Indigenous Land Rights and Deforestation: Evidence from the Brazilian Amazon

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Abstract:

Concerns over the expropriation of and encroachment on indigenous communities' lands have led to greater formalization of these communities' rights in a number of developing countries. We study whether formalization of indigenous communities' land rights affects the rate of deforestation in both the short and medium terms. Beginning in 1995, the Government of Brazil formalized the rights of several hundred indigenous communities whose lands cover more than 40 million hectares in the Amazon region and provided support for these rights' enforcement. We study the program's impacts using a long time-series of satellite-based forest cover data. Using both matched samples of treated and comparison communities and plausibly exogenous variation in the timing of formalization, we find no effect of these protections on satellite-based greenness measures. This is true even for communities that received support for surveillance and enforcement of these rights. Notably, we observe low counterfactual rates of deforestation on communities' lands between 1982 and 2014, suggesting that indigenous land rights programs should not uniformly be justified on the basis of their forest protection, at least in the medium term.

Keywords: Land tenure, forest cover, satellite-based, impact evaluation

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AidData is a research and innovation lab located at the College of William & Mary that seeks to make development finance more transparent, accountable, and effective. Users can track over $40 trillion in funding for development including remittances, foreign direct investment, aid, and most recently US private foundation flows all on a publicly accessible data portal on AidData.org. AidDta's work is made possible through funding from and partnerships with USAID, the World Bank, the Asian Development Bank, the African Development Bank, the Islamic Development Bank, the Open Aid Partnership, DFATD, the Hewlett Foundation, the Gates Foundation, Humanity United, and 20+ finance and planning ministries in Asia, Africa, and Latin America.

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1. Introduction

Concerns over the expropriation of and encroachment on indigenous communities' lands have led to greater formalization of these communities' rights in a number of developing countries. When enforced, the improvement in these rights can enable indigenous communities to prevent incursions into their territories. Of particular importance are rights for communities inhabiting tropical forests, where ambiguity over and weak enforcement of land rights often lead to unsustainable resource extraction and conversion to agricultural uses. In Brazil, for example, these concerns led the Government to enshrine its commitment to formalizing indigenous people's territorial rights in its 1988 constitution. Since then, indigenous territories have been formalized on more than one-fifth of the Brazilian Amazon, often in locations near the expanding deforestation frontier.

A number of recent studies examine the relationship between indigenous control and stewardship of lands and deforestation rates (Nelson et al. 2001, Nepstad et al 2006, Nelson and Chomitz 2011, Nolte et al. 2013, Pfaff et al 2014, Vergara-Aseno and Potvin 2014). Using both global and within-country comparisons, these studies find that indigenous lands generally exhibit lower deforestation rates than those with other governance forms, be they privately owned, publicly owned but eligible for sustainable use, or publicly owned protected areas.

Thus, indigenous communities have generally experienced less frequent deforestation, but their forests now appear increasingly threatened. The policy-relevant question is whether improving these communities' rights can protect their lands from increasing deforestation. However, the aforementioned studies only consider indigenous control as a static set of rights, while the policy question is whether *changes* in these rights alter the use patterns on these lands.

A notable exception is Buntaine, Hamilton, and Millones (2015), which finds no impacts of tenure formalization in one region of Ecuador. However, the external validity of these results is limited.[1] At the same time, a broader literature assesses the impacts of improvements in private and communal land tenure systems, largely covering non-indigenous lands.[2] Robinson et al (2014) conduct a meta-analysis of 118 sites covered by 36 papers in this literature that plausibly control for potential confounds and find generally positive effects. Taken together, these literatures suggest that formalizing the land rights of

[1] Buntain, Hamilton, and Millones (2015) also do not account for spatial autocorrelation in error terms or observables, possibly because such autocorrelation potentially saps the statistical power available in small-scale studies.

[2] A wider literature studies the impacts of other policy options, including protected areas (e.g., Cropper et al 2001, Andam et al 2008, Joppa and Pfaff 2011, Blackman et al 2011, Sims 2010) payments for environmental services (e.g., Pfaff et al 2008, Robalino et al 2008, Honey-Roses et al 2011, Alix-Garcia et al 2012), forest concessions (e.g., Mertens et al 2004) and agricultural investments (e.g., Deininger and Minten 2002).

indigenous communities may serve as a viable policy to conserve tropical forests. However, to date, no study has reliably assessed this claim.

These literatures highlight the dual empirical challenges in assessing impacts of changes in indigenous tenure: one needs (1) carefully documented time variation in the extent of rights, and (2) sufficient spatial variation for statistical analysis robust to spatial clustering and potential spillovers. Micro-studies of one region document the timing of rights improvements but lack statistical power once spatial effects are adequately addressed. Global studies provide sufficient spatial variation but do not document the extent of rights across an array of national legal systems.

We overcome these limitations by studying the Brazil Indigenous Lands Project (PPTAL), which formalized the land rights of 106 indigenous communities covering more than 38 million hectares of largely forested area between 1995 and 2008. We carefully document the dates at which different phases of formalization were completed, as well as the geographic extent of comparable indigenous communities whose lands were not formalized as part of the process. We merge these data with a 30-year time series of satellite-based greenness measures, thus obtaining long pre-intervention records with which to control for communities' pre-existing trends and identify statistically comparable lands. Using both matched samples of treated and comparison communities and plausibly exogenous variation in the timing of formalization, we find no effect of these protections on forest cover. These non-effects obtain in cross-sectional comparisons over the full study period and shorter-term effects detectable in grid cell-level panel models with community-level fixed effects. We further decompose the effects by whether a community also received support for surveillance and enforcement, detecting no differential impacts from the combined treatment of this support and demarcation. Employing higher resolution imagery available for the latter part of our sample period, we again find no significant gains in greenness, even in forested areas closer to the boundaries of the communities. Taken together, we find consistent estimates of only negligible treatment effects of PPTAL, estimates that are not limited by insufficient precision.

Notably, we observe relatively low counterfactual rates of deforestation on communities' lands between 1982 and 2014. These results suggest that while indigenous communities may indeed experience lower deforestation rates on their lands, their forests are not threatened by insecure title. The relevant policy implication is that indigenous land rights program should not necessarily be justified on the basis of their forest protection in the absence of counterfactual evidence on their deforestation trajectories, at least in the medium term.

This paper is organized as follows: in section 2, we detail the study context, while section 3 describes the data on community lands, satellite-based greenness, and covariates. In section 4, we describe the cross-sectional model and present its results, while section 5 focuses on grid cell-level panel methods. We offer discussion and conclusions in section 6.

2. Study Context

In the early 1900s, the Brazilian Government began to offer protection to the indigenous population, treating Indians as wards of the state and guaranteeing protection of traditional lands (Ortiga 2004). The majority of indigenous peoples resided in the nine states of the legal Amazon[3], and by the 1980s, indigenous lands accounted for 89 million hectares (17.5%) of the land area in the region, most of which maintained native forest cover despite its use for subsistence (World Bank 2007). Yet indigenous lands lacked formal legal recognition, indigenous populations continued to suffer from stigma and violence, and a series of federal ministries established to oversee the state's protection struggled with corruption, lack of resources, and illegal activities by miners and loggers (Ortiga 2004). International pressure to stem the destruction of Brazil's rainforests also came to a head in the 1980s, due to the size of the Amazon and its global importance for watershed, biodiversity, and climate maintenance. Indigenous populations provided a model of sustainable development, exemplifying the Brazilian view that its rain forests are both a natural resource to be protected and a source of wealth to be utilized (World Bank 2007).

In 1988, Brazil adopted a new constitution that aimed to legally recognize indigenous lands. Article 231 stipulates that Indians shall have their original rights to the lands they traditionally occupy recognized through demarcation and registration of land title, "it being incumbent upon the Union to demarcate them, protect and ensure respect for all of their property." One year later, the International Labor Organization (ILO) adopted Convention No. 169 Concerning Indigenous and Tribal Peoples in Independent Countries, which recognizes "the rights of ownership and possession of the peoples concerned over the lands which they traditionally occupy" (International Labor Organization 1989). Nearly 20 years later, the United Nations would adopt the UN Declaration on the Rights of Indigenous Peoples, stipulating that "indigenous peoples have the rights to the lands, territories and resources which they have traditionally owned, occupied or otherwise used or acquired" (United Nations 2007).

The indigenous land rights conferred in the Brazilian Constitution differ from individual property rights in the following three respects:

[3] The Legal Amazon includes the following Brazilian states: Acre, Amapa, Amazonas, Para, Rondonia, Roraima, and parts of Maranhao, Mato Grosso, and Tocantins.

(1) Indigenous lands are inalienable and un-mortgageable (Ortiga 2004, Katz 2010) and perceived as a cultural heritage site because of the special relationship of indigenous peoples to their land (Wiessner 2011).
(2) Indigenous land titles are collective rather than individually held (Katz 2010).
(3) Indigenous land titles provide indigenous peoples with the right to use everything above ground for their livelihood, such as fishing, hunting, gathering, and shifting cultivations.

In addition to granting indigenous land rights, Article 67 of the Temporary Provisions of the 1988 Constitution further required the demarcation of all 532 recognized indigenous areas by 1993. However, five years later, only 50% of indigenous lands had been demarcated. The missed deadline was largely due to inadequate resources, though the national ministry responsible for demarcation faced a number of challenges, as it had for its prior two decades of existence. The National Indian Foundation (FUNAI) had been established in 1967 to provide services to indigenous populations and protect indigenous areas, including oversight of the demarcation and regularization process. Since its establishment, FUNAI had suffered from administrative and financial difficulties, as well as illegal activities and volatility on the frontier and significant challenges in access, surveillance, and enforcement of often-remote indigenous lands (World Bank 2007).

