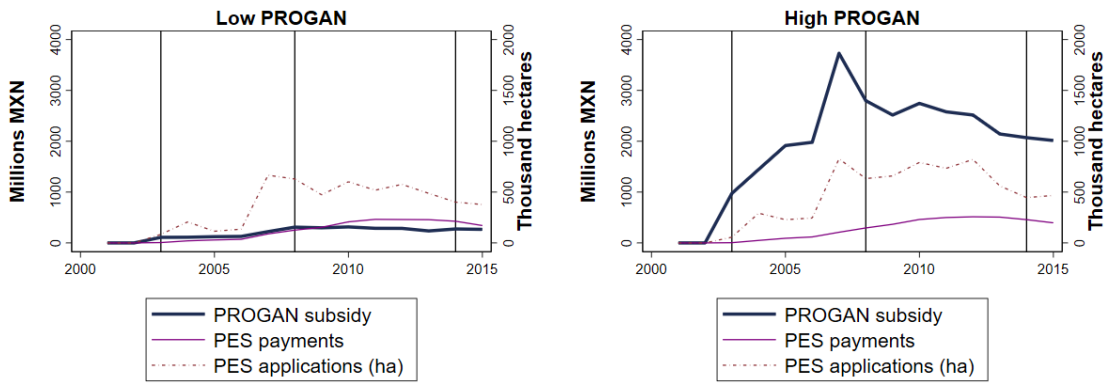
4.1 Program growth and competition

Enrollment in PROGAN and PES increased substantially over our study period. The quantity of subsidies paid out to PROGAN participants dwarf those paid for PES. The programs have less overlap in some areas than in others. Figures 2a and 2b compare PES applications and payments to PROGAN in municipalities with below and above median PROGAN participation. In municipalities with low PROGAN participation, PES payments increase more over time, whereas in those with high PROGAN participation, PES payments are relatively lower. Further, Table B5 shows that the average area enrolled in PES is nearly twice as high in low PROGAN municipalities.

Figure A1 shows the geographic intensity of the PROGAN subsidy in 2008 and all PES recipients over the course of our study. While many PES recipients are located in low PROGAN municipalities in the center of the country, the map shows big overlaps, particularly in coastal municipalities. There is also evidence that these two programs operate within the very same beneficiary household or community. A 2016 survey of over 850 PES applicants between 2011 and 2014 (Alix-Garcia et al., 2019) found that 36% of livestock-owning households in villages that had applied for PES had received a payment from PROGAN in the previous year. Therefore, although we observe that municipalities with lower PROGAN tend to have higher PES, there are still geographies with considerable presence of both programs. The next section examines more rigorously whether there is substitution in enrollments.

4.2 Enrollment effects

If PROGAN decreases enrollment in PES, then it may indirectly reduce the amount of deforestation the program is able to avoid. This section examines the effect of the livestock subsidy on willingness to enroll in PES between 2004 and 2015. The dependent variable is the total number of hectares that apply to the PES program divided by the



(a) (b)

Figure 2: Total payments for PROGAN, total payments for PES, and area of land applying for PES. Vertical lines represent application years for PROGAN (i.e., 2003, 2008, 2014). Municipalities with below median levels of PROGAN are on Figure (a), and above median municipalities on Figure (b).

total hectares in eligible zones for each given year. We include characteristics within PES eligible zones to control for changes in the quality of land available for PES participation.

Table 3: Regressions of PES submitted on PROGAN enrollment

	PES submitted (% of eligible zones)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	-6.0139***	-2.9789	-3.0356	-4.6521	-3.2131
	(1.5916)	(1.8162)	(1.8735)	(3.6486)	(3.3019)
Adjusted R2	0.029	0.036	0.037	0.064	0.066
Observations	18,708	18,708	18,708	18,708	18,708
Year FE	X	X	X	X	X
State FE		X	X		
Municipality FE				X	X
El. zones controls			X		X

Note: Years 2004-2015. Mean of DV in 2004 is 7.3. The panel is unbalanced. Robust standard errors are clustered by municipality. Controls included in columns (3) and (5) are eligible zones-specific. They include road network, the percentage within communal land, the percent of the municipality that is located in an eligible zone, the baseline characteristics of pasture (both natural pasture and pasture associated with livestock production). * p< 0.10, ** p<0.05, *** p<0.01.

Generally speaking, the results presented in Table 3 show that there is no statistically significant impact of PROGAN on PES enrollment, regardless of the level of controls and specification. The point estimates are large, so we cannot rule out all levels of enrollment effects. Bias might enter into the estimation through simultaneity or because there is an

omitted variable driving changes in the willingness to enroll in PES that is correlated with the choice of the number of animals to enroll during the allowable enrollment years. The latter is less likely with municipal fixed effects, but might occur if there are trends, such as technological change, that drive investment in livestock differentially across municipalities with higher and lower PROGAN enrollment. To address the issue of strategically increasing herd size prior to the year of enrollment, we include estimates with leads (Table E1). Although there are some specifications that indicate a weakly significant simultaneous impacts, they are are not consistent, and the sum of the lead and contemporaneous terms are small and not statistically different than zero. We also run aregression with a balanced panel where the dependent variable is the percent of municipal area submitted to PES (Table E2). To exploit only the exogenous variation in PROGAN stemming from programmatic adjustments in payment levels, random delays in payment timing, and changes in the value of the peso, we restrict the sample to the years 2004 to 2007, when no new PROGAN enrollment decisions were made (Table E3). Column (4) shows that there may have been effects up to a reduction of 4% in the hectares submitted per eligible zone, although this effect disappears when we add the eligible zones controls (column (5)). If PROGAN reduces enrollment in the PES, we would be understating the interactions on the deforestation side.

Further tests reveal no evidence of reverse causality. We examine this in a regression of PROGAN enrollment on PES area enrolled (Table E4) and on PES area submitted (Table E5) for the years 2004, 2008 and 2014 using the PES eligible zones as an instrument for PES enrollment. These results suggest that PROGAN did not affect the willingness to enroll in PES, and similarly, that PES did not affect the willingness to enroll in PROGAN. This means that if the estimations in next section show interactions between the two programs, they are unlikely to occur due to reduced enrollment in the PES program or due to simultaneity in the enrollment choice.

4.3 Deforestation effects: interactions of PROGAN and PES

Our main estimation for understanding interactions between PROGAN and PES measures deforestation at an aggregated level. This both reduces the noise that arises from imperfect satellite measures of deforestation and implicitly accounts for spillover effects that might occur within a municipality. However, its weakness is that the measure of the PES treatment is very small in magnitude at a municipal level – ranging only from zero to 1.18 percent of the municipal area. In Appendix F, we examine the subset of land that ever applied for the PES program. This reveals the impact of the PES program on land that was submitted for enrollment, which gives insight into the probable location of the deforestation effects induced by PROGAN.

As in equation 3.1, we examine regressions with state or municipal fixed effects combined with year effects and standard errors clustered at the municipality level. The dependent variable is the percent deforestation over baseline forest cover, and we are interested in the interaction between the PES program, measured as the percent of the municipal area enrolled in the program, and the PROGAN subsidy. In some estimations we restrict the sample to municipalities that ever had PES enrollment, and in others we apply the baseline municipal forest area as weight.

Table 4 shows the results of interactions between the two programs. Although the effect of the PES alone is not our main focus, we include two estimations that show just the PES effect (columns (1) and (2)), and two columns without interactions between the programs. This table and tables with just state effects are available in the Appendix. All columns are unweighted with the exception of column (7). The even columns restrict the sample to only those municipalities where there was ever PES enrollment.

Higher levels of PES are associated with lower deforestation in both the main and restricted samples. Including the PROGAN subsidy does not substantially change the independent PES impact. However, adding the interaction term between the two programs does: these terms are all negative and statistically different than zero. The effect

of PES where there is zero PROGAN enrollment is not statistically different from zero, although the impact of PROGAN where there is no PES is positive and statistically different from zero in most specifications.

A one standard deviation increase in PROGAN increases deforestation by 1.838*0.154 = 0.283 percentage points (Column (3) Table 1). The effect of a one standard deviation increase of PES alone (column (1), Table 4), is -0.171*0.367 =-0.063. The sum of these is an increase in deforestation of 0.22 percentage points. The interaction term (column (5)) shows that deforestation resulting from PROGAN is lower in municipalities where there is higher PES. However, this effect was not sufficiently large on average to eliminate the increase in deforestation from the livestock subsidy. For a municipality without PES, the average livestock subsidy increased the deforestation rate by 11%.[11] In municipalities with average PES coverage, the effect of the average livestock subsidy was 3 percentage points lower (extracted from column (7), weighted average PES = 0.022). To visualize these results, we present the interaction effects of PROGAN and PES on deforestation in Figure 3. A one standard deviation increase in PES would result in a reduction of deforestation nearly compensating the deleterious effects of PROGAN.

The results are robust to restricting the analysis to the first PROGAN wave. In this case, the deforestation effect of the subsidy and the deterrent effect of PES were about 50% bigger in the first round than for our whole study period (Table E6).

Appendix F details our analysis of all the land that was submitted to the PES program over this period at the parcel level. Using rejected land as a counterfactual for land that was enrolled, we estimate the interaction between the municipality aggregate measures of PROGAN and enrollment in PES at the parcel level. The estimates show that PROGAN increases the probability of deforestation on land that was submitted but not enrolled in the program. The evidence demonstrates that on enrolled land, PES payments served to offset this increase in the probability of deforestation, but were not

[11] We multiply the average subsidy per ha (.01546 kMXN/ha) by the estimated coefficient from column (5) by the average subsidy, and divide by the year 2002 deforestation: 2.17 x .01546)/0.29% = 11%.

Table 4: Regressions of deforestation on PES and PROGAN

	Deforestation (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subsidy/ha (kMXN)			1.8342***	1.1584**	2.1765***	1.8341***	2.0019***
			(0.5664)	(0.4632)	(0.5988)	(0.4504)	(0.4215)
Enrolled PES/ha (%)	-0.1713**	-0.1297*	-0.1422*	-0.1151	-0.0151	-0.0153	0.2372
	(0.0782)	(0.0714)	(0.0779)	(0.0718)	(0.0793)	(0.0690)	(0.1791)
Subs./ha (kMXN) ×					-18.6229***	-15.1916***	-25.2848***
Enr. PES/ha (%)					(5.5178)	(4.8375)	(7.4173)
Adjusted R2	0.362	0.250	0.363	0.250	0.363	0.251	0.503
Observations	30,269	12,110	30,269	12,110	30,269	12,110	30,269
Year FE	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X
Forest cover weights							X
Municipalities ever PES		X		X		X	

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. Columns 2, 4, and 6 include only municipalities that ever had PES enrollment and the seventh column includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

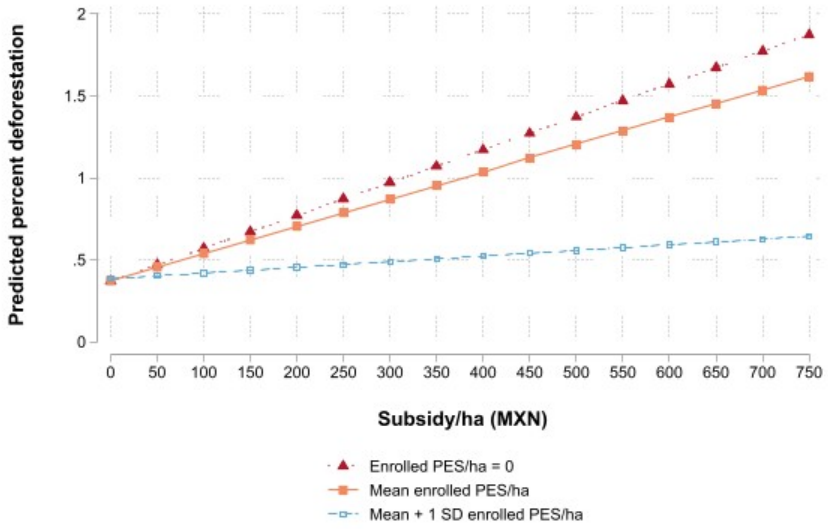


Figure 3: Marginal interaction effects of PROGAN and PES on deforestation. Marginal effects are calculated according to the specification presented in column (5), Panel A of Table 4. The PROGAN subsidy/ha label represents the full range of the program. Marginal effects on deforestation are depicted for: no PES enrollment, PES/ha enrollment at the average, and given a one standard deviation increase from the average enrolled PES/ha.

sufficient to produce additionality beyond that. The combination of results implies that deforestation from PROGAN is occurring both on unenrolled PES land and also on forest that was never submitted to the program.

