Paper Abstract

Can PES Save the Forest? The Effects of an Avoided Deforestation Initiative in the Brazilian Amazon

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The Earth's climate is changing. Global temperatures have risen at around 0.2°C per decade over the past 30 years, bringing the global mean temperature to the warmest level on record—all the ten warmest years on record have occurred since 1990. Over the last 50 years, sea levels have increased and both the frequency and the intensity of extreme weather events have changed. A consensus is growing that climate change is a result of greenhouse gases caused by human activity.

There is a belief that these changes will have effects on morbidity and mortality through (1) increases in malnutrition and consequent disorders—affecting mostly low-income populations; (2) changes in the incidence and geographical range of infectious diseases; and (3) increases in the number of deaths, disease episodes, and injuries from heat waves, floods, storms, fires, and droughts. It has also been suggested that climate change may affect human migration, with millions of people displaced by shoreline erosion, coastal flooding, and agricultural disruption. Poor communities are seen as the most vulnerable—90 percent of deaths related to natural disasters occur in developing countries—because such communities are often situated in risk-prone areas and rely on public infrastructures, such as water, energy and transportation, that are affected by disaster-related episodes.

Tropical deforestation is the second largest source of greenhouse gas emissions, accounting for 20 percent of the world's carbon dioxide (CO_2) emissions (Gullison et al., 2009). Tropical forests store 25 percent of the carbon in the terrestrial biosphere and the decay and burning of wood releases carbon into the atmosphere (Bonan, 2008). Tropical deforestation is responsible for more emissions than all cars, trucks, ships, and airplanes combined. Deforestation also reduces biodiversity, disturbs water regulation, and destroys livelihoods for many of the world's poorest.

Reducing emissions from deforestation and degradation (REDD) is considered as one of the fastest and cheapest ways of reducing carbon emissions (Stern, 2006). The potential of REDD activities to mitigate climate change has led to great interest in these initiatives. The 2009 United Nations Climate Change Conference (UNCC) accord—in which developed countries committed to give $30 billion over the next three years to help developing countries adapt to climate change and cope with its impacts—references *"[s]caled up, new and additional (...) funding*" to "*enhance action on mitigation,*" including REDD.

The (potential) contribution of reducing tropical deforestation for climate change mitigation—and consequently the success of international accords in REDD through financial-incentive mechanisms—depends crucially on how large are the reductions in deforestation associated to avoided deforestation (AD) initiatives. Despite the promises these initiatives hold for reducing CO2 emissions, little is known about how effective they are.

This paper uses quasi-experimental econometric methods to study the effects on deforestation of a large AD initiative in the Brazilian Amazon. It will answer important questions such as whether AD initiatives work, how large is the effect on deforestation (and consequently on carbon emissions), and whether there are spillover effects to non-participant areas.

We study the case of the Forest Allowance Program, an initiative implemented in the state of Amazonas that pays the local population a monthly allowance for environmental services and increases deforestation monitoring and enforcement. The initiative extends so far to an area of more than 10 million hectares that is larger than Portugal. It is estimated that deforestation in protected areas of the state of Amazonas could emit as much as 3.5 billion tons of CO_2 into the atmosphere—which correspond to the annual emissions of China—at an estimated cost of 73.5 billion dollars to society.

The Forest Allowance Program was initially implemented in the Juma Sustainable Development Reserve in September of 2007.[1] Since then, the state government of Amazonas has implemented it in another 14 State Conservation Units (CUs). It has three main initiatives: (1) providing families that commit to sustainable development a monthly allowance of R$50 (approximately $28) as a reward for their environmental services[2]; (2) strengthening environmental monitoring and control by using satellite imagery and regular inspections on the ground; and (3) making investments to promote the engagement of the local population in sustainable production of forest products, such as oils, nuts, wood, fruits, and native honey.[3] The largest CU participating in the program has an area of 1.124 million hectares, while the smallest has an area of roughly 103 thousand hectares. There are 7,389 families living in these CUs (there are on average 493 families living in each CU), 6,943 of which (corresponding to 94%) receive PES.

We use two empirical strategies to estimate the effects of the program on deforestation. We initially investigate in a differences-in-difference framework whether the growth in deforestation rates in conservation units (CUs) participating in the program slowed down (relative to the growth in non-participant CUs) after the introduction of the program. We then proceed to compare the growth in deforestation rates of contiguous areas on opposite sides of participant CUs' boundaries. For this purpose, a panel dataset with geographically detailed deforestation estimates was constructed particularly for this project with the conversion of satellite imagery into area-specific annual deforestation estimates.

The first empirical strategy estimates the effect of the program on deforestation using a differences-in-difference approach. The strategy relies on the assumption that deforestation growth in control CUs provide a good counterfactual to the growth in treatment CUs in the absence of the program. Hence, we will estimate:

$$Y_{rt} = \alpha_0 + \alpha_1 D_{rt} + f(t) * (1 - D_r) + \mu_t + \theta_r + \varepsilon_{rt}, \tag{1}$$

[1]The Juma Sustainable Development Reserve is the only CU among the 15 participating in the program whose funding comes from carbon trade, characterizing it as a REDD initiative.

[2]Regular in loco inspections and satellite imagery are used to monitor deforestation. A family that does not comply with the program requirements loses the right to receive the monthly allowance.