The Indigenous Lands Project (PPTAL) responded to the need for greater resources and attention to carry out the regularization process. It was one part of a larger multi-donor effort to conserve the Amazon Rain Forests in Brazil known as the Pilot Programme for the Protection of Brazilian Rain Forests (PPG7). PPTAL was implemented by FUNAI from 1995 to 2008, with funding from KfW and the Rain Forest Trust Fund managed by the World Bank. The project's main objective was to "improve the conservation of natural resources in indigenous lands and increase the well-being of indigenous people." The project consisted of three main components: i) regularization of indigenous lands; ii) surveillance and protection of indigenous lands; and iii) capacity building and assessments (World Bank 2007).

This paper focuses mainly on the project's first and second goals to regularize and protect indigenous lands. The process of regularization, or registering lands in municipal, state, and federal registries, has several stages. An anthropological study is required to initially identify boundaries, and a series of approvals are then required to finalize the boundaries -- first from FUNAI (the delimitation stage), followed by the Minister of Justice (the demarcation stage), the president of Brazil (the approval stage), and finally entrance into municipal, state, and federal registries (the regularization stage). Disputes to the initial boundaries and any subsequent changes are handled during the delimitation stage, such that the boundaries are finalized, physically marked, and officially sanctioned by a government ministry once a community completes the demarcation stage. As documented in an ex post evaluation completed by KfW, the project exceeded its demarcation goals and by its completion, 106 indigenous lands had been demarcated, 81 of which were officially registered. An additional 73 indigenous lands were in the identification and delimitation stages. The project records monitored 181 total indigenous lands that participated in the project in some capacity, but we could only geographically locate 151 lands.[4] The evaluation approach further restricted the pool of communities for analysis, as discussed below. Figure 1 maps the communities in our sample.

The second component of PPTAL focused on surveillance and protection of indigenous lands. In particular, the project supported the community-led creation and implementation of surveillance plans in 65 lands. The surveillance plans varied in specifics, but generally supported maintenance of boundaries, GPS training, surveillance routines, transportation acquisition, and the establishment of control posts. As discussed below, we further consider this stage as a separate treatment along with demarcation.

We make use of variation in the timing of the demarcation and enforcement support stages for causal identification. Project documents indicate that communities were prioritized for demarcation based on a preliminary assessment of the threats to the natural environment and physical and cultural threats to the indigenous populations. Each community initially studied under the PPTAL project was rated shortly after project inception, with early support provided to communities seen to be under greatest threat. However, this prioritization does not appear to correlate closely with satellite data on preexisting changes in forest conditions. As discussed below in section 4, we observe no meaningful difference in pre-trends in our main outcome of interest between 1982 and 1995 across communities' demarcation years.

3. Data

3.1 Outcome Data

We use 30 years of remotely-sensed satellite imagery for each community from the NASA Land Long Term Data Record (LTDR). This data was processed to calculate a commonly employed land cover metric that captures on-the-ground biomass, the Normalized Difference Vegetation Index (NDVI). The NDVI ranges from 0 to 1, where 0 indicates rocky or barren terrain, and 1 indicates densely forested terrain. This data was retrieved from version 4 of the LTDR, which uses processed satellite information from the AVHRR and MODIS satellites (including corrections for detrimental factors such as atmospheric

[4] Little is known to the authors about these 30 missing indigenous lands. We are not aware of any systematic differences, though factors that made the demarcation process more difficult (e.g. land disputes) may indicate a greater need for demarcation, thus increasing the value of the intervention.

artifacts, clouds, and other sources of noise) at the 4 km^2 pixel size. It was received at a global scale for each day during the time series[5], with approximately 26 million pixels in each image.

Fig 2 illustrates this dataset as contrasted to a heavily studied instance of deforestation in the Manicoré Region, Brazil. The top image is drawn from a report by the World Resource Institute on satellite-based forest clearing detection, and is a circa-2004 visible-band image used to contrast different datasets (Wheeler et al. 2014). The bottom image is the raw continuous measurement data from the LTDR NDVI dataset during the same year. While there are important tradeoffs between the LTDR and other satellite datasets, in this case the LTDR data record provided not only sufficient spatial resolution to capture key deforestation trends (as illustrated in these images), but also a continuous time record extending back over 30 years.

A common critique of NDVI is that it is heavily saturated and noisy over areas such as the Amazon, preventing its use for some applications (i.e., forest densification). Here, NDVI provides a strong proxy for deforestation, as (a) the difference in NDVI values between forested and deforested lands is very large, and (b) the daily time-step of the available data over the entire time series allows us to heavily mitigate data quality concerns.

We aggregate the daily NDVI into annual measures, the finest timing for most of our covariates. To do so, we calculate the maximum and mean NDVI values in each year. The maximum value approximates the point of maximum observable plant productivity (i.e., the “greenest” period of the year) providing the best measurement of total vegetation in any given year. However, maximum values are more sensitive to noise in the data. The mean values are more robust, but can fail to represent the true total amount of vegetation due to the differential “averaging out” of vegetative maximums through winter periods. We thus use the maximum NDVI as our main outcome measure and conduct robustness checks employing the mean NDVI instead.

As a robustness check discussed in Section 6, we alternatively use the GIMMS NDVI measure derived from only the MODIS-era (Feb. 2000 onwards) imagery and available at the 250m spatial resolution.

[5] This analysis is conducted using the SciClone High Performance Cluster computing environment at William and Mary, reducing the 283 billion pixels of data to yearly aggregate summaries for each community studied.

3.2 Treatment Data

We obtained data from PPTAL's implementing agency FUNAI on the month and year in which each of 151 communities were initially studied, as well as the dates at which communities completed the demarcation and approval stages (for the subset of communities that did so). In addition, we also obtained data on the dates at which provision of support for community enforcement began in the 45 communities where this support was provided.

The completion of the demarcation stage was a major milestone for each community when the community receives the first layer of official approval from the Ministry of Justice. The community lands' physical boundaries remain unchanged after this point, though additional formal declarations take place after this stage. At the same time, most communities whose lands reached this stage were subsequently regularized, so one can consider this treatment status as reaching *at least* the demarcation stage. We use administrative data from the PPTAL project identifying each community that received support for land rights enforcement as a second indicator of treatment.

3.3 Covariate Data

Covariate data was collected from a variety of sources. A long-term climate data record was retrieved from the University of Delaware[6] providing precipitation and temperature data over the full panel series at a 0.5 degree resolution on a monthly time-step; this was permuted to produce yearly mean, minimum, and maximum values. Population data at 5-year intervals was retrieved from the Gridded Population of the World (GPW) data record, produced by CIESIN at Columbia University[7]. Slope and elevation data was derived from the NASA Shuttle Radar Topography Mission (SRTM)[8]. Distance to rivers was calculated based on the USGS Hydrosheds database[9]. Distance to roads was calculated based on the Global Roads Open Access Database (gRoads) which represents roads circa 2010[10].

4. Community-Level Long Changes

We use both propensity score matching and community-level fixed effects to adjust for the non-random demarcation of indigenous communities. We begin by examining changes over the full treatment period

[6] http://climate.geog.udel.edu/~climate/
[7] http://sedac.ciesin.columbia.edu/data/collection/gpw-v3
[8] http://www2.jpl.nasa.gov/srtm/
[9] http://hydrosheds.cr.usgs.gov/index.php
[10] http://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1

in a community-level analysis, comparing both treated and never-treated communities as well as early and late treated communities. In section 5, we turn to a grid cell-year panel model to improve precision in our estimates.

We first consider differences between treated and untreated communities over the full treatment period. To do so, we match communities on the basis of pre-program levels and trends in deforestation, as well as covariates (land area, population, slope, elevation, distance to the closest river and road, and pre-program levels and trends in temperature and precipitation). All variables are aggregated to the community level. The first stage estimation results are shown in Table 1 Column 1. As our aim is to estimate the propensity based on as many observable characteristics as feasible, it is not surprising that many individual covariates are not significant. Importantly, we find that baseline levels of NDVI are correlated with demarcation treatment. Communities whose lands cover larger areas are also much more likely to receive treatment.

After estimating the propensity scores, we match communities (without replacement). For our demarcated and never-demarcated sample, we are initially limited by the existence of only 45 never demarcated lands (and 106 ever demarcated lands). We drop communities with propensity scores outside of the range of common support (0.23-0.9), leaving us with 28 pairs of treatment and control communities. Table 2 provides descriptive statistics for these communities, both before and after matching. Our results indicate that we construct treatment and control groups that are similar in their likelihood to receive treatment, although they may differ in individual covariates.

Figure 3 shows the changes in NDVI levels from 1982 to 2010 comparing the averages for the matched pairs of communities that were demarcated and those not. Figure 3a shows the raw annual time series, with considerable fluctuations in land cover due to temperature, precipitation, and other factors. Nonetheless, the graph portrays a relatively stable period with no definitive change in NDVI for both treatment and control communities, though treatment communities tend to have higher mean NDVI on average throughout. Figure 3b shows the smoothed series for each community, with sample-wide year fixed effects controlled for in the underlying data. In both cases, we find no evidence of a divergence between treatment and comparison communities. At the same time, the figures also indicate wide dispersion in the experiences of individual communities (shown in the dotted lines).

We estimate the program impacts on the long changes in NDVI by constructing our outcome variable as the difference between the baseline level of deforestation (in 1995) and the level of deforestation during the final year of the interval.[11] Our estimating equation is thus:

[11] Results are qualitatively similar when the outcome variable is the change in the *rate* of deforestation between the pre-program and post-program periods.

$$\Delta NDVI_{ip} = \alpha + \beta T_{ip} + \theta NDVI_{ip1995} + \theta \Delta NDVI_{ip\,1982,1995} + \Gamma X_{ip} + D_p + \epsilon_{ip}$$

Where T_{ip} is an indicator of treatment for community *i* in matched pair *p*, D_p is a set of dummies for matched pairs, X_{ip} is a vector of controls, $NDVI_{ip1995}$ is the pre-treatment level for the community and $\Delta NDVI_{ip1982,1995}$ is the pre-trend between 1982 and the last pre-treatment year.