5 Can PROGAN be targeted to support livestock and also limit deforestation impacts?

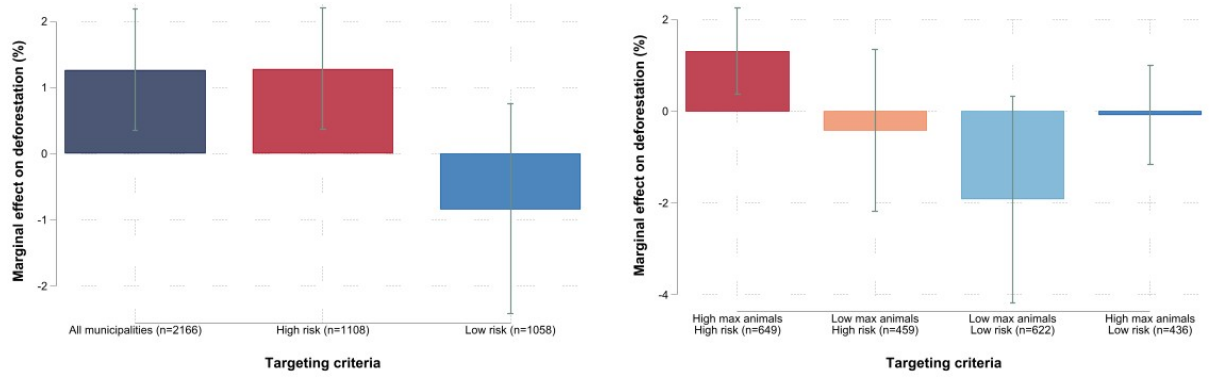
Because these programs may be working at cross-purposes in terms of environmental outcomes, this begs the question of whether it is possible to adjust the structure of PROGAN in order to minimize its deforestation footprint while also supporting livestock owners. There are many possible structural changes – for example, PROGAN could promote specific technologies rather than giving lump-sum transfers per livestock head. Adjustments of agricultural policy to limit environmental impacts have became increasingly popular in high income countries. Reforms in the United States (1996, 2002) and in the European Community (1992, 2003) provide examples of changes in regulation where farm programs have contained environmental conditionalities (ex.: conserving wetlands, highly erodible lands, etc.) (Baylis, Coppess, Gramig, & Sachdeva, 2022; Baylis, Peplow, Rausser, & Simon, 2008; Claassen et al., 2017). This section discusses the question of targeting. In particular, we examine whether a different spatial distribution of PROGAN could direct payments areas with high pasture potential and low deforestation risk.

Without knowing the policymaker's objective function, it is impossible to know what kind of program distribution would be optimal. We provide here a simple analysis founded on the stated goals and targeting criteria of both programs. The current structure of PROGAN payments is based upon the maximum sustainable number of animal equivalents per hectare. If we assume that a higher number according to this measure indicates greater potential livestock productivity, and if the goal of the program is to increase livestock productivity in a sustainable way under the same budget, more PROGAN payments should be given to places with a higher maximum. If most forests

provide similar environmental benefits, PES payments should be targeted to places where deforestation risk is higher, since those are areas where environmental services are threatened and additionality in avoided deforestation is greatest. Indeed, it has been found in other work that the program is more effective in areas at higher deforestation risk (Alix-Garcia et al., 2015). The question is whether or not these programs are currently distributed according to these criteria, and if there is a space where deforestation risk is low and maximum animal equivalents are high.

Figure G1 shows the relationship between program distribution and variables that proxy for these priorities. For the former, we exploit the pasture coefficients from SAGARPA to calculate an average maximum sustainable number of livestock per hectare within the municipality and for the latter we use the average predicted deforestation risk aggregated to the municipal level. In both cases, the relationship between recipients per hectare and these targeting criteria is positive. However, there is significant noise around these relationships. There are a large number of places with high potential for livestock and low deforestation risk that could be good targets for PROGAN (Figure G2), and also municipalities with very high concentration of PROGAN payments (above the 75th percentile) and relatively low livestock potential. If we sum up total PROGAN allocations, over 62 percent of them went to municipalities with below median livestock potential.

Do environmental outcomes change in municipalities with high deforestation risk or animal potential? Figure 4 examines this possibility by estimating the interaction between PROGAN, maximum sustainable animals, and deforestation risk. The outcome of interest is municipal deforestation and the specification parallels the municipality regressions, with municipal and year fixed effects. There are two main findings here First, all of the deforestation induced by PROGAN is taking place in municipalities with high risk of deforestation. Second, payments in areas with high livestock potential and low deforestation risk do not increase deforestation, and there are quite a few municipalities that fall into this category. There are also areas with high livestock potential and



(a) (b)

Figure 4: Linear combination that examines the optimal targeting of PROGAN based on whether the municipality is above or below the average deforestation risk, as well as above or below the average maximum sustainable animals. Linear combinations for Figure 4a comes from Table 1 for the first bar and from column (2) of Table G1 for the other bars. Linear combinations for Figure 4b come from column (6) of Table G1.

high deforestation risk. Whether or not these areas should continue being prioritized by PROGAN depends upon the policymakers' objective function. PES payments alongside PROGAN payments may induce producers to sustainably intensify livestock production in areas with high deforestation risk. Without higher PES payments in these places, however, additional avoided deforestation is unlikely. Policymakers would be trading off conservation for livestock producer welfare goals.

The FAO's evaluation of PROGAN in 2013 notes that there is a lack of complementarity between PROGAN and other programs run by SAGARPA and other ministries charged with natural resource conservation, which offers low hanging fruit for improving program management (Alvarez & Santos, 2013). These small targeting changes could represent a simple programmatic improvement that could reduce PROGAN's environmental impact.

6 Conclusion

This paper examines the interactions between agricultural subsidies and conservation. The agricultural subsidy increased municipal deforestation rates by 7% on average. We also illustrate how the subsidy interacts with a conservation program. Producers are

taking advantage of both types of supports – enrollment in one does not preclude enrollment in the other. We are limited in our ability to observe substitution within properties due to the fact that our livestock subsidy data is not sufficiently spatially explicit. However, the results that we have suggest that cash transfers for livestock have a deleterious effect on forest outcomes, particularly in forest that is not enrolled in the PES program.

The combination of the increase in deforestation rate, a decrease in the measurable proportion of fodder planted, and no change in the weight trends of cattle association with greater PROGAN intensity suggest that the subsidy is not encouraging intensification. It is not obvious that intensification will lead to better environmental outcomes, since it may lead to an increase in pasture land due to higher marginal productivity (Villoria, Byerlee, & Stevenson, 2014). However, it is fairly certain that extensification increases deforestation. Although we cannot rule out the possibility that the program increased productivity of cattle production, it is also not controversial to point out that accompanying future livestock supports with training in sustainable animal production may achieve superior results in terms of both productivity and environmental impact.

The environmental subsidies do help limit some of the impacts of PROGAN, but this sort of program dueling is probably inefficient, and could be avoided by more careful targeting of both livestock subsidies and environmental supports. Adjusting targeting to municipalities or areas with lower deforestation risk and higher livestock potential would reduce its environmental impact and might even end up encouraging production in areas where producers have higher return livestock production systems. The targeting of the PES program uses eligible zones in a way that could easily be replicated for PROGAN – areas with high animal production potential and low deforestation risk could be prioritized in the distribution of payments. However, without any conditionality or training in sustainable production methods, the second outcome may not occur (Bragança et al., 2022). Certainly more complicated targeting schemes could also be created. For example, one might create a set of targeting criteria that directly use

metrics of animal production potential and deforestation risk at a property level. The PES program does such specific property-level targeting within eligible zones using a points scheme for each application. However, refined targeting stategies also come with increased administrative costs. Given limited administrative resources and a goal of distributing as much support as possible to rural areas, even a simple approach could result in significant improvements.

We would be remiss if we did not mention that improving the sustainability of meat production is a key ingredient in the constellation of policies to support climate change mitigation. Many experts propose demand-side interventions to reduce meat consumption (Willett et al., 2019), however, supply side interventions are likely to play a substantial role. Our analysis raises questions about the benefits of non-targeted agricultural subsidies, and suggests limiting policies that increase the extensive agriculture rent as part of next actions to limit climate change and as part of the next REDD+ agenda (Angelsen & Rudel, 2013). In a world where many of the places contributing large shares of carbon emissions from land use are poor, thinking carefully about policy designs that respect livelihoods as well as conservation outcomes is the main path to sustainability.

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Online Appendix

Agricultural Subsidies: Cutting into Forest Conservation?

Fanny Moffette and Jennifer Alix-Garcia

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A Additional program information

A.1 PROGAN: application and renewal processes

The application process is straightforward: producers register at local or state offices of SAGARPA. They enter into the National Livestock Registry the number of livestock and the total number of hectares they have of different types of land (pasture, irrigated agriculture, non-irrigated agriculture, etc.). Once the producer is added to the Registry, a personal identification number is generated. Each time producers want to register for a wave, they need to update their information. The second step is to fill out a form asking for the PROGAN subsidy, provide their personal identification number, and present documents proving their ownership or their right to use the land. These are documents that the majority of Mexican producers have on hand, and do not present a significant barrier to application.

Starting in 2008, verification of the inventory by a local authority was required. Further, since for each wave, producers commit to improving vegetation cover and increasing fodder production within their land, the program's rules state that compliance must have been verified with the authorized technician to be eligible for subsequent payments. If land degradation was observed, then the rules suggest that payments could be canceled. The producers pay for local technicians (possibly inducing situations of conflict of interest). We generally note that there is little guidance regarding the monitoring of these rules. For example, in the rules of PROGAN for 2008, the definition for reforestation is "planting trees and shrubs with the purpose of reconstituting vegetation coverage with species of interest to forestry, forage and to attract pollinators"

A.2 PROCAMPO: examining fodder production as a mechanism

This study uses data from PROCAMPO (a program also managed by SAGARPA) to analyze yearly changes in pasture production. In response to North American Free

Trade Agreement (NAFTA), Mexico's government developed this crop subsidy to protect farmers from changes in prices stemming from international competition. The program targeted farmers that had planted at least one of nine staple crops during the 1991-93 agricultural cycles (corn, beans, rice, wheat, sorghum, barley, soybeans, cotton and/or cardamom). Stating that they had planted one of those staple crops allowed farmers to receive this subsidy for each cultivated hectare. Beginning in 1996, the program subsidized farmers for other types of crops, with the ongoing constraint that it still applies only to land registered when the program opened. To continue receiving the subsidy, farmers needed to continue producing on the same parcel each year. Each year between 1994 and 2015, this program has subsidized around 3 million producers, or approximately 14 million hectares per year. Recipients range from large businesses to small landowners that cultivate for subsistence or sell at a small scale. In 2015, 300 different crops were subsidized, ranging from the initial staple crops to pineapple and pasture. Payments are annual but do not vary by crop type.

A.3 PROGAN and PES: program comparison

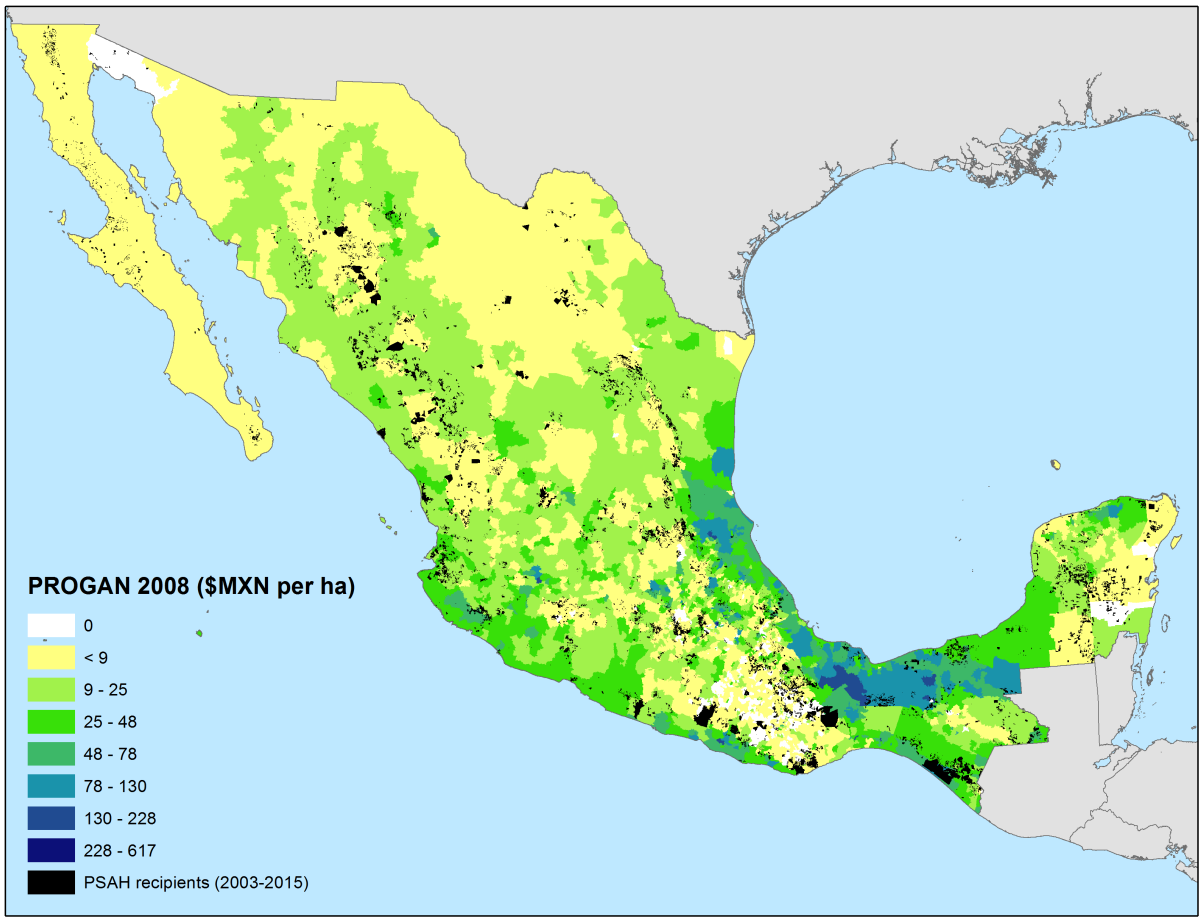


Figure A1: PROGAN real subsidy per hectare in 2008 and accepted PES parcels 2003-2015

