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More Than Just Carbon: The Socioeconomic Co-Benefits of Large-Scale Tree Planting

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Abstract

One potential nature-based solution to jointly address poverty and environmental concerns is large-scale tree planting. This study examines the National Greening Program (NGP) in the Philippines, a major tree planting initiative involving 80,522 localized projects that directly or indirectly generated hundreds of thousands of jobs. Utilizing a dynamic difference-in-differences approach that leverages the staggered implementation of the NGP, we find a significant and sizable reduction in poverty, measured via traditional and remotely sensed indicators. The NGP also spurred structural shifts, notably decreasing agricultural employment while boosting unskilled labor and service sector jobs. Our analysis estimates that the NGP sequestered 71.4 to 303 $MtCO_2$ over a decade, achieving a cost efficiency of \$2 to \$10 per averted tCO_2. These findings underscore the potential of tree planting as a dual-purpose strategy for climate mitigation and poverty alleviation.

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1. Introduction

The United Nations' Sustainable Development Goals emphasize that ecosystem services and biodiversity conservation are essential to human well-being and have thus defined a dual agenda where development targets for people and planet sit alongside each other in a unifying framework (United Nations, 2015).[1] Designing and implementing effective policies that coherently interact to provide incentives for sustainable land use and land management has become ever more important (Seymour and Harris, 2019), especially in light of potential synergies between climate mitigation and poverty alleviation (Alix-Garcia *et al.*, 2015; Jayachandran *et al.*, 2017; Ferraro and Simorangkir, 2020).

Tree planting is a potential nature-based solution (NBS) that is uniquely positioned to address environmental and poverty concerns.[2] On the poverty side, tree planting schemes can be used to create jobs and transfer productive agroforestry assets to receiving individuals or communities. Locally, forests contribute to welfare through fuel wood, fodder, timber, watershed protection, and wildlife habitat (Alix-Garcia *et al.*, 2013). On the environmental side, tree planting schemes can be used for climate mitigation and adaptation efforts. Forests offer a wide range of environmental benefits, including the maintenance of habitat, biodiversity, and soil fertility, pollution control, climatic regulation, carbon sequestration, stabilizing hydrological flows, mitigating floods, landslides, and soil erosion (Pattanayak and Butry, 2005; Bhattacharjee and Behera, 2017; Alix-Garcia and Wolff, 2014). Additionally, there has been a boom in the design of local and international policy instruments to prevent further deforestation and to encourage forest growth (Alix-Garcia and Wolff, 2014). In this sense, tree planting can potentially align three goals from climate mitigation (sequestering carbon), adaptation (utilizing ecosystem functions to reduce flooding and landslides) and poverty reduction (through job creation and agroforestry asset transfers).

In this paper, we examine the causal impact of a large-scale tree planting program on both economic and land use outcomes. We focus on the National Greening Program (NGP) in the Philippines, which was launched in 2011 through an executive order by the Aquino administration (Executive Order No. 26, 2011). The NGP is primarily a reforestation program with the goal of planting 1.5 billion trees on 1.5 million hectares across the Philippines. This represents an expansion in forest cover of 11.4 percent

[1] These goals have been reinforced with the establishment of the 2021-2030 UN Decade on Ecosystem Restoration, which draws on the conclusions of the Dasgupta Review (Dasgupta, 2021) in claiming that the preservation and restoration of biodiversity and ecosystem services is fundamental for the transition to a sustainable economic development trajectory.

[2] The restoration of trees remains among the most effective strategies for climate change mitigation (Bastin *et al.*, 2019) and photosynthetic carbon capture by trees is likely to be among our most effective strategies to limit the increase in global CO_2 concentrations (Griscom *et al.*, 2017; Lewis *et al.*, 2019). Over 50 percent of the 193 signatories to the Paris Agreement list land use and forest as a priority area to achieve CO_2 emissions reductions (UNFCCC, 2022). Furthermore, tree planting is an important part of almost all proposed pathways to 'net zero' emissions with estimated capital requirements on a scale of hundreds of billions of dollars (Grosset *et al.*, 2023).

over the 13.2 million hectares of natural forest in 2010 (Global Forest Watch, 2023). Furthermore, the NGP is designed in such a way that it achieves co-benefits beyond reforestation and carbon sequestration. The NGP pays local organizations for three years for seedling production, site preparation, and maintenance. After the three-year period dedicated to the establishment of the plantation, the local organization assumes full managerial control of the agroforestry assets and retains all generated proceeds. From 2011 - 2016, the payments NGP municipalities received for preparing and planting sites was 1.5 percent of their internal revenue allotment, the primary channel through which the central government reallocates funds to municipalities. Additionally since the program began, the NGP has planted hundreds of thousands of hectares, and directly employed or further generated hundreds of thousands of jobs.

We conduct a large-scale analysis across the Philippines linking NGP tree planting projects with small area poverty estimates, high-resolution data on forest coverage, and create a novel measure of economic deprivation based on the proportion of built settlements associated with no nighttime luminosity. Leveraging data which spans the period 2000-2016, we ask three main questions: whether the tree planting scheme was effective in increasing forest cover, whether the NGP reduced poverty, and whether the NGP induced structural transformation in terms of sectoral employment and labor reallocation. We implement a dynamic difference-in-differences (DID) identification strategy by Callaway and Sant'Anna (2021) that exploits the timing of being treated by the NGP. Our empirical strategy compares the pre-planting and post-planting periods between earlier treated NGP municipalities and a pool of municipalities who have either 'not-yet' been treated by the time of the program implementation, or are never treated throughout the duration of the panel.

We provide novel evidence demonstrating that large-scale tree planting can have ancillary co-benefits beyond providing a carbon sink. First, we assess whether the NGP was effectively implemented, and find that municipalities enrolled in the tree planting program experienced a 4 percent increase in forest cover relative to control units. Subsequently, we show that the program led to broad changes in poverty, measured through traditional and remotely sensed indicators. We find that treated municipalities experience a decrease in poverty of 6 percentage points and a decrease in the share of unlit settlements of 8 percentage points. The main results are robust to the inclusion of geographic, socioeconomic, and market access controls, as well as alternative difference-in-differences estimation methods. Furthermore we document significant heterogeneity, where municipalities that are poorer and have a higher proportion of unlit settlements receive the greatest benefit from the NGP. A discernible scale effect is also identified, in which municipalities with a higher hectare to project ratio have a relatively higher impact on poverty. Last, we perform the analysis at the village level and find that treated villages experience a decrease in unlit settlements of 5-7 percentage points relative to control villages.

This study then adapts the dynamic DID estimator to estimate spillover effects in a novel way. To do so, we exploit 32,472 control villages and compare (1) control villages that have a neighbor who is treated earlier by the NGP to a pool of villages who have 'not-yet' had a neighbor treated by the time of the treatment, and (2) control villages that have a neighbor who is treated by the NGP to control villages that never have a neighbor treated by the NGP. We find evidence of spillovers where neighboring control villages experience a 4.5 percentage point reduction in the share of unlit settlements when a neighbor receives the tree planting program relative to control villages who do not have a treated neighbor.

Next we examine broader structural changes induced by the NGP through sectoral reallocation in employment and changes in labor supply. We first document that municipalities that received the NGP experience reductions in the percentage of individuals working in the agriculture sector. At the same time, we find evidence that labor is reallocated to more productive sectors with increases in unskilled manual labor and services. Last, we find no evidence that the NGP effected the labor supply through population changes or migration. Taken together, this supports the notion that the tree planting program created economic activity, as opposed to economic activity being created through shifts in the labor supply or induced migration.

Finally, we make several calculations to value the NGP's carbon sequestration benefits. We first calculate the yearly amount of CO_2 sequestered per tree plantation, the total amount of CO_2 sequestered by all 80,522 NGP tree plantations and the cost per ton of CO_2 emissions sequestered. For policymakers with a primary emphasis on carbon emissions, the NGP achieves a reduction in CO_2 at a cost of \$2 to \$10 tCO2-eq. Last, we estimate that the NGP sequestered CO_2 valued between \$163 million and \$9.57 billion and find at the plantation level that the average sequestration benefits surpass the implementation costs between years 6 and 9.

There is a growing body of economic research that seeks to determine the causal impact of conservation programs on the delivery of protecting forests and other forest ecosystem services (Pattanayak *et al.*, 2010; Ferraro *et al.*, 2012). Much of this work has focused on avoided deforestation programs or payment for ecosystem services (PES) (Alix-Garcia *et al.*, 2015; Wilebore *et al.*, 2019; Jayachandran *et al.*, 2017).[3] PESs have emerged as a policy solution to realign the private and social benefits that result from decisions related to the environment by paying individuals or communities to undertake actions that increase levels of desired ecosystem services (Jack *et al.*, 2008). Another aspect of this literature is focused on whether there is an inherent trade-off between environmental quality and poverty alleviation (Jayachandran, 2023) and policies trying to maximize economic prosperity alongside environmental quality rarely occur (Jayachandran, 2022). The effectiveness of environmental policies often hinge on the alignment of instruments across policy sectors with conflicting goals (Harahap *et al.*, 2017). An important distinction that sets the NGP apart from previous PES programs is that the Department of Environment and Natural Re-

[3]See Pattanayak *et al.* (2010) for a review of the environmental effectiveness of avoided deforestation and Pfaff *et al.* (2013) for a review of how PES could address the underlying drivers of deforestation. See also Bulte *et al.* (2008) and Samii *et al.* (2014) for a review of the relationship between PES and poverty alleviation.

sources (DENR) pays local organizations to produce seeds, prepare sites, plant trees, maintain sites, and all proceeds from the forestry plantations accrue to the NGP beneficiary communities. This is important as the NGP creates jobs and transfers productive forestry assets into communities, which are likely to create continued growth once the payments and program stop. We provide evidence to support this through sustained reductions in poverty.

A second contribution of this study relates to the nascent literature focused on multi-faceted interventions that grant productive assets along with cash transfers. Work by Banerjee *et al.* (2015) and Bandiera *et al.* (2017) finds that a multi-faceted program is sufficient but not necessary for generating economically meaningful and sustainable impacts for those in extreme poverty, while Banerjee *et al.* (2022) find that neither transferring a productive asset nor providing access to a savings account, on their own, generates meaningful and sustainable impacts on the population. Furthermore, Balboni *et al.* (2022) shows that large transfers, which create better jobs for the poor, are an effective means of getting people out of poverty traps and reducing global poverty. Our findings are in line with this emerging literature on large asset transfer programs by showing that transferring productive agroforestry assets is another way to generate lasting and economically meaningful impacts over time. An important next step in this literature is understanding which components of the bundle are necessary to generate large benefits (Sedlmayr *et al.*, 2020). We attempt to disentangle the impacts of the asset transfer and payments, and find that both the provision of tree assets and financial payments to communities significantly contribute to poverty reduction. Furthermore, a central focus of development economics has focused on identifying policies that enable structural transformation away from low productivity agriculture (Banerjee and Newman, 1998; Bryan *et al.*, 2014). However, there has been much less work on the structural transformation of conservation programs. We provide the first evidence that conservation programs can lead to structural transformation as the NGP lead to a reduction in the number of individuals working in agriculture and an increase in unskilled manual labor and service sector labor.

2. Context and Specifics of the National Greening Program

The Philippines is one of the most populated tropical countries in the world with 109 million people across 7,000 islands. Forest cover in the Philippines has declined from 17.8 million hectares or about 60 percent of the total land area in 1934 to about 7.2 million hectares or 23.9 percent in 2011 (Department of Environment and Natural Resources, 2011). In 2000, the Philippines ranked among the top ten deforestation countries contributing to 17-20 percent of global greenhouse gas emissions from global forest loss (Food and Agriculture Organization of the United Nations, 2005), but the country has subsequently made strides in recovery, achieving modest annual forest gains of 55,000 hectares as of 2010 (Food and Agriculture Organization of the United Nations, 2010). From 2001 to 2022, forests emitted 38.5 $MtCO_2$ per year and removed 96.9 $MtCO_2$ per year, representing a net carbon sink of 58.3 $MtCO_2$ per year. Additionally over this time frame, the Philippines lost 1.42 million hectares of tree cover, equivalent to a 7.6 percent decrease in tree cover since 2000 or 848 $MtCO_2$ emissions (Global Forest Watch, 2023).

The National Greening Program (NGP) is a highly ambitious tree-planting scheme. Launched in 2011 by the Aquino administration through Executive Order No. 26 (2011), the program set out to plant billions of trees across the Philippines. With an initial budget of PHP 31 billion (∼$721m), it sought to plant 1.5 billion seedlings on 1.5 million hectares of land nationwide from 2011 to 2016 (Calderon, 2016). This represents an 11.4 percent increase in the 2010 forest stock or replanting more than the 1.42 million hectares of forest cover lost from 2001 to 2021. In 2015, the program expanded through Executive Order No. 193 (2015) which extended its coverage from 2016 to 2028 and set the goal of rehabilitating all remaining unproductive, denuded and degraded forest lands, estimated at 7.1 million hectares, or around 53 percent of the country's total forested area (Department of Environment and Natural Resources, 2019; Global Forest Watch, 2023).

Designed primarily as a reforestation program, the NGP seeks to restore vegetation cover. Explicit provisions in the implementation of the NGP include: 1) utilizing a forest and landscape restoration (FLR) approach to restore landscape functionality, economic productivity, and ecological integrity; 2) planning and mapping to identify production and protection zones, and match species with sites; and 3) funding to support capacity building, monitoring, and database development (Department of Environment and Natural Resources, 2019). The program is designed in such a way as to also target poverty reduction, promote food security, environmental stability, biodiversity conservation, and the enhancement of climate change mitigation and adaptation. Other aims of the program are to: 1) contribute to reducing poverty among upland and lowland poor households, indigenous peoples, and in coastal and urban areas; 2) implement sustainable management of natural resources through resource conservation, protection, and productivity enhancement; 3) provide food, goods and services such as timber, fiber, non-timber forest products, aesthetic values, air enhancement values, water regulation values, and mitigate climate change by expanding forest cover that serves as a carbon sink; 4) promote public awareness as well as instill social and environmental consciousness on the value of forests and watersheds; 5) enhance the formation of positive values among the youth and other partners through shared responsibilities in sustainable management of tree plantations and forest resources, and 6) consolidate and harmonize all greening efforts of the government, civil society, and the private sector (Department of Environment and Natural Resources, 2019).

Tree planting mostly takes place on degraded or deforested lands, but also includes land such as mangrove and protected areas, ancestral domains, civil and military reservations, urban areas under the greening plans of the Local Government Units (LGUs), inactive and abandoned mining sites, and other suitable lands (Executive Order No. 26, 2011). The NGP addresses the local socio-economic needs through paying people's organizations (POs) for producing seedlings, preparing, planting and maintaining plantation sites.[4] More specifically, the DENR forms partnerships with POs who receive payment for their role in preparing the sites (strip brushing, hole digging, and staking the target areas), planting seedlings, and maintaining and implementing protective measures (weeding/brushing, fertilizer application, and the creation of fire breaks or green breaks).[5] The DENR overseas the provision of nursery establishment, seedling production, site identification, technical support, and program monitoring, while PO's are in charge of preparing the sites, planting seedlings, and maintaining and protecting the trees (Commission on Audit Performance Report, 2019).[6] From 2013 onwards, the production of seedlings became a part of the duties and responsibilities of the implementing POs, who were encouraged to establish their nurseries near or adjacent to the planting sites to minimize hauling stress and costs. More importantly, all profits generated from seedling production and the tree plantations are directed towards the implementing PO, ensuring that they benefit directly from their efforts.

To assist NGP coordinators in implementing the program, the DENR hired extension officers (EO) who hold degrees in forestry or environmental science to help provide technical assistance to POs and upland communities through extension services. Additionally the NGP promoted the planting of indigenous species as well as species naturally growing in the targeted area. According to Department of Environment and Natural Resources (2012), the following factors were considered in choosing the species: 1) suitability of the prevailing site conditions, 2) purpose/s for which they are planted, 3) availability of planting materials, and 4) market for commercial potential. POs were allowed to plant their preferred species as long as it was compatible with the previous list of site conditions.

The goal of the NGP is to achieve a yearly survival rate of 85 percent. Between 2011 and 2015, the national annual survival rate was 83 percent, except for 2015, where the program recorded a survival rate of 82 percent (Israel, 2016). To achieve such a high survival rate, there were several forms of monitoring to ensure POs were

[4]POs are a group of people which may be an association, cooperative, federation, or other legal entity established by the community to undertake collective action to address community concerns and need, and mutually share the benefits from the endeavor.

[5]In the initial stages of the NGP, the DENR gave priority to POs holding existing CBFMA/PACBRMA agreements, as they were already organized and represented the current occupants and cultivators of the forest lands (Commission on Audit Performance Report, 2019). The primary distinction between the two agreements lies in their application: PACBRMA pertains to protected areas, whereas CBFMA is relevant to production areas that may also seek cutting permits from the DENR. These agreements offer a 25-year term (renewable for an additional 25 years), providing tenurial security and incentives for the development, utilization, and management of specific portions of the forest lands. However, due to an insufficient number of POs with such agreements, the DENR had to permit POs without any tenure instruments to participate as well as to LGUs with a proposed development in line with the Forest Land Use Plan (Commission on Audit Performance Report, 2019).

[6]A uniform strategy was applied across all tree planting sites and the DENR came up with a standard unit costs for reforestation species (categorized by commodity) to be planted with their equivalent density per hectare. Appendix B further outlines the standard template payment structures for seedling production, site preparation, and site maintenance.

complying with the standards of the program. The DENR monitored the compliance of seedling suppliers and plantation sites through their provincial environment and natural resource offices (PENRO) and community environment and natural resource offices (CENRO). Each PENRO had an Inspection and Acceptance Committee (IAC) that inspected reports on the compliance of the POs or private suppliers. The reports were generated by the EOs who visited each site to check whether the plantations achieved a seedling survival rate of 85 percent and took geo-tagged photos as proof of compliance. Once the IAC approved each report, the PENRO would allow processing and release of payment. At the end of year 3, the DENR issued a Certificate of Site Development that contained the survival rate and geo-tagged photos comparing images taken in year 1 and year 3 (see Figure A.4 for an example).

Table 1 outlines the program's accomplishments from 2011 to 2022. During the first decade of the program, the NGP planted 2,181,684 hectares, generated 5,858,004 jobs, and directly employed 845,014 people (Department of Environment and Natural Resources, 2022).[7]

3. Data

Our main analysis is based on a municipality-by-year dataset compiled from various sources and measured at different levels of granularity: (1) project-level data on where and when tree-planting projects occurred; (2) small area poverty estimates from the Philippines Statistical Authority; and (3) remotely sensed data, comprised of several variables measured at the 1km x 1km grid cell level (0.083x0.083 arc-degrees). Table A.1 provides summary statistics at the municipality level for each of the variables used in the analysis.

National Greening Program (NGP): Data on the NGP comes from the Philippines' Department of Environment and Natural Resources (DENR) which provides yearly tree planting accomplishments from 2011 – 2016. The dataset includes information on 80,522 individual tree planting projects. Information is also provided on the Barangays (village) that were treated, how many hectares were planted, the type of organization leading the project, commodity type and species type. Figure A.1 plots the distribution of tree planting sites by hectares. The average tree planting site is 16 hectares and the distribution further shows that the majority of these projects are less than 20 hectares.[8] Furthermore in Figure A.3, we classify each tree planting site by its main component as a reforestation, agroforestry, mixed agroforestry/reforestation or urban reforestation site. The majority of the tree

[7]The NGP provided jobs to various program participants such as members of people's organizations, extension officers and laborers. However there is no information on whether this labor participation is full time or part time as well as on other details that could provide a better picture of the employment contribution of the NGP (Israel and Arbo, 2015).

[8]In Figure A.2 we also plot a relative measure for the distribution of the total number of hectares planted from 2011 - 2016 relative to the municipality area.