Table 3 displays regression results estimating the treatment effects in this matched pair sample. Column 1 estimates treatment effects without additional covariates (beyond the matched pair fixed effects), while Column 2 adds all covariates to the model. Without additional covariates, we observe positive treatment effects equivalent to a gain of approximately one tenth of an NDVI point (where one point is the full range of NDVI), although the effect is not statistically significant. However, once covariates are introduced (in Column 2), treatment effects are negative in sign and not significant. That the results with covariates differ from those without is not surprising, given that the small sample size constrains the extent of balance on these covariates during the matching stage. Taken together, these results indicate that treatment effects in the cross-sectional comparisons of demarcated and non-demarcated communities do not appear to be consistent or robust.

For the comparison of early and late demarcated communities, we follow a similar approach, first estimating propensity scores, trimming and matching across our sample. In Column 2 of Table 1, we show the first stage results estimating early demarcation status among only demarcated communities. Again, we find that larger communities were more likely to be treated early, although NDVI baseline levels and pre-trends are not clearly correlated with early demarcation. We drop communities with propensity scores outside of the range of common support (0.11-0.93), leaving 33 pairs of treatment and control communities. Table 2 again provides descriptive statistics for these communities, both before and after matching.

Figure 4 shows that NDVI levels for the matched sample track quite closely over the observed timeframe, both in the raw (Fig 4a) and the smoothed data (Fig 4b). Notably, the early and late demarcated community means follow similar paths both before PPTAL (pre-1995) and once treatment began (post-1995).

In Figure 5, we show that the finding that early demarcation is not correlated with pre-program trends is not an artifact of our definition of "early" demarcation. In fact, demarcation year appears to be largely independent of changes in NDVI prior to 1995.

Table 4 shows the regression results for the early vs. late demarcation comparisons. We compare outcomes over two time periods: 1995-2001 (when early communities were at least partly treated and no late communities were yet treated) and 2001-2010 (when all early communities had been treated and late communities were partially treated). In the early time period with no covariates (Column 1), we find no statistically significant effects of early demarcation on NDVI. Once covariates are included (Column 2), we obtain a negative coefficient of -0.12, although this is not statistically different from zero. If the effects of demarcation materialize rapidly, one would expect this time period to be the relevant window in which to observe them. If these effects instead emerge only after a lag of five or more years, the latter part of our treatment period (2001-2010) is the relevant window in which to observe them. The results for this latter period (shown in Column 3), indicate no statistically significant impacts of early demarcation.

We also examine the impact of combined demarcation and enforcement support using the same model. We run the same first-stage matching equation defining treatment as having ever been demarcated *and* received enforcement support. We then construct 44 pairs of communities and run similar regressions to those presented in Table 3, comparing ever-demarcated and never-demarcated, with results shown in Table 5. When not conditioning on covariates beyond pair fixed effects (Column 1) we obtain a large, positive and significant effect of 0.24 NDVI points. However, conditioning on covariates reduces this effect to 0.08, not statistically distinguishable from zero in our sample. Notably, this may be because smaller, less populated communities located further from a major road appear to be both more likely to have received enforcement support and less likely to have experienced forest loss.

5. Grid Cell-Year Panel Model

We also examine treatment impacts in a panel structure using annual data at the grid cell level. We do so for several reasons. First, because our sample of communities is somewhat limited, statistical precision is naturally a concern. We improve precision by utilizing greater specificity in both covariates and the timing of treatments. Our climatic and forest cover variables are both available at the cell level, allowing us to reduce statistical variability in our outcome measures conditional on climate conditions. To do so, we construct several climate variables, including the mean, maximum and minimum monthly temperatures and rainfall in each year at the cell level. We use two-way clustering of standard errors by community and year, as this is the scale at which treatment is assigned (following Cameron, Gelbach, and Miller 2011). This approach provides additional granularity while accounting for spatial autocorrelation among cells in the same community.

Moreover, because communities varied in their date of treatment (demarcation), our cross-sectional propensity score matching results are complicated by the fact that treatment duration varies considerably within our treatment group (some communities are demarcated for most of the time period studied, while others only receive treatment toward the end of the period). In our panel model, our treatment indicator instead reflects whether the community-specific demarcation had already occurred in that given year, thus capturing effects only in the specific timespan after each community's respective treatment. We then separately introduce a second treatment indicator for whether a community had begun receiving enforcement support by that year.

Third, while propensity score matching using pre-program levels, recent trends, and other covariates can eliminate much of the difference between treated and untreated communities, one may nonetheless argue that unobserved differences across such communities remain. In the panel model, we control for community fixed effects, thus eliminating time-invariant differences in NDVI levels and other characteristics. When we do so, we limit our sample to only ever-demarcated community pixels.

To ensure that regression-based extrapolation does not produce biased treatment effects, we again limit our sample by dropping observations in communities whose propensity for early treatment (pre-2001) is outside the common support (0.13-0.9). In the robustness checks section, we document that our results are unaffected by this trimming.

We construct a cell-year level panel dataset for 1982-2010. Table 6 presents summary statistics for this dataset, weighted by community cell counts.

Using this dataset, we estimate the following equation:

$$NDVI_{ict} = \alpha + \beta_1 Demarcated_{ict} + \beta_2 Enforcement_{ict} + \Gamma Climate_{ict} + D_c + D_t + \epsilon_{ict}$$

Where $Demarcated_{ict}$ indicates whether cell *i* in community *c* has been demarcated by year *t*, $Enforcement_{ict}$ indicates whether enforcement support has begun, $Climate_{ict}$ is a vector of the aforementioned temperature and precipitation controls, D_c is a vector of community-specific fixed effects and D_t are year fixed effects. We estimate treatment effects via ordinary least squares[12], with two-way clustering of standard errors by community and year.

[12] Very few of our observations are at the maximum of our NDVI measures (0.03% of cell-year observations with NDVI > 0.99) or minimum (0.2% of cell-year observations with NDVI = 0), so linear models are appropriate.

Table 7 presents the effects on max NDVI.[13] Column 1 shows estimation of a model with only community-level fixed effects (and no time controls), with treatment associated with 0.042 reduction in NDVI. These effects obtain even when adding time-varying climate and population controls (Column 2). However, these effects appear entirely due to the secular trend in NDVI in our sample: Column 3 adds linear year effect as a control, with the treatment effect reduced by 90% and no longer statistically different from zero. Column 4 incorporates year-specific fixed effects and obtains very similar results. Our estimated coefficients on treatment are quite small in these specifications and precisely estimated (with standard error in Column 4 equal to 0.005).

Examining effects of community enforcement (Column 5 of Table 7), we observe that forest cover improved in general over time. Controlling for these secular improvements over time, we observe no significant effects of enforcement support on forest cover. Notably, this is not due to limited statistical precision; our point estimates are reasonably small, as are standard errors.

We also consider whether results vary by the baseline deforestation pressures on each community's land. Pfaff et al (2015) document that deforestation rates vary considerably across indigenous lands, partly based on distance to the deforestation frontier. Because many of the lands are in states in the Legal Amazon where agricultural conversion and timber extraction have occurred relatively more slowly, averaging effects across all pixels could mask improvements in high pressure areas. We identify high pressure pixels in several ways. First, we use each pixel's pre-1995 NDVI trends as a measure of pre-existing pressure. We also consider higher-pressure pixels as those where these pre-trends are in the bottom 50% of the distribution. Because the pre-1995 NDVI changes may be subject to variability or considerable fluctuations, we also predict these trends on the basis of cross-sectional covariates that are persistent over time. We add nighttime lights and several agricultural production prior to 1995 to the set of covariates in Tables 3 and 4.[14] Again, we use both linear terms in the predicted NDVI trends and a dichotomous measure that categorizes these predicted NDVI trends into the bottom 50%. We then interact each of these various measures with our time-varying treatment status to assess whether treatment effects are more (or less) pronounced in higher pressure areas. The results, shown in Columns 6-9 of Table 7, indicate that there is no statistically distinguishable heterogeneity in the treatment effects using any of these measures of higher pressure.

Enforcement of community rights was affected not only by the project itself but also by the broader regulatory environment in Brazil, which itself experienced important improvements in the latter part of our study period. Beginning in 2004, the Brazilian federal government began integrating several

[13] We obtain qualitatively similar results using the annual mean of NDVI as our outcome measure of interest.
[14] These measures are corn value and yield, rice yield, sugarcane value and yield.

technological features into its monitoring and coordination efforts, including a satellite-based system formally known as the Real-Time System for Detection of Deforestation (DETER). The satellite imagery was used to identify deforestation hot spots and alert federal, state, and local law enforcement. Assuncao et al (2014) show that exogenous variation in this monitoring capability due to cloud cover in specific 15-day intervals significantly affected deforestation, and Hargrave and Kis-Katos (2013) provide corroborating panel data evidence.[15] We therefore assess whether the effects of the demarcation treatment became significant in the presence of these broader sources of enforcement support, with results shown in Table 8. We interact a post-2004 indicator with the demarcation treatment status in Columns 1 and 2 and the PPTAL-supported enforcement treatment status in Columns 3 and 4. We find no statistically distinguishable changes in NDVI due to treatment status across these enforcement windows when looking at demarcation treatment status. The enforcement treatment effect and interaction are significant when we include linear year effects (Column 3), but that significance disappears when we include year-specific fixed effects instead (Column 4). These results indicate that it is not likely that treatment effects of demarcation materialized only once adequate enforcement support was in place.[16]

6. Robustness Checks

We conduct a variety of robustness checks to verify that our results are not due to unobserved time-varying community characteristics, features of our propensity score estimation, sample trimming, or level of aggregation. We begin by assessing whether our null results on treatment effects are due to unobserved community characteristics that vary over time and are correlated with both treatment status and NDVI. To do so, we add community-level trends as controls to our baseline cell-year panel models (in addition to the community-level fixed effects). Table 9 shows the results of these estimations. In all columns, we observe coefficients on demarcation status that are quite similar in magnitude and statistical significance to those of Columns 3 and 4 in Table 7, where community trends are not incorporated. In Columns 2 and 4, we consider the effects of demarcation + enforcement status. The coefficients of these effects are larger in magnitude that those in prior estimates, but they remain <0.01 NDVI points and statistically insignificant. Thus, it is unlikely that our estimates are biased by time-varying omitted variables correlated with treatment status and outcomes.