Table A1: Program summaries and comparison

	PROGAN (livestock)	**PES (forest)**
Eligibility	- National - File with the National Livestock Registry - Ownership or land right	- Falls in eligible zone - Highest point scores (starting in 2006) - Ownership or land right - Constraint: no overgrazing - Minimum forest cover: 50-80%
Timing	- 3 waves: 2003-2007, 2008-2013 and 2014-2015 - One payment per year	- 5-year contract if accepted - One payment per year
Minimum	- None	- 50 ha per applicant
Maximum	- Varies based on the pasture coefficient - Ceiling of 300 animal equivalent units per person (wave 1, 2, and 3), or 1000 per business (wave 3 only)	- 2000-6000 ha per applicant
Mexican pesos	- See Figure 1a	- See Table A2
US$	- US$843/year/producer on average (2011)	- Common properties: US$130/year/ person (>1 month of work at minimum wage) - Private property: US$3,050/year/hh (12 % of hh income) (Alix-Garcia, Sims, & Yanez-Pagans, 2015)
Size	- 344,430 producers (2011)	- 3,884,247 ha (2011)

Table A2: PES payment levels per ha, 2003-2015

Modality and ecosystem/risk	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Hydrological												
Cloud forest	471	453	452	452	447	443						
Cloud forest/ very high							1,003	970	932	897	863	840
Cloud forest/ all other							638	617	593	571	549	535
Oak forest				398	394	390						
Other forests	353	340	345	345	342	338						
All other							325	314	302	290	279	272
Biodiversity												
All veg.				346	394	374						
Rainforest							501	483	466	449	431	420
Dry tropical/ very high/high							348	337	324	312	300	292
Arid/semi-arid							255	247	237	228	220	214

Note: Payment levels extracted from program rules of operation provided by CONAFOR and forest types verified through discussion with CONAFOR. Modalities refers to the type of ecosystem service being targeted. Amounts are in 2010 pesos.

B Additional data and descriptive statistics

B.1 Cattle slaughtering quantity and price data

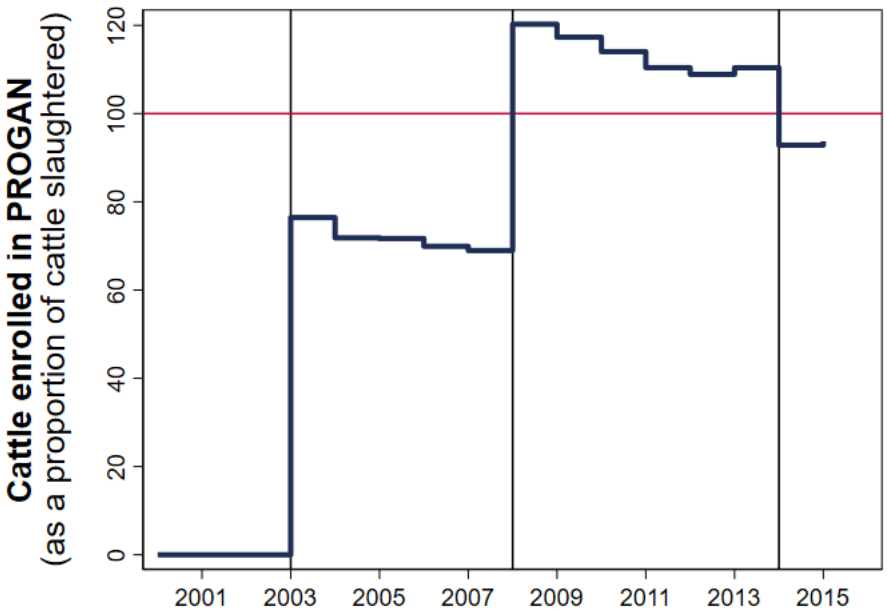


Figure B2: Percent of annual slaughtered cattle head enrolled in PROGAN.

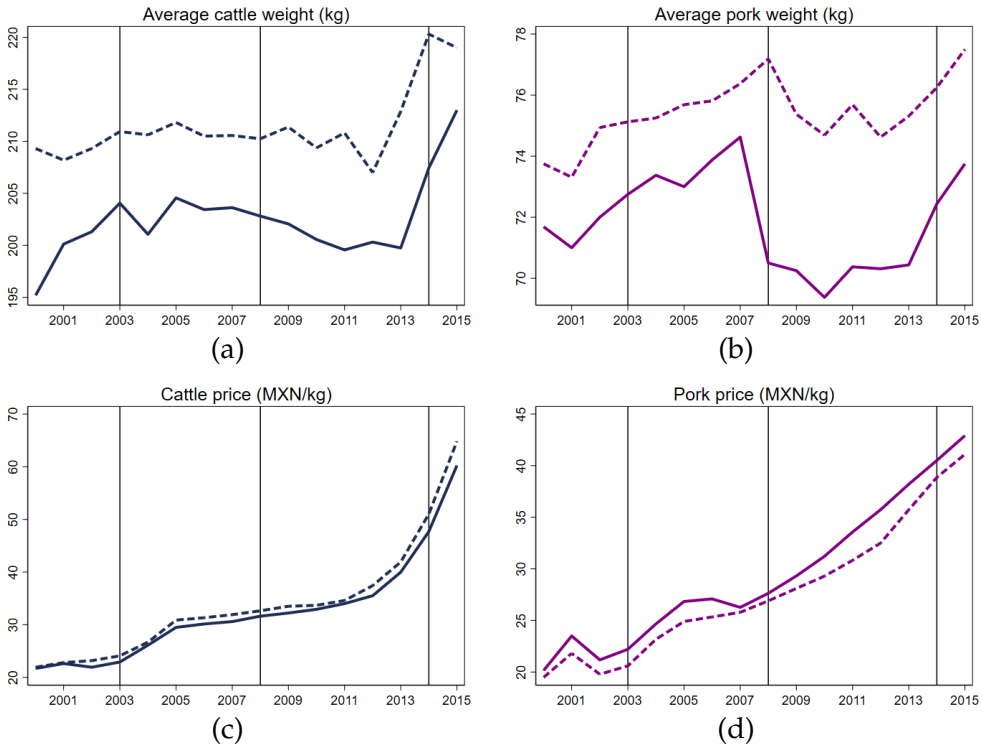


Figure B3: For each figure, the solid line represents the state with above median level of cattle enrolled in PROGAN and the dotted line the states below the median level. Figures on the left represent the cattle market and figures on the right the pork market. Data comes from SAGARPA (CITE).

B.2 Maximum sustainable number of livestock

We construct the average maximum sustainable number of livestock per hectare within the municipality using the pasture coefficients (SAGARPA) (i.e. the number of hectares to sustain one animal unit), and the baseline characteristics of the land (INEGI). Specifically, we calculate:

$$\begin{aligned} MaxPROGAN_m = agric_rainfed_m * \frac{1}{PA_m^{ar}} + agric_irrigated_m * \frac{1}{PA_m^{ai}} \\ + nat_pasture_m * \frac{1}{PA_m^{np}} + livestock_pasture_m * \frac{1}{PA_m^{lp}} \\ + other_m * \frac{1}{PA_m^{o}}). \end{aligned}$$

The maximum sustainable number of animals per hectare ($MaxPROGAN_m$) varies by municipality because the pasture coefficients and the characteristics of the land vary per municipality. We use four different type of lands: rainfed agriculture, irrigated agriculture, natural pasture, pasture associated with livestock production and all other uses of land. The geographical distribution of the maximum sustainable number of livestock is illustrated in Figure B4.

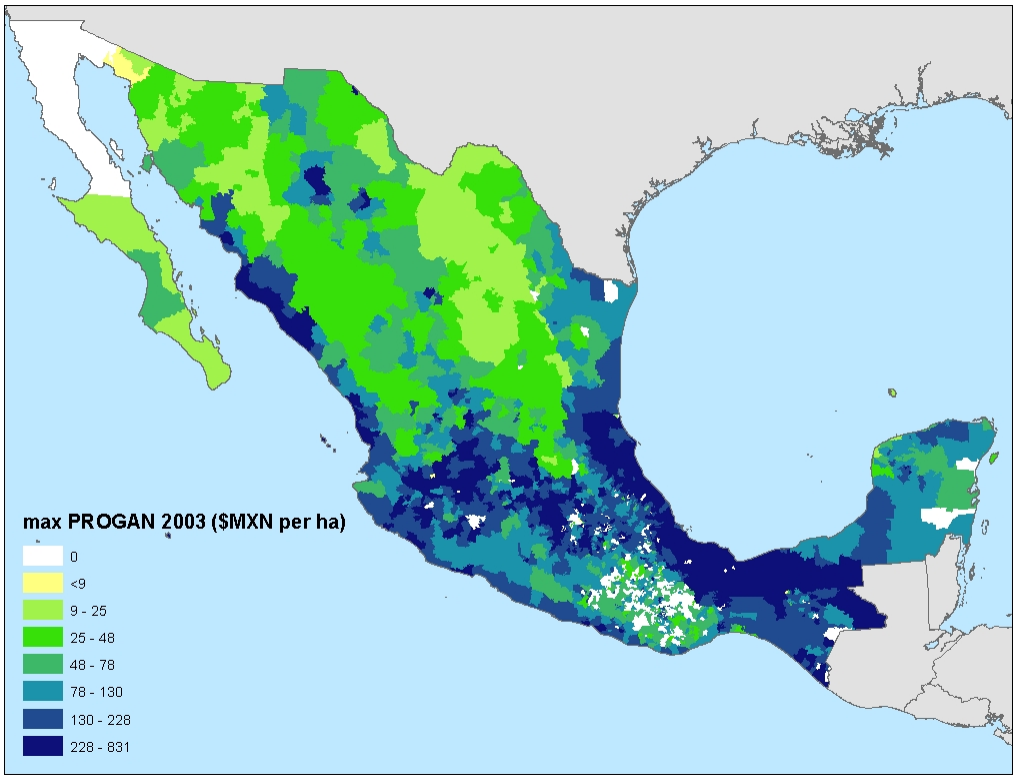


Figure B4: Maximum PROGAN subsidy per hectare. Average calculated according to 2003 subsidy per animal and pasture coefficients for different types of land.

B.3 Deforestation risk

We estimate the following equation with a lasso probit:

$$Defor_i = \beta_1 FC2000_i + \beta_2 DistCity_i + \beta_3 RoadDensity_i + \beta_4 DistUrban_i + \beta_5 M(Elevation)_i + \beta_6 SD(Elevation)_i + \beta_7 M(Slope)_i + \beta_8 SD(Slope)_i + \gamma' Biome_i + \delta' State_i + u_i,$$

where $Defor_i$ is the binary indicator of whether there has ever been a cumulative deforestation of more than 5 hectares in the grid-cell i in 2001 and 2002 (i.e. the pre-program years). Covariates included are baseline forest cover ($FC2000_i$), distance to city ($DistCity_i$), road density ($RoadDensity_i$), distance to nearest urban area ($DistUrban_i$), average and standard deviation of elevation ($M(Elevation)_i, SD(Elevation)_i$), average and standard deviation of slope ($M(Slope)_i, SD(Slope)_i$), biome indicators ($Biome_i$), and state indicators ($State_i$). Lasso uses cross-validation, which implies that the sample is divided in a training and a testing sample. The training sample is in itself divided into a number of cross-validation samples. For each subsample, the cross-validation sample is set aside, and the remainder is used to predict outcomes for the excluded subsample. The model is fit to the training data for a given value of the regularization parameter. Since the performance of cross-validation rarely increases for values greater than 10, the regularization parameter (*lambda*) is chosen through 10-fold cross-validation. The regularization parameter is chosen based on the one that minimizes the mean squared prediction error for each subsample (Athey & Imbens, 2016). Results from this estimation are presented in Table B3. Results are then used to predict the deforestation risk for each 5 km x 5 km grid-cell, which is aggregated at the municipality level.