Table 1: National Greening Program and Enhanced National Greening Program Accomplishment Report

Year	Target Area	Area Planted	Percent Accomplished	Seedlings Planted	Jobs Generated	Persons Employed
National Greening Program (NGP)						
2011	100,000	128,558	129%	89,624,121	335,078	47,868
2012	200,000	221,763	111%	125,596,730	380,696	55,146
2013	300,000	333,160	111%	182,548,862	466,990	65,198
2014	300,000	334,302	111%	205,414,639	1,079,792	152,008
2015	350,000	360,357	103%	351,014,239	915,729	123,519
2016	247,683	284,089	115%	415,564,211	842,792	114,584
Subtotal (NGP) 2011-2016	1,497,683	1,662,229	111%	1,369,762,802	4,021,077	558,323
Enhanced National Greening Program (ENGP)						
2017	193,803	206,136	106%	182,185,530	582,070	84,315
2018	136,466	141,310	104%	138,020,616	393,903	62,375
2019	19,617	21,925	110%	25,851,359	268,171	46,313
2020	46,907	47,299	101%	37,206,581	367,195	55,141
2021	94,667	95,666	101%	70,751,170	225,588	38,547
2022	46,265	7,119	15.39%	6,089,153		
Subtotal (ENGP) 2017-2022	537,724	519,455	97%	460,104,409	1,836,927	286,691
Total (NGP & ENGP)	2,035,407	2,181,684	107%	1,829,867,211	5,858,004	845,014

Notes: This table has been reproduced from the Department of Environment and Natural Resources. Source: Department of Environment and Natural Resources (2022).

planting sites are either agroforestry or reforestation projects. For the main analysis, we aggregate the data up to the municipality-year level and define treatment as the first year in which an NGP project occurred and treated thereafter. Table 2 shows the frequency of municipalities treated within each "group" as the NGP was rolled out. Around 20 percent of municipalities are never treated by the NGP, and approximately 76 percent of municipalities are treated within the first three years of the program. Figure 1 illustrates the spatial and temporal variation of the treated and control municipalities and the year in which the municipalities first received treatment. Furthermore, Figures A.5 and A.6 illustrate the spatial variation of the program based on the cumulative number of tree planting projects and the cumulative number of hectares planted per municipality, where there appears to be a fairly even distribution of treatment intensity throughout the Philippines.

Table 2: NGP Timing by Treatment Pool

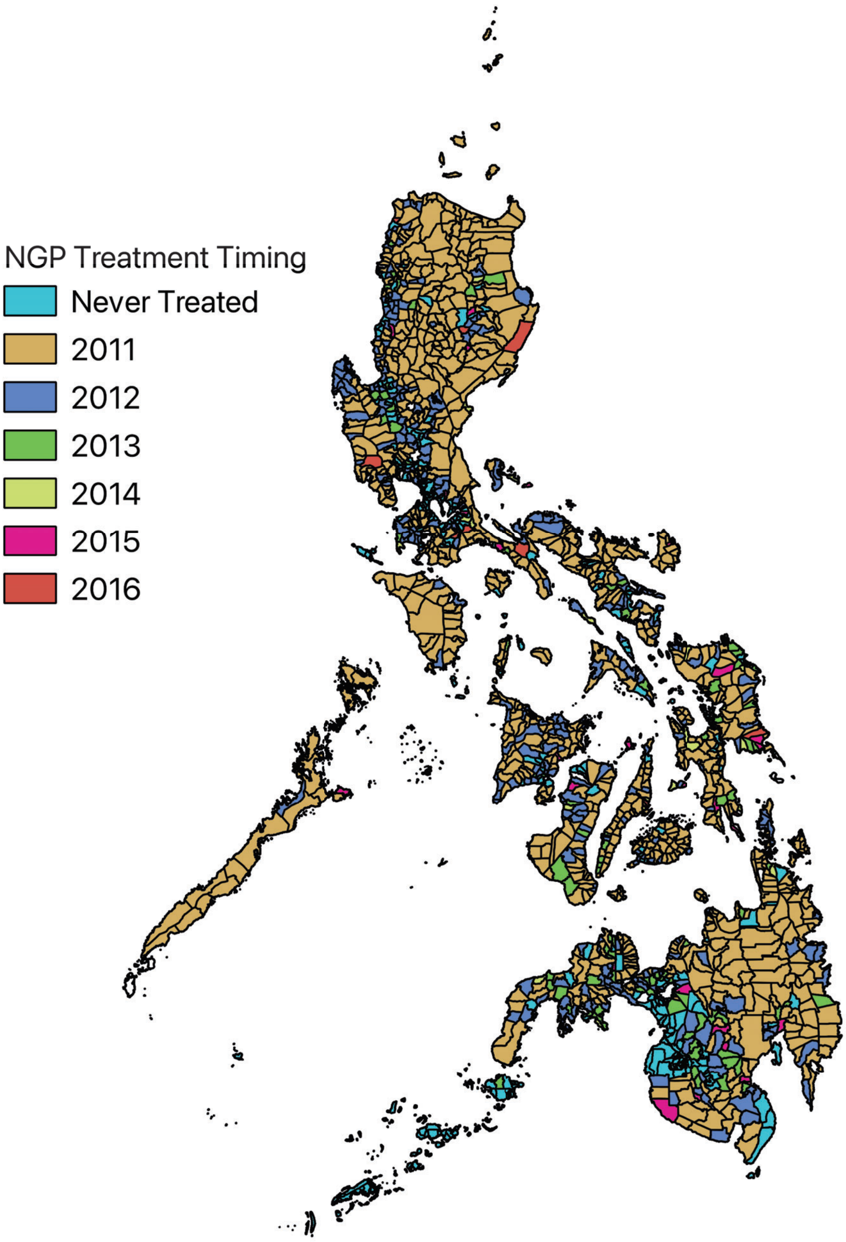
NGP Treatment Timing	Frequency	Percent	Cumulative
Never Treated	322	19.77	19.77
2011	837	51.38	71.15
2012	301	18.48	89.63
2013	99	6.08	95.7
2014	27	1.66	97.36
2015	31	1.9	99.26
2016	12	0.74	100
Total	1,629	100	

Notes: This table presents the frequency of municipalities within each year the pool was first treated by the NGP. The group 'Never Treated' is the pool of control municipalities who are never treated during the duration of the panel.

Poverty Indicators: Two sources of data are used to measure poverty. First, we obtain estimates for the incidence of poverty from the Philippine Statistics Authority (PSA) which compiles official poverty statistics from the Family Income and Expenditure Survey (FIES) and data on food prices. The small area poverty estimates are provided every three years from 2000 - 2018 for each municipality and are expressed as a percentage of households that fall below the poverty threshold. Second, we calculate the percentage of unlit settlements at the municipality and village (*barangay*) level, expanding on McCallum *et al.* (2022), and employ it as a remotely sensed proxy for poverty. This indicator allows us to overcome known problems connected with the use of night-time lights (NTLs) as a predictor of economic activity[9] in low income countries, where NTLs are sparse and only loosely

[9]Previous studies have shown a correlation between night-time lights (NTLs) and economic activity

Figure 1: NGP Timing by Treatment Pool



Notes: This figure presents identifying variation for the year in which municipalities first received an NGP project. *Source*: Author's own calculations.

correlated with income and wealth, especially at the left tail of their distributions (Neal *et al.*, 2016). The unlit settlements percentage indicator is constructed by combining data on NTLs, which we retrieve from Li *et al.* (2020)[10], with newly released data on building footprints, which we obtain from the Global Human Settlement Layer (GHSL) 1 km GHS-SMOD product, available at 5-years intervals between 2000 and 2015. In particular, for each administrative unit i under consideration, we first calculate the total building footprint F_{it} from the GHS-SMOD product. We then reclassify the NTLs dataset to a binary raster, and interact it with the GHS-SMOD product to obtain an unlit building footprint raster. For each administrative unit i we then sum all (fractions) of 1km^2 pixels of the unlit building footprint raster[11], and divide them by the total building footprint to obtain the percentage of unlit settlements, as follows:

$$Unlit_{it} = \frac{1}{F_{is}} \sum_{j=1}^{J} NTL_{jt} \bigg|_{NTL_{jt}=0} \cdot F_{js} \tag{1}$$

where $j = 1, ..., J$ are the 1km^2 pixels contained in administrative unit (municipality or village) i. Subscript s denotes that e.g. building footprint constructed at $s = 2000$ is used to construct $Unlit_{it}$ for $t = 2000, 2001, 2002, 2003, 2004$ due to data limitations.

Our approach thus expands on McCallum *et al.* (2022) by producing the first panel series of the percentage of unlit settlements, combining time-varying information on both NTLs and building footprint and hence taking into account secular growth trends.

Climatic variables: We extract all climatic variables from the TerraClimate dataset, accessed via Google Earth Engine (Abatzoglou *et al.*, 2018). In particular, we retrieve monthly observations of maximum and minimum temperature, precipitation accumulation, and wind speed at 10m, at a 0.1° scale.[12] Monthly data are then collapsed into yearly observations by taking averages, and aggregated up to the municipality level by extracting the mean level of each 0.1° pixel contained in a municipality, in identical fashion to the procedure described above for NTLs.

(Donaldson and Storeygard, 2016), lights and economic growth (Henderson *et al.*, 2012), and as a proxy for economic activity within fine geographic areas such as subnational administrative units (Hodler and Raschky, 2014; Alesina *et al.*, 2016). See Donaldson and Storeygard (2016) and Ghosh *et al.* (2013) for a summary of applications using nighttime lights data as a proxy for economic activity.

[10]Who produce a time-consistent time series of NTL observations by intercalibrating DMSP-OLS and VIIRS values, thereby acknowledging well-understood concerns with the year-on-year intercalibration of satellites' sensor settings. These may render the NTLs time series inconsistent and prone to measurement error, especially in light of our treatment switching on in 2011.

[11]Here, building footprint for the year 2000 is used to calculate the percentage of unlit settlements for years 2000-2004; footprint for 2005 is used to calculate the percentage for years 2005-2009; footprint for 2010 is used to calculate the percentage for years 2010-2014; footprint for 2015 is used to calculate the percentage for years 2015-2018.

[12]Approximately 5km at the equator.

Landcover Data: To test whether the NGP was successful in increasing forest cover, we take advantage of landcover data from European Space Agency (Land Cover, CCI, 2017). Satellite data provide pixel level classifications which correspond to different land cover classes. Land cover data is provided at a spatial resolution of 300m on an annual basis from 1992 – 2020.

4. Identification and Empirical Strategy

The main concern in attempting to causally identify the effect of the NGP on economic and environmental outcomes is due to the implausibility of random assignment of Philippine municipalities to the program. A standard OLS regression using indicator variables to "switch on" the participation status for treated municipalities would overlook the basic fact that program assignment is likely to be prioritized in areas with greater potential for conservation or greater scope for poverty reduction initiatives, thereby providing biased estimates of the program's effectiveness.

In order to address this, the analysis leverages the staggered roll-out of the NGP to quantify the impact tree-planting has on socioeconomic and land-use outcomes. Our main specification compares pre-planting and post-planting periods across NGP municipalities which have been treated by the program in its earlier phase and municipalities that have 'not yet' been enrolled in the NGP. We further compare and contrast these estimates with more canonical dynamic settings in which we compare treated municipalities to 'never treated' municipalities. In order to address the limited sample size at the municipality level, we additionally perform the analysis at the village level where the number of treated and control units is substantially higher.

More specifically, we implement a dynamic DID proposed by Callaway and Sant'Anna (2021) among other new DID estimators robust to heterogeneous treatment effects, because this DID estimator applies to "staggered" designs in which treatment can "switch on" in different time periods and units do not forget about their treatment experience. By estimating treatment effects for each treatment cohort at any time period included in the analysis, the dynamic DID estimator is able to causally identify the effect of the NGP on each cohort of treated municipalities under a couple identifying assumptions. The first is the irreversibility of treatment assumption which is ensured by the program design: once a municipality receives a tree-planting scheme, it is extremely unlikely to reverse its course. Second, the dynamic DID estimator relies on an extension of the standard DID assumption of parallel trends, allowing for parallel outcome trends between treatment and control observations, conditional on a matrix of covariates. This assumption can hold with respect to observations 'not yet treated' (units who have not received the program yet but will do so at some future date) or 'never treated' (units that never receive the NGP program) observations. We leverage the availability of both groups to estimate the effect of the NGP and compare estimates to assess the eventual presence of selection bias. Finally, the sample must respect an 'overlap condition', that is, there must be a region of common support for the propensity to be treated between treatment and control units. While this is not directly testable, specifications using only treated and 'not yet treated' observations, as the estimation sample provide a useful indication in this regard: it is plausible that municipalities where treatment is implemented at a later stage are well within the region of common support for the likelihood of treatment. Moreover, our subnational, disaggregated setting ensures the maximum possible level of comparability across observational units included in the sample.

4.1. Municipality-level Analysis

Our main specification is based on a municipality-by-year dataset. We estimate the following dynamic DID specification:

$$Y_{m,t} = \sum_{\phi=-10}^{-1} \beta_{-\phi} NGP_{m,t-\phi} + \sum_{\phi=0}^{6} \beta_{+\phi} NGP_{m,t+\phi} + \tau_t + \rho_{m,t} + \gamma_m + \epsilon_{m,t} \tag{2}$$

where $Y_{m,t}$ is estimated separately for the log of forest cover, small area poverty estimates and the percentage of unlit settlements for municipality m, in time t. The coefficient of interest is $\beta_{(+\phi)}$ which is the estimated group-time treatment effect. This is interpreted as the average treatment effect for group g at time t, where "group" is defined by the time period when units are first treated. Time, cohort and municipality fixed effects are denoted as τ_t, $\rho_{m,t}$, and γ_m, respectively, which control for the unobserved invariant effect of time, cohorts and municipalities. Following Callaway and Sant'Anna (2021), the base year in pre-treatment years is the immediately preceding year. Throughout the analysis, we implement doubly robust standard errors based on Sant'Anna and Zhao (2020) and cluster the error term at the municipality level.

4.2. Village-level Analysis

In order to reinforce the main analysis, we perform an additional analysis at the village-level for which we have data. We follow the same strategy as the municipality-level analysis, but exploit the roll-out of the NGP at the village level. Table 3 shows the frequency with which villages become treated as the NGP was rolled out, while Figure A.9 illustrates the spatial and temporal variation of treated and control villages.

For the village-level analysis we estimate the following dynamic DID specification:

$$Y_{v,t} = \sum_{\phi=-10}^{-1} \beta_{-\phi} NGP_{v,t-\phi} + \sum_{\phi=0}^{6} \beta_{+\phi} NGP_{v,t+\phi} + \tau_t + \rho_{v,t} + \gamma_v + \epsilon_{m,t} \tag{3}$$

Table 3: Village-level NGP Timing by Treatment Pool

NGP Treatment Timing	Frequency	Percent	Cumulative
Never Treated	32,472	78.75	78.75
2011	2,523	6.11	84.87
2012	2,427	5.89	89.24
2013	1,803	4.37	93.54
2014	721	1.75	95.26
2015	909	2.20	97.43
2016	378	0.92	100
Total	41,233	100	

Notes: This table presents the frequency of villages within each year the pool was first treated by the NGP. The group 'Never Treated' is the pool of control villages who are never treated during the duration of the panel.

where $Y_{v,t}$ represents the percentage of unlit settlements for village τ_v, in time τ_t. The coefficient of interest is $\beta_{(+\phi)}$ which is the estimated group-time treatment effect and is interpreted as the average treatment effect for group g at time t. Time, cohort and village fixed effects are denoted as τ_t, $\rho_{v,t}$, and γ_v, respectively, which control for the unobserved invariant effect of time, cohorts and villages. We implement doubly robust standard errors based on Sant'Anna and Zhao (2020) at the municipality level to address possible spatial correlation of the error term which allows the errors to be spatially correlated across villages within the same municipality.

4.2.1. Spillover Analysis

The net impact of a forest policy encompasses effects within the spatial unit boundary, as well as spillover impacts outside, referred to as policy-induced leakage effects (Börner *et al.*, 2020). In order to understand whether the NGP led to economic spillovers in surrounding villages, we take advantage of the high resolution village level data. We draw inspiration from Ferraro and Simorangkir (2020) regarding their methodology for assessing the spillover effects of Indonesia's national antipoverty program, however, we tailor this approach to fit within the context of the dynamic DID framework. For this part of the analysis, we focus the sample on 32,472 never-treated villages and exploit when a village's neighbor is treated by the NGP. We compare pre-planting and post-planting periods across (1) control villages which experience a neighbor treated by the NGP relative to a pool of control villages who never have a neighbor treated by the NGP during the duration of the panel and (2) the roll-out of the program where control villages who experience a neighbor treated by the NGP in earlier years are compared to a pool of control villages who experience a neighbor treated by the NGP in later years. Table 4 shows the frequency with which control municipalities are treated by the NGP. There are 18,706 or 57 percent of control villages that never have a treated neighbor for the duration of the panel, while in 2011, 16 percent of control villages had at least one neighbor that was treated by the NGP.

Table 4: Control Village Neighbor's NGP Timing by Treatment Pool

Neighbors Treatment Timing	Frequency	Percent	Cumulative
No Neighbor Treated	18,706	57.61	57.61
2011	5,312	16.36	73.97
2012	4,295	13.23	87.19
2013	2,185	6.73	93.92
2014	793	2.44	96.36
2015	844	2.60	98.96
2016	337	1.04	100
Total	32,472	100	

Notes: This table presents the frequency of control villages within each year the pool first had a neighbor treated by the NGP. The group 'No Neighbor Treated' is the pool of control villages who never have a neighbor that is treated by the NGP during the duration of the panel.

To estimate spillover effects, the following dynamic DID specification is estimated:

$$Y_{v,t} = \sum_{\phi=-10}^{-1} \beta_{-\phi} Neighbor_{v,t-\phi} + \sum_{\phi=0}^{6} \beta_{+\phi} Neighbor_{v,t+\phi} + \tau_t + \rho_{v,t} + \gamma_v + \epsilon_{m,t} \quad (4)$$

where $Y_{v,t}$ represents the percentage of unlit settlements in village v, in time t. $Neighbor_{v,t}$ "switches on" to the value of 1 when a control village has a neighbor treated by the NGP in time t, or remains 0 if no neighbor is ever treated by the NGP. Again, we implement doubly robust standard errors and cluster the error term at the municipality level.

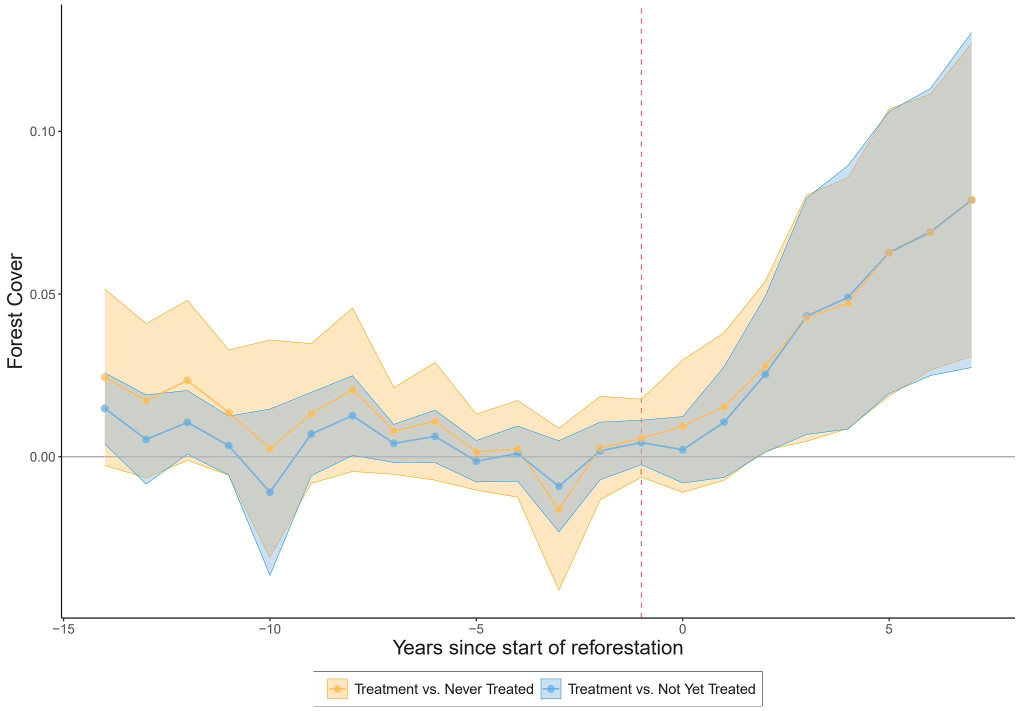
5. Results

This section presents several pieces of evidence on the impact of tree planting. First, we assess whether the NGP was effective at increasing forest cover in Figure 2. Then we present our main results on the economic effects of tree planting in Figure 3 and Table 6. In the Appendix, we aggregate the estimated treatment effects in two different ways. First, we aggregate the treatment effects into cohort level event studies (Figure A.13 - Figure A.16). Second we aggregate the results into an average cohort effect of the NGP (Figure A.17 - Figure A.20). Last we present the results from the village-level analysis to reinforce the main analysis as well as estimate spillover effects.