[15] Moreover, beginning in 2008, Brazil's national environmental regulatory agency (IBAMA) launched a second program (known as PPCDAm-II) of intensified field inspections and several complementary initiatives. Arima et al (2014) and Borner et al (2014) both study the impacts of these enforcement efforts and document large reductions in deforestation in affected municipalities. However, these effects occur largely outside the window during which demarcation status varied (1997-2008) and so are not clearly estimable in our data.

[16] The estimates also suggest that our null results are not likely due to confounding demarcation treatment with enforcement improvements among our comparison observations. Even in the pre-2004 window (when comparison observations were not yet benefitting from improved enforcement) we find no statistically significant effects of demarcation status.

We next limit our propensity score estimation to only the four primary variables that significantly correlate with early demarcation (shown in Table 1 Column 2): slope, elevation, distance to the nearest road and pre-trends in minimum annual temperatures. Using this subset of covariates, we estimate and predict propensity scores for our full sample of 151 communities, trimming the sample and matching communities into 37 pairs on the basis of these scores. Table 10 presents the cell-year panel model results for cells in this subsample. Our findings are quite similar to those in Table 7, with no statistically significant effects of either demarcation or demarcation and enforcement treatments once secular time trends are accounted for.

Similarly, in Table 11, we present cell-year level panel results with the full (untrimmed and unmatched) sample of cells. As in Table 7, we find no statistically significant effects of either treatment status once linear time trend or year fixed effects are included in the specification.

Lastly, we assess whether our results vary when considering alternative levels of aggregation. The modifiable area unit problem could bias our estimates if the LTDR-based cells do not appropriately reflect treatment units. Moreover, the spatial configuration of community lands could obscure important treatment effects. For example, treatment might differentially protect tree cover near the communities' boundaries, which are at highest risk of deforestation, while interior forests remain unaffected. Such boundary effects might only be detectable using smaller cells than those offered by LTDR (which are approximately 5km x 5km). We therefore test whether both larger and smaller units of aggregation generate consistent estimates.

In Table 12, we conduct the equivalent panel analysis using community-level annual data (rather than cell-level). While our main results cluster standard errors at the community level, they are not weighted by community size, so could reflect differential treatment effects among larger or smaller communities. Table 12 indicates this is not likely to be the case, as estimates are comparable in both coefficients and standard errors to those obtained at the cell-year level in Table 7.

Finally, we consider whether higher resolution imagery might detect treatment effects, particularly along the boundaries of the communities. GIMMS-based NDVI measures are available at 250m spatial resolution beginning in the year 2000. We can therefore use this dramatically higher resolution measure to test demarcation treatment effects among our late-demarcated communities. We sample 10,000 MODIS-based cells from within our community boundaries and construct an annual level panel dataset, with our time-varying climatic control variables spatially joined to these finer cells. We eliminate 112 already-deforested cells that had extremely low NDVI values in 2000, leaving us with 9,882 forested cells. We then implement a similar estimation, using community-level fixed effects and weighting by the inverse of community size to avoid over-representing effects among larger communities. We employ two-way clustering of standard errors at the community and year levels to account for spatial and temporal unobservables.

The results, shown in Table 13, indicate that greenness does appear to improve following demarcation, but only very minimally. Once we account for year-specific fixed effects in column 4, treatment effects are approximately 0.86 NDVI points, roughly 0.063 standard deviations on the GIMMS scale (note the support of GIMMS-based NDVI is 0-250; its sample SD = 13.6, with summary statistics reported in Table 14). These effects are not statistically significant but reasonably precisely estimated (the minimum detectable treatment effect in this estimation would be 0.11 SD units). We then interact the treatment status with the cell's distance from the boundary of the community in which it falls, with results in column 5 of Table 13. Treatment effects among cells closest to the boundary (where the distance is effectively 0) are 1.25 NDVI points (0.09 SD), or roughly 45% higher than the average treatment effects in the sample. Such effects could still be understated if the interaction is highly non-linear in distance from the boundary. We therefore categorize cells as being "close" to the boundary (within 5km) or "far" (beyond 5km) from the boundary. Treatment effects among cells close to the border remain quite similar, roughly 1.23 NDVI points. Thus, using high resolution imagery to detect changes among the portions of community lands at greatest risk, we obtain some treatment effects along the borders, although such effects are quite small in magnitude.

7. Conclusions

Using a varied set of empirical approaches, we find no evidence that formalizing indigenous land rights or supporting surveillance and enforcement by the communities in our sample had an effect on forest cover during the study period. Once we condition forest cover measures on local climate conditions and geographic factors, we observe no statistically distinguishable effects from the treatments implemented through the Brazil Indigenous Lands Project (PPTAL). Using both within-treatment group comparisons based on the timing of treatment and cross-group comparisons with untreated but similar lands, we obtain similar null results. These null results are not due to imprecision; using pixel-year level outcomes that are stripped of climatic fluctuations, we could detect effects that are 0.8% of the sample mean forest cover.

At the same time, these results should be considered in the broader context of deforestation pressures on indigenous lands in the Brazilian Amazon. It is worth reiterating that our measure of deforestation (Normalized Difference Vegetation Index - NDVI) seems to be relatively stable on average during the 1982-2010 time period for these communities (to the extent we observe any average changes over the time period, these are increasing, indicating *reforestation*). This is consistent with other evidence that the deforestation rate on indigenous lands has, on average, remained quite low. This does not indicate that deforestation did not occur in the Amazon region as a whole during this time, or within some of the selected communities (as indeed, Pfaff et al 2015 show), but rather that the overall rate among the project communities was relatively low. In other words, many indigenous communities did not face as great a deforestation threat as often feared—an encouraging result. Moreover, it is possible that deforestation pressures among indigenous communities in the Amazon will increase in the coming decades, and that PPTAL's impacts will be felt at that point.

Lastly, because PPTAL was partly driven by constitutional, human rights, and well-being concerns for the rights of the indigenous communities, the lack of forest cover impacts does not imply the program was unsuccessful on these other dimensions. At the same time, we now have more evidence about the mix of policy interventions that help combat deforestation in Brazil specifically and more broadly than what was available in 1995, when the PPTAL project was launched. Among these policies are investments in monitoring technology and enforcement efforts (Hargrave and Kis-Katos 2013, Arima et al, Assuncao et al 2014, Borner et al 2014, Borner et al 2015), payments for ecosystem services (Borner et al 2010) and interventions in the beef and soy supply chains (Nepstad et al 2014). Moreover, there is also better data available on the deforestation rates in individual community lands. While the PPTAL project did attempt to prioritize lands for demarcation on the basis of their risks, available data appear to have been coarse and potentially inconsistent. Thus, future programs aimed at avoided deforestation and other conservation outcomes on indigenous lands may be better positioned to target scarce resources to high-pressure communities.

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Tables and Figures

Figure 1. PPTAL communities

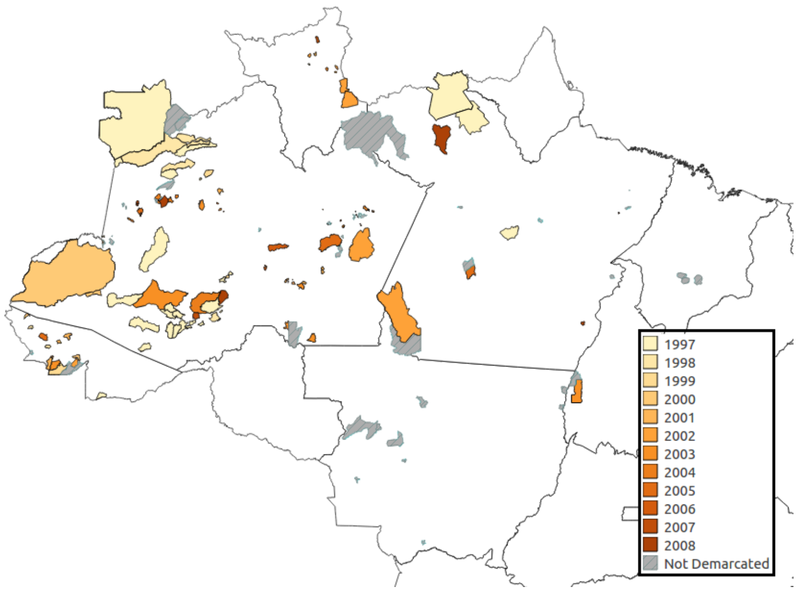
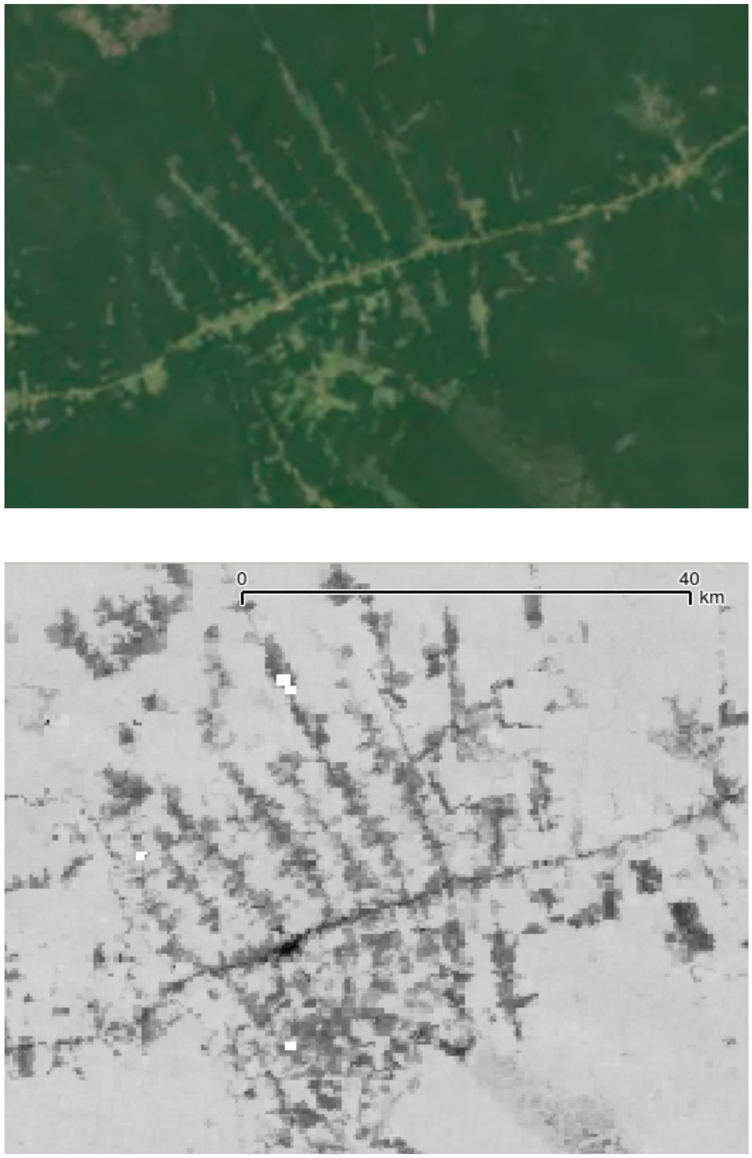