Table B3: Lasso probit regression to predict deforestation risk

	Deforestation (0/1)
Forest cover (2000, ha)	0.000665
Km to nearest city	0.000004
Road density (km)	-0.000031
Km to nearest urban area	0.000001
Mean elevation (m)	-0.000454
Sd(slope)	-0.030846
Mean slope	-0.017330
Agriculture	-1.111352
Montane forest	0.267109
Pine oak forest	0.145967
Grasslands	-0.559924
Xeric scrub and desert	-0.169729
Mangroves	-0.800154
Constant	-0.793854
Selected lambda	.0013915
No. of non-zero coeff.	43
Observations	79,954

Note: Outcome is the pre-programs binary indicator of deforestation for years 2001 and 2002. Unit of analysis is the 5 km x 5 km grid-cell. Robust standard errors are clustered by municipality. Selection method is cross-validation with 10 cross-validation folds. Number of original covariates is 51. We do not show coefficients associated to the state indicator variables for space reasons. Lasso regression is clustered by municipality.

B.4 Additional descriptive statistics tables

Table B4: Rule changes and missed payments by wave

	Wave 1	Wave 2	Wave 3
CRITERIA			
Max eligible	300	300	1000
Animals	Cattle only	Cattle, cow, goats and sheep	Cattle, cow, goats and sheep
Categories	None	[A] small producers (<=35) and [B] larger producers (> 35)	[A] small producers & *ejidatarios* (<=35) and [B] larger producers (> 35)
Stronger enforcement of max sustainable number of livestock	no	yes	yes
SUBSIDY			
Subs/animal	$300 (year 1), $400 (year 2), $500 (year 3), $600 (year 4)	$375 if category A, $300 if category B	$350 if category A, $280 if category B
% of committed payment that didn't occur	5.1%	7.6%	-2.9%
MUNICIPALITY LEVEL			
Nbr new municipalities	1,465	488	57

Table B5: Summary statistics across municipalities with high and low PROGAN enrollment

	All municipalities		High PROGAN		Low PROGAN		N.d.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Livestock subsidy - PROGAN							
Subsidy/ha (MXN, 2003)	3.75	(9.30)	6.45	(11.84)	0.46	(1.26)	0.50
Subsidy/ha (MXN, 2014)	16.65	(21.67)	26.42	(23.48)	4.76	(10.61)	0.84
Eq. animals/ha (2003)	0.03	(0.06)	0.05	(0.07)	0.00	(0.00)	0.70
Eq. animals/ha (2014)	0.06	(0.07)	0.09	(0.08)	0.01	(0.01)	0.96
Maximum animals/ha	0.41	(0.28)	0.49	(0.30)	0.32	(0.21)	0.49
Baseline natural pasture/ha	0.09	(0.13)	0.08	(0.13)	0.10	(0.13)	-0.11
Baseline pasture associated with livestock/ha	0.08	(0.17)	0.13	(0.21)	0.01	(0.04)	0.60
Payment for environmental services - PES							
Enrolled PES/ha (%, 2004)	0.005	(0.03)	0.003	(0.02)	0.007	(0.04)	-0.089
Enrolled PES/ha (%, 2014)	0.018	(0.05)	0.013	(0.03)	0.025	(0.07)	-0.160
% ha submitted/ha ez (2004)	1.94	(11.51)	2.06	(11.81)	1.80	(11.14)	0.02
% ha submitted/ha ez (2014)	1.17	(5.98)	1.06	(5.51)	1.30	(6.51)	-0.03
Total submitted ha (2004)	230.86	(1381.98)	246.22	(1385.21)	212.13	(1378.51)	0.02
Accepted ha (2004)	287.55	(1255.87)	336.85	(1373.88)	231.89	(1106.10)	0.06
Rejected ha (2004)	177.86	(1211.88)	187.67	(1354.16)	166.78	(1028.86)	0.01
Total submitted ha (2014)	392.13	(2410.63)	375.64	(2046.04)	412.22	(2792.31)	-0.01
Accepted ha (2014)	314.26	(1118.59)	303.82	(1026.08)	326.06	(1215.34)	-0.01
Rejected ha (2014)	803.57	(2994.99)	939.70	(2931.63)	649.88	(3060.06)	0.07
Av. perc. in eligible zone (2004-2015)	0.36	(0.25)	0.32	(0.23)	0.42	(0.27)	-0.28
Replacement of crop with pasture							
% PROCAMPO in fodder (2000)	0.99	(3.81)	1.04	(3.64)	0.94	(3.99)	0.02
% PROCAMPO in fodder (2014)	2.11	(8.89)	2.66	(9.96)	1.45	(7.33)	0.10
PROCAMPO area (2000)	5792.99	(14097.67)	7677.45	(15669.53)	3493.69	(11498.71)	0.22
Forests							
% deforestation (2001)	0.34	(1.03)	0.44	(1.18)	0.22	(0.80)	0.16
% deforestation (2014)	0.15	(0.31)	0.22	(0.37)	0.07	(0.17)	0.38
Deforestation 2001-2014 (%)	0.04	(0.09)	0.06	(0.09)	0.03	(0.07)	0.28
Deforestation 2001-2014 (ha)	1033.19	(4728.29)	1330.60	(4876.15)	671.92	(4518.41)	0.10
Baseline forest/ha	0.32	(0.29)	0.30	(0.28)	0.34	(0.30)	-0.10
Deforestation risk	0.22	(0.23)	0.25	(0.24)	0.17	(0.20)	0.26
Other municipal variables							
Marginality index (2000)	0.09	(0.98)	-0.01	(0.91)	0.22	(1.05)	-0.16
Marginality index (2015)	0.09	(0.99)	-0.05	(0.89)	0.25	(1.08)	-0.21
Population/ha (2015)	0.18	(0.27)	0.13	(0.23)	0.19	(0.28)	-0.16
Municipality area (Mha)	0.08	(0.21)	0.09	(0.14)	0.07	(0.27)	0.06
Slope	8.26	(6.01)	6.61	(5.35)	10.26	(6.16)	-0.45
Average elevation	1329.87	(850.46)	1038.77	(842.14)	1683.46	(716.20)	-0.58
Observations	2166		1188		978		2166

Note: Low and high PROGAN groups are based on whether the median animal equivalent per hectare of a given municipality is above or below the average. Columns (1), (3) and (5) present the means. Columns (2), (4), and (6) the standard deviations. Normalized differences in column (7) are a scale-free measure of the difference in distributions between the sample of High PROGAN municipalities and the sample of Low PROGAN municipalities. Its advantage is that it is directly interpretable in terms of how much average standard deviation is the mean from one sample to the mean of the other sample (Imbens & Wooldridge, 2009). Baseline land characteristics come from INEGI, and marginalization index and population from CONAPO.

Table B6: Distribution of the four payments over the extended period of five years of the first wave

	Payment number				
Payment year	1^{st}	2^{nd}	3^{rd}	4^{th}	Total
2003	84,876	0	0	0	84,876
2004	126,388	36,797	0	0	163,185
2005	481	148,876	68,580	0	217,937
2006	53	21,772	119,647	0	141,472
2007	37	734	17,645	196,312	214,728
Total	211,835	208,179	205,872	196,312	822,198

Note: During the first wave, a total of 822,198 payments were distributed. According to the program rules, all first payments should have occurred in 2003, all second payments in 2004, all third payments in 2005, and all fourth payments in 2006. This table illustrates the deviation between the original planning and the actual distribution of individual payments.

Table B7: Geographical distribution of the four payments over 2003-2007

Region	Variable	Mean	SD	Minimum	Maximum
Centronorte	First payment	2003.587	.4945	2003	2006
	Average payment year	2005.209	1.35	2003	2007
Centrosur	First payment	2003.27	.4446	2003	2005
	Average payment year	2004.961	1.439	2003	2007
Noreste	First payment	2003.163	.3851	2003	2006
	Average payment year	2005.121	1.428	2003	2007
Noroeste	First payment	2003.524	.4998	2003	2006
	Average payment year	2005.232	1.372	2003	2007
Occidente	First payment	2003.803	.4016	2003	2006
	Average payment year	2005.468	1.238	2003	2007
Oriente	First payment	2003.826	.3937	2003	2007
	Average payment year	2005.327	1.215	2003	2007
Sureste	First payment	2003.273	.4497	2003	2007
	Average payment year	2005.18	1.453	2003	2007
Suroeste	First payment	2003.777	.4329	2003	2007
	Average payment year	2005.393	1.240	2003	2007
Total	First payment	2003.603	.497602	2003	2007
	Average payment year	2005.289	.320732	2003	2007

Note: We divide the country into eight regions and extract the average, standard deviation, minimum and maximum for the first payment and the average payment year. Region Noroeste includes the states of Baja California Sur, Chihuahua, Durango, Sinaloa and Sonora. Region Noreste includes the states of Coahuila, Nuevo León, Tamaulipas, as well as the region Lagunera. Region Occidente includes the states of Colima, Jalisco, Michoacán, and Nayarit. Region Oriente includes the states of Hidalgo, Puebla, Tlaxcala, and Veracruz. The region of Centrosur includes the states of Estado de México and Morelos. The region Suroeste includes the states of Chiapas, Guerrero, and Oaxaca. The region Sureste includes the states of Campeche, Quintana Roo, Tabasco, and Yucatán.

Enrollment characteristics, PROGAN cohorts

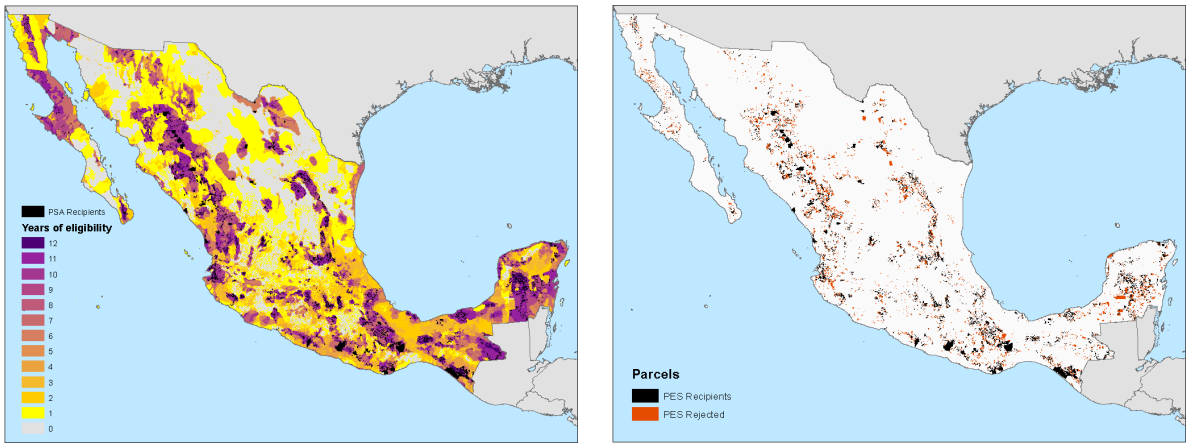
The table and figures below show the variation in cohort characteristics among municipalities enrolling at different times and intensity in PROGAN.

Table B8: Summary characteristics PROGAN municipalities by enrollment period

	Ln(Mun area) ha	Ln(Slope) deg	Ln(Elev) m	Defor risk	Max animals	Baseline pasture	Baseline livestock	Baseline forest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsidy/ha (kMXN)	0.038***	-0.030***	-0.067***	0.005***	0.005***	-0.001***	0.009***	-0.000
	(0.005)	(0.003)	(0.006)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Year=2008 × Subsidy/ha (kMXN)	-0.034***	0.020***	0.045***	-0.002***	0.001	0.000	-0.005***	0.000
	(0.005)	(0.003)	(0.006)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Year=2014 × Subsidy/ha (kMXN)	-0.035***	0.019***	0.043***	-0.002***	0.002**	-0.000	-0.005***	0.001
	(0.005)	(0.003)	(0.006)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Constant	3.175***	2.055***	6.876***	0.196***	0.396***	0.092***	0.043***	0.322***
	(0.033)	(0.019)	(0.033)	(0.005)	(0.006)	(0.003)	(0.003)	(0.007)
ymean	3.320	1.943	6.627	0.215	0.414	0.089	0.077	0.321

Note: Dependent variables are listed in column headers and means of dependent variables in the footer. We present the continuous measure of subsidy per ha and then its interactions with enrollment years in 2008 and 2014. This means the baseline variable measures the correlation between subsidy intensity and the outcome characteristics in 2004. * p< 0.10, ** p<0.05, *** p<0.01.

B.5 Additional descriptive figures



(a) (b)

Figure B5: Eligible zones frequency (a) and PES accepted and rejected parcels (b): 2004-2015

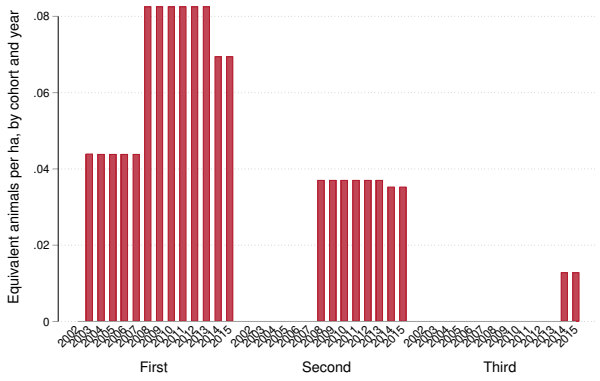


Figure B6: Animals per ha enrolled according to wave and year.