5.1. Impact on Forest Cover

We first assess whether the NGP was effective in its primary objective of restoring vegetation cover. In Figure 2 we find that NGP municipalities experience a steady increase in forest cover each year after the implementation of the tree planting program. On average, forest cover increases by 4 percent (Table 5) after the start of the program. We further analyze the dynamic effect by each cohort (Figure A.13) to show that this increase is mainly driven by the 2011 and 2012 cohorts, as well as show that on average all cohorts (besides 2014) experience a positive increase in forest cover (Figure A.17). This evidence reassures us that the program was effective in its main objective of reforestation and acts as a background check on the dynamic DID assumptions of "treatment irreversibility": once a municipality is treated by the program, the treatment does not switch off. If tree planting led to subsequent clearing and extraction of timber for sale in local and international markets, the ecosystem services provided by the program would be lost and the assumption would be violated. As forest cover persistently and significantly increases, without any reversal towards zero, up to 7 years after the first NGP roll-out, this possibility is sufficiently ruled out by the empirical evidence.

Figure 2: Impact of NGP on Forest Cover



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the log of forest cover. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Table 5: Impact of NGP on Forest Cover

	Forest Cover	
	(1) Not Yet Treated	(2) Never Treated
NGP	0.043***	0.044***
	(0.013)	(0.013)
Observations	29268	29268

Notes: This table presents estimates for the effect that the NGP had on the log of forest cover, identified using a DID based on the roll-out of the NGP. 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment. 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

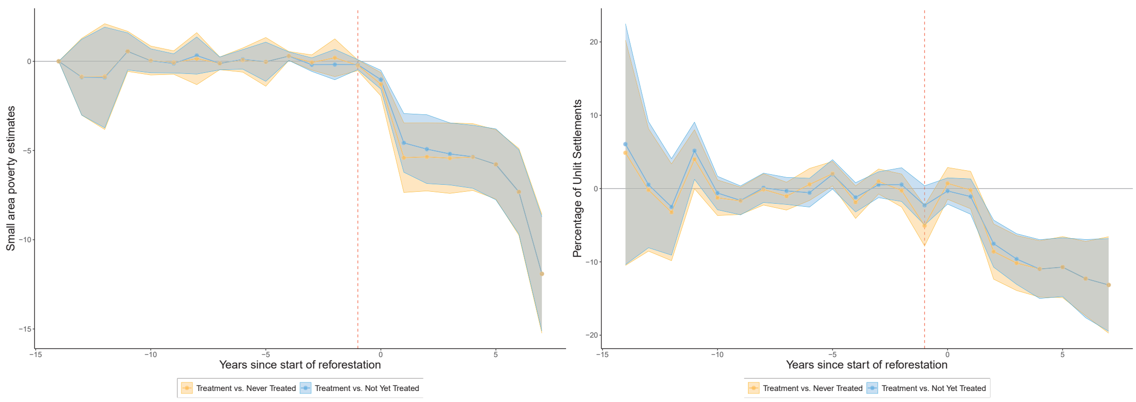
5.2. Impact on Economic Outcomes

Next, we evaluate the socioeconomic co-benefits that large-scale tree planting can yield. In Figure 3, we show that treated and control municipalities exhibit similar pre-NGP trends, which provides evidence in support of the parallel trends assumption. The confidence intervals of pretreatment trends 95 percent generally include zero difference, therefore, sufficient to rule out substantial selection between treatment and control municipalities.

Municipalities that receive a tree planting project experience reductions in poverty incidence measured through both traditional and remotely sensed indicators. In Figure 3, Panel A, and Table 6 columns 1 and 2, we show NGP municipalities experience a reduction in poverty incidence of 6 percentage points. Figure A.14 further shows the dynamic effects by cohort and the effects appear to accumulate over time as the 2011 and 2012 cohort point estimates continue to decrease each year after the NGP. Secondly, in Figure 3 Panel B and Table 6 columns 3 and 4, we show that the tree planting program lead to a decrease in the percentage of unlit settlements, with municipalities that receive a tree planting project experiencing an 8 percentage point decrease.[13] Furthermore, Figure A.15 illustrates that there is a sustained decrease in the percent of of unlit settlements. Both figures illustrate how persistent the effects are, as 7 years after the first year of implementation the effects are still significant and without any reversal towards zero in terms of levels.

Figure 3: Impact of NGP on Socio-Economic Measures

Panel A | Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on small area poverty estimates (Panel A) and the percent of unlit settlements (Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

[13] We further present results from a standard two-way fixed effect (TWFE) estimation in Table A.6 where the results (compared to the never treated) are slightly underestimated though qualitatively similar to our CS-DID specifications.

Table 6: Impact of NGP on Socio-Economic Measures

	Small Area Poverty Estimates		Percentage Unlit Settlements	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated
NGP	-5.759***	-5.981***	-8.209***	-8.169***
	(0.628)	(0.661)	(1.082)	(1.138)
Observations	27954	27954	24210	24210

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and the percentage of unlit settlements identified using a DID based on the roll-out of the NGP. 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment. 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

5.2.1. Robustness

We perform several robustness checks on our main analysis. Each of these robustness tests along with insignificant pre-treatment trends in the main results provide confidence that the empirical strategy is correctly identifying the impact of the tree planting program.

Conditional parallel trends: While the main CS-DID estimates are well identified, as shown by unconditional parallel trends between treatment and control cohorts in pre-intervention periods, we investigate the robustness of our results to conditioning the CS-DID estimator on a set of characteristics which may influence poverty. In Tables A.3 and A.4, we show that there are statistically significant pre-treatment differences across geographic and market access characteristics between various comparisons of the treatment and control groups. We deal with the selection issue by re-running equation (1) and condition on the following time-varying characteristics: population, precipitation, and maximum temperature, as well as the following time-invariant controls: slope, elevation, number of villages within a municipality that have access to the national highway, number of markets, number of commercial establishments, and number of bank establishments.[14] The results are presented in Table A.5 where we show effect sizes that are smaller than the main results in Table 6.

Other DID estimations: We rerun the main analysis following Sun and Abraham (2021), which is very similar to Callaway and Sant'Anna (2021) but corrects for the

[14]Each time-invariant control is interacted with a linear time trend. Data on the number of villages within a municipality that have access to the national highway, number of markets, number of commercial establishments, and number of bank establishments come from the 2010 Census of Population and Housing Barangay Schedule.

possibility that coefficients on a given lead or lag could be contaminated by the effects from other periods. Table A.7 presents the results which remain quantitatively similar to Table 6. Further, we employ the De Chaisemartin and d'Haultfoeuille (2024) staggered DID estimator, which estimates treatment effects across units whose treatment status changes from $t-1$ to t, effectively restricting the estimation to the switchers considered at the time in which they switch treatment. Table A.8 reports the results, which are slightly lower but consistent to the ones using the CS-DID estimator.

Other outcome variables: We repeat the main analysis using two other dependent variables.[15] First we use nighttime lights as a proxy for economic activity and show in Appendix C.1 that municipalities that received a tree planting project experienced an increase in nighttime luminosity of 24 percent. This is an increase of 0.2 standard deviations over the pre-treatment nighttime light mean. Second, we measure the percentage of municipality and village populations living in unlit areas, following the procedure by Smith and Wills (2018) that combines disaggregated data on nighttime lights and population. This measure differs from nighttime lights as it mainly focuses on extreme rural poverty by counting the number of people who live in darkness at night rather than using light as a proxy for economic activity. Figure C.2 and Table C.2 report the results, which are comparable in magnitude to those using the share of unlit settlements.

Other threats to identification: Last, we address several potential threats to the identification strategy by estimating equation (1) and restricting the dataset in three different ways. We present the results for small area poverty estimates in Table A.9 and the percent of unlit settlements in Table A.10 and show that the results remain quantitatively similar to the main results with the restricted samples.

Typhoon Haiyan, one of the strongest storms ever recorded, made landfall in 2013 over Eastern Samar in Visayas region and brought sustained winds of 315 kph and caused a 5-meter storm surge. This category 5 typhoon is considered one of the strongest tropical cyclones ever recorded globally and left 6,300 dead, 1,061 missing, 28,689 injured and affected 591 municipalities (National Disaster Risk Reduction and Management Council, 2013). The total estimated cost of damage to physical assets, including both public and private assets, was PhP424 billion or 3.7 percent of GDP (National Economic and Development Authority, 2013). Figure A.10 presents a map of the affected municipalities. One could argue that Typhoon Haiyan affected different ecosystems found in the region, including mangroves and forest cover, as well as impacted livelihoods, poverty incidence, and economic activity. To ensure that our main results are not biased due to Typhoon Haiyan, we exclude municipalities affected by the typhoon and show in columns 1 and 2 that the results remain quantitatively similar.

[15] See Appendix C.1 for more detail on how we process and construct the nighttime lights and percentage of unlit population.

Second, the southwestern provinces on the island of Mindanao have been effected by conflict stemming from the Moro Islamic Liberation Front (MILF), an Islamist separatist movement. In 2014, the Philippines' government and the MILF signed a final peace agreement called the Comprehensive Agreement on Bangsamoro, which called for Muslim self-rule in parts of Mindanao in exchange for the deactivation of rebel forces. To ensure our results are not impacted by the conflict, we drop municipalities in the Mindanao region and rerun the main analysis. The results are presented in columns 3 and 4 and show that there is a reduction in the main effect on small area poverty estimates, where NGP municipalities experience a 2 percentage points reduction in poverty, but the effect on remotely sensed deprivation remains quantitatively similar.

Last, the Aquino administration implemented a conditional cash transfer (CCT) program targeting poor families prior to the NGP, called the Pantawid Pamilyang Pilipino Program (4Ps hereafter). The main aim of the 4Ps program was to provide cash-grants to families with children aged 0-14 years suffering from chronic hunger and provides incentives to access schooling and healthcare to mitigate future poverty.[16] The program was piloted in 2007 and launched on a wider scale starting in 2008 before reaching the full country in 2011. Figure A.11 presents a map of how the 4Ps CCT program was rolled-out from 2008 - 2010. In columns 5 and 6 we exclude municipalities that received the CCT program prior to the introduction of the NGP and show that the results remain quantitatively similar to the main results.

5.3. Village-level Impact on Economic Outcomes and Spillovers

Village-level Economic Outcomes: Next we present the results from the village-level analysis to reinforce the findings in Table 6. In columns 1 and 2 of Table 7, we find that treated villages experience a decrease in unlit settlements by 5 percentage points relative to control villages. The results remain quantitatively similar to Table 6, but the estimates are slightly smaller. In Figure A.12, treated and control villages follow similar pre-NGP trends, and the effect on remotely sensed poverty is experienced within a year after the implementation of the NGP, however there is a slight negative trend commencing just prior to the implementation of the NGP. Again the event study indicates the effects are persistent in that 7 years after the implementation of the NGP the estimates are still significant and the trend is continually increasing. These results are further broken down by cohorts in Figure A.16 and A.20 where we show consistent positive decreases in unlit settlements.

[16] On average 4P households received a monthly grant of \$2.72 per person in 2013. The program has been subjected to rigorous impact evaluations that show the CCT has successfully promoted safer facility-based birth deliveries, improved children's access to health care services, improved usage of subsidized health care benefits, encouraged children's enrolment and attendance in school, and did not show disincentive effects on adults' labor participation (Acosta and Velarde, 2015). At the national level, the 4Ps program is estimated to have reduced total poverty by 1.4 percentage points, and among the beneficiary households, the CCT reduced total poverty by 6.5 percentage points (Acosta and Velarde, 2015).

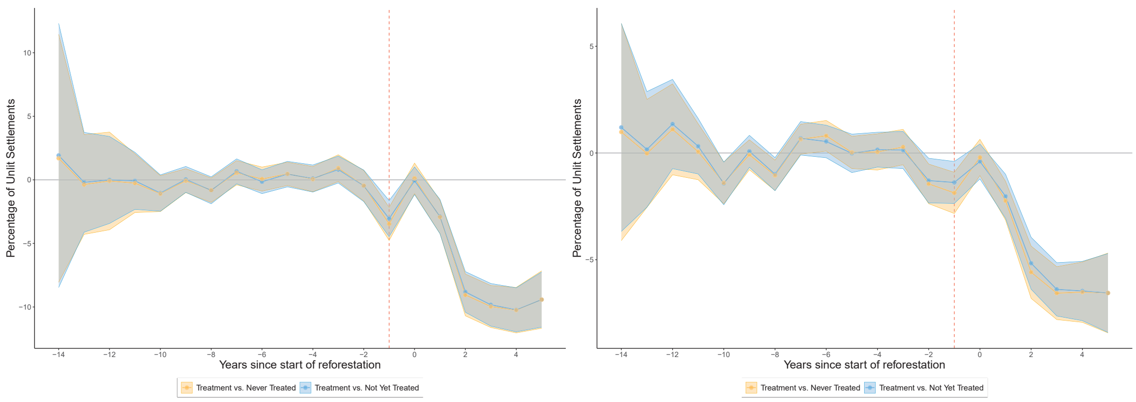
Spatial Spillovers at the Village level: The results presented in Table 7 do not take into account the potential policy-induced leakage effects from NGP treated villages onto neighboring villages. In instances where the impact of a policy change is analysed within administrative borders, but its effect is susceptible to cross administrative boundaries, traditional estimation procedures may give rise to biased results. This is due to a violation of the Stable Unit Treatment Value Assumption (SUTVA), which results in the control unit's outcomes being contaminated by the treatment. In such cases, it is possible that the control unit does not necessarily reproduce the treated unit's potential outcomes, and is therefore not a suitable counterfactual (Butts, 2023).

To address this issue we remove all immediate neighbors of treated units from the main sample, slightly modifying the approach of Butts (2023), and re-estimate the main regression with a comparison group which is constituted of villages located further away from the treated units. The results, reported in Table 7 columns 3 and 4 (Figure 4 - Panel A) identifies a 7 percentage point decrease in unlit settlements from the NGP program on the treated units, which is slightly smaller but quantitatively similar to the main results in Table 6.

To investigate whether there are spillovers, we exclude all treated units from our sample, as outlined in Section 4.2.1, and, following Ferraro and Simorangkir (2020), and assign treatment status to the immediate geographic neighbors of treated units using rook contiguity as a criterion. In this specification, the control unit i is considered treated in year t if t is the first year in which one of its neighbors is treated by the NGP program. We then run the same dynamic DID specification as the main analysis in order to identify the impact of the NGP on neighboring villages. The results of this analysis are reported in Table 7 columns 5 and 7 (Figure 4 - Panel B), and identify spillovers onto control villages, with a 4.5 - 4.6 percentage point decrease in unlit settlements.

Figure 4: Impact of NGP on Unlit Settlements at the Village Level

Panel A Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the percentage of unlit settlements using the modified sample (Panel A) and the spillover effects of the NGP had on the percentage of unlit settlements (Panel B) at the village level. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Table 7: Impact of NGP on Percent of Unlit Settlements at the Village Level

	Percentage of Unlit Settlements					
	Full Sample		Modified Sample		Spillover Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated
NGP	-5.34***	-5.45***	-6.63***	-6.68***	-4.18***	-4.28***
	(0.494)	(0.456)	(0.444)	(0.469)	(0.356)	(0.358)
Observations	390448	390448	282000	282000	325392	325392

Notes: This table presents estimates for the effect that the NGP had on the percentage of unlit settlements at the village level identified using a DID based on the roll-out of the NGP. 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment. 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Heterogeneity by Municipality and Plantation Level Characteristics

Next we examine whether there are heterogeneous impacts across different levels of baseline poverty and unlit settlements as well as scale effects across tree planting sites.

Heterogeneity by Municipality Characteristics: We first explore heterogeneity based on levels of small area poverty estimates and unlit settlements in 2010, right before the NGP was implemented. To do this we split the sample at the median to create an above median and below median group.

The results are presented in Table 8 and Figure 5 where we find differential effects between the two groups. Above median or poorer municipalities experience a reduction in poverty, but the effect is mostly concentrated in poorer municipalities that experience a reduction in poverty of around 10 percentage points. As for unlit settlements, the results again appear to be driven mostly by poorer municipalities. Municipalities with a below median level of unlit settlements experience a 9 percentage point decrease in remotely sensed deprivation. However stronger, the effect appears to level off after a couple years for municipalities with an above median level of unlit settlements.

Table 8: Heterogeneous Impact of NGP on Socio-Economic Measures

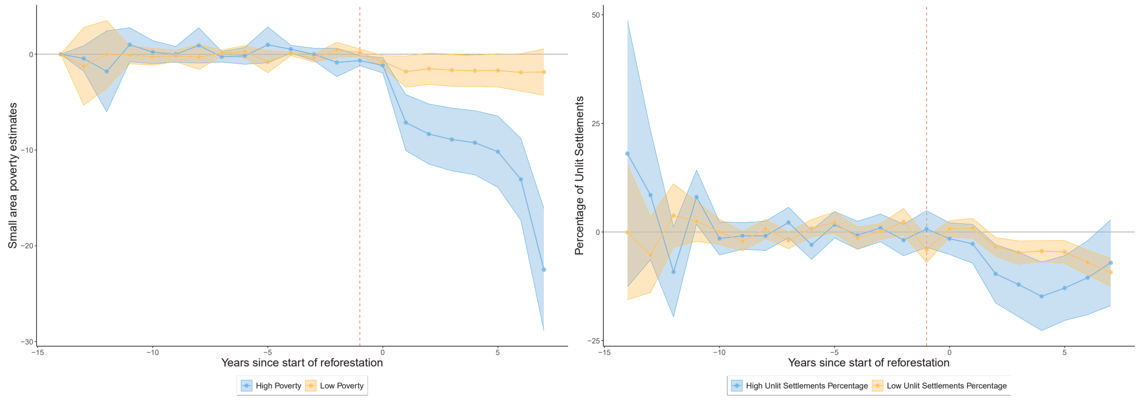
	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median
NGP	-10.06***	-1.618***	-8.915***	-3.99***
	(1.064)	(0.522)	(1.889)	(0.696)
Observations	14166	13788	10224	13986

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and log of nighttime lights identified using a DID based on the roll-out of the NGP. 'Above Median' represents municipalities with an above median ratio level of poverty or nighttime lights and 'Below Median' represents municipalities with a below median level of poverty or nighttime lights. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Heterogeneity by Plantation Level Characteristics: We next explore heterogeneity based on tree plantation characteristics. To do this, we first construct a relative measure of the total hectares planted in relation to the number of project sites. The intention of this measure is to test whether the municipalities planted many small scale plantations or planted a few large scale plantations. For example a higher ratio would indicate a small number of larger tree plantations, where as a smaller ratio would indicate a larger number of smaller tree plantations. The constructed ratio is then broken down at the median and the results are interpreted

Figure 5: Heterogeneous Impact of NGP on Socio-Economic Measures

Panel A Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on small area poverty estimates (Panel A) and the percentage of unlit settlements (Panel B). 'High Poverty' represents municipalities with an above median ratio level of poverty and 'Low Poverty' represents municipalities with a below median level of poverty. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

relative to control municipalities.

The results are presented in Table 9 and Figure 6. In terms of poverty reduction there does not appear to be much of a difference between the two groups. Remotely sensed poverty reduction appears to be stronger among municipalities with a higher ratio of hectares to plantations. Municipalities with an above average ratio of hectares to number of projects observe a 12 percentage point reduction in poverty, compared to 5 percentage points for municipalities with an above average ratio of hectares to number of projects. The results indicate that all types of projects alleviate poverty, but there is a scale effect where high hectare to project ratio ones have a relatively higher impact on economic activity.

7. Payment vs. Tree Planting Assets

In the next analysis, our aim is to separate the impacts of financial incentives provided to communities to establish and maintain tree plantations from the impact of the tree assets themselves. Our motivation lies in identifying which components of the bundled policy are necessary to generate the benefits in terms of poverty alleviation. We estimate the following regression:

$$Y_{m,t} = \beta_0 + \beta_1 NGP_{m,t} + \beta_2 ln(Payment)_{m,t} + \tau_t + \rho_{m,t} + \gamma_m + \epsilon_{m,t} \qquad (5)$$

Table 9: Impact of NGP on Socio-Economic Measures (Hectares/Projects Ratio)

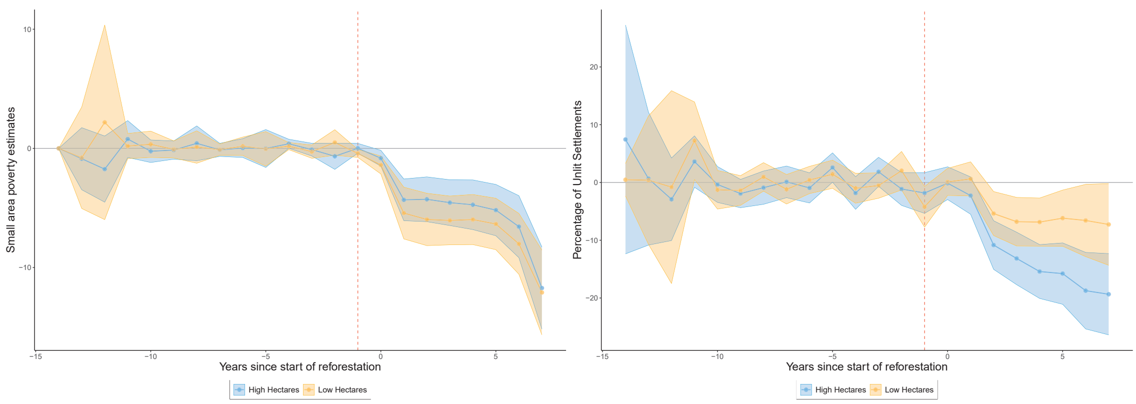
	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median
NGP	-5.273***	-6.408***	-11.957***	-4.792***
	(0.650)	(0.696)	(1.258)	(1.176)
Observations	16524	16344	14256	14688

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and log of nighttime lights identified using a DID based on the roll-out of the NGP. 'Above Median' represents municipalities with an above median ratio of hectares to number of plantations and 'Below Median' represents municipalities with a below median ratio of hectares to number of plantations. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 6: Impact of NGP on Socio-Economic Measures (Hectares/Projects Ratio)

Panel A

Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on small area poverty estimates (Panel A) and the percentage of unlit settlements (Panel B). 'High Hectares' represents municipalities with an above median ratio of hectares to number of plantations and 'Low Hectares' represents municipalities with a below median ratio of hectares to number of plantations. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

where $Y_{m,t}$ is estimated separately for small area poverty estimates and the percentage of unlit settlements for municipality m, in time t. $Payment_{m,t}$ is the log of payments received in the first three years by municipality m in time t. Time, cohort and municipality fixed effects are denoted as τ_t, $\rho_{m,t}$, and γ_m. We cluster the standard errors at the municipality level to accommodate potential intra-municipality correlation.