Figure 2: Comparison imagery from Manicoré Region, Brazil



Top image is drawn from a report by the World Resource Institute on satellite-based forest clearing detection, and is a circa-2004 visible-band image used to contrast different datasets (Wheeler et al. 2014). The bottom image is the raw continuous measurement data from the LTDR NDVI dataset during the same year.

Figure 3a. Max NDVI time series

Demarcated vs. Not Demarcated

Figure 3b. Demarcated vs. not demarcated, normalized by year

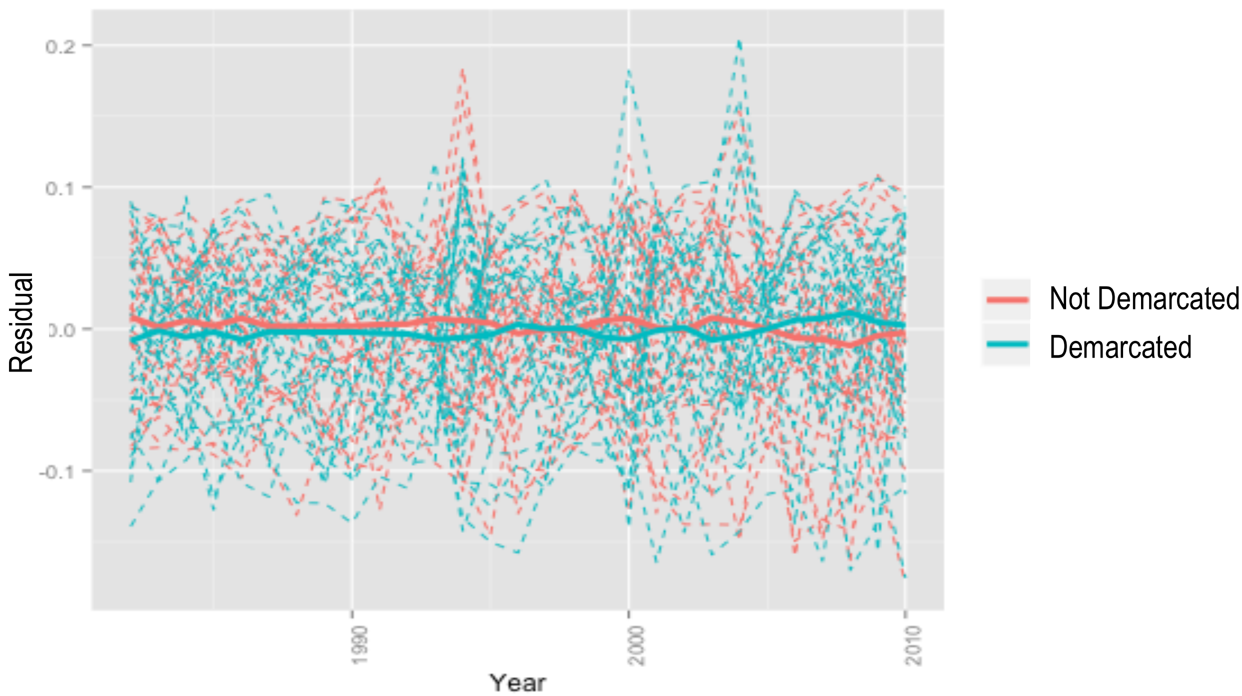


Figure 4a. Max NDVI time series

Early vs. Late Demarcation

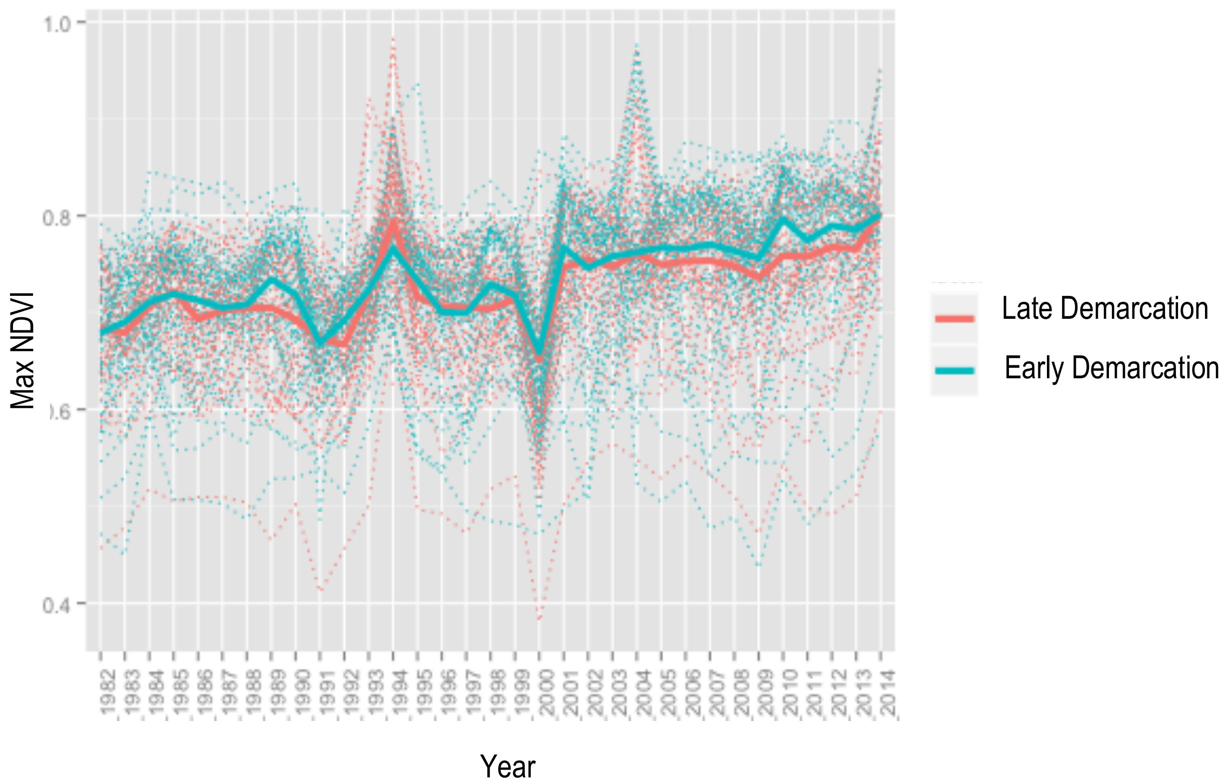


Figure 4b. Early demarcation vs. late demarcation, normalized by year

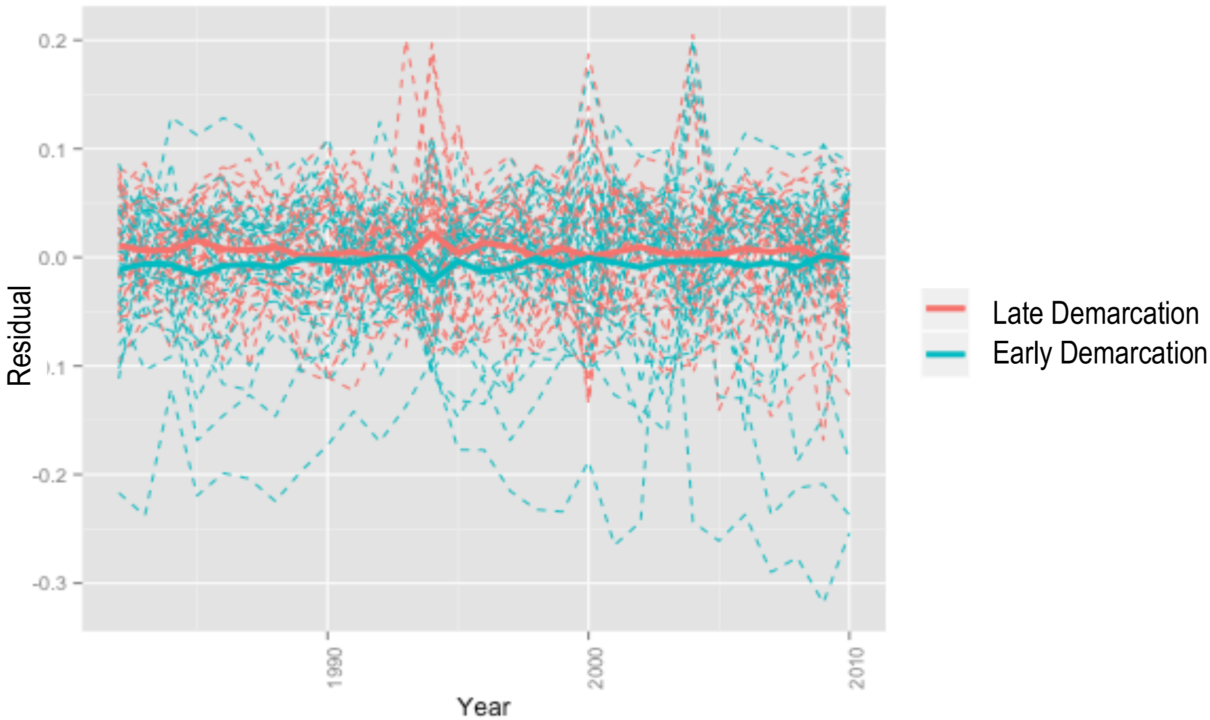


Figure 5. Demarcation year and NDVI pre-trend, at community level

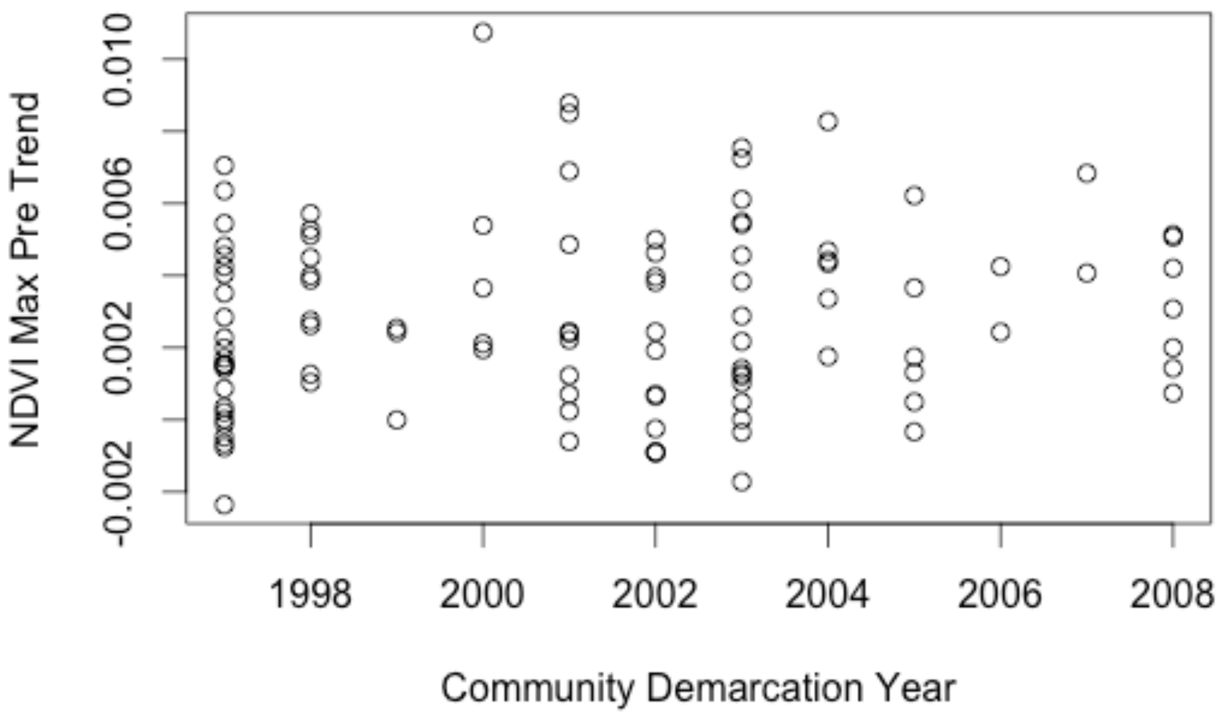


Table 1. Propensity score estimation

PSM First Stage Results

	Dependent variable:	
	Ever Demarcated	Early vs. Late
	(1)	(2)
Pre Trend Min Precipitation	-0.981^{***}	0.485
	(0.380)	(0.442)
Pre Trend Mean Precipitation	0.791	-0.023
	(0.512)	(0.548)
Pre Trend Max Precipitation	-0.005	-0.143
	(0.215)	(0.237)
Pre Trend Mean Temperature	-11.296	-99.363
	(51.351)	(73.892)
Pre Trend Min Temperature	62.561^{**}	71.668^{*}
	(25.838)	(42.785)
Pre Trend Max Temperature	-7.254	1.235
	(18.303)	(22.022)
Pre Trend NDVI Mean	-171.478	-297.666
	(279.370)	(362.650)
Pre Trend NDVI Max	97.690	107.018
	(93.568)	(110.253)
Max NDVI Baseline	9.427^{***}	4.133
	(3.568)	(4.561)
Population Baseline	-0.231^{*}	-0.259
	(0.129)	(0.182)
Mean Temperature Baseline	0.290	-0.641
	(0.537)	(0.611)
Mean Precipitation Baseline	0.010	0.031
	(0.019)	(0.021)
Area (hectares)	0.00000	0.00000
	(0.00000)	(0.00000)
Slope	-0.674	-3.096^{***}
	(0.648)	(0.997)
Elevation	0.002	0.021^{***}
	(0.005)	(0.007)
Distance to River	0.0002	-0.0001
	(0.001)	(0.001)
Distance to Road	-0.00000	-0.00001^{***}
	(0.00000)	(0.00000)
Constant	-14.262	8.991
	(14.202)	(16.662)
Observations	151	106
Log Likelihood	-68.637	-54.735
Akaike Inf. Crit.	173.274	145.469
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2. Summary statistics for outcomes and covariates

	All Communities			Demarcated Communities		Matched Pair Communities			
	All Communities	Never Demarcated	Ever Demarcated	Late Demarcation	Early Demarcation	Never Demarcated	Ever Demarcated	Late Demarcation	Early Demarcation
N	151	45	106	53	53	28	28	33	33
Area (hectares)	320600.1	207015.2	368738.5	186614.9	550862.1	126790.9	259563.8	246964.2	180929.5
Population Density, 1990	1.5	1.85	1.31	1.62	0.99	1.95	1.93	1.33	1.21
NDVI Mean, 1995	0.28	0.29	0.28	0.28	0.28	0.28	0.28	0.28	0.28
NDVI Max, 1995	0.72	0.7	0.72	0.72	0.73	0.72	0.71	0.74	0.73
Mean Temperature, 1995	24.5	24.27	24.58	24.7	24.46	24.71	24.68	24.73	24.64
Mean Precipitation, 1995	162.4	158.4	164.1	162.0	166.2	168.8	163.7	165.2	165.6