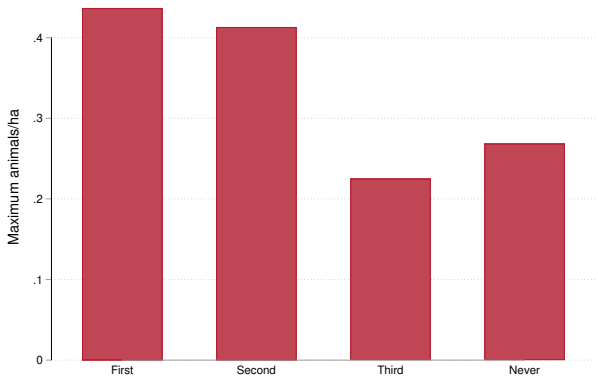


Figure B7: Average potential animals per hectare by municipal enrollment wave.

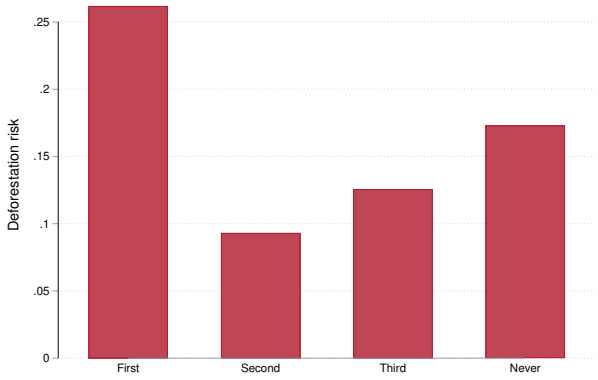


Figure B8: Average municipal deforestation risk according to first wave in which a municipality enrolled.

C Robustness: deforestation effects of PROGAN

C.1 Additional figures

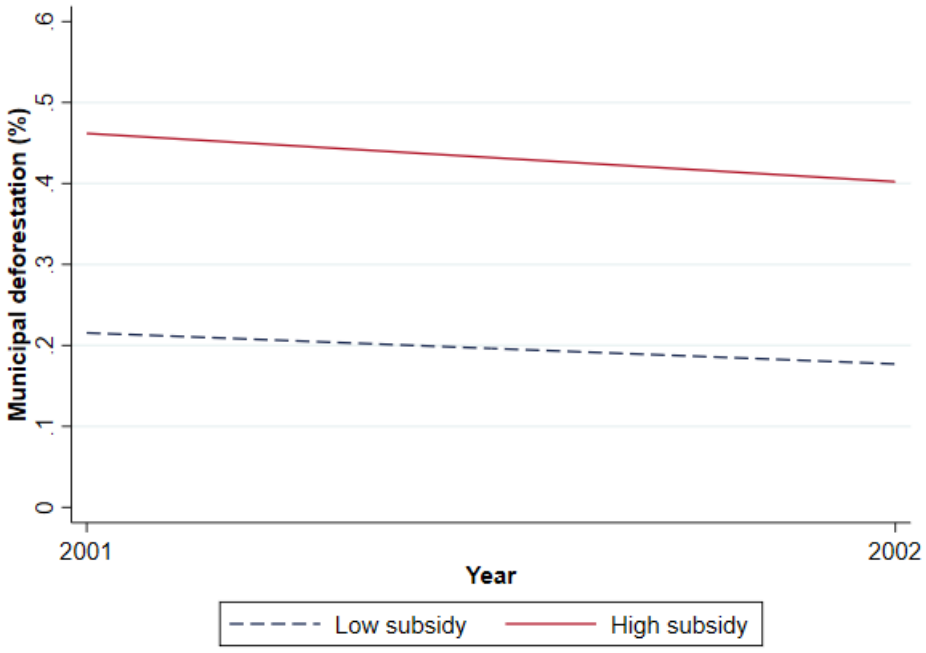


Figure C1: Graph shows a linear fit on municipal deforestation rates for 2001 and 2002, dividing the sample by median of subsidy levels, where the median is calculated over the entire time period of PROGAN.

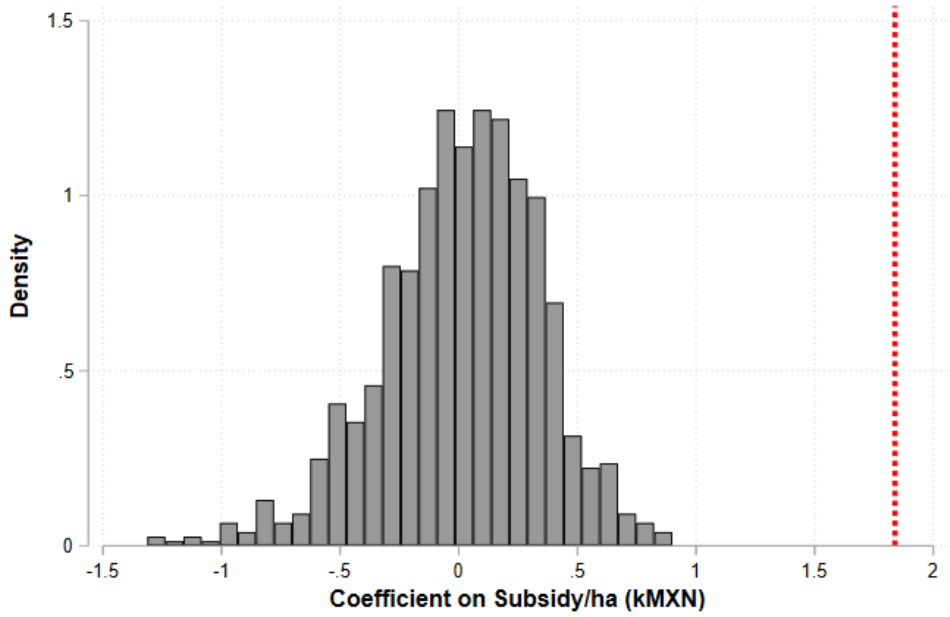


Figure C2: Falsification exercise: randomizing PROGAN subsidy at the municipality level. The histograms come from point estimates of PROGAN impact on deforestation using the full set of municipal and time fixed effects from Equation 3.1. The program variables are randomized and the impact re-estimated 1,000 times. The vertical dotted lines represent the point estimate in the specification of column (3), Table 1.

C.2 Additional tables

Table C1: Pre-program trends of deforestation in high versus low intensity PROGAN

	Deforestation (%)				
Panel A	(1)	(2)	(3)	(4)	(5)
High subsidy/ha x yr	0.0001***	0.0001***	-0.0213	-0.1053	-0.0706
	(0.0000)	(0.0000)	(0.0753)	(0.1089)	(0.0750)
Adjusted R2	0.011	0.156	0.403	0.080	0.562
Observations	4,332	4,332	4,332	1,730	4,332
Panel B					
Avg. subsidy/ha x yr	0.0030***	0.0036***	0.7041	-0.7575	-1.3559
	(0.0005)	(0.0005)	(1.7344)	(1.9378)	(1.5112)
Adjusted R2	0.013	0.159	0.403	0.078	0.562
Observations	4,332	4,332	4,332	1,730	4,332
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Pre-program trends for the years 2001-2002. Panel A uses a binary variable indicating if a municipality had above median subsidy and we show the interaction between this variable and the time trend. Panel B uses the same specification but replace the binary variable with the average subsidy from 2003 through 2015. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth column includes weights for baseline forest cover. * p< 0.10, ** p<0.05, *** p<0.01.

Table C2: Regressions of deforestation on PROGAN during the first wave exclusively

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	6.2173***	4.9497***	2.8026***	1.5940**	2.3181***
	(0.6184)	(0.6405)	(0.5754)	(0.7072)	(0.6119)
Adjusted R2	0.028	0.181	0.472	0.344	0.476
Observations	10,810	10,810	10,810	4,325	10,810
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2003-2007. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

Table C3: Regressions of deforestation on PROGAN, comparing only municipalities enrolled in the first wave with the never enrolled municipalities

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	6.1780***	5.9261***	2.5042***	1.0500**	1.2884**
	(0.3688)	(0.4209)	(0.4629)	(0.4258)	(0.5012)
Adjusted R2	0.029	0.139	0.378	0.274	0.504
Observations	22,661	22,661	22,661	9,450	22,661
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C4: Regressions of deforestation on PROGAN during the first wave exclusively, only compared to never enrolled

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	7.0285***	6.1307***	3.2884***	0.8169*	1.8188*
	(0.9512)	(0.9689)	(0.8027)	(0.4635)	(0.9672)
Adjusted R2	0.014	0.148	0.456	0.278	0.439
Observations	9,717	9,717	9,717	4,050	9,717
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2003-2007. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. The sample excludes municipalities that enrolled in the second and third waves. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C5: Regressions of deforestation on PROGAN and leads of PROGAN

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
F.Subsidy/ha	2.7275***	2.4661***	-0.2757	-0.2633	-0.7289
	(0.6469)	(0.6291)	(0.3457)	(0.3063)	(0.7618)
Subsidy/ha (kMXN)	3.9809***	3.6452***	1.9848***	1.3479**	1.6138**
	(0.6669)	(0.6456)	(0.5333)	(0.5679)	(0.6425)
Adjusted R2	0.029	0.145	0.361	0.249	0.502
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C6: Regressions of deforestation on PROGAN for municipalities with more than 50 ha of eligible zones

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	6.3578***	5.6952***	1.8383***	1.2148**	1.2660***
	(0.3347)	(0.3636)	(0.5706)	(0.4851)	(0.4792)
Adjusted R2	0.027	0.144	0.361	0.249	0.501
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C7: Regressions of deforestation on PROGAN for municipalities without 50 ha of eligible zones

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	6.3578***	5.6952***	1.8383***	1.2148**	1.2660***
	(0.3347)	(0.3636)	(0.5706)	(0.4851)	(0.4792)
Adjusted R2	0.027	0.144	0.361	0.249	0.501
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C8: Regressions of deforestation on PROGAN - robustness analyses

	Deforestation (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy/ha (kMXN)	1.8444***	1.2692***	1.8118***	1.2666***	1.4462***	1.2869***
	(0.5701)	(0.4793)	(0.5692)	(0.4788)	(0.5226)	(0.4672)
Murders	0.0004	0.0001				
	(0.0007)	(0.0002)				
Year × Bank branches (2008)			-0.0002	0.0000		
			(0.0001)	(0.0001)		
Adjusted R2	0.361	0.502	0.362	0.501	0.379	0.509
Observations	30,269	30,269	30,269	30,269	30,269	30,269
Year FE	X	X	X	X	X	X
State FE						
Municipality FE	X	X	X	X	X	X
State x Year FE					X	X
Forest cover weights		X		X		X

Note: Years 2001-2014. Data source for the panel on murders is from the Mexican Department of Health Information (DGIS) and for the bank branches is the National Banking and Stock Commission (CNBV). Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C9: Pre-program trends of deforestation in high versus low intensity PROGAN

	Deforestation (%)				
Panel A	(1)	(2)	(3)	(4)	(5)
High eq. animal/ha x yr	0.0001***	0.0001***	-0.0641	-0.0961	-0.0709
	(0.0000)	(0.0000)	(0.0752)	(0.1096)	(0.0721)
Adjusted R2	0.008	0.153	0.403	0.080	0.562
Observations	4,332	4,332	4,332	1,730	4,332
Panel B					
Avg. eq. animals/ha x yr	0.0008***	0.0009***	-0.1132	-0.2061	-0.3928
	(0.0001)	(0.0001)	(0.3613)	(0.5889)	(0.4550)
Adjusted R2	0.010	0.156	0.403	0.078	0.562
Observations	4,332	4,332	4,332	1,730	4,332
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Pre-program trends for the years 2001-2002. Panel A uses a binary variable indicating if a municipality had above median enrollment and we show the interaction between this variable and the time trend. Panel B uses the same specification but replace the binary variable with the average enrollment from 2003 through 2015. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth column includes weights for baseline forest cover. * p< 0.10, ** p<0.05, *** p<0.01.

Table C10: Regressions of deforestation on PROGAN enrollment

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Eq. animals/ha	2.1284***	1.9456***	0.5778***	0.2615	-0.0650
	(0.0765)	(0.0881)	(0.1195)	(0.1623)	(0.2008)
Adjusted R2	0.029	0.144	0.361	0.249	0.501
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table C11: Regressions of deforestation on PROGAN - heterogeneous results by cohort

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Baseline effect PROGAM subs./ha (kMXN)	7.9736***	6.3839***	2.3183***	0.9847***	2.0224**
	(0.9878)	(0.8867)	(0.6494)	(0.3759)	(0.7947)
Additional effect, 2006-2010	-2.4213**	-1.3354	-0.5997	0.2330	-0.9541
	(1.0952)	(0.9657)	(0.4578)	(0.4324)	(0.6160)
Additional effect, 2011-2015	-1.3408	0.0762	-0.4704	0.6891	-0.6798
	(1.0618)	(0.9343)	(0.6948)	(0.7407)	(0.8239)
Adjusted R2	0.028	0.144	0.361	0.249	0.502
Observations	30,269	30,269	30,269	12,110	30,269
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2001-2014. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p< 0.10, ** p< 0.05, *** p< 0.01.