The results are presented in Table 10. Columns 1 and 4 initially isolate the effects on small-area poverty estimates and remotely sensed deprivation, paralleling the methodological approach in A.6. In column 2, a 1 percent increase in the payment to POs decreases small area poverty estimates by 0.24 percentage points. Conversely, column 5 shows that a 1 percent increase in payments to POs is associated with a 0.6 percentage point decrease in unlit settlements. When controlling for both the NGP intervention and payments in columns 3 and 6, the analysis shows that the receipt of both agroforestry assets and financial payments contribute to poverty reduction.

Table 10: Impact of Payment vs. Tree Planting Asset

	Small Area Poverty Estimates			Percentage of Unlit Settlements		
	(1)	(2)	(3)	(4)	(5)	(6)
NGP	-4.693***		-3.300***	-9.873***		-4.912***
	(0.553)		(0.582)	(0.918)		(1.064)
Log Payment		-0.240***	-0.128***		-0.622***	-0.452***
		(0.0253)	(0.0231)		(0.0478)	(0.0538)
Constant	35.57***	34.94***	35.57***	44.91***	43.98***	44.92***
	(0.168)	(0.0841)	(0.168)	(0.285)	(0.164)	(0.284)
Observations	26,009	26,009	26,009	24,182	24,182	24,182
R-squared	0.841	0.840	0.841	0.844	0.845	0.845
Control Mean	33.323	33.323	33.323	38.919	38.919	38.919

Notes: This table presents estimates for the effect that the NGP and payments to municipalities has on small area poverty estimates and the percentage of unlit settlements, identified using a DID based on whether a municipality received the NGP program or not. Standard errors are clustered at the municipality level. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8. Broader Sectoral Changes

Now we move on to analyze whether the NGP had broader sectoral changes in the distribution of employment as a form of structural change. Overall labor productivity growth in the economy can be achieved either through existing economic activities capital accumulation or technological changes as well as through labor moving from low-productivity to high-productivity activities (Diao *et al.*, 2019). Both of these channels are plausible as tree planting can switch agriculture production to high value crops, as well as through moving surplus labor to other sectors in the economy. Moreover, climate and environmental change can directly change the lands productivity as well as shift the relative returns to land-based livelihoods (Barrett *et al.*, 2023). Previous studies have examined China's Grain for Green program, one of the largest conservation set-aside programs in the world and found that the program has relaxed liquidity constraints for participating households and increased off-farm employment (Uchida *et al.*, 2009; Groom *et al.*, 2010; Kelly and Huo, 2013), however these studies come with significant data limitations. Gaining an understanding of whether tree planting contributes to the process of structural transformation is crucial, and empirical research in this area has been relatively unexplored.

The NGP provides a unique context to understand broader structural changes that may occur from tree planting programs as the NGP is a country-wide program that transferred a large amount of productive assets into communities as well as created jobs both directly and indirectly. In order to explore how different sectors changed as a result of the NGP, we geolocate individual's employment data from the Philippines Demographic and Health Surveys (DHS) in 2008 and 2017.[17] We use repeated cross sections of individual-level data aggregated at the municipality level to estimate the following two-period DID model:

$$Sector_{i,m,t} = \beta_0 + \beta_1 NGP_{m,t} + \tau_t + \gamma_m + \epsilon_{m,t} \tag{6}$$

where $Sector_{i,m,t}$ is estimated separately for the percentage of individuals who do not work, work in services, work in agriculture, work in unskilled manual labor or work in skilled labor for municipality m, in time t.[18] Time and municipality fixed effects are denoted as τ_t, and γ_m, respectively, and standard errors are clustered at the municipality level.

Table 11 presents the results and provides evidence that the NGP had different impacts on sectoral reallocation, where some sectors gained employment while others lost employment. First, the percentage of individuals working in the agriculture sector decreased by 3.8 percent in NGP municipalities relative to non-NGP municipalities. On the contrary, the percentage of individuals working in unskilled manual labor increased by 5.6 percent and services by 2.6 percent. Together both results provide support that individuals moved out of agriculture and some of this surplus

[17] DHS-provided GPS coordinates for enumeration areas (EAs) exhibit some degree of unreliability as they undergo adjustments before being made public. To ensure survey respondents' anonymity, DHS EA coordinates in urban locations are displaced 0-2 kilometers, rural locations are displaced 0-5 kilometers and 1 percent of the sample is displaced 0-10 kilometers. A DHS survey round exists for 2013, but there are no GPS coordinate data to attribute EA clusters to a given municipality.

[18] Services include occupations such as housekeeping and restaurant services, finance and sales associates and administrative professionals. Unskilled manual labor includes occupations such as manufacturing labor, building caretakers, mining, and construction laborers. Skilled manual labor includes textile, garment and related trades, assemblers, wood treaters, and food processing.

labor likely moved into unskilled manual labor and service sector labor. Lastly, there does not appear to be labor reallocation propagating through to skilled labor.

There are two limitations to this part of the analysis. First, the analysis looks at broad changes across sectors but due to data limitations we are unable to look at within- sector productivity changes. This is important as the reduction in individuals working in the agriculture sector could mask productivity gains as individuals move from low-productivity agriculture to high-productivity agroforestry. Second, since we only have data from two periods before and after the implementation of the NGP, we are unable to investigate how overall employment varies over time and whether the labor effects are temporary or more permanent.

Table 11: Impact of NGP on Employment in Different Sectors

	(1) Not Working	(2) Services	(3) Agriculture	(4) Unskilled	(5) Skilled
NGP	0.0342	0.0258*	-0.0379*	0.0564***	0.00221
	(0.0259)	(0.0150)	(0.0198)	(0.0196)	(0.0127)
Constant	0.430***	0.0821***	0.125***	0.0290***	0.0374***
	(0.00981)	(0.00570)	(0.00749)	(0.00743)	(0.00480)
Observations	488	488	488	488	488
Treated Municipalities	370	370	370	370	370
Control Municipalities	118	118	118	118	118
R-squared	0.611	0.594	0.741	0.603	0.634

Notes: This table presents estimates for the effect that the NGP has on employment in different sectors, identified using a DID based on whether a municipality received the NGP program or not. Standard errors are clustered at the municipality level. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

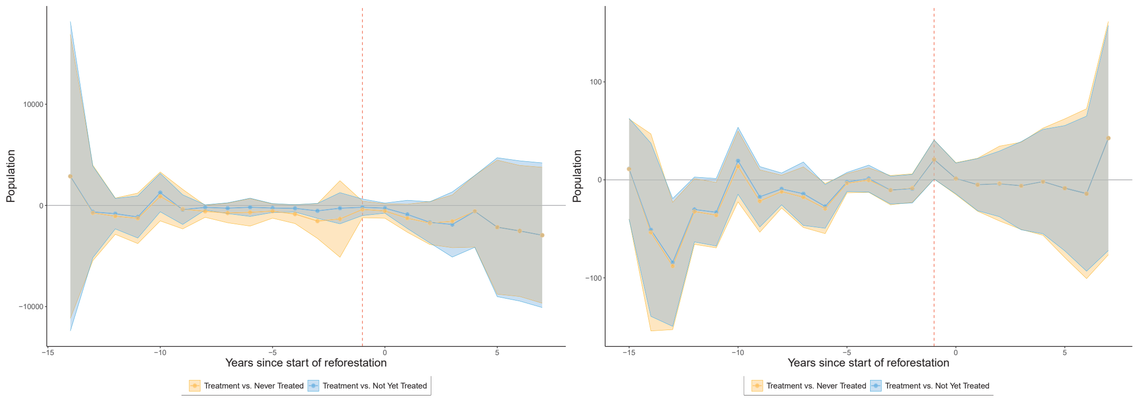
8.1. Changes in Labor Supply

Next, we investigate whether the NGP lead to broader changes in labor supply. One could argue that the estimated impacts on poverty alleviation could be the result of changes to labor supply through either population growth or migration. In order to investigate this channel we re-estimate equation (1) and (2) where the dependent variable is the population for municipality m in time t or village v in time t, respectively. Remotely sensed population estimates provide yearly high-resolution disaggregated census counts within administrative boundaries, and capture the full potential activity space of people throughout the course of the day and night rather than just a residential location (Sims *et al.*, 2022).

The results are presented in Figure 7 where Panel A presents the results at the municipality level and Panel B presents the results at the village level. At both the municipality and village level, we find no evidence that the NGP changed the level of population relative to either control. This further provides evidence that the tree planting program generated economic activity rather than economic activity being spurred on by changes in the labor supply or inducing migration.

Figure 7: Impact of NGP on Population

Panel A Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on population at the municipality level (Panel A) and at the village level (Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

9. Valuing the Sequestration Benefits of the NGP

Last, we calculate the yearly amount of CO_2 sequestered per tree plantation, the total amount of CO_2 sequestered by the NGP, the cost per ton of CO_2 emissions, the average break-even points at the plantation level for when the benefits derived from sequestering CO_2 surpass the implementation costs, and finally, the total monetary benefit from sequestering CO_2.

In order to make the back of the envelope-calculations, we rely on estimates provided by Balangue (2016) who calculated the annual rate of carbon sequestration per hectare using a 99 hectare NGP plantation.[19] Two estimates are provided for the dominant tree species and the co-dominant tree species within the plantation. We use the dominant tree species annual CO_2 sequestration rate per hectare to provide a high end estimate (high sequestration) and the co-dominant tree species to provide a low end estimate (low sequestration).

We first calculate how much CO_2 is sequestered by the NGP by taking the CO_2 sequestration rate per hectare and multiplying it by the number of hectares for

[19] Balangue (2016) first calculates the total biomass in volume of a tree by using the potential stumpage area, the crown volume, and the root volume. To convert the volume of the tree to tons, the total biomass of the tree is multiplied by a factor of 0.7 tons per cubic meter of wood. Lastly, to derive how much CO_2 is sequestered per tree, the density of the wood is multiplied by a factor of 0.35 carbon per ton of wood.

each of the 80,522 plantations. This derives the annual metric tons of sequestered CO_2 per plantation. In Figure 8 we plot the average yearly amount of sequestered CO_2 (in metric tons) per plantation. Summing up the annual sequestered CO_2 per plantation, we find that in total, the NGP sequestered between 71.4 $MtCO_2$ (low sequestration rate) and 303 $MtCO_2$ (high sequestration rate) over 10 years. Using the more conservative low sequestration estimate, this is equivalent to the greenhouse gas emissions from 16,993,330 gasoline-powered passenger vehicles driven in one year or the CO_2 emissions from 18.4 coal-fired power plants in one year.[20] For policymakers focused exclusively on carbon emissions, the NGP reduces CO_2 emissions at a cost ranging from \$2 to \$10 per ton. This is the same range that other reforestation programs estimate for dollars per ton of CO_2 (Jayachandran *et al.*, 2017; Jack, 2013), and is significantly below most available technologies today (Gillingham and Stock, 2018).[21]

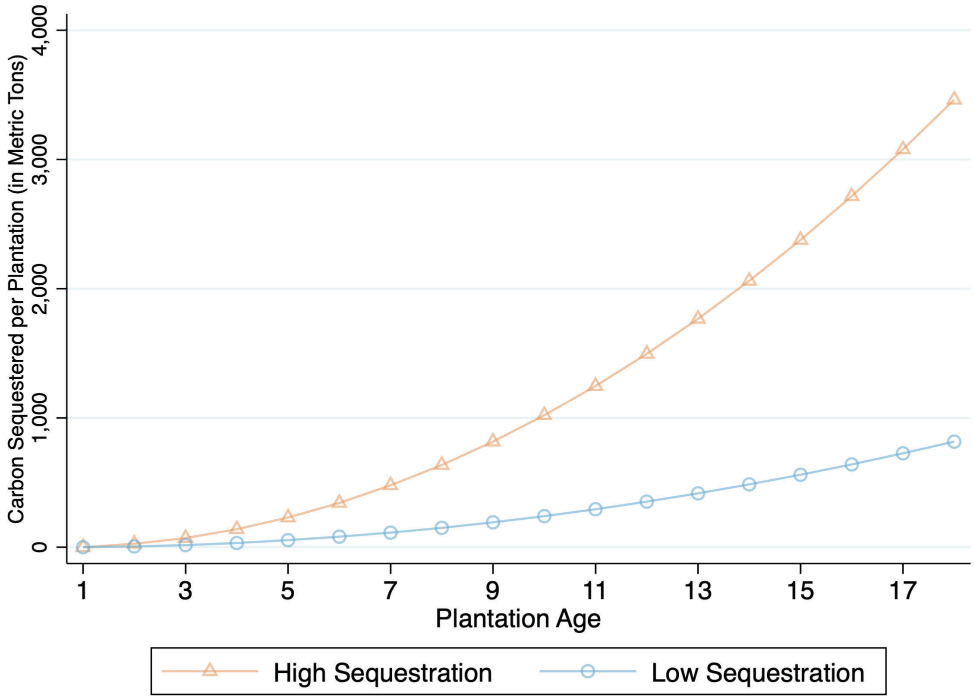
Next, we calculate the economic value associated with a permanent reduction of CO_2 in the atmosphere by converting the sequestered amount of CO_2 into a monetary valuation. We first multiply the total annual CO_2 sequestered per plantation by the annual social cost of carbon under a 3 percent and 5 percent discount rate (US EPA, 2016).[22] To determine break-even points, we subtract the annual monetary benefits derived from the sequestered CO_2 minus the annual costs (3 year payments to the communities for preparation, planting and maintenance). Figure 9 plots the average plantation's yearly CO_2 sequestration benefits, highlighting that the positive benefits commence between years 6 and 9 at a 3 percent discount rate. By summing the total annual monetary benefits over 10 years and subtracting the total annual costs for each plantation, we estimate that the NGP sequestered CO_2 valued between \$163 million and \$9.57 billion.

[20] This is equivalent to planting 1,180,605,139 tree seedlings grown for 10 years, which quantitatively reaffirms the figure reported in Table 1, where the program claims to have planted 1,369,762,802 seedlings in the first 6 years.

[21] There is still an important distinction to be made based on temporary and permanent forest sequestration as POs could still decide to cut down timber producing plantations or convert NGP plantations to another land use later on. However, Groom and Venmans (2023) outline an approach that in principle illustrates that delaying emissions, even when offset projects are temporary and risky, is still valuable in welfare terms.

[22] We opt for conservative estimates for the social cost of carbon and follow Berkouwer and Dean (2022) in their valuation of charcoal consumption emissions reductions. US EPA (2016) estimates for the social cost of carbon at a 3 percent discount rate range from \$31 in 2010 to \$47 per ton of carbon in 2026. However, recent estimates for the social cost of carbon range from \$40-\$100 (Cai and Lontzek, 2019) up to \$185 per ton of carbon (Rennert *et al.*, 2022).

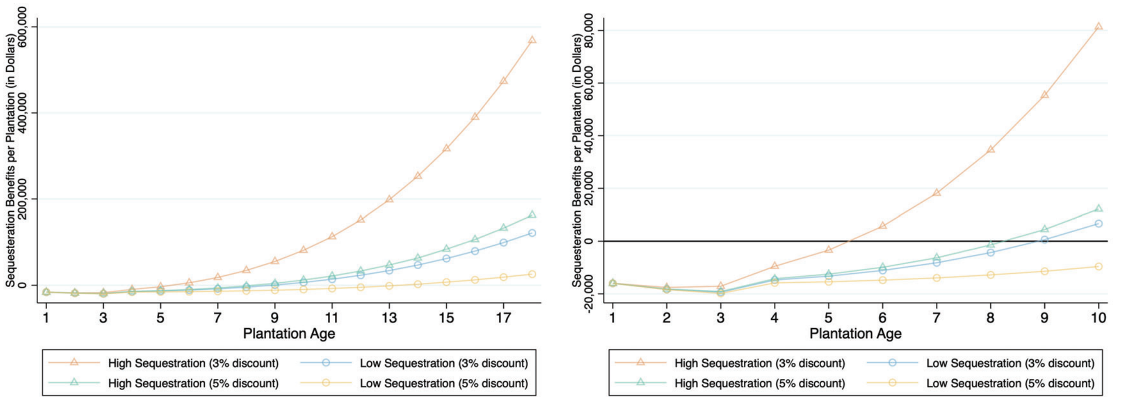
Figure 8: Sequestered Carbon per Plantation



Notes: This figure plots the average plantation's yearly amount of sequestered CO_2 in metric tons. High sequestration refers to the CO_2 sequestration rate per hectare of the dominant tree species and the low sequestration refers to the CO_2 sequestration rate per hectare of the co-dominant tree species.

Figure 9: Carbon Sequestration Benefits per Plantation

Panel A Panel B



Notes: This figure plots the average plantation's yearly benefits from sequestering CO_2 in dollars. High sequestration refers to the CO_2 sequestration rate per hectare of the dominant tree species and low sequestration refers to the CO_2 sequestration rate per hectare of the co-dominant tree species. For each of the sequestration rates we additionally apply a 3 percent and 5 percent discount rate to the social cost of carbon calculation. Panel B zooms in to show how delayed carbon benefits heavily depend on the discount rate.

10. Conclusions

The current global enthusiasm around tree planting as a means of climate change mitigation and adaptation has raised several questions about the optimal design of such projects and the ancillary economic and ecological benefits. In this paper, we study the National Greening Program (NGP), which planted billions of trees in the Philippines from 2011 to 2016. We implement a dynamic difference-in-differences identification strategy that compares the pre-planting and post-planting periods between earlier treated NGP municipalities and a pool of municipalities who have either 'not-yet' been treated by the time of the program implementation, or are never treated throughout the duration of the panel.

Our main results show that the NGP lead to a reduction in traditionally measured poverty of 6 percentage points, and a decrease in the percentage of unlit settlements of 8 percentage points. Furthermore, we set up a novel approach that measures spillover effects by taking advantage of high frequency village level data for when control villages experience a neighbor receiving the NGP. The results indicate that neighboring control villages experience a decrease in remotely sensed poverty of 4.5 percentage points when their neighbor receives the NGP. We then examine broader structural changes and find evidence of sectoral reallocation, as municipalities that received the NGP experienced a decrease in the percentage of individuals working in agriculture and an increase in the percentage of individuals working in unskilled manual labor and service sector labor. Last, we show that the economic activity generated by the NGP is not likely due to changes in labor supply. Taken together, the NGP appears to have created economic activity through transferring agroforestry assets to communities and shifting individuals into higher productivity sectors.

There are nonetheless valid concerns around large-scale tree planting such as the land required, the timing and permanence of the CO_2 reductions and the potential ecological impacts (Grosset *et al.*, 2023). Critics argue that extensive afforestation initiatives may result in the loss of cropland and consequently compromise food security. Another concern surrounding the use of tree planting as a climate change mitigation strategy is the issue of timing. Although greenhouse gas emissions reductions occur immediately, trees take years to grow. Moreover, the permanence of tree planting as a solution is also in question due to the risk of large-scale mortality caused by drought, invasive species, cyclones, and wildfires (Leverkus *et al.*, 2022). Applying simple planting strategies across a broad spectrum of landscapes can provide a limited set of ecological services (Lamb *et al.*, 2005) and reduce native biodiversity (Xu, 2011; Hua *et al.*, 2016). Tree plantations are frequently characterized by densely packed monocultures of non-native species, established to meet growing commercial demands and minimize reliance on natural forest exploitation (Chazdon *et al.*, 2016; D'Amato *et al.*, 2017; Pirard *et al.*, 2016; Dasgupta, 2021). While these aspects are important to keep in mind when designing future tree planting projects, the results of this study show that large-scale tree planting is possible to align climate mitigation and poverty reduction policies.