Slope (degrees)	0.71	0.81	0.66	0.71	0.61	0.73	0.72	0.61	0.58
Elevation (m)	138.5	164.9	127.3	106.8	147.8	102.75	111.15	106.19	114.7
River Distance (m)	1760	1736.2	1770.5	1799.6	1741.4	1770.79	1669.48	1862.85	1754.2
Road Distance (m)	98970.0	81722.5	106285.4	115645.7	96925.1	105356.0	124691.4	100293.9	112417.2

Table 3. Demarcated vs. non-demarcated regression results

Regression Results		
	Dependent variable:	
	Max NDVI 1995-2010	
	(1)	(2)
Treatment	0.135	-0.055
	(0.120)	(0.086)
Pre-Trend NDVI		-0.099
		(0.137)
Baseline NDVI		-0.503**
		(0.207)
Area (hectares)		0.075
		(0.163)
Baseline Population Density		-0.074
		(0.180)
Baseline Temperature		0.324
		(0.338)
Temperature Trends		0.272
		(0.209)
Baseline Precipitation		-0.768***
		(0.210)
Precipitation Trends		0.408**
		(0.186)
Slope		0.214
		(0.300)
Elevation		0.459
		(0.446)
Distance to River		-0.233
		(0.134)
Distance to Road		0.565***
		(0.177)
Observations	56	56
R^2	0.610	0.935
Adjusted R^2	0.205	0.761
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: Table 3 displays regression results estimating the treatment effects in 28 matched pair communities, where treatment is demarcation. We compare outcomes over the entire period, 1995-2001. Column 1 estimates treatment effects without additional covariates (beyond the matched pair fixed effects), while Column 2 adds all covariates to the model. The PSM first stage results are displayed in Table 1 Column 1.

Table 4. Early vs. late demarcated regression results

Regression Results

	Dependent variable:		
	Max NDVI 1995-2001		Max NDVI 2001-2010
	(1)	(2)	(3)
Treatment (Early Demarcation)	-0.018	-0.115	-0.018
	(0.140)	(0.101)	(0.166)
Pre-Trend NDVI		-0.242	0.357
		(0.157)	(0.224)
Baseline NDVI		-0.627^{***}	0.269
		(0.213)	(0.305)
Area (hectares)		-0.248	0.084
		(0.212)	(0.297)
Baseline Population Density		-0.129	-0.074
		(0.228)	(0.265)
Baseline Temperature		-0.332	0.278
		(0.341)	(0.427)
Temperature Trends		-0.357	0.666^{**}
		(0.229)	(0.255)
Baseline Precipitation		0.674	0.025
		(0.394)	(0.493)
Precipitation Trends		0.087	0.230
		(0.293)	(0.506)
Slope		0.099	-1.464^{***}
		(0.409)	(0.489)
Elevation		0.463	0.954
		(0.573)	(0.721)
Distance to River		-0.063	0.085
		(0.182)	(0.233)
Distance to Road		-0.712^{*}	-0.430
		(0.380)	(0.448)
Observations	66	66	66
R^2	0.374	0.842	0.695
Adjusted R^2	-0.271	0.488	0.008
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: Table 4 displays regression results estimating the treatment effects in 33 matched pair communities, where treatment is demarcation in 1995-2001. We compare outcomes over two time periods: 1995-2001 (Column 1 and 2, when early communities were at least partly treated and no late communities were yet treated) and 2001-2010 (Column 3, when all early communities had been treated and late communities were partially treated). The PSM first stage results are shown in Table 1 Column 2.