D Robustness: intensification effects of PROGAN

Table D1: Regressions of PROCAMPO fodder (%) on PROGAN pre-program trends analysis

	Fodder (%)			
	(1)	(2)	(3)	(4)
High subsidy/ha (kMXN) x yr	-0.0001	-0.0001	0.0736	-0.0251
	(0.0001)	(0.0001)	(0.0933)	(0.1957)
Adjusted R2	0.001	0.191	0.542	0.492
Observations	8,552	8,552	8,552	8,552
Year FE	X	X	X	X
State FE		X		
Municipality FE			X	X
PROCAMPO weights (1999)				X

Note: Years 1999-2002. Robust standard errors are clustered by municipality. * p< 0.10, ** p<0.05, *** p<0.01.

Table D2: Regressions of PROCAMPO fodder (%) on PROGAN for first wave only

	Fodder (%)			
	(1)	(2)	(3)	(4)
Subsidy/ha (kMXN)	-13.8149***	-2.7715**	-0.3680	1.3804
	(1.5106)	(1.0908)	(0.7776)	(0.9274)
Adjusted R2	0.001	0.458	0.948	0.946
Observations	10,670	10,670	10,670	10,670
Year FE	X	X	X	X
State FE		X		
Municipality FE			X	X
PROCAMPO weights (1999)				X

Note: Years 2003-2007. Pre-mean of dependent variable is 1.3%. Robust standard errors are clustered by municipality. * p< 0.10, ** p<0.05, *** p<0.01.

E Robustness: agricultural subsidies and conservation programs

E.1 Robustness: enrollment effects

Table E1: Regressions of PES submissions on PROGAN (% submitted), with leads

	PES submitted (% of eligible zones)				
	(1)	(2)	(3)	(4)	(5)
F.Subsidy/ha (kMXN)	3.5209	5.2843	5.6565	8.0842	6.9758
	(3.5877)	(3.6593)	(3.6679)	(4.9792)	(4.9892)
Subsidy/ha (kMXN)	-8.2254***	-5.5596**	-5.7427**	-6.3381**	-4.6668
	(2.8076)	(2.6605)	(2.6629)	(2.9736)	(2.9042)
Adjusted R2	0.034	0.040	0.041	0.060	0.063
Observations	16,104	16,104	16,104	16,104	16,104
Year FE	X	X	X	X	X
State FE		X	X		
Municipality FE				X	X
El. zones controls			X		X

Note: Years 2004-2015. Mean of DV in 2004 is 7.3. Panel is unbalanced. Robust standard errors are clustered by municipality. Controls included in columns (3) and (5) are eligible zones-specific. They include road network, the percentage within communal land, the percent of the municipality that is located in an eligible zone, the baseline characteristics of pasture (both natural pasture and pasture associated with livestock production). * p< 0.10, ** p<0.05, *** p<0.01.

Table E2: Regressions of PES submissions on PROGAN (area submitted)

	PES submitted (% of municipal area)		
	(1)	(2)	(3)
Subsidy/ha (kMXN)	-0.0430***	-0.0372***	-0.0158*
	(0.0057)	(0.0059)	(0.0090)
Adjusted R2	0.011	0.022	0.131
Observations	28,098	28,098	28,098
Year FE	X	X	X
State FE		X	
Municipality FE			X

Note: Years 2004-2015. Mean of DV in 2004 is .0032. Panel is balanced. Robust standard errors are clustered by municipality. * p< 0.10, ** p<0.05, *** p<0.01.

Table E3: Regressions of PES submissions on PROGAN (% submitted), first wave only

	PES submitted (% of eligible zones)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	-7.2724***	-4.7918*	-4.6334*	-19.5982**	-12.8969
	(2.4013)	(2.7049)	(2.6766)	(8.1967)	(8.4078)
Adjusted R2	0.059	0.064	0.065	-0.003	0.003
Observations	6,722	6,722	6,722	6,722	6,722
Year FE	X	X	X	X	X
State FE		X	X		
Municipality FE				X	X
El. zones controls			X		X

Note: Years 2004-2007. Mean of DV in 2004 is 7.3. Panel is unbalanced. Robust standard errors are clustered by municipality. Controls included in columns (3) and (5) are eligible zones-specific. They include road network, the percentage within communal land, the percent of the municipality that is located in an eligible zone, the baseline characteristics of pasture (both natural pasture and pasture associated with livestock production). * p< 0.10, ** p<0.05, *** p<0.01.

Table E4: Regressions of PROGAN enrollment on PES enrollment – instrumental variables approach

Second-stage	(1)	(2)	(3)
Cum. enrolled PES ha/mun ha	-0.0575***	-0.112***	-0.0151
	(-6.12)	(-10.48)	(-1.21)
p-value AR-test	1.94e-10	1.32e-36	0.222
F-stat	358.3	370.1	171.7
First-stage:			
Cum. eligible zone ha/mun ha	0.0669***	0.0690***	0.0649***
	(18.93)	(19.24)	(11.35)
Observations	6488	6488	6488
Year FE	X	X	X
State FE		X	
Municipality FE			X

Note: Years 2003, 2008, and 2014. Dependent variable is the number of animals enrolled in PROGAN for each wave. Treatment is the sum of all PES enrolled hectares per municipal hectare between each wave (before 2003, between 2003-2007, and between 2008 and 2013). Instrument is the sum of all eligible zones per municipal hectare between each wave. Robust standard errors are clustered by municipality. * p< 0.10, ** p<0.05, *** p<0.01.

Table E5: Regressions of PROGAN enrollment on PES willingness to enroll – instrumental variables approach

Second-stage			
	(1)	(2)	(3)
Cum. ha applied to PES/mun ha	-0.183***	-0.347***	-0.0958
	(-6.18)	(-10.96)	(-1.20)
p-value AR-test	1.94e-10	1.32e-36	0.222
F-stat	503.0	525.4	40.53
First-stage:			
Cum. eligible zone ha/mun ha	0.0210***	0.0223***	0.0102***
	(22.43)	(22.92)	(5.51)
Observations	6488	6488	6488
Year FE	X	X	X
State FE		X	
Municipality FE			X

Note: Years 2003, 2008, and 2014. Dependent variable is the number of animals enrolled in PROGAN for each wave. Treatment is the sum of all PES hectares submitted to PES per municipal hectare between each wave (before 2003, between 2003-2007, and between 2008 and 2013). Instrument is the sum of all eligible zones per municipal hectare between each wave. Robust standard errors are clustered by municipality. * p$<$ 0.10, ** p$<$0.05, *** p$<$0.01.

E.2 Robustness: effect of PROGAN and PES on deforestation

Table E6: Regressions of deforestation on PROGAN and PES, first wave only

	Deforestation (%)				
	(1)	(2)	(3)	(4)	(5)
Subsidy/ha (kMXN)	7.5742***	6.2596***	3.2817***	2.2424***	3.1716***
	(0.4158)	(0.4597)	(0.5129)	(0.6943)	(0.6460)
Enrolled PES/ha (%)	-0.4323***	0.2140**	-0.4605	-0.3425	0.3920
	(0.0889)	(0.1072)	(0.6153)	(0.6251)	(0.6915)
Subsidy/ha (kMXN) $\times$ Enrolled PES/ha (%)	-77.2791***	-64.5725***	-34.5013***	-25.1943***	-38.4832***
	(5.8133)	(5.5817)	(6.9296)	(7.7679)	(9.2088)
Adjusted R2	0.034	0.191	0.473	0.346	0.478
Observations	10,810	10,810	10,810	4,325	10,810
Year FE	X	X	X	X	X
State FE		X			
Municipality FE			X	X	X
Forest cover weights					X

Note: Years 2003-2007. Unweighted pre-mean of dependent variable is 0.29%, weighted pre-mean of dependent variable is 0.34%. Robust standard errors are clustered by municipality. The fourth column includes only municipalities that ever had PES enrollment and the fifth includes weights for baseline forest cover. * p$<$ 0.10, ** p$<$ 0.05, *** p$<$ 0.01.

F Supplemental analysis: parcel level deforestation

This appendix examines the interaction between PROGAN and PES on the land that applied for the PES program. We are interested in the direct effect of increases in PROGAN enrollment or payments, and the interaction of that effect with PES payments. The unit of analysis is a piece of land with a unique application history, to which we refer as "parcel". We employ a layer created by Alix-Garcia, Sims, and Orozco-Olvera, 2017, which overlays all applicant parcels and divides them up, creating spatial histories.[12] This approach eliminates the problem of double counting areas in the panel analysis of applicants, but generates challenges with the unit of analysis; many very small parcels resulting from the year-to-year overlaps are often not meaningful units of analysis. To help address this issue, we drop unique history parcels with less than 10 hectares of forest cover in 2000.

To estimate impact we apply fixed effects at the level of the property (p) where the boundaries are known – this is the case for common properties – at the level of the municipality for private properties.[13] As shown in Section 4.2, our sample of accepted and rejected parcels has not been affected by the availability of PROGAN. Therefore, any impact on deforestation does not occur through changing the deforestation risk profile of applicants. The identification of the PROGAN and interaction effects rely on the assumption that after controlling for property fixed effects, time fixed effects, and controls, there are not unobserved factors that change deforestation decisions at the parcel level and simultaneously the municipal participation in PROGAN and PES.

[12]For example, suppose a community submits a parcel in 2011 that is rejected, and then they submit a parcel in 2012 that overlaps the 2011 parcel, but this new application is accepted. This sequence of activities generates three parcels in the dataset: one with a history of being rejected in 2011 and then accepted in 2012, one with a history of being rejected in 2011, and another with a history of being accepted in 2012.

[13]Common properties in Mexico are known as ejidos. Ejidos comprise the majority of the land in rural Mexico and house a significant amount of forest. This tenure structure arose as a result of the Mexican Revolution after 1917, and have fixed membership over time, with rights only passing on to one family member over generations. Although some ejidos were dissolved as a result of a 1992 reform of the sector, they remain a dominant land tenure arrangement in rural Mexico.

The estimation equation is:

$$Pr(Y_{ipt} = 1) = f(\alpha + \beta_1 PES_{ipt} + \beta_2 PROGAN_{m(ip)t} + \beta_3 PES_{ipt} x PROGAN_{m(ip)t} + \mathbf{X}_{ipt}\gamma + \psi_p + \theta_t + u_{ipt}), \tag{F.1}$$

where Y_{ipt} takes a value of one if parcel i in property p experiences any deforestation in year t. The binary treatment variable PES_{ipt} is equal to one when the parcel is enrolled and equal to zero otherwise.[14] We use the municipal livestock subsidy per hectare to measure PROGAN intensity: $PROGAN_{m(ip)t}$, though are results hold if we substitute animals per hectare into the equation. $\mathbf{X}_{ipt}$ includes a variable equal to one if the parcel was ever accepted into the program, and also parcel-level values of distance to major city and road, elevation, slope, locality level poverty in 2010, percent of the parcel that was forested in 2000, and whether or not the municipality in which the parcel is located is majority indigenous. To accommodate property level fixed effects ψ_p, we include ejido means of all of the included X variables as well as all of the treatment variables. Year fixed effects θ_t are also included. The standard errors u_{ipt} are clustered at the property level. We estimate the equation using a random effects logit and report marginal effects. This transformation, originally proposed by Mundlak, 1978, avoids the incidental parameters problem and allows us to use a non-linear estimator that better matches the data generating process (Alix-Garcia & Millimet, 2023).

Although the treatment effect of PES on its own is not our primary parameter of interest, we also want to ensure that characteristics of the rejected parcels are as similar as possible to those of the accepted parcels. To this end, we keep only applicants that have passed a first round of screening and have sent geo-referenced property boundaries. We also exploit the fact that for later years of the program, parcels received a "score"

[14]This variable is staggered, since different parcels enroll at different times. This makes the binary treatment effect difficult to interpret due to the changing counterfactual over time (Goodman-Bacon, 2021). However, our coefficient of interest is continuous – the interaction of this variable with the intensity of participation in PROGAN. This means that we are not able to apply the existing adjustments for staggered difference in differences.

based upon a series of observable characteristics. Within each state, program, and year, applications with the highest score were accepted until state budgets were exhausted. Our main specification restricts the sample to only those properties which received a normalized score of between -10 and 10 points. This includes 99% of the area of land ever submitted to the program. We explain this process in more detail below.

Table F1 presents the average and the normalized differences of parcel and municipality characteristics for the accepted and the rejected applicants. We compare the full sample as well as the sample with recentered point scores between the -10 and 10 points around the central cutoff value for the state, program, and year. The restricted sample improves the comparability between the accepted and the rejected parcels on the following characteristics: whether the parcels are within a protected area, elevation, slope, the distances to roads and the percent majority indigenous, and at the municipal level, the frequency in eligible zones and the marginality index.