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A. Appendix

A.1. Summary Statistics

Table A.1: Summary statistics at the municipality level

Variable	Mean	SD	Min	Max	N
Small Area Poverty Incidence	33.3	18	0.28	97.5	28907
Unlit Settlements (%)	38.1	36.7	0	100	27417
Nighttime lights (DN)	3.15	5.88	0	48.3	29322
Forest Cover (ha)	676	1349	0	18776	29268
Number of NGP projects	14.8	42.5	1	744	5605
Extent of NGP projects (ha)	238	456	0.05	17223	5605
Cash transfer (PHP)	914803	2437032	0	97643312	13032
Population count	57434	118640	0	2898835	29322
Precipitation (mm)	235	70.5	87.1	640	28998
Maximum temperature (°C)	30.6	1.42	20.1	33.6	28998
Minimum temperature (°C)	22.8	1.48	12.6	25.7	28998
Wind speed (m/s)	1.94	0.503	0.451	3.87	28998
Slope	7.31	5.06	0.367	25.1	29286
Elevation	234	271	2.32	1899	29286
Unemployment (%)	0.457	0.167	0	1	1148
Agricultural employment (%)	0.124	0.155	0	1	1148
Services employment (%)	0.0838	0.0752	0	0.407	1148
Unskilled manufacturing empl. (%)	0.0329	0.0627	0	0.667	1148
Skilled manufacturing empl. (%)	0.0487	0.072	0	1	1148
Access to highways	19.5	13.9	1	168	28044
Access to markets	4.42	4.74	1	78	26226
Commercial establishments (2010)	299	599	0	14545	28602
Manufacturing establishments (2010)	43.2	107	0	3105	28602
Bank establishments (2010)	11	45.5	0	1184	28602
Affected by typhoon Haiyan (%)	0.381	0.486	0	1	29322
Received CCT (%)	0.357	0.479	0	1	29322
Located in Mindanao province (%)	0.234	0.424	0	1	29322

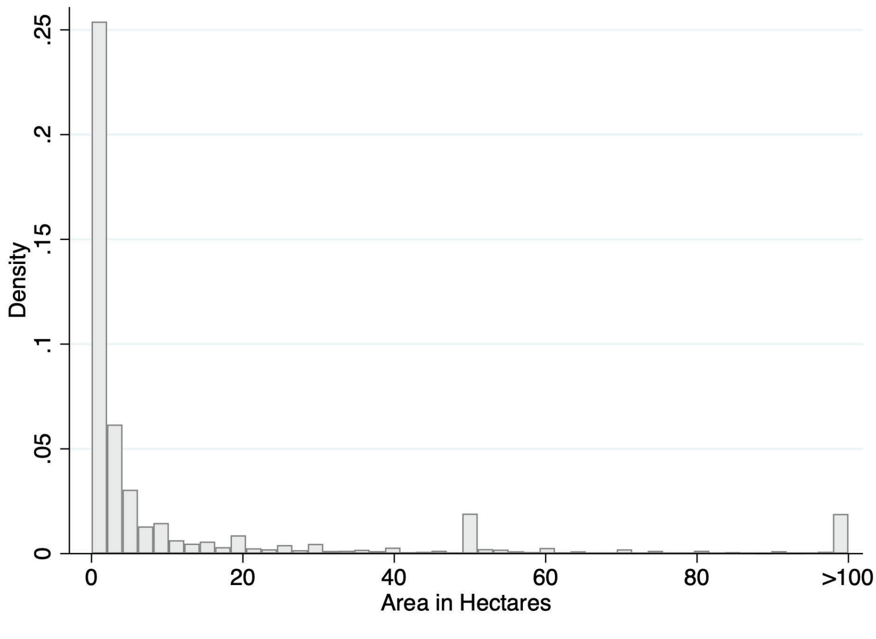
Notes: This table presents summary statistics at the municipality level for each of the variables used in the analysis.

Table A.2: Summary statistics at the village level

Variable	Mean	SD	Min	Max	N
Unlit Settlements (%)	30	39.8	0	100	515574
Nighttime lights (DN)	1.68	2.91	0	37.7	783104
Number of NGP projects	0.104	2.03	0	362	783104
Extent of NGP projects (ha)	79	154	0	6318	16623
Cash transfer (PHP)	35303	264028	0	28294182	329728
Population count	2246	5815	0	269881	783104
Precipitation (mm)	231	69.6	68.2	662	776074
Maximum temperature (°C)	30.9	1.23	18.4	34	776074
Minimum temperature (°C)	23.2	1.3	11	25.8	776074
Wind speed (m/s)	1.96	0.521	0.417	3.92	776074
Slope	4.97	5.06	0	32.7	783104
Elevation	151	248	-1.02	2203	783104

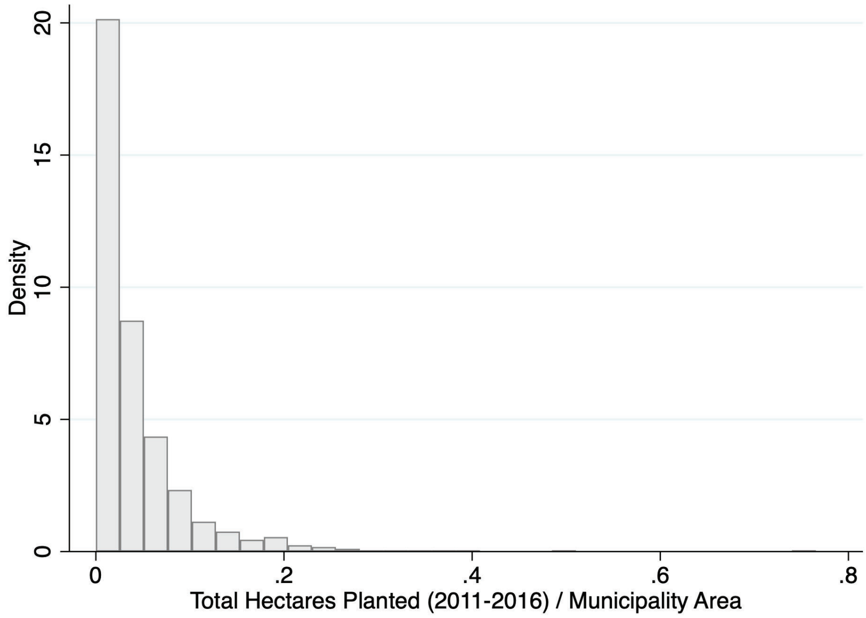
Notes: This table presents summary statistics at the village level for each of the variables used in the analysis.

Figure A.1: Distribution of Tree Planting Sites by Hectares



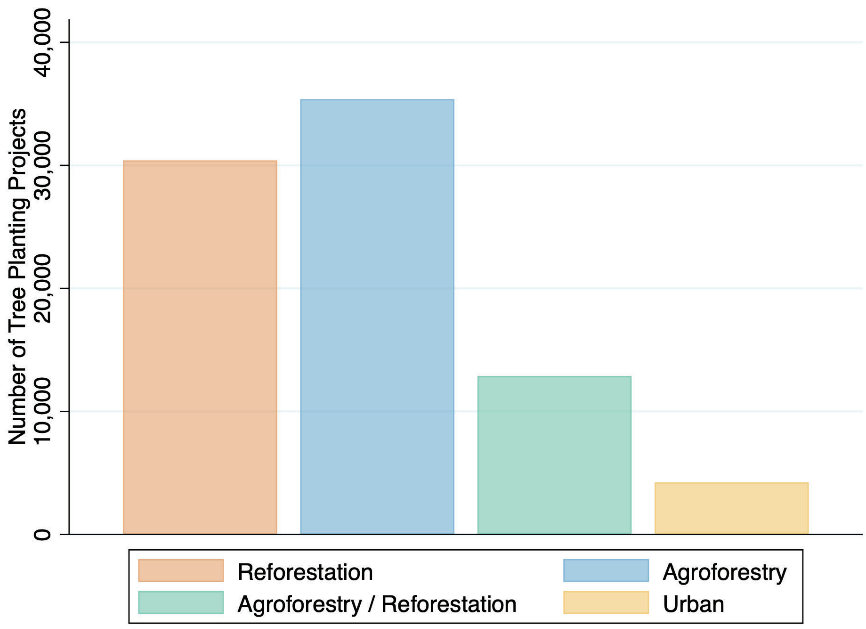
Notes: This figure plots the distribution of each tree planting site's area in hectares. The average tree planting site is 16 hectares.

Figure A.2: Distribution of Total Tree Planting Area Relative to Municipality Area



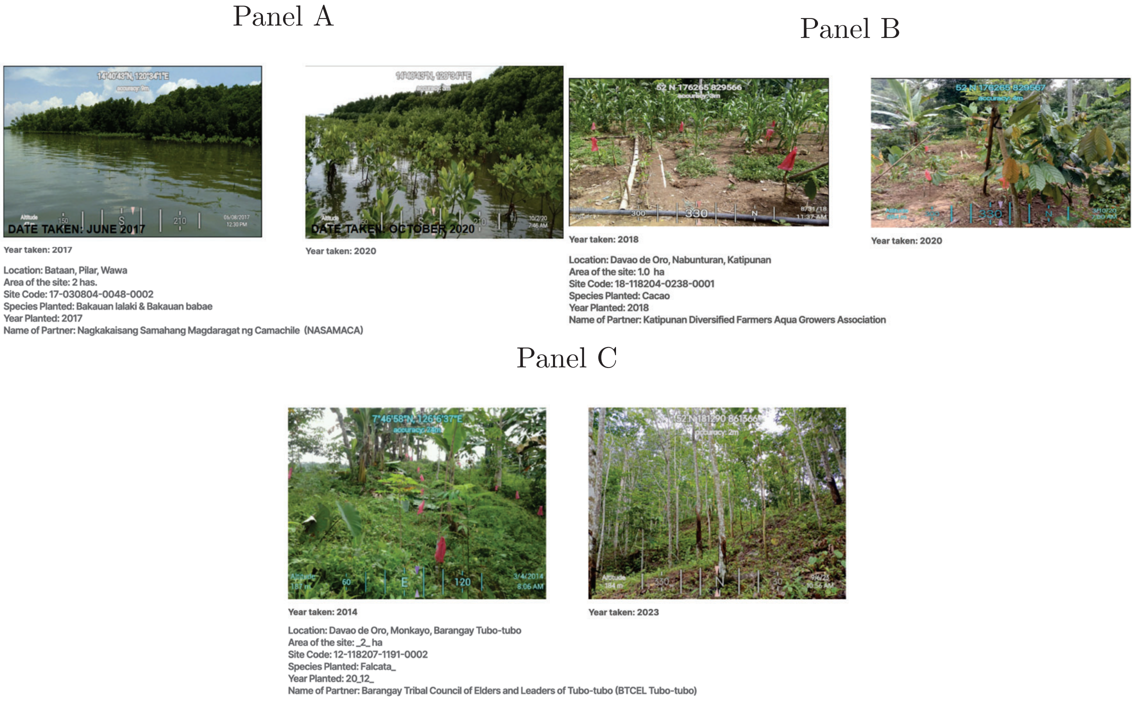
Notes: This figure plots the distribution of the total number of hectares planted from 2011 - 2016 relative to the municipality area.

Figure A.3: Classification of Tree Planting Sites



Notes: This figure classifies the number of tree planting projects into reforestation, agroforestry, agroforestry / reforestation, and urban reforestation.

Figure A.4: Before and After Geo-tagged Photos of NGP Plantations



Notes: This figure shows three before and after geo-tagged photos of NGP plantations. Photos taken by the National Greening Program Coordinating Office, Forest Management Bureau.

A.2. Pre-treatment Balance Tests

Table A.3: Balance Across Municipality Geographic Characteristics, 2010

Geographic Characteristics	(1) Early Treated (2011 - 2013)	(2) Late Treated (2014 - 2016)	(3) Early vs Late Treated
Municipality Area	1.213e+08***	4.656e+07***	7.469e+07***
	(1.178e+07)	(1.339e+07)	(2.318e+07)
Slope	3.578***	2.226***	1.352**
	(0.305)	(0.553)	(0.570)
Elevation	105.5***	26.13	79.37**
	(16.90)	(29.83)	(31.05)
Log Population	0.0891	-0.357**	0.446***
	(0.0705)	(0.178)	(0.115)
Observations	1,557	404	1,317

Notes: This table presents pre-treatment estimates from a balance test across different geographic characteristics in 2010 for (1) earlier treated municipalities (2011 - 2013) vs. control municipalities, (2) later treated municipalities (2014 - 2016) vs. control municipalities, and (3) earlier treated municipalities (2011 - 2013) vs. later treated municipalities (2014 - 2016). Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

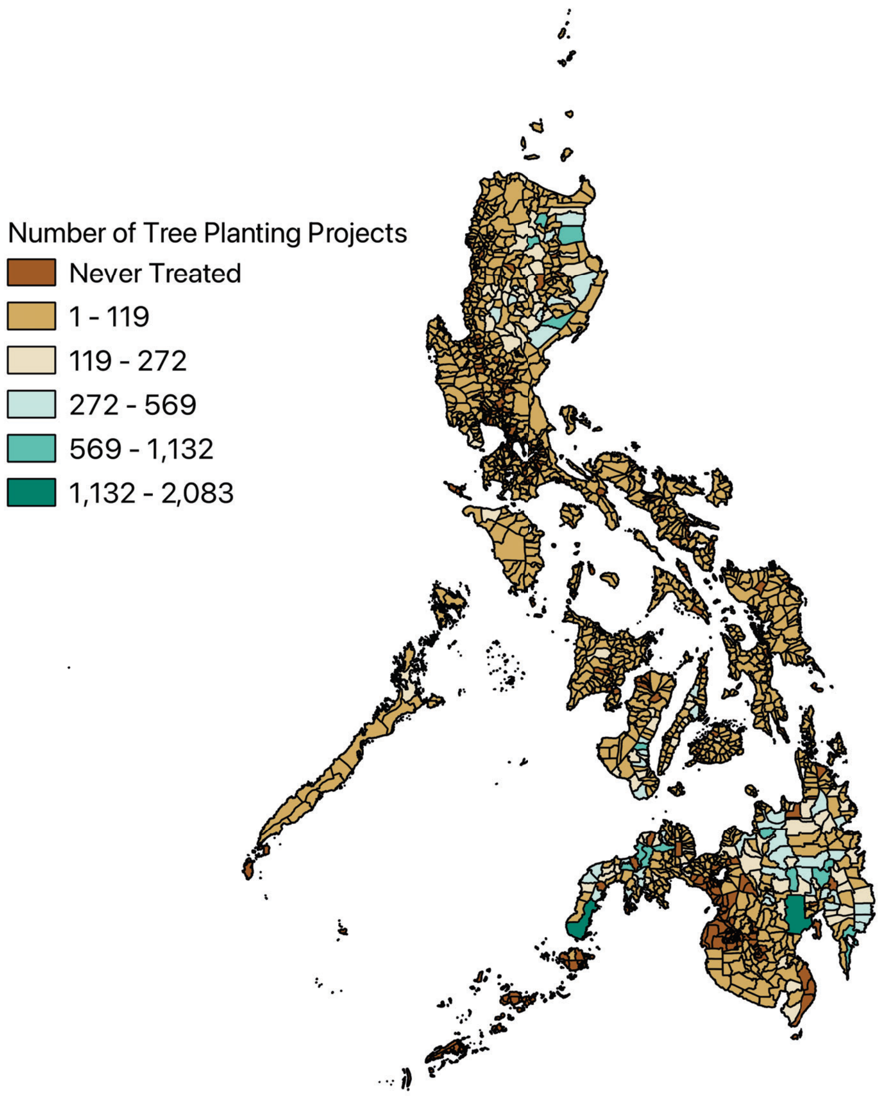
Table A.4: Balance Across Municipality Market Access Characteristics, 2010

Market Access Characteristics	(1) Early Treated (2011 - 2013)	(2) Late Treated (2014 - 2016)	(3) Early vs Late Treated
Access to National Highway	5.304***	0.315	4.989***
	(0.886)	(1.822)	(1.535)
Number of Markets	0.0930	-1.368*	1.461***
	(0.297)	(0.716)	(0.475)
Number of Commercial Establishments	-48.67	-145.6	96.89**
	(37.62)	(113.2)	(49.21)
Number of Manufacturing Establishments	-19.11***	-35.55	16.44***
	(6.718)	(23.27)	(6.192)
Number of Bank Establishments	-11.84***	-14.26	2.415
	(2.851)	(10.30)	(2.187)
Average Bus Ticket Price	-3.764	-10.72	6.951
	(11.25)	(14.17)	(21.36)
Observations	1,559	404	1,319

Notes: This table presents pre-treatment estimates from a balance test across different measures of market access in 2010 for (1) earlier treated municipalities (2011 - 2013) vs. control municipalities, (2) later treated municipalities (2014 - 2016) vs. control municipalities, and (3) earlier treated municipalities (2011 - 2013) vs. later treated municipalities (2014 - 2016). Access to national highway represents the number of villages within a municipality that have access to the national highway. Significant at $^{*}p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