[3]The program also makes investments in education, health, transportation, and telecommunications in CU communities and provides financial support to organize and strengthen community associations that overlook the program.

where Y_{rt} is the deforestation rate of CU *r* at year *t*, D_{rt} is a dummy variable that is equal to 1 if CU *r* had been treated by year *t*, D_r is a treatment status dummy, $\square$ is a year fixed effect, $\square$ is a CU-specific (time-invariant) fixed effect, and $f(t)$ is a cubic function that allows for differential time trends between control and treatment areas:

$$f(t) = \alpha_2 t + \alpha_3 t^2 + \alpha_4 t^3. \tag{2}$$

The year fixed-effects μ_t capture the (pre-program) time trend common to control and treatment CUs while the cubic function $f(t)$ captures the deviation specific to control CUs from this common trend. The estimation of (1) will deliver an unbiased estimate of the causal effect on deforestation if the error term ε_{rt} is orthogonal to D_{rt}.

This strategy relies on the assumption that (once we control for differential pre-program time trends) the time trend of deforestation in control CUs after the program provides a good counterfactual to what the time trend of deforestation in treatment CUs would have been had the program not been implemented. This assumption would be, however, violated—and one would underestimate the reduction in deforestation associated to the program—if the government chose to implement the program in areas that were at greater risk of deforestation and would have had faster deforestation growth in the absence of the program.

We will therefore use a second empirical strategy that refines on the difference-in-differences approach by comparing the growth in deforestation rates in contiguous areas on opposite sides of treatment CUs' boundaries. The underlying idea of this strategy is that—because of the proximity—areas just outside the treatment CUs' boundaries provide a good counterfactual to areas inside the CU close to the boundary. We estimate the following equation:

$$Y_{prt} = \gamma_0 + \gamma_1 D_{rt} + \gamma_2 D_p + \gamma_3 \left(D_{rt} * D_p\right) + \chi_{prt}, \tag{3}$$

where *p* indexes a plot that may lie on either side of a CU's boundary, $\square$ is the deforestation rate of plot *p* in reserve *r* at year *t*, $\square$ is a dummy variable that is equal to 1 if CU *r* had been treated by year *t*, $\square$ is a dummy variable that is equal to 1 if plot *p* is within the reserve boundaries, and χ_{prt} is an error term. The strategy compares the growth in deforestation rates after the introduction of the program of areas just outside the CUs' boundaries to areas just inside. We allow for reserve-fixed effects and differential time trends between areas inside and outside the boundaries. In particular, we assume that the error term can be decomposed in the following way:

$$\chi_{prt} = g(t) * \left(1 - D_p\right) + \mu_t + \theta_r + \xi_{prt}, \tag{4}$$

$$g(t) = \gamma_4 t + \gamma_5 t^2 + \gamma_6 t^3, \tag{5}$$

where is a year fixed effect, is a reserve-specific fixed effect, and is an error term. The year fixed-effects μ_t capture the (pre-program) time trend common to inside and outside areas while the cubic function $g(t)$ captures the deviation specific to outside areas from this common trend.

Previous work has looked at the effects of AD initiatives on deforestation. Studies that investigated payments for environmental services (PES) programs—in which individuals or communities are compensated for undertaking actions that contribute to environmental conservation—in Costa Rica and Mexico have found small or no effects on deforestation (Sanchez-Azofeifa et al., 2007; Pfaff et al., 2008; Robalino et al., 2008; Alix Garcia et al., 2010). A related literature found larger effects of establishing protected areas on deforestation and forest fires (Andam et al., 2008; Nelson and Chomitz, 2009; Joppa and Pfaff, 2010). The major challenge for these evaluations is to identify the counterfactual deforestation rate—the deforestation rate that would have prevailed in the absence of the program. The avoided deforestation associated with an initiative is the difference between the counterfactual and the actual deforestation rate.

These studies have estimated the effect of such programs on deforestation rates by comparing the deforestation rates of areas included in the program—i.e., the treatment areas—to those of areas not included—i.e., the control areas. But the treatment areas are different from control areas (e.g., the government may choose to implement the program in areas at greater risk of deforestation or landholders may choose to participate only if the opportunity cost of the land is low), which suggests that they would have had different deforestation rates even if the program had not been implemented. To address these baseline differences, these studies use matching estimators that compare deforestation rates in treatment areas to control areas with similar observable characteristics. The issue with this approach is that treatment and control areas may differ along dimensions researchers do not observe, in which case the estimates of the program effect on deforestation will be biased. The quasi-experimental econometric methods we will use yield estimates that—under some assumptions—are unbiased even if there are unobservable differences between treatment and control areas.

Moreover, to the best of our knowledge, our study is the first to use panel data to estimate the effects of AD programs. The studies cited above rely on cross-sectional variation, which requires strong identification assumptions. In contrast, this study will use cross-sectional, time and spatial variation, adding credibility to our estimates.

The results from this paper have broader implications for the design of policies to reduce emissions from deforestation and degradation (REDD). Despite the promises these initiatives hold for reducing CO2 emissions, little is known about how effective they are. This study will provide reliable estimates on the effectiveness of AD policies, based on rich satellite imagery data and quasi-experimental econometric methods. Perhaps most importantly, we will provide credible estimates of the cost per ton of greenhouse gases abated from a deforestation program. This will allow for a comparison of the cost effectiveness of AD programs, relative to other policies (e.g., energy efficiency requirements for buildings, appliances, and cars) at reducing greenhouse gases.