Sample selection: PES parcels

The criteria for enrollment into the PES program have evolved over time. Starting in 2006, a points score was established in order to bring transparency into the selection process. Points were based upon characteristics of the application as well as geographic features calculated based upon GIS layers. Across all years, application outside of eligible zones were rejected. In the years prior to 2006, applications were often rejected due to lack of sufficient forest cover, and in the later years because of relatively insufficient point scores. Since point scores did not exist for properties that applied before 2006, a new score is imputed for those parcels.

We create recentered point scores for each parcel according to their specific state, year of application and program type in order to select a sample of similar parcels. For parcels submitted after 2006, we simply use the existing point scores. For earlier parcels, we impute them from a regression of real point scores for 2006-2015 on various

characteristics used to calculate the point scores.[15] We then calculate the minimum point score for acceptance in each state, year and program type. We subtract the minimum score for acceptance in each parcels state-year-type category from its actual or imputed score. We match the recentered point scores with the panel of parcels, and for the units of analysis that applied more than once, calculate the average recentered point scores based on each time the parcel was submitted. Figure F1 compares the histogram of the recentered point scores for the accepted and rejected groups. As expected, accepted parcels have significantly higher recentered point scores than rejected parcels.

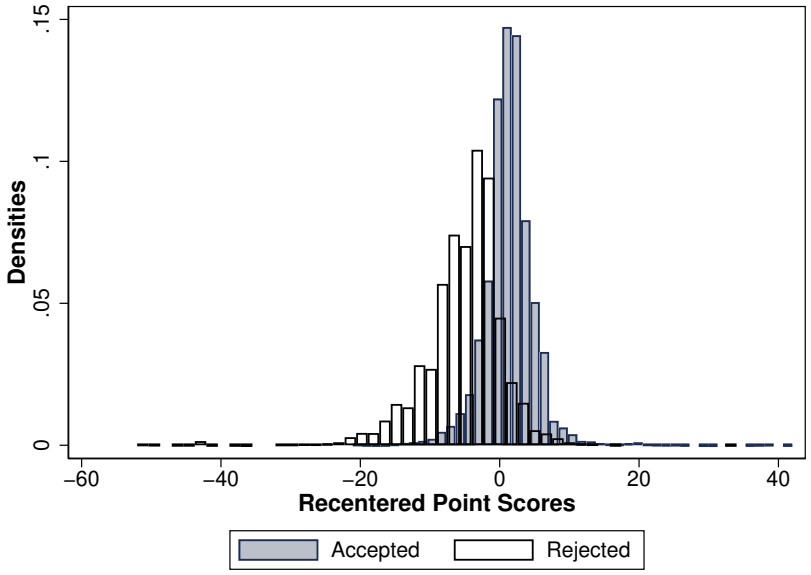


Figure F1: Density distribution of recentered point scores for accepted and rejected parcels. The histogram includes predicted values for parcels that applied before 2006 and real point scores for parcels that applied in or after 2006.

[15]Characteristics are: state indicators, year of application, PES type, IHS(average slope), IHS(average elevation), IHS(forest cover 2003), IHS(submitted parcel size), deforestation risk, communal land indicator, and also indicators of whether the submitted parcel falls within a Biosphere, a Federal park, a State park, a municipal park, a RAMSAR site or a privately or communally owned certified area. Hyperbolic sine transformation (IHS) (Burbidge, Magee, & Robb, 1988) is similar to a logarithmic, which reduces the influence of outliers, but at the difference that it is identified at zero.

Table F1: Summary statistics for accepted and rejected parcels

	All parcels			*Restricted with rec. pt. scores*		
	Accepted	Rejected	N.d.	Accepted	Rejected	N.d.
Parcels' forests						
% forest cover (2000)	79.30	70.13	0.22	79.39	70.50	0.21
Forest cover (2000), ha	217.26	203.84	0.01	217.64	206.04	0.01
Parcels' characteristics						
Parcel area (ha)	394.16	517.40	-0.05	394.55	528.51	-0.05
Parcel ha submitted (2004)	5653.10	2530.00	0.28	5680.95	2522.77	0.29
Parcel ha submitted (2014)	1059.62	1049.56	0.01	1067.94	1037.10	0.02
Ejidos (2004)	0.50	0.48	0.03	0.50	0.48	0.04
Ejidos (2014)	0.51	0.49	0.04	0.52	0.48	0.05
Protected area (2004)	0.37	0.24	0.21	0.36	0.25	0.18
Protected area (2014)	0.43	0.28	0.23	0.43	0.29	0.20
Average elevation (mt)	1393.06	1248.09	0.11	1367.10	1272.70	0.07
Average slope (degree)	14.92	13.88	0.09	14.88	14.05	0.07
Distance to any road (meters)	4283.26	4976.34	-0.11	4319.49	4858.46	-0.08
Distance to city with > 5,000 people	28.59	31.61	-0.10	28.85	31.60	-0.09
Distance to highway > 80km/h (meters)	18439.56	18411.33	0.00	18664.53	18590.97	0.00
Distance to highway > 60 km/h (meters)	7526.64	8481.90	-0.09	7603.18	8460.36	-0.08
Distance to major city (km)	101.40	108.78	-0.09	102.07	107.73	-0.07
Deforestation risk	0.04	0.05	-0.04	0.04	0.04	-0.03
Percent of majority indigenous	29.25	22.29	0.11	29.76	24.49	0.08
Percent acquifer	10.25	7.23	0.08	9.98	7.30	0.07
Parcels' scores						
Recentered point scores	1.35	-5.22	0.94	1.18	-3.57	1.01
Municipal characteristics						
Eq. animals/ha (2003)	0.03	0.04	-0.06	0.03	0.04	-0.03
Eq. animals/ha (2014)	0.05	0.06	-0.03	0.05	0.05	-0.01
Subsidy/ha (kMXN, 2003)	0.01	0.01	-0.10	0.01	0.01	-0.06
Subsidy/ha (kMXN, 2014)	0.02	0.02	0.00	0.02	0.02	0.02
Average pasture coefficient	3.24	3.36	-0.05	3.22	3.38	-0.06
Baseline livestock density	0.07	0.07	-0.02	0.07	0.07	0.00
Baseline pasture density	0.05	0.05	-0.07	0.05	0.05	-0.07
Eligible zones/ha (2006-2014)	0.66	0.58	0.24	0.67	0.60	0.21
Marginality index (2005)	0.22	0.12	0.08	0.23	0.17	0.05
Marginality index (2010)	0.22	0.13	0.06	0.23	0.18	0.04
Observations	12866	12828	25694	12351	10897	23248

Note: Columns (1)-(3) present full sample and columns (4)-(6) present the sample restricted to the recentered point scores between the -10 and 10 points around the central cutoff value for the state, program, and year. Normalized differences are in columns (3) and (6) (Imbens & Wooldridge, 2009) and averages in the remaining columns. Parcel data and their land characteristics are from Alix-Garcia et al. (2017), deforestation data from Hansen et al., 2013, PROGAN and PROCAMPO from SAGARPA, and marginalization index and population from CONAPO.

Results: parcel level

Table F1 shows the results of Equation F.1 on our preferred sample (restricted between -10 and 10 on the normalized point score). Table F3 shows estimates using the full sample. In columns (2) and (5), PROGAN is defined as the subsidy per hectare, and in columns (3) and (6), as the number of animal equivalent units per hectare. All specifications include property (municipality for private properties) fixed effects and the last three columns include a weight for the area of the parcel.

We observe consistently negative effects, though not always statistically significant, of PES alone, mostly positive point estimates of the subsidy, with inconsistent levels of significance for these. The interaction terms are negative and statistically significant in the unweighted estimates and not statistically significant in the weighted ones.

Table F1: Parcel level regressions of deforestation on PES and PROGAN

	Deforestation (0/1)			
	(1)	(2)	(3)	(4)
PES recipient (0/1)	-0.0037	0.0000	-0.0111**	-0.0129*
	(0.0025)	(0.0029)	(0.0056)	(0.0069)
PROGAN subsidy		0.0060		0.2401
		(0.0549)		(0.1878)
PES x Subsidy/ha		-0.1716**		0.0434
		(0.0681)		(0.2081)
Pseudo-R2	0.155	0.159	0.102	0.105
Observations	324,114	324,114	324,114	324,114
Year FE	X	X	X	X
Property FE	X	X	X	X
Area weights			X	X

Note: Years 2001-2014. The sample is the full sample of parcels within the municipalities considered in all sections of the paper. The estimator is a correlated random effects logit with effects at the ejido level for common properties and the municipality level for private properties. Robust standard errors are clustered by ejido for common properties and by municipality for private properties. * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

We suspect that treatment heterogeneity across parcels of different parcel sizes explains the differences between these two estimates, and also that the problem is more severe here, since the range in sizes is very large – from 10 to 6,000 ha. In addition to possible behavioral effects, such as the fact that resource extraction is likely to slow as the resource becomes more scarce, mechanically there is significantly much more measurement error in the smaller areas. To examine the effects of this heterogeneity, we split the sample into above and below median parcel sizes (the median is 152 ha). The above median parcels contain nearly 9.5 million hectares, whereas the below median parcels contain around 800,000 – only 7.7% of the area ever submitted to the program (Table F2). In this sample of larger parcels, we observe positive effects of the subsidy alone, meaning that municipalities with greater PROGAN intensity have higher deforestation rates on unenrolled land that applied to the program. The interaction terms are negative, statistically significant, and slightly larger in magnitude than the direct effect of PROGAN. Figure F1 shows a visualization of the effects of a one standard deviation increase in the intensity of PROGAN on applicants in general and then the sum of this with the effect

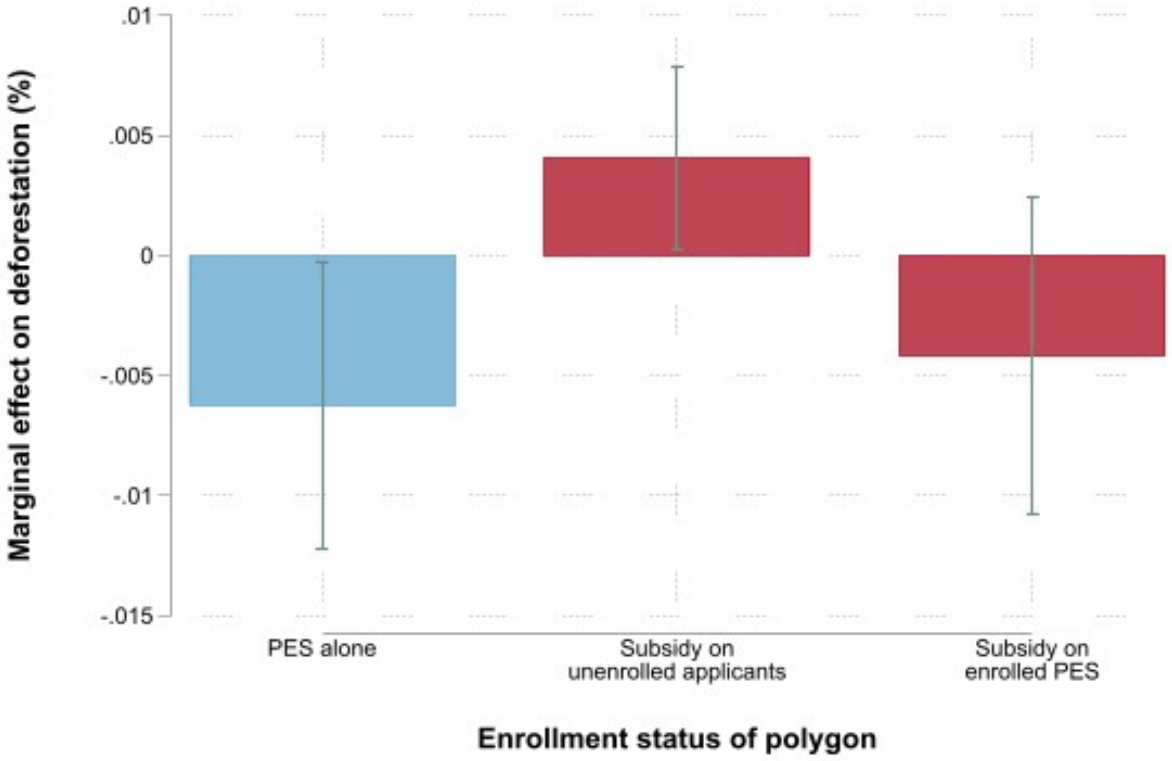


Figure F1: Marginal effects are for a one standard deviation increase in the intensity of PROGAN on land that applied to the PES (Subsidy x 1 SD increase in subsidy), and then the sum of this effect with the interaction of PROGAN intensity and enrollment in the PES (PES recipient + (PROGAN subsidy + PES x subsidy)x 1 SD increase in subsidy). Error bars are for 90% confidence. The estimates come from parcels greater than the median area (152 ha), using Table F2. The first bar is from column (4). The second two bars come from column (5).

of enrollment. Although PES enrollment eliminates the increase in the propensity to deforest caused by PROGAN, the evidence is that the PES effect is not substantial enough to actually generate avoided deforestation in areas with high PROGAN intensity. In these places and for parcels that ever applied to PES, the environmental program serves only to maintain the status quo in the face of the deforestation incentives generated by PROGAN.