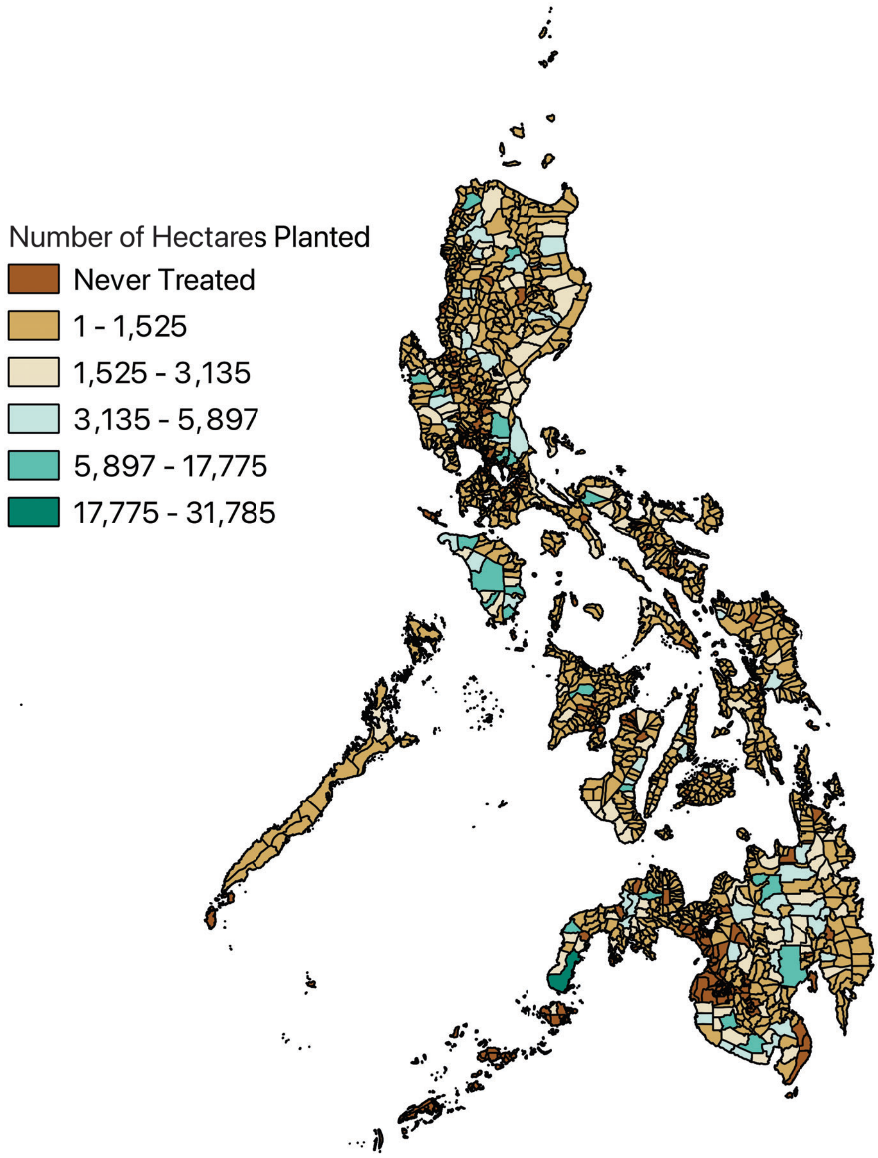
A.3. Additional Figures

Figure A.5: Number of tree planting projects per municipality, 2011 - 2016



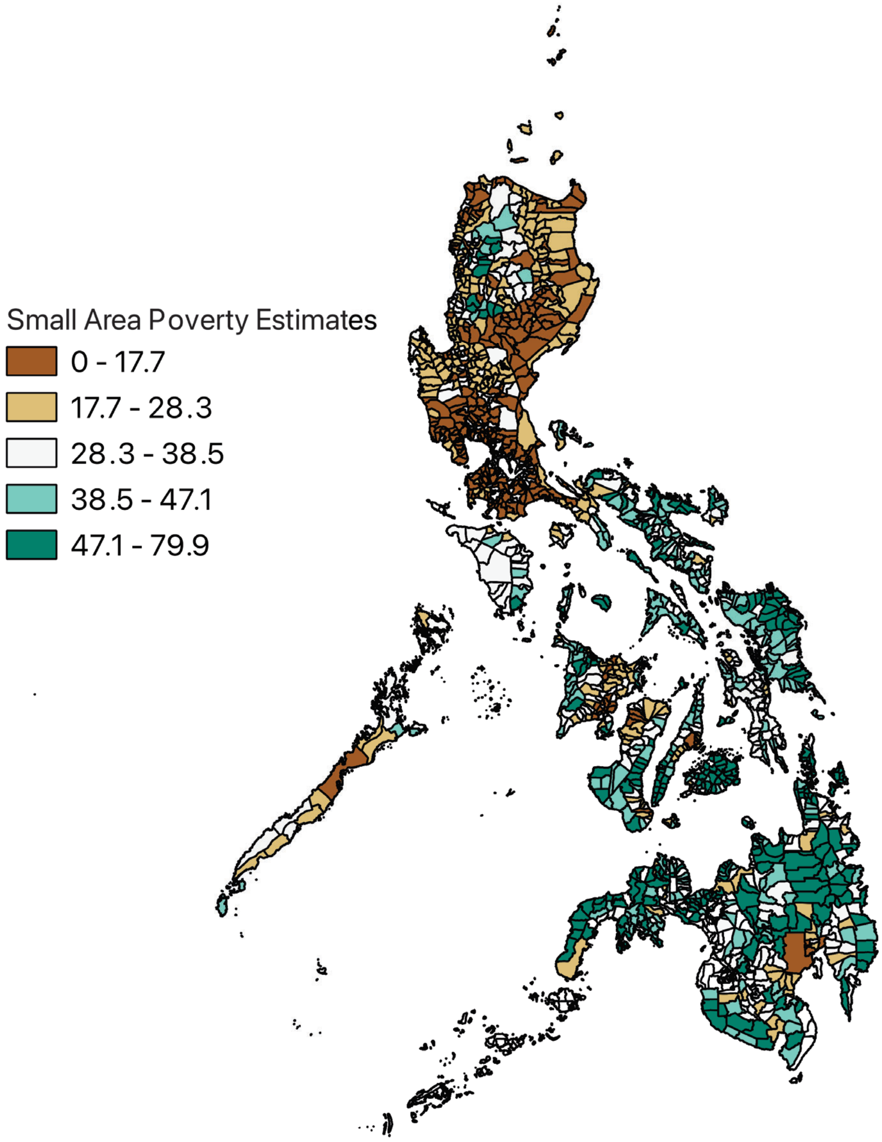
Notes: This figure presents the cumulative number of tree planting projects implemented in each municipality from 2011 - 2016. *Source*: Author's own calculations.

Figure A.6: Number of hectares planted per municipality, 2011 - 2016



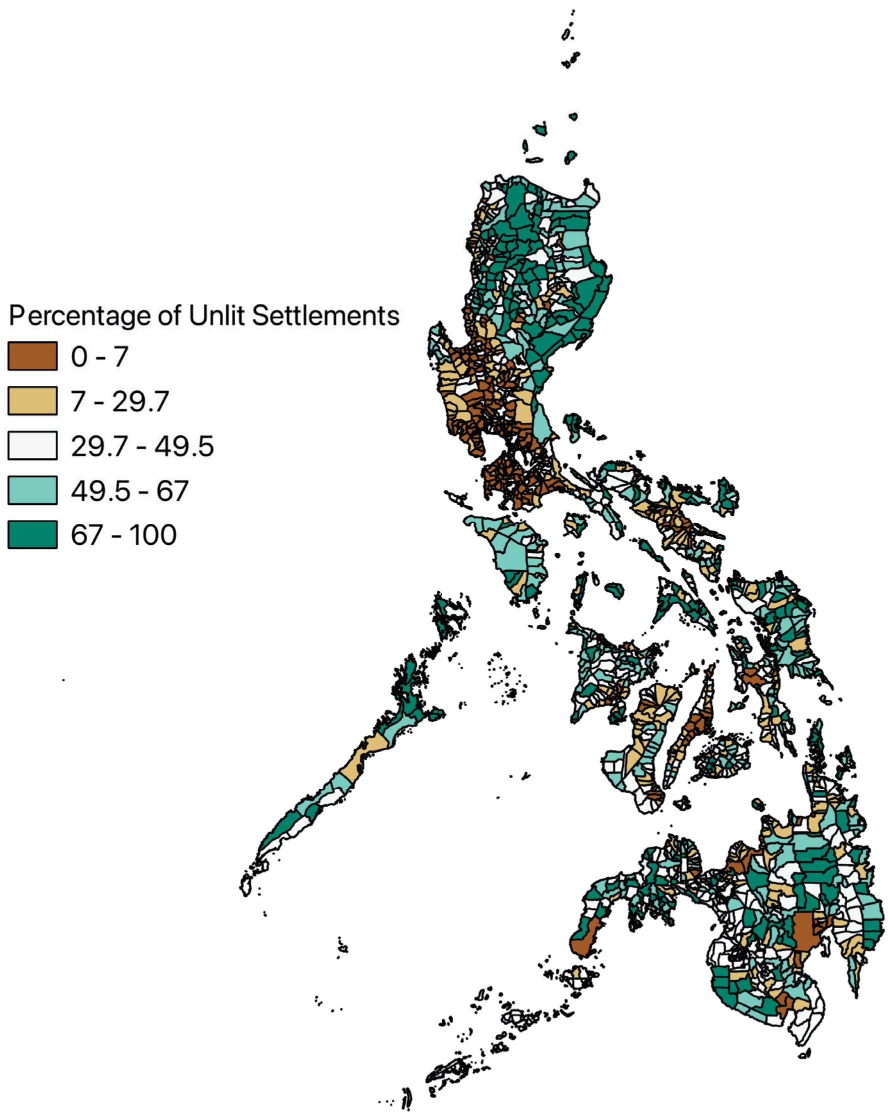
Notes: This figure presents the cumulative number of hectares planted in each municipality from 2011 - 2016. *Source*: Author's own calculations.

Figure A.7: Small Area Poverty Estimates, 2010



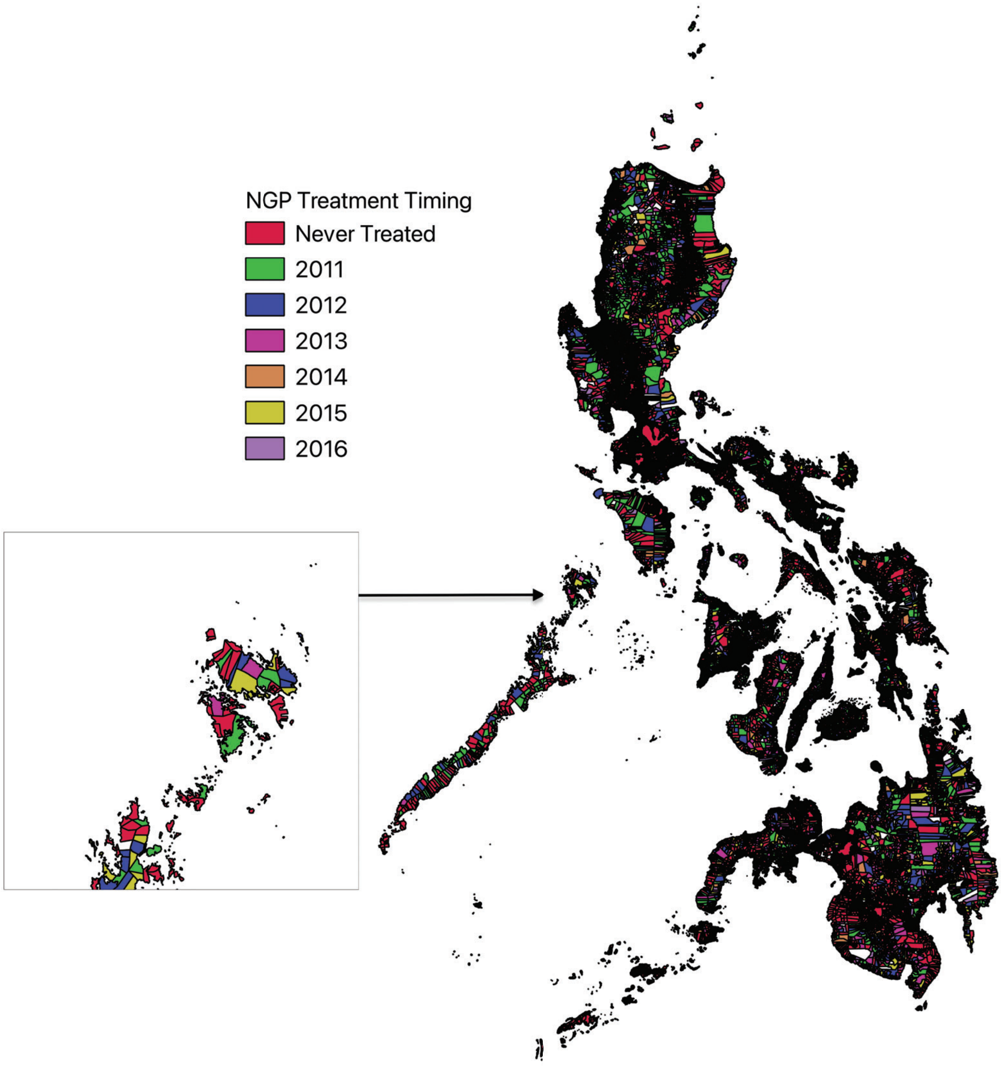
Notes: This figure presents the small area poverty estimates in 2010. *Source*: Author's own calculations.

Figure A.8: Percentage of Unlit Settlements, 2010



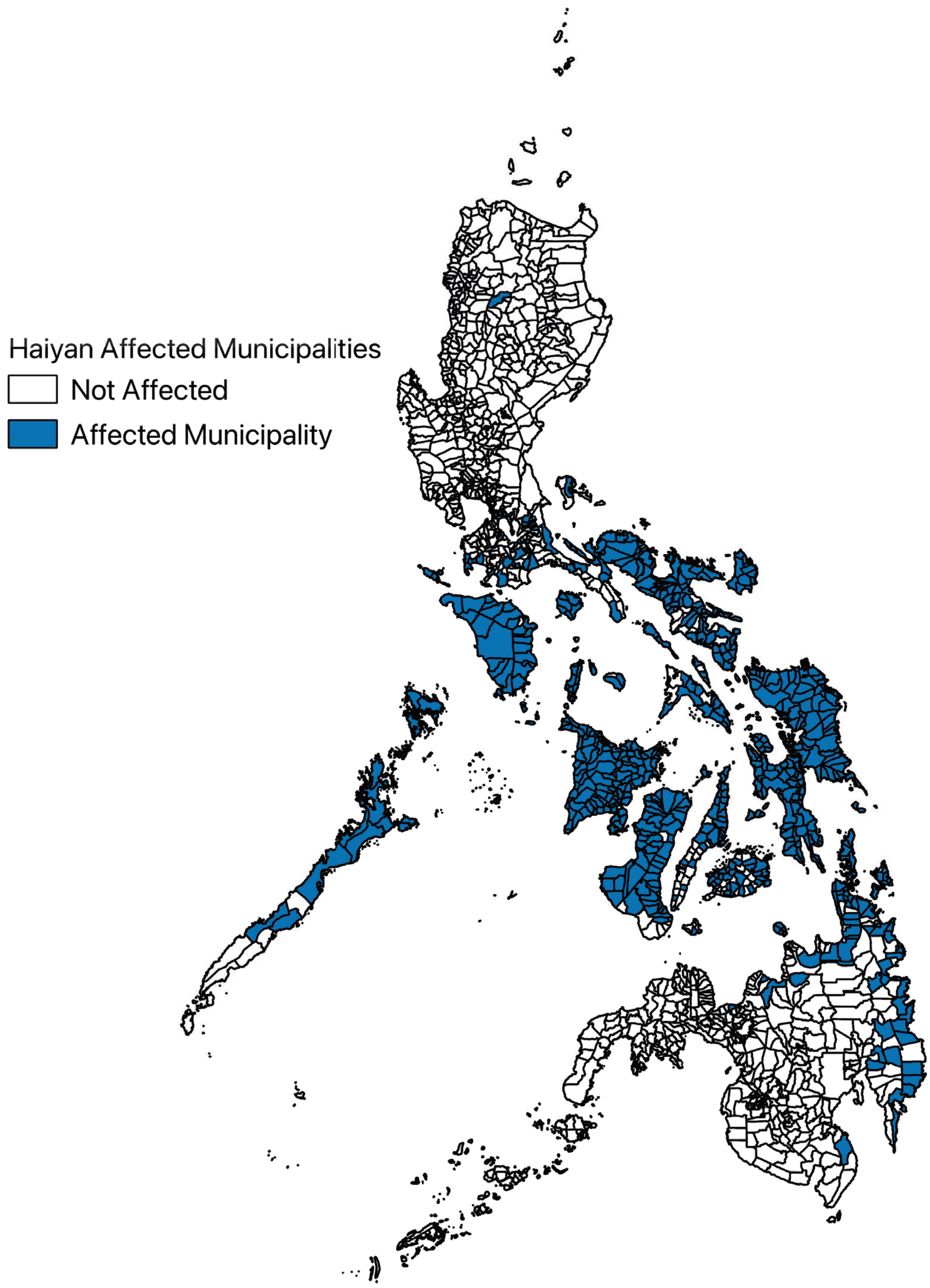
Notes: This figure presents the percentage of unlit settlements in 2010. *Source*: Author's own calculations.

Figure A.9: Village-level NGP Timing by Treatment Pool



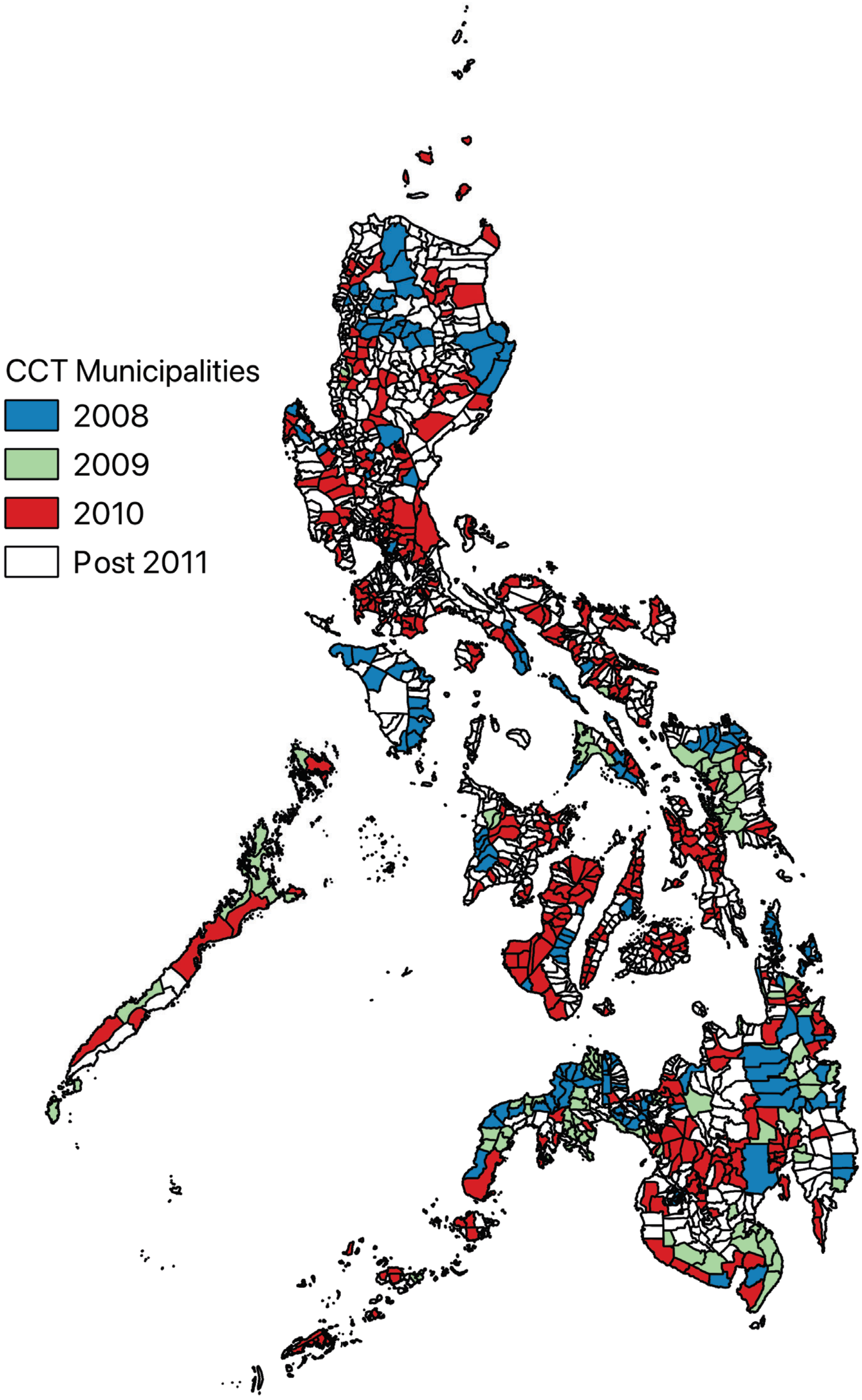
Notes: This figure presents identifying variation for the year in which villages first received an NGP project. *Source*: Author's own calculations.

Figure A.10: Typhoon Haiyan Affected Municipalities, 2013



Notes: This figure presents identifying variation for the municipalities that were affected by Typhoon Haiyan in 2013. *Source*: Author's own calculations based on data from the National Disaster Risk Reduction and Management Council (NDRRMC).

Figure A.11: 4Ps CCT Timing by Treatment Pool



Notes: This figure presents identifying variation for the year in which municipalities first received the 4P's CCT program. *Source*: Author's own calculations based on data from Fernandez and Olfindo (2011).