Table 5. Enforcement and surveillance support regression results

Regression Results

	Dependent variable:	
	Max NDVI 1995-2010	
	(1)	(2)
Treatment (Demarcation + Enforcement Support)	0.269^{**}	0.083
	(0.117)	(0.102)
Pre-Trend NDVI		-0.283^{**}
		(0.114)
Baseline NDVI		-0.778^{***}
		(0.141)
Area (hectares)		-0.459^{***}
		(0.141)
Baseline Population Density		-0.399^{**}
		(0.179)
Baseline Temperature		-0.004
		(0.202)
Temperature Trends		0.057
		(0.195)
Baseline Precipitation		-0.357
		(0.221)
Precipitation Trends		0.254
		(0.165)
Slope		0.080
		(0.255)
Elevation		0.785
		(0.480)
Distance to River		0.057
		(0.126)
Distance to Road		-0.233
		(0.154)
Observations	88	88
R^2	0.413	0.830
Adjusted R^2	-0.188	0.522
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: Table 5 displays regression results estimating the treatment effects in 44 matched pair communities, where treatment is having received both demarcation and support for enforcement. We compare outcomes over the entire period, 1995-2010. Column 1 estimates treatment effects without additional covariates (beyond the matched pair fixed effects), while Column 2 adds all covariates to the model.

Table 6. Summary statistics for LTDR grid cell level panel dataset, weighted by community size

Statistic	Mean	St. Dev.	Min	Max
NDVI	0.785	0.066	0.000	0.996
Slope (degree)	0.493	0.336	0.064	12.451
Distance to Road (m)	52,489.8	85,412.3	660.120	489,285.400
Distance to River (m)	1,553.555	823.956	238.354	5,301.389
Elevation (m)	81.2	67.051	8.087	653.734
Area (hectares)	49,626.77	232,966.3	142.298	8,544,482.000
Population Density	1.691	2.014	0.057	11.177
Mean Temperature	24.386	0.658	21.525	29.277
Mean Precipitation	170.731	23.945	93.490	359.596
Max Temperature	25.387	0.809	22.307	31.165
Max Precipitation	301.657	43.713	161.469	689.705
Min Precipitation	58.63	25.367	5.921	230.447
Min Temperature	23.447	0.773	16.728	27.115
NDVI Pre Trend	0.003	0.002	-0.004	0.016
Predicted NDVI Pre Trend	0.003	0.001	0.001	0.005

Table 7. LTDR grid cell-year panel model results

Regression Results

	Dependent variable:								
	Max NDVI								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (Demarcation)	0.042^{***}	0.038^{***}	0.004	0.005	0.005	0.005	0.003	0.004	0.008
	(0.007)	(0.008)	(0.012)	(0.005)	(0.004)	(0.005)	(0.008)	(0.006)	(0.006)
Treatment (Demarcation + Enforcement Support)					0.002				
					(0.003)				
Population		-0.075	-0.059	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
		(0.059)	(0.054)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Mean Temp		-0.003	0.006	-0.010	-0.010	-0.010	-0.009	-0.010	-0.010
		(0.013)	(0.014)	(0.008)	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)
Mean Precip		0.0002	0.0001	-0.00002	-0.00002	-0.00002	-0.00001	-0.00002	-0.00002
		(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Max Temp		0.001	-0.005	0.003	0.004	0.003	0.004	0.003	0.003
		(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Max Precip		-0.00004	-0.00003	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
		(0.0001)	(0.0001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Min Temp		0.002	-0.002	0.002	0.002	0.002	0.002	0.002	0.002
		(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Min Precip		-0.0003^{**}	-0.0003^{**}	-0.0001^{**}	-0.0001^{**}	-0.0001^{***}	-0.0001^{**}	-0.0001^{**}	-0.0001^{**}
		(0.0001)	(0.0001)	(0.00004)	(0.00004)	(0.00004)	(0.0001)	(0.00005)	(0.00005)
Predicted NDVI Pre-Trend (Cat)						-0.001			
						(0.004)			
Predicted NDVI Pre-Trend(Cat)*Treatment						0.001			
						(0.003)			
Predicted NDVI Pre-Trend							3.373		
							(14.855)		
Predicted NDVI Pre-Trend * Treatment							0.657		
							(2.273)		
NDVI Pre-Trend (Cat)								-0.003	
								(0.006)	
NDVI Pre-Trend(Cat)*Treatment								0.002	
								(0.004)	
NDVI Pre-Trend									0.779
									(2.406)
NDVI Pre-Trend*Treatment									-0.824
									(1.414)
Year			0.002^{***}						
			(0.0005)						
Observations	246,007	246,007	246,007	246,007	246,007	246,007	246,007	246,007	246,007
Community Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Note:							*p<0.1; **p<0.05; ***p<0.01		

Notes: We construct a cell-year level panel dataset for 1982-2010 for all communities that were demarcated. Table 7 presents the effects of demarcation on max NDVI for all demarcated communities, where treatment begins in the year of demarcation. Column 1 shows estimation of a model with only community-level fixed effects (and no time controls), while Column 2 adds time-varying climate and population controls. Column 3 adds linear year effects as a control and Column 4 incorporates year-specific fixed effects. Column 5 adds a second treatment variable for cells in communities that received enforcement support in addition to demarcation. We also consider whether results vary by the baseline deforestation pressures on each community's land. Columns 6 and 7 incorporate predicted NDVI trends (based on cross-sectional covariates that are persistent over time) interacted with demarcation treatment, both through a categorical measurement (where high-pressure are those pixels where pre-trends are in the bottom 50% of the distribution) in Column 6 and a linear measurement in Column 7. Columns 8 and 9 include actual rather than predicted pre-trends, also using both categorical (Column 8) and linear (Column 9) measurements interacted with treatment. Columns 6-9 all include community and year-specific fixed effects. We use two-way clustering of standard errors by community and year for all models.

Table 8. LTDR grid cell-year panel model results with post-2004 interaction

Regression Results

	Dependent variable:			
	Max NDVI			
	(1)	(2)	(3)	(4)
Treatment (Demarcation)	0.006	0.006	-0.0002	0.004
	(0.012)	(0.005)	(0.010)	(0.004)
Treatment (Demarcation + Enforcement Support)			0.013^{**}	0.004
			(0.006)	(0.004)
Treatment (Demarcation)*Post2004	-0.010	-0.003		
	(0.010)	(0.092)		
Treatment (Dem + Enf)*Post2004			-0.013^{**}	-0.004
			(0.006)	(0.092)
Population	-0.063	-0.002	-0.061	-0.002
	(0.059)	(0.012)	(0.059)	(0.012)
Mean Temp	0.006	-0.010	0.006	-0.010
	(0.014)	(0.008)	(0.015)	(0.008)
Mean Precip	0.0001	-0.00002	0.0001	-0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Max Temp	-0.005	0.003	-0.005	0.004
	(0.007)	(0.004)	(0.008)	(0.004)
Max Precip	-0.00003	-0.00001	-0.00003	-0.00001
	(0.00005)	(0.00002)	(0.00005)	(0.00002)
Min Temp	-0.002	0.002	-0.002	0.002
	(0.006)	(0.003)	(0.006)	(0.003)
Min Precip	-0.0002^{**}	-0.0001^{**}	-0.0002^{**}	-0.0001^{**}
	(0.0001)	(0.00004)	(0.0001)	(0.00004)
Year	0.002^{***}		0.002^{***}	
	(0.001)		(0.001)	
Observations	246,007	246,007	246,007	246,007
Community Fixed Effects?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

Notes: We construct a cell-year level panel dataset for 1982-2010 for all communities that were demarcated. Table 8 presents the effects of demarcation on max NDVI for all demarcated communities, where treatment begins in each cell's year of demarcation or the year in which it received post-demarcation enforcement support. To reflect a deforestation monitoring environment strengthened by enhanced satellite technology, we interact a post-2004 indicator with the demarcation treatment (Column 1 and 2) and with the demarcation + enforcement treatment (Column 3 and 4). Community fixed effects are included in all models, linear year effects in Columns 1 and 3, and year fixed effects in Columns 2 and 4. All standard errors are clustered at the community level. We use two-way clustering of standard errors by community and year for all models.

Table 9: LTDR grid cell-year panel, with community-level trends (community FEs + year interactions)

Regression Results

	Dependent variable:			
	Max NDVI			
	(1)	(2)	(3)	(4)
Treatment (Demarcation)	0.004	0.0005	0.005	0.004
	(0.013)	(0.011)	(0.005)	(0.004)
Treatment (Demarcation + Enforcement Support)		0.009		0.005
		(0.010)		(0.004)
Population	-0.060	-0.056	-0.001	-0.001
	(0.060)	(0.062)	(0.007)	(0.007)
Mean Temp	0.005	0.005	-0.012	-0.012
	(0.018)	(0.016)	(0.009)	(0.009)
Mean Precip	0.0001	0.0001	-0.00001	-0.00001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Max Temp	-0.004	-0.004	0.005	0.005
	(0.010)	(0.008)	(0.004)	(0.004)
Max Precip	-0.00003	-0.00003	-0.00001	-0.00001
	(0.0001)	(0.0001)	(0.00002)	(0.00002)
Min Temp	-0.001	-0.001	0.002	0.002
	(0.008)	(0.007)	(0.004)	(0.003)
Min Precip	-0.0003^{**}	-0.0003^{**}	-0.0001^{**}	-0.0001^{**}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year	0.003^{***}	0.003^{***}	0.004^{***}	0.004^{***}
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Observations	246,007	246,007	246,007	246,007
Community Fixed Effects?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	Yes	Yes
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Using the cell-year level panel dataset for 1982-2010 for all communities that were demarcated, we add community-level trends as controls in addition to community-level fixed effects. Column 1 estimates demarcation treatment effects with linear year effects, while Column 3 adds year fixed effects. Column 2 estimates demarcation + enforcement support treatment effects with linear year effects, while Column 4 adds year fixed effects. All standard errors are clustered at the community level. We use two-way clustering of standard errors by community and year for all models.