These results are the same for the entire set of parcels (Table F3). They also hold when we restrict estimations to parcels that received point scores normalized for their

state, program and year between -5 and 5 (Table F4), for the full set of parcels, and for those greater than the median size. For both sets of estimations the direct effect of the subsidies is positive and its interaction with the PES program negative. Only the effect of PES alone and the direct effect of the PROGAN subsidy are statistically significant, and only in the sample of large parcels. We also estimate impacts on the full and on the large parcels using an estimator that corrects for misclassification error in the dependent variable (Alix-Garcia & Millimet, 2023), and observe similar negative interaction terms between the subsidy and the program (Table F5).

Robustness checks: Effect of PROGAN and PES on Deforestation at the Parcel Level

Table F2: Parcel level regressions of deforestation on PROGAN and PES, below and above median parcels

	Deforestation (0/1)					
	Below median			Above median		
	(1)	(2)	(3)	(4)	(5)	(6)
PES recipient (0/1)	-0.0020	0.0006	-0.0062*	-0.0013	-0.0122**	-0.0151*
	(0.0032)	(0.0038)	(0.0036)	(0.0043)	(0.0062)	(0.0077)
PROGAN subsidy		-0.0672		0.1779*		0.3179
		(0.0512)		(0.1003)		(0.2283)
PES x Subsidy/ha		-0.0803		-0.3027**		0.0986
		(0.0731)		(0.1252)		(0.2634)
Pseudo-R2	0.100	0.103	0.132	0.137	0.086	0.089
Observations	162,988	162,988	161,126	161,126	161,126	161,126
Year FE	X	X	X	X	X	X
Ejido FE	X	X	X	X	X	X
Area weights			X	X		

Note: Years 2001-2014. Robust standard errors are clustered by ejido for common properties and by municipality for private properties. The estimator is a correlated random effects logit with effects at the ejido level and marginal effects reported. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table F3: Parcel level regressions of deforestation on PROGAN and PES, full sample

	Deforestation (0/1)			
	(1)	(2)	(3)	(4)
PES recipient (0/1)	-0.0044*	-0.0009	-0.0137**	-0.0155**
	(0.0025)	(0.0029)	(0.0054)	(0.0066)
PROGAN subsidy		0.0039		0.1766
		(0.0545)		(0.1755)
PES x Subsidy/ha		-0.1565**		0.0587
		(0.0673)		(0.1995)
Pseudo-R2	0.155	0.158	0.103	0.105
Observations	358,330	358,330	358,330	358,330
Year FE	X	X	X	X
Ejido FE	X	X	X	X
Area weights			X	X

Note: Years 2001-2014. Sample is the full unrestricted sample. Robust standard errors are clustered by ejido for common properties and by municipality for private properties. The estimator is a correlated random effects logit with effects at the ejido level and marginal effects reported. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table F4: Parcel level regressions of deforestation on PROGAN and PES, more restricted sample

	Deforestation (0/1)			
	(1)	(2)	(3)	(4)
PES recipient (0/1)	-0.0049	0.0014	-0.0087	-0.0108
	(0.0039)	(0.0047)	(0.0065)	(0.0096)
PROGAN subsidy		0.2341**		1.3154***
		(0.1132)		(0.3629)
PES x Subsidy/ha		-0.3870***		-0.0036
		(0.1340)		(0.4206)
Pseudo-R2	0.131	0.135	0.088	0.089
Observations	122,514	122,514	122,514	122,514
Year FE	X	X	X	X
Ejido FE	X	X	X	X
Area weights			X	X

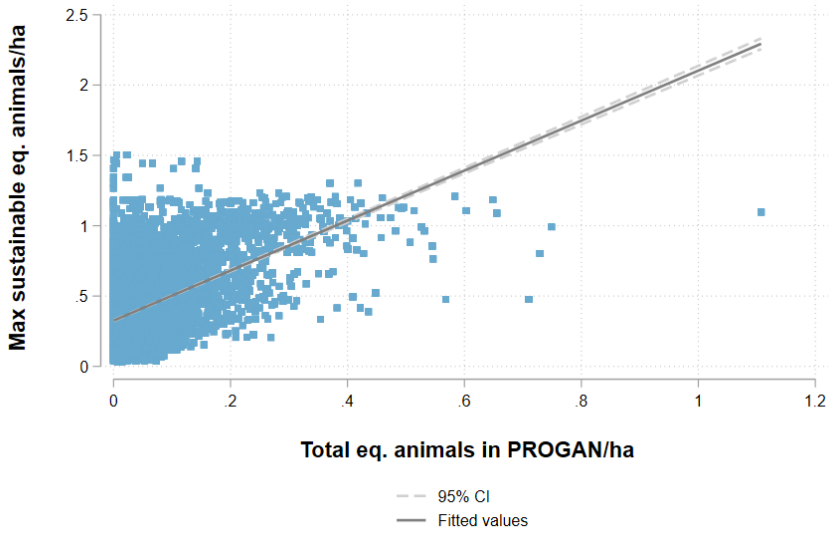
Note: Years 2001-2014. Sample restricted by point scores as described in column heading. Robust standard errors are clustered by ejido for common properties and by municipality for private properties. The estimator is a correlated random effects logit with effects at the ejido level and marginal effects reported. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table F5: Parcel level regressions of deforestation on PROGAN and PES, misclassification correction model

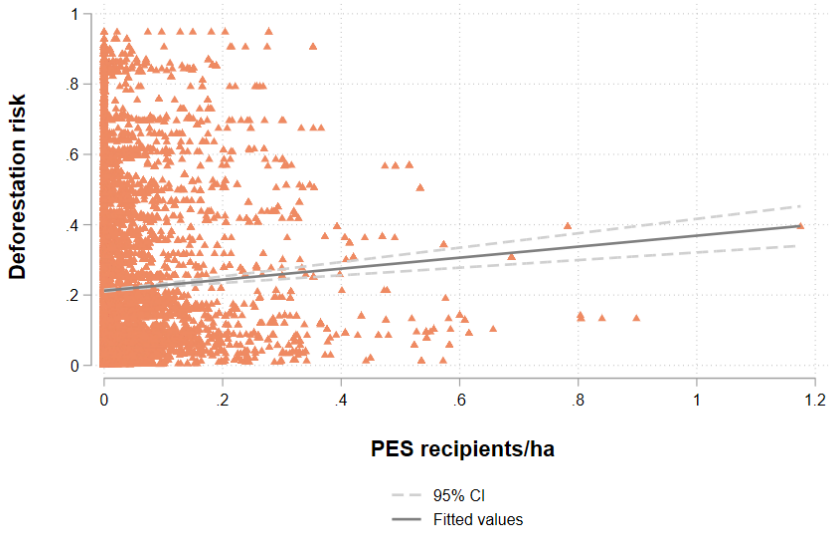
	Deforestation (0/1)			
	Full sample		Parcels $>$ 152 ha	
	(1)	(2)	(3)	(4)
PES recipient (0/1)	-0.004	0.006	-0.005	0.006
	(0.005)	(0.005)	(0.007)	(0.022)
PROGAN subsidy		-0.039		0.482
		(0.116)		(0.352)
PES x Subsidy/ha		-0.409***		-0.769
		(0.145)		(1.228)
Observations	325388	325374	161798	161798
G0	0.000	0.001	0.000	0.002
G1	0.409	0.327	0.408	0.390
logL	-129480.860	-129128.984	-79771.587	-79504.737
Year FE	X	X	X	X
Ejido FE	X	X	X	X

Note: The estimator is the misclassification adjusted logit with ejido level means of all covariates and standard errors clustered at the ejido level. Marginal effects evaluated at sample means are displayed. G0 and G1 are the probability of a false positive and negative, respectively, evaluated at sample means. The false positive and negative rates depend on the number of L7 cloud-free scenes and its interaction with average slope, and with ln(parcel area). Time fixed effects included in all models. * p$<$ 0.10, ** p$<$ 0.05, *** p$<$ 0.01.

G Additional figure and table for PROGAN targeting (Section 5)



(a)



(b)

Figure G1: Targeting criteria versus program distribution. Figure a shows the maximum number of animals that can be sustainably enrolled in PROGAN and the intensity of the number of animals enrolled in PROGAN. Figure b shows the deforestation risk and the intensity of PES recipients in hectares. Linear fits and 95% confidence intervals are included.

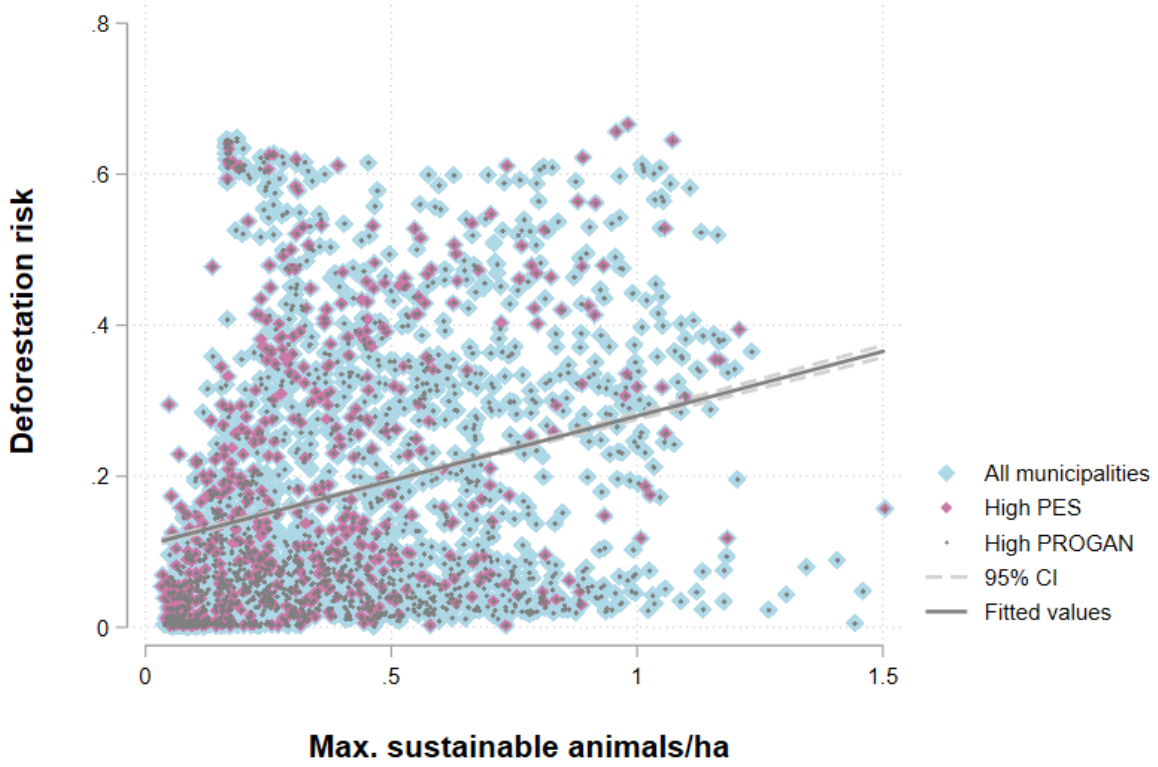


Figure G2: Programs' relative to targeting criteria. Each diamond represents a municipality and year. X-axis is maximum animal equivalents per ha, y-axis measures ln(deforestation risk). Municipalities have an additional pink diamond overlaid when they have PES enrollment above the 75th percentile, and a gray x if they have PROGAN enrollment above the 75th percentile.

Table G1: Impacts of targeting to maximize program benefits

	% Deforestation					
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy/ha (kMXN)	2.0567***	1.2803***	1.2762	-0.6582	2.2157*	-0.4164
	(0.6558)	(0.4631)	(0.8740)	(0.8242)	(1.3367)	(0.8926)
Subs./ha (kMXN) x Low defor. risk	-1.2127*	-2.1192***			-2.3796	-1.5034
	(0.6943)	(0.7083)			(1.5743)	(1.1858)
Subs./ha (kMXN) x High max animals			0.5945	1.9629**	-0.1858	1.7254*
			(0.9367)	(0.8021)	(1.4402)	(0.9066)
Subs./ha (kMXN) x Low risk x High max animals					1.4037	0.1091
					(1.7114)	(1.2226)
Adjusted R2	0.007	0.039	0.007	0.039	0.007	0.039
Observations	30,269	30,269	30,269	30,269	30,269	30,269
Year FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Weights		X		X		X

Note: Years 2001-2014. The sample contains the municipalities considered in all sections of the paper. Robust standard errors are clustered by municipality. * p< 0.10, ** p< 0.05, *** p< 0.01. Weights are baseline forest cover.