A.4. Additional Tables

Table A.5: Impact of NGP on Socio-Economic Measures

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated
NGP	-3.125***	-2.861***	-4.348**	-5.583**
	(0.619)	(0.708)	(2.186)	(2.659)
Controls	✓	✓	✓	✓
Observations	24984	24768	21546	21546

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and percentage of unlit settlements identified using a DID based on the roll-out of the NGP. 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment. 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Control variables are: population, precipitation, maximum temperature, slope, elevation, number of villages with access to the national highway, number of markets, number of commercial establishments, number of bank establishments. All time-invariant coefficients are interacted with a linear time trend. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4.1. Alternative Estimators

Table A.6: Impact of NGP on Socio-Economic Measures: Standard TWFE-DID

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
DID_{TWFE}	-4.636***	-3.522***	-8.301***	-5.301***
	(0.4602)	(0.4414)	(0.8810)	(0.9131)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	28,907	25,827	29,322	26,028
Adjusted R^2	0.86529	0.86588	0.91762	0.91991

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and percentage of unlit settlements identified using a standard TWFE DID design. Standard errors clustered at the municipality level are reported in parentheses. Control variables are: population, precipitation, maximum temperature, slope, elevation, number of villages with access to the national highway, number of markets, number of commercial establishments, number of bank establishments. All time-invariant coefficients are interacted with a linear time trend. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Impact of NGP on Socio-Economic Measures: Staggered DID following Sun and Abraham (2021)

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
DID_{SA}	-6.388***	-5.685***	-7.542***	-5.772***
	(0.6056)	(0.6272)	(1.110)	(1.204)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	28,907	25,827	29,322	26,028
Adjusted R^2	0.86695	0.86702	0.92043	0.92201

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and percentage of unlit settlements identified using a DID based on the roll-out of the NGP using the Sun and Abraham (2021) procedure. Standard errors clustered at the municipality level are reported in parentheses. Control variables are: population, precipitation, maximum temperature, slope, elevation, number of villages with access to the national highway, number of markets, number of commercial establishments, number of bank establishments. All time-invariant coefficients are interacted with a linear time trend. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Table A.8: Impact of NGP on Socio-Economic Measures: Staggered DID following De Chaisemartin and d'Haultfoeuille (2024)

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
DID_{SA}	-5.412***	-4.738***	-7.317***	-6.405***
	(0.5239)	(0.5658)	(1.015)	(1.195)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	12,040	10,719	11,325	10,135

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates and percentage of unlit settlements identified using a DID based on the roll-out of the NGP using the De Chaisemartin and d'Haultfoeuille (2024) procedure. Standard errors clustered at the municipality level are reported in parentheses. Control variables are: population, precipitation, maximum temperature, slope, elevation, number of villages with access to the national highway, number of markets, number of commercial establishments, number of bank establishments. All time-invariant coefficients are interacted with a linear time trend. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Table A.9: Impact of NGP on Small Area Poverty Estimates: Robustness

	Excluding Haiyan		Excluding Mindanao		Excluding CCT	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated	(5) Not Yet Treated	(6) Never Treated
NGP	-6.892***	-7.063***	-2.048***	-2.051***	-5.421***	-5.582***
	-0.808	-0.811	-0.449	-0.461	-0.691	-0.703
Observations	17010	17010	21780	21780	17910	17910

Notes: This table presents estimates for the effect that the NGP had on small area poverty estimates identified using a DID based on the roll-out of the NGP. Columns 1 and 2 exclude municipalities affected by Typhoon Haiyan, columns 3 and 4 exclude municipalities in the region of Mindanao, and columns 5 and 6 exclude municipalities that received the 4Ps CCT prior to the NGP. Standard errors clustered at the municipality level are reported in parentheses. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

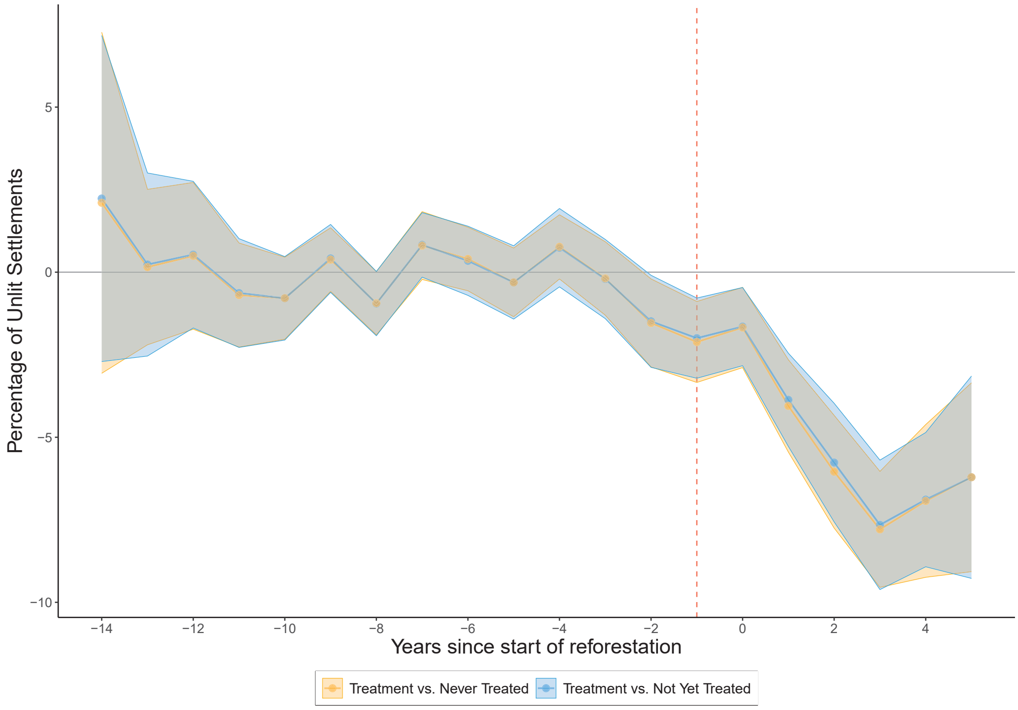
Table A.10: Impact of NGP on Unlit Settlements: Robustness

	Excluding Haiyan		Excluding Mindanao		Excluding CCT	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated	(5) Not Yet Treated	(6) Never Treated
NGP	-8.633***	-8.453***	-9.657***	-9.791***	-7.485***	-7.499***
	(1.249)	(1.323)	(1.108)	(1.201)	(1.164)	(1.256)
Observations	14562	14562	19098	19098	15984	15984

Notes: This table presents estimates for the effect that the NGP had on the percentage of unlit settlements identified using a DID based on the roll-out of the NGP. Columns 1 and 2 exclude municipalities affected by Typhoon Haiyan, columns 3 and 4 exclude municipalities in the region of Mindanao, and columns 5 and 6 exclude municipalities that received the 4Ps CCT prior to the NGP. Standard errors clustered at the municipality level are reported in parentheses. Significant at $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.5. Village-level Impacts

Figure A.12: Impact of NGP on Unlit Settlements at the Village Level



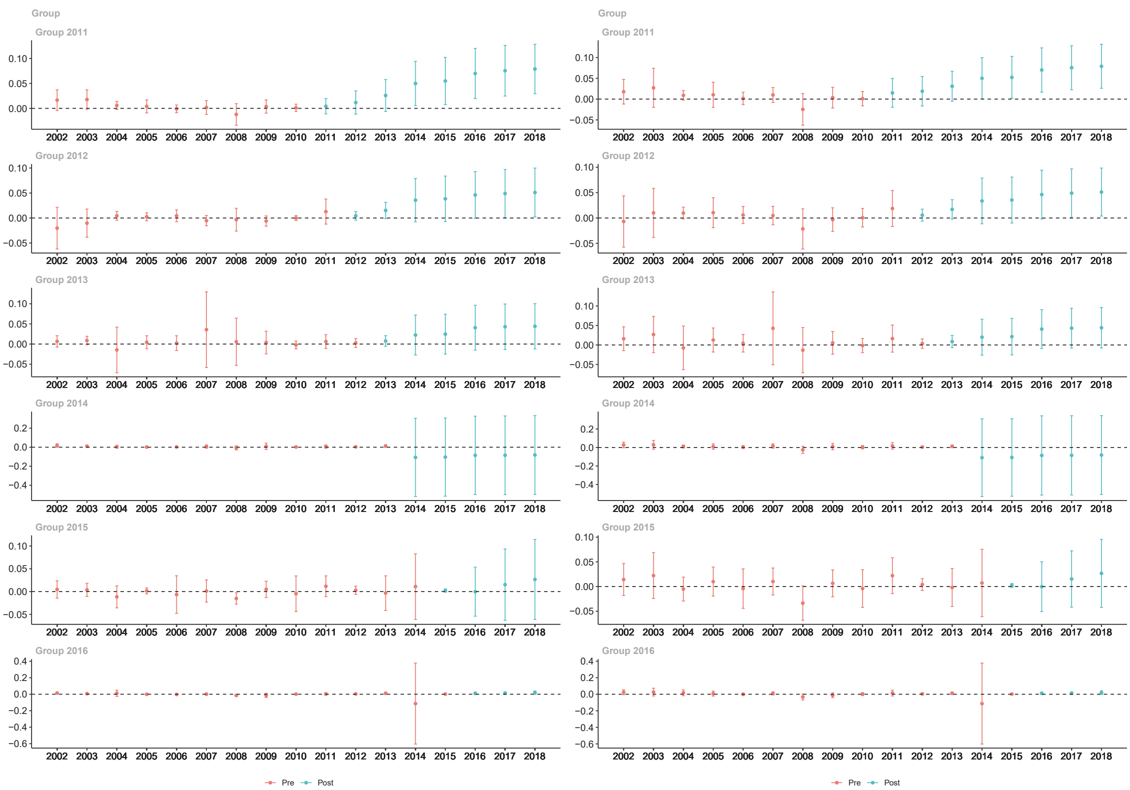
Notes: This figure presents the full sample estimates from an event study specification for the effect the NGP had on the percentage of unlit settlements at the village level. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

A.6. Dynamic Effects By Cohort

A.6.1. Event studies by cohort

Figure A.13: Dynamic Impact of NGP on Forest Coverage

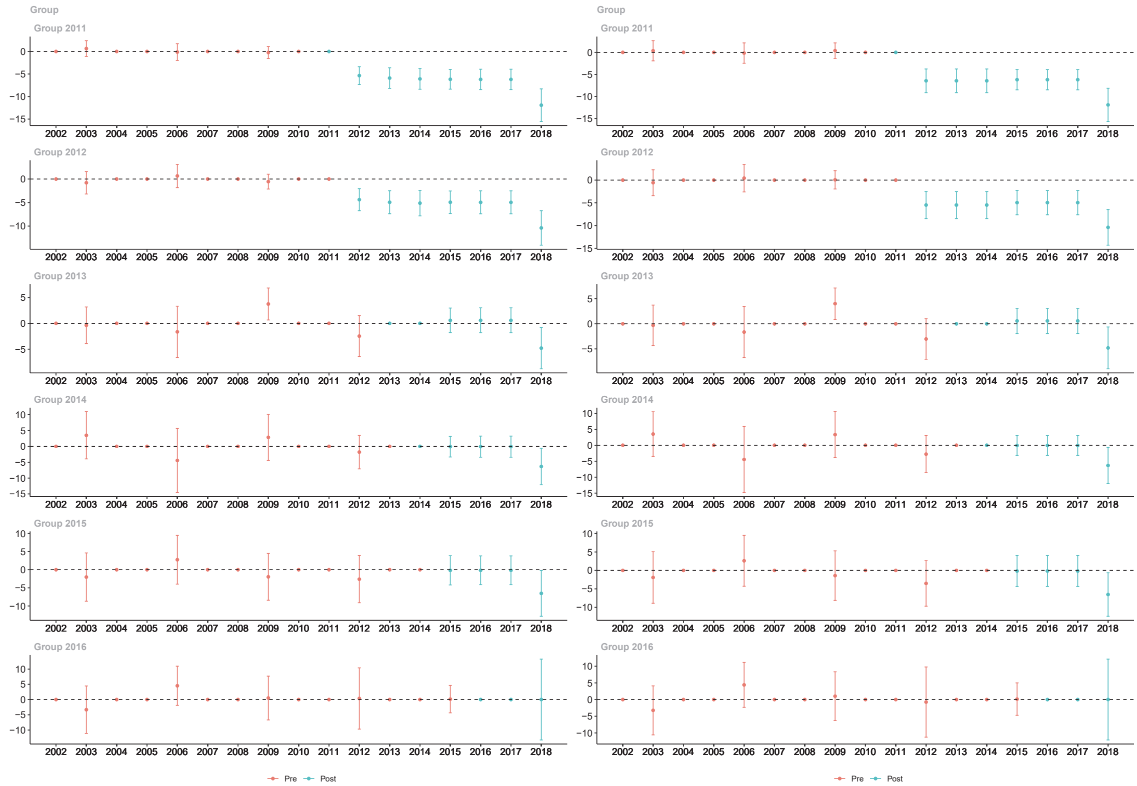
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



Notes: This figure presents estimates from an event study specification for each cohort effect the NGP had on the log of forest cover. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.14: Dynamic Impact of NGP on Small Area Poverty Estimates

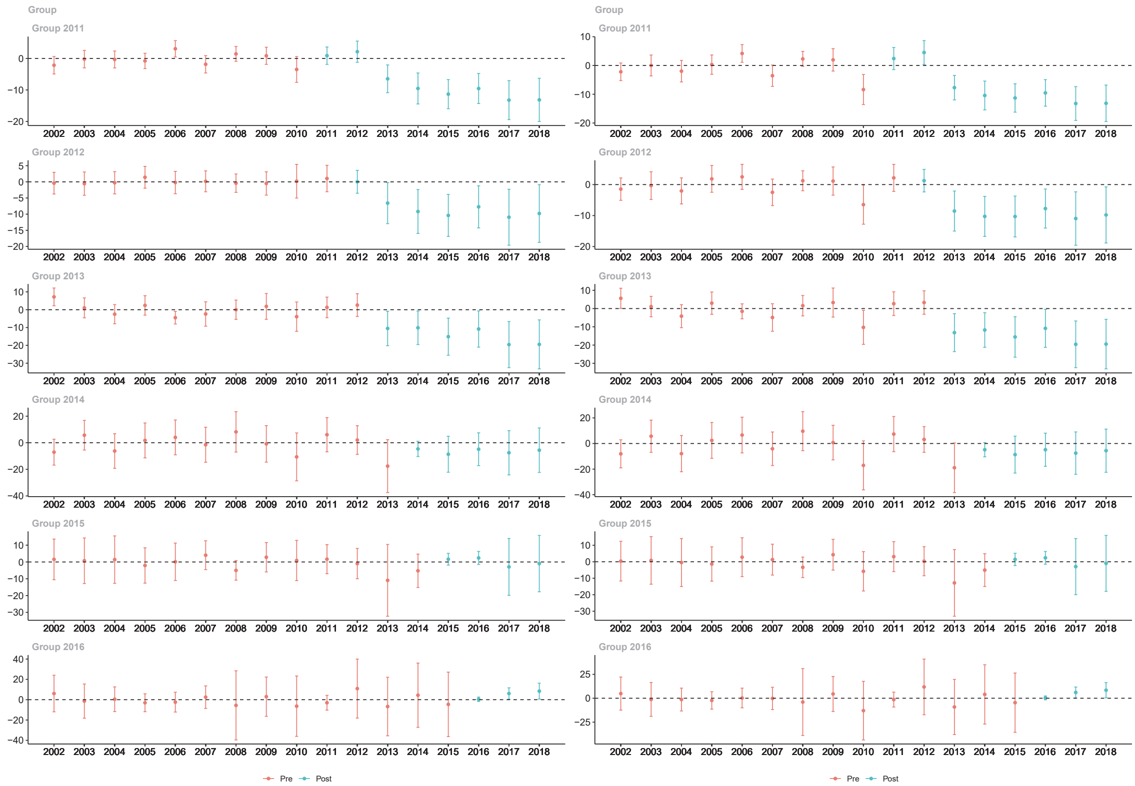
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



Notes: This figure presents estimates from an event study specification for each cohort effect the NGP had on small area poverty estimates. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.15: Dynamic Impact of NGP on Unlit Settlements

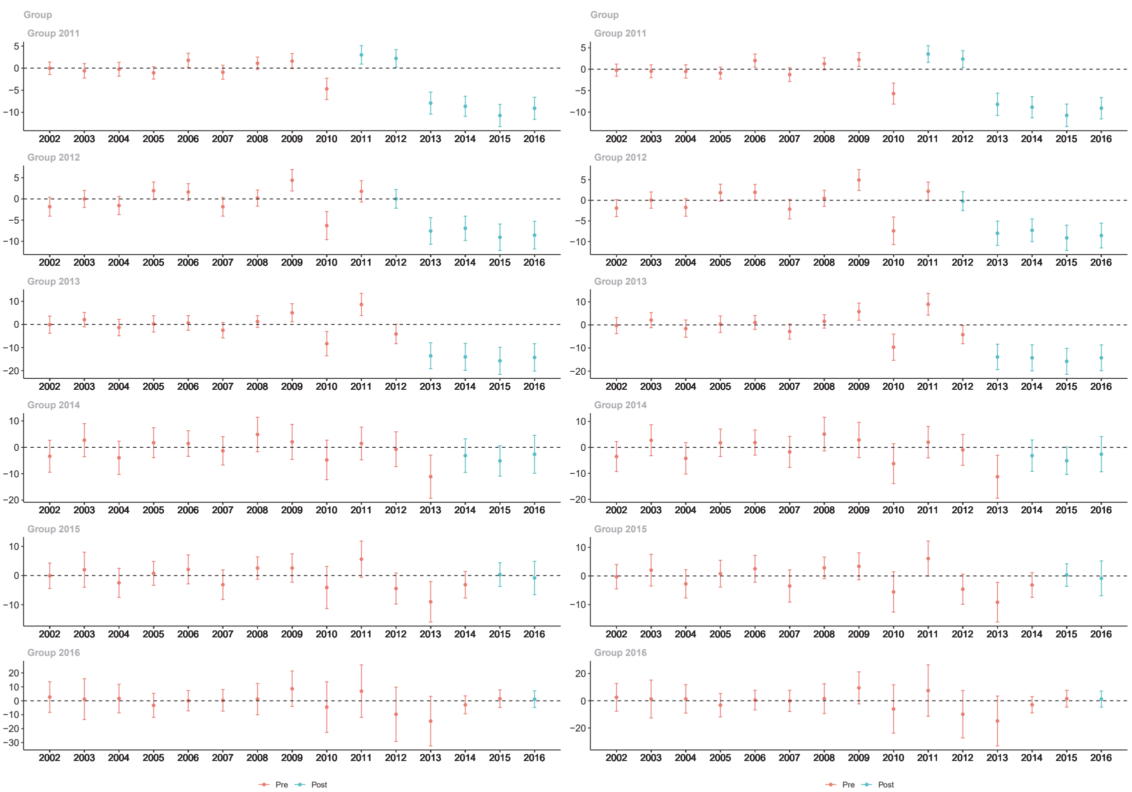
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



Notes: This figure presents estimates from an event study specification for each cohort effect the NGP had on the percentage of unlit settlements. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.16: Dynamic Impact of NGP on Unlit Settlements at the Village Level

Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated

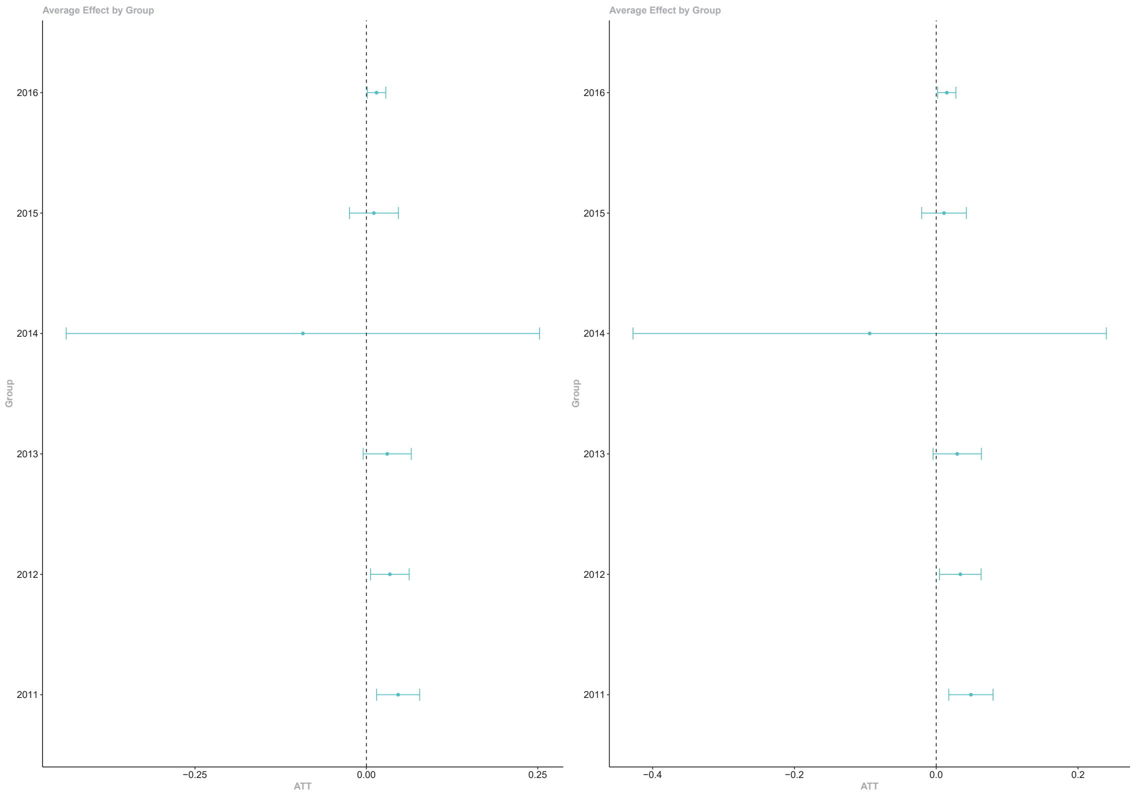


Notes: This figure presents estimates from an event study specification for each cohort effect the NGP had on the percentage of unlit settlements at the village level. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the village level. Confidence intervals are set at 95 percent.

A.6.2. Average treatment effect by cohort

Figure A.17: Average Cohort Impact of NGP on Forest Coverage

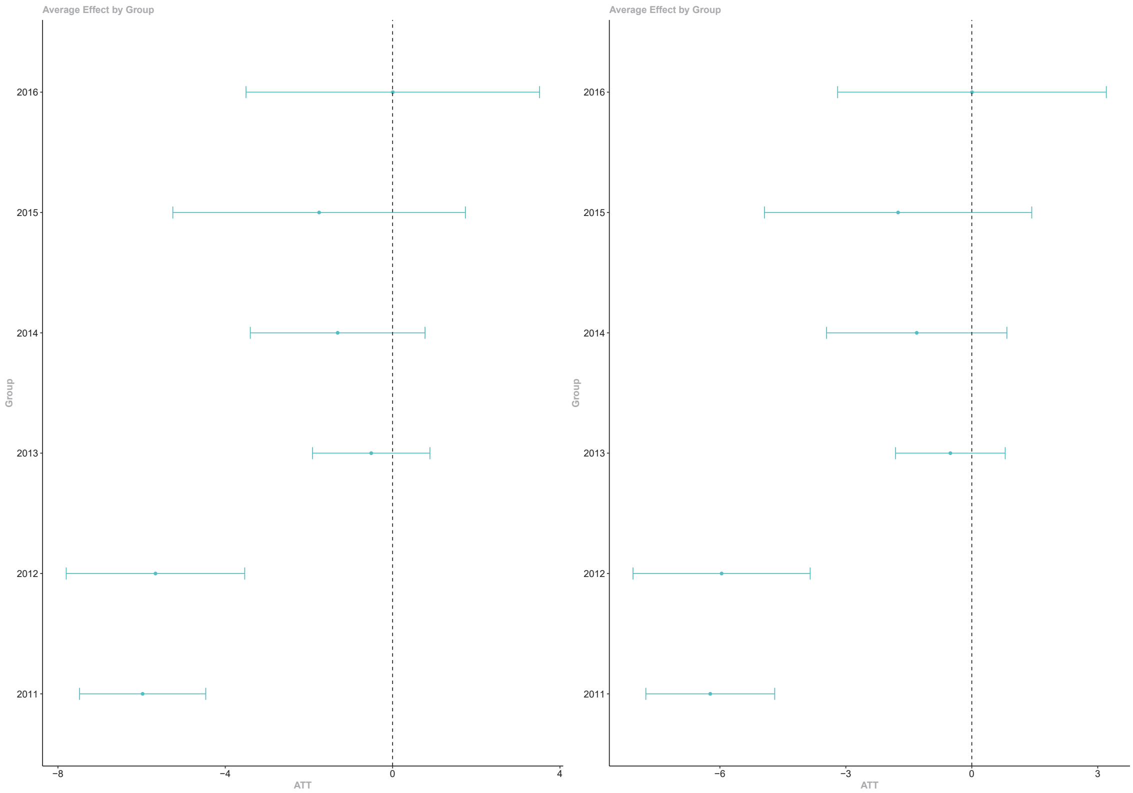
Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



Notes: This figure presents the average cohort effect that the NGP had on forest cover. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.18: Average Cohort Impact of NGP on Small Area Poverty Estimates

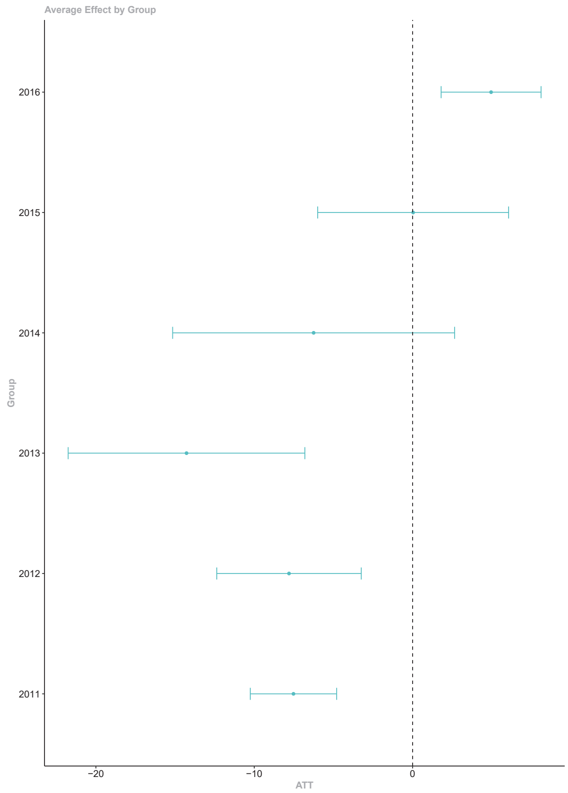
Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



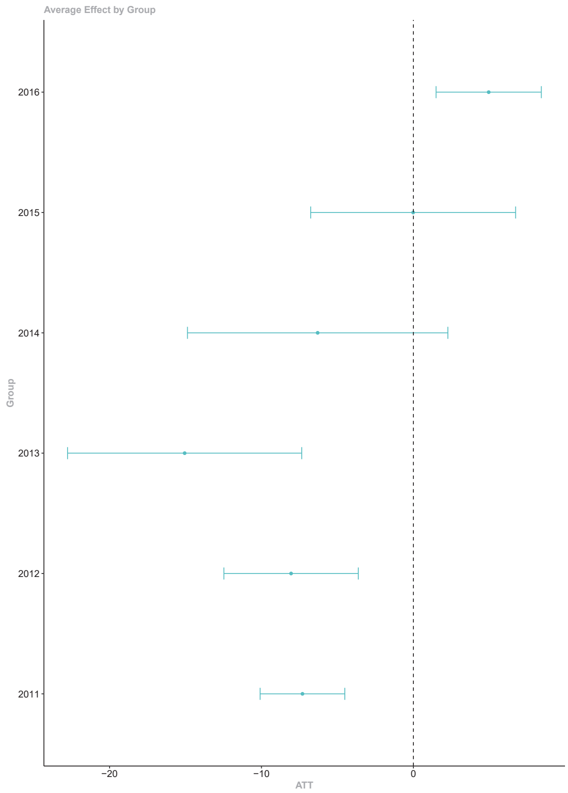
Notes: This figure presents the average cohort effect that the NGP had on small area poverty estimates. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.19: Average Cohort Impact of NGP on Unlit Settlements

Panel A: Treatment vs. Not Yet Treated



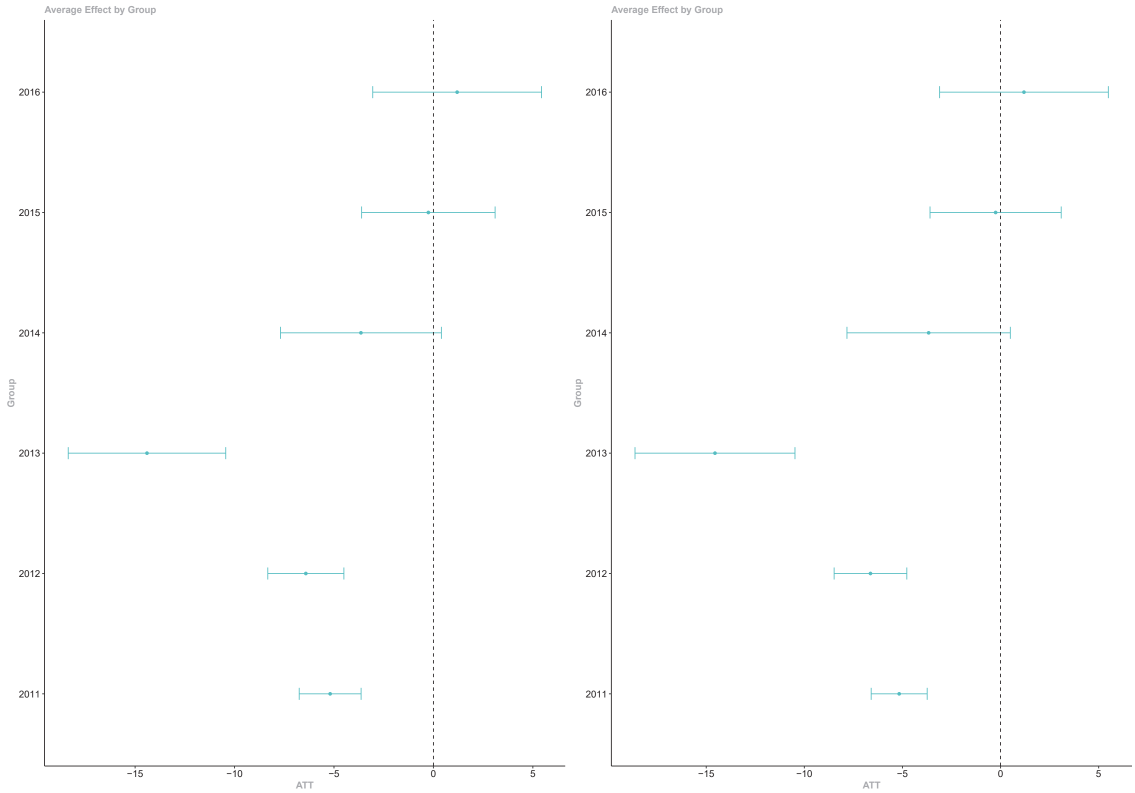
Panel B: Treatment vs. Never Treated



Notes: This figure presents the average cohort effect that the NGP had on the percentage of unlit settlements. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.20: Average Cohort Impact of NGP on Unlit Settlements at the Village Level

Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



Notes: This figure presents the average cohort effect that the NGP had on the percentage of unlit settlements at the village level. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates for treated cohorts versus never treated cohorts. Doubly robust standard errors are clustered at the village level. Confidence intervals are set at 95 percent.

B. Payment Structure of the NGP

This section provides additional information on specific aspects of the NGP and how it was implemented. The following list outlines the standardized payment contracts used by the DENR for seedling producers, site preparation and maintenance. Then Table B.1 breaks down the 3-year process cycle of site preparation and maintenance and the standardized unit cost of activities.

- Seedling producers contracts follow: 1) 15 percent upon approval of the agreement, 2) 75 percent upon delivery and due inspection of the seedlings and 3) 10 percent upon issuance of certificate of completion and acceptance.

- Site preparation contracts follow: 1) 15 percent upon approval of the agreement, 2) 50 percent upon completion of strip brushing, hole digging, and staking according to the agreed density and planting standards, 3) 40 percent upon completion of hauling and planting of seedlings according to agreed density and planting standards and 4) 10 percent upon planting the target number of seedlings.

- Payments for maintenance follow: 1) 15 percent upon production of 25 percent of total seedling requirements of the NGP site, 2) upon completion of at least 70 percent of total target on maintenance and protection activities, 3) upon completion of at least 30 percent of total target on maintenance and protection activities and 4) 10 percent upon accomplishing the total target for the maintenance and protection as well as attaining an 85 percent survival rate.[23]

Table B.1: Standard Unit Cost of Activities

Activities	Cost per Hectare (in PhP)
Site Validation, Assessment and Planning	450
Site Preparation (hauling, hole digging, brushing, etc.) and Planting	3,000
Transportation and Mobilization of Partners	2,000
Maintenance and Protection of Established Plantations	
1st Year	1,000
2nd Year	3,000
3rd Year	2,000

C. Appendix - For Online Publication

C.1. Data on Nighttime Lights and Unlit Population Percentage

We repeat our main analysis using nighttime lights (NTLs) as a proxy for economic activity and the share of population living in unlit areas (UP) as a proxy for poverty. Previous studies have shown a correlation between lights and economic activity (Donaldson and Storeygard, 2016), lights and economic growth (Henderson *et al.*, 2012), and as a proxy for economic activity and welfare within fine geographic areas such as subnational administrative units (Hodler and Raschky, 2014; Burlig and Preonas, forthcoming; Alesina *et al.*, 2016)[24].

Data on NTLs is obtained from the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Center (NGDC) which processes the data and computes average annual light intensity for every location on earth. We acknowledge well-understood concerns with the year-on-year intercalibration of DMSP-OLS

[23]Maintenance and protection activities include ring weeding, strip brushing and site preparation intended for replanting activities, including replanting of the area.

[24]See Donaldson and Storeygard (2016) and Ghosh *et al.* (2013) for a summary of applications using nighttime lights data as a proxy for economic activity.

and VIIRS satellites' sensor settings, plus the retirement of DMSP-OLS in 2013 in favour of VIIRS, may render the NTLs time series inconsistent and prone to measurement error.[25]

Given the NGP roll-out in 2011, eventual increases in NTLs observed after the treatment could be due to the VIIRS satellite's greater accuracy. To address this issue, we opt to employ recently released Harmonised NTLs from Li *et al.* (2020) who produce a time-consistent time series of NTL observations by intercalibrating DMSP-OLS and VIIRS values. We calculate the average digital number for each municipality by taking the mean of 1km^2 pixels which exactly overlap municipal boundaries.[26] Further data quality concerns may regard low variability at the top of the digital number distribution due to a large frequency of top-coded values (Kocornik-Mina *et al.*, 2020). This not a problem in our setting as the descriptive statistics show the maximum coded value of nighttime light emitted is 48.27, out of a maximum possible digital number of 63.

Additionally, following the insights of Smith and Wills (2018), we exploit the relationship between nighttime radiance and population density to calculate the municipality and village-level share of population living in darkness at night. The approach is similar to the construction of the share of unlit settlements (McCallum *et al.*, 2022) used in the main analysis, but makes use of remotely sensed population data at a 30 arcsecond resolution obtained from LandScan (Sims *et al.*, 2023) in combination with NTLs.

We first reclassify the NTLs dataset to a binary raster where cells $j = 1$ are associated with no nighttime radiance, and cells $j = 0$ are lit. We then interact this intermediate input with the LandScan population rasters for 2000-2016, and obtain the count of population living in unlit cells at any time t, which we call $Unlit_{it}^{count}$. For each administrative unit i (in turn, municipality or village) we then also calculate Pop_{it}, i.e. the total population count at any time t. We obtain the share $Unlit_{it}^{share}$ by dividing these two quantities.

$$Unlit_{it}^{share} = \frac{1}{Pop_{it}} \sum_{j=1}^{J} NTL_{jt} \Big|_{NTL_{jt}=0} \cdot Pop_{jt} \tag{7}$$

where $j = 1, ..., J$ are the 1km^2 pixels contained in administrative unit (municipality or village) i.

[25]There are two notable issues with the use of nighttime lights. First, nighttime light data come from two different satellites. DMSP-OLS Nighttime Lights (1992-2013) provides composite aggregates of annual data on lights from cities, towns and other sites with persistent lighting or gas flares, but temporary events such as fires are discarded. VIIRS Nighttime Lights (2012 – 2020) provides a new consistently processed time series of annual global nighttime lights from monthly cloud-free average radiance grids.

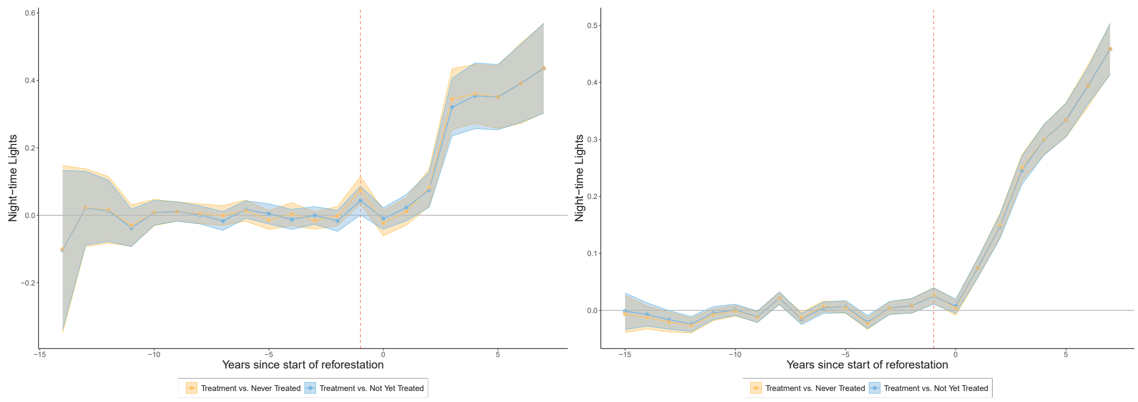
[26]We use exact pixel boundaries if a municipal boundary overlaps a pixel.

C.2. Results

We re-estimate equation 1 and 2 at the municipality and village level, respectively, for NTLs and unlit population share outcomes. In Figure C.1 Panel A and Table C.1 columns 1 and 2, we show that the tree planting program lead to an increase in economic activity, with municipalities that received a tree planting project experiencing an increase in nighttime luminosity of 24 percent. Figure C.1 Panel B further confirms the results at the village level and shows that the effect is persistent in that 7 years after the implementation of the NGP the estimates are still significant and the trend is continually increasing. Table C.1 also estimates spillover effects at the village level and indicates that neighboring control villages experience and increase in nighttime lights of a 18.4 percent. Similar results are observed for the unlit population percentage outcomes, in Table C.2 and Figure C.2. These effects are similar in magnitude with respect to the coefficients of the main regressions using the share of unlit settlements, confirming the robustness of our approach to a different definition of poverty. The NGP has driven down the share of municipal population living in darkness at night by about 8 percentage points, with similar effects (7.4-7.5 percentage points) observed at the village level. Our analysis continues to identify significant spillovers, of about half the size of the main effects.

Figure C.1: Impact of NGP on Nighttime Lights

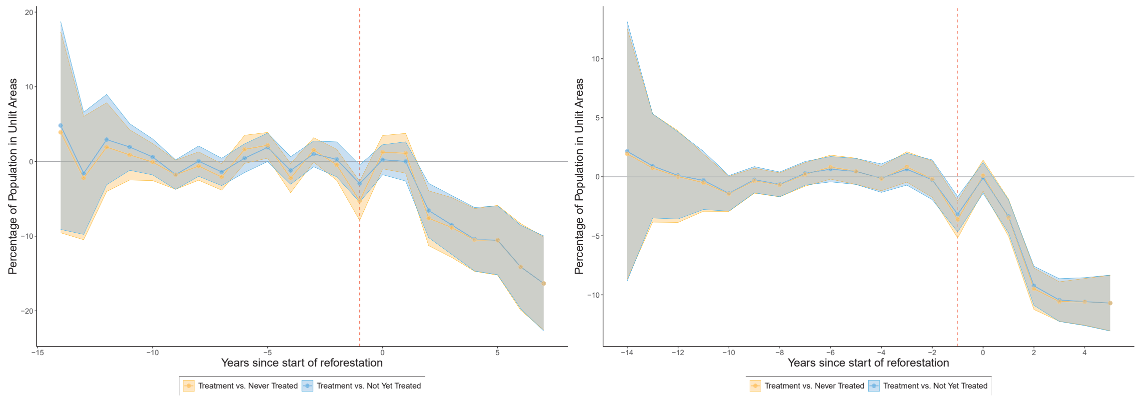
Panel A | Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the log of nighttime lights at the municipality level (Panel A) and at the village level (Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure C.2: Impact of NGP on Unlit Population Percentage

Panel A | Panel B



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the percentage of population living in unlit areas at the municipality level (Panel A) and at the village level (Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Table C.1: Impact of NGP on Nighttime Lights

	Municipality Level		Village Level		Village Level Spillovers	
	(1)	(2)	(3)	(4)	(5)	(6)
	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated
NGP	0.243***	0.244***	0.245***	0.2455***	0.1848***	0.1846***
	(0.025)	(0.022)	(0.006)	(0.007)	(0.005)	(0.005)
Observations	27954	27954	543476	543476	622003	622003

Notes: This table presents estimates for the effect that the NGP had on the log of nighttime lights identified using a DID based on the roll-out of the NGP at the municipality and village level. In column (1) 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment and in column (2) 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. In columns (3) and (5) 'Not Yet Treated' compares control villages who experience a neighbor treated by the NGP in earlier years are compared to a pool of control villages who experience a neighbor treated by the NGP in later years while in columns (4) and (6) 'Never Treated' compares control villages which experience a neighbor treated by the NGP relative to a pool of control villages who never have a neighbor treated by the NGP during the duration of the panel. In columns (3) and (4) we further modify the sample by removing all immediate neighbors of treated units from the main sample in order to address possible contamination. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.2: Impact of NGP on Unlit Population Percentage

	Municipality Level		Village Level		Village Level Spillovers	
	(1)	(2)	(3)	(4)	(5)	(6)
	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated	Not Yet Treated	Never Treated
NGP	-8.279***	-8.201***	-7.3999***	-7.4512***	-3.9122***	-4.0428***
	(1.311)	(1.240)	(0.460)	(0.509)	(0.376)	(0.381)
Observations	21834	21834	255216	255216	297296	297296

Notes: This table presents estimates for the effect that the NGP had on the percentage of unlit settlements identified using a DID based on the roll-out of the NGP at the municipality and village level. In column (1) 'Not Yet Treated' compares earlier treated NGP municipalities to a pool of municipalities who have 'not-yet' been treated by the time of the treatment and in column (2) 'Never Treated' compares NGP municipalities which see tree planting relative to a pool of control municipalities who are never treated during the duration of the panel. In columns (3) and (5) 'Not Yet Treated' compares control villages who experience a neighbor treated