Table 10: LTDR Grid Cell-Year Panel, with trimming using only significant propensity score predictors at community level (slope, elevation, road distance, pre-trend in minimum annual temp)

Regression Results

	Dependent variable:				
	Max NDVI				
	(1)	(2)	(3)	(4)	(5)
Treatment (Demarcation)	0.024^{**}	0.024^{**}	0.001	0.006	0.007
	(0.011)	(0.011)	(0.013)	(0.005)	(0.005)
Treatment (Demarcation + Enforcement Support)	0.024^{***}	0.019^{*}	0.007		-0.002
	(0.009)	(0.010)	(0.012)		(0.003)
Population		-0.090	-0.082	-0.004	-0.004
		(0.070)	(0.064)	(0.016)	(0.016)
Mean Temp		0.013	0.021	0.003	0.003
		(0.016)	(0.017)	(0.011)	(0.011)
Mean Precip		0.0003	0.0003	0.0001	0.0001
		(0.0002)	(0.0002)	(0.0001)	(0.0001)
Max Temp		-0.003	-0.010	-0.003	-0.003
		(0.008)	(0.009)	(0.007)	(0.007)
Max Precip		-0.0001	-0.0001	-0.00004	-0.00004
		(0.00005)	(0.00005)	(0.00004)	(0.00004)
Min Temp		-0.005	-0.006	-0.0005	-0.0005
		(0.009)	(0.008)	(0.003)	(0.003)
Min Precip		-0.0003^{**}	-0.0003^{**}	-0.0001^{**}	-0.0001^{**}
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year			0.002^{***}		
			(0.001)		
Observations	404,405	404,405	404,405	404,405	404,405
Community Fixed Effects?	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01		

Notes: Table 10 presents regression results when we limit our propensity score estimation to only the four primary variables that significantly correlate with early demarcation: slope, elevation, distance to the nearest road and pre-trends in minimum annual temperatures see Table 1 Column 2). We estimate propensity scores and trim and match the sample at the community level, and Table 10 presents the cell-year panel model results for cells in this subsample of communities. Column 1 provides an estimation with only community-level fixed effects (and no time controls), while Column 2 adds time-varying climate and population controls. Column 3 adds linear year effects and Columns 4 and 5 include year fixed effects. All standard errors are clustered at the community level. We use two-way clustering of standard errors by community and year for all models.

Table 11: LTDR grid cell-year panel, with no sample trimming or matching

Regression Results

	Dependent variable:				
	Max NDVI				
	(1)	(2)	(3)	(4)	(5)
Treatment (Demarcation)	0.025^{**}	0.025^{**}	0.0005	0.006	0.006
	(0.011)	(0.011)	(0.012)	(0.005)	(0.005)
Treatment (Demarcation + Enforcement Support)	0.023^{***}	0.019^{*}	0.007		-0.002
	(0.009)	(0.010)	(0.011)		(0.003)
Population		-0.089	-0.080	-0.003	-0.003
		(0.068)	(0.063)	(0.013)	(0.013)
Mean Temp		0.013	0.021	0.003	0.003
		(0.016)	(0.016)	(0.011)	(0.011)
Mean Precip		0.0003	0.0003	0.0001	0.0001
		(0.0002)	(0.0002)	(0.0001)	(0.0001)
Max Temp		-0.004	-0.011	-0.003	-0.003
		(0.008)	(0.008)	(0.007)	(0.007)
Max Precip		-0.0001	-0.0001	-0.00004	-0.00004
		(0.00005)	(0.00005)	(0.00003)	(0.00004)
Min Temp		-0.004	-0.006	-0.001	-0.001
		(0.009)	(0.008)	(0.003)	(0.003)
Min Precip		-0.0003^{**}	-0.0003^{**}	-0.0001^{**}	-0.0001^{**}
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year			0.002^{***}		
			(0.001)		
Observations	422,066	422,066	422,066	422,066	422,066
Community Fixed Effects?	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01		

Notes: Table 11 presents regression results when we limit our propensity score estimation to only the four primary variables that significantly correlate with early demarcation: slope, elevation, distance to the nearest road and pre-trends in minimum annual temperatures see Table 1 Column 2). All models identify the results when using the full (untrimmed and unmatched) sample of cells. Column 1 provides an estimation with only community-level fixed effects (and no time controls), while Column 2 adds time-varying climate and population controls. Column 3 adds linear year effects and Columns 4 and 5 include year fixed effects. All standard errors are clustered at the community level. We use two-way clustering of standard errors by community and year for all models.

Table 12: Community-year panel model

Regression Results

	Dependent variable:					
	Max NDVI					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (Demarcation)	0.035***	0.018**	0.006	0.0001	-0.001	-0.001
	(0.008)	(0.007)	(0.008)	(0.005)	(0.008)	(0.008)
Treatment (Enforcement)	0.019**	0.014*	0.011	-0.0004		0.001
	(0.009)	(0.008)	(0.009)	(0.006)		(0.006)
Population		0.041**	0.013	0.005	0.005	0.005
		(0.020)	(0.014)	(0.006)	(0.006)	(0.006)
Mean Temp		0.002	-0.012	0.023	0.023	0.023
		(0.022)	(0.020)	(0.016)	(0.015)	(0.015)
Mean Precip		0.0001	0.00000	-0.0002	-0.0002	-0.0002
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Max Temp		0.011	0.012	-0.001	-0.001	-0.001
		(0.013)	(0.013)	(0.006)	(0.006)	(0.006)
Max Precip		0.00004	0.00003	0.0001**	0.0001**	0.0001**
		(0.0001)	(0.0001)	(0.00004)	(0.00004)	(0.00004)
Min Temp		-0.001	0.002	-0.014	-0.014	-0.014
		(0.012)	(0.011)	(0.009)	(0.009)	(0.009)
Min Precip		0.0001	0.0001	0.0003**	0.0003**	0.0003**
		(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Year			0.002**			
			(0.001)			
Treatment(Dem)*Post 2004					-0.004	-0.004
					(0.011)	(0.012)
Post 2004*Road Dist					0.00000	0.00000
					(0.00000)	(0.00000)
Treatment(Dem)*Road Dist					0.00000	0.00000
					(0.00000)	(0.00000)
Treatment(Dem)*Post 2004*Road Dist					-0.00000	-0.00000
					(0.00000)	(0.00000)
Observations	1914	1914	1914	1914	1914	1914
Community Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	No	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01		

Notes: Table 12 presents the results when the panel analysis uses community-level annual data (rather than cell-level). We consider both demarcation and demarcation + enforcement treatments. Column 1 provides an estimation with only community-level fixed effects (and no time controls), while Column 2 adds time-varying climate and population controls. Column 3 adds linear year effects and Columns 4-6 include year fixed effects. Columns 5 and 6 add interactions with a post-2004 dummy to reflect a strengthened monitoring environment due to enhanced satellite technology, with easier enforcement of observed deforestation expected in communities of lesser distance. Column 5 examines demarcation treatment only, while Column 6 examines both demarcation and enforcement support.

Table 13: GIMMS cell-year panel, weighted by community size

Regression Results

	Dependent variable:					
	Max NDVI					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (Demarcation)	-0.374	-0.425	1.241**	0.861	1.252	1.229
	(0.591)	(0.578)	(0.627)	(0.772)	(0.969)	(0.798)
Population		1.199	1.330**	1.358	0.665	1.289
		(0.824)	(0.630)	(0.991)	(0.818)	(0.959)
Mean Temp		-0.010	0.002	0.009	0.013*	0.010
		(0.016)	(0.014)	(0.009)	(0.007)	(0.009)
Mean Precip		-0.794	-0.747	-0.868	-2.185**	-1.204**
		(0.587)	(0.586)	(0.559)	(1.077)	(0.579)
Max Temp		-1.259*	-1.180**	-1.384**	-0.922	-1.343**
		(0.691)	(0.559)	(0.692)	(0.577)	(0.671)
Max Precip		-0.003	-0.005	-0.006*	-0.007*	-0.006*
		(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Min Temp		0.047	-0.147	-0.179	-0.033	-0.161
		(0.391)	(0.416)	(0.416)	(0.354)	(0.402)
Min Precip		-0.010	-0.015	-0.014	-0.010	-0.014
		(0.015)	(0.013)	(0.012)	(0.012)	(0.012)
Year			-0.235***			
			(0.076)			
Treatment(Dem)*Boundary Distance					-0.030	
					(0.029)	
Treatment(Dem)*Boundary Distance (Cat)						-0.506
						(0.364)
Observations	148,230	148,230	148,230	148,230	148,230	148,230
Community Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	No	No	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01		

Notes: We construct a cell-year level panel dataset for 2000-2014 for all communities that were demarcated 2002 and later. Table 13 presents the effects of demarcation on max NDVI for all demarcated communities, where treatment begins in the year of demarcation. The unit of analysis is a point dropped randomly in the selected communities, and the greenness at each point is measured with GIMMS 250m resolution data. Column 1 shows estimation of a model with only community-level fixed effects (and no time controls), while Column 2 adds time-varying climate and population controls. Column 3 adds linear year effects as a control and Column 4 incorporates year-specific fixed effects. Column 5 adds an interaction between treatment and the distance from each point to the community's boundary. Column 6 uses a categorical variable of the distance to the community's boundary. Columns 4-6 include community and year-specific fixed effects. We use two-way clustering of standard errors by community and year for all models. All models are weighted by community size.

Table 14: Summary statistics for GIMMS grid cell level panel, weighted by community size

Statistic	Mean	St. Dev.	Min	Max
NDVI	228.448	13.566	12.000	250.000
Slope (degree)	0.474	0.740	0.000	21.058
Distance to Road (m)	37,257.11	54,437.07	0.000	275,087.3
Distance to River (m)	1,616.025	1,204.758	0.000	8,062.258
Elevation (m)	94.554	78.908	5.000	670.000
Area (hectares)	78,272.18	286,238.7	142.298	2,381,796.000
Population Density	1.404	1.706	0.179	13.356
Mean Temperature	24.66	0.613	22.174	29.373
Mean Precipitation	175.323	23.650	91.613	280.847
Max Temperature	25.594	0.746	22.666	30.779
Max Precipitation	300.132	45.549	145.729	509.611
Min Precipitation	59.728	27.768	6.307	226.166
Min Temperature	23.789	0.731	16.728	28.539
Distance to Boundary (km)	2.252	3.723	0.002	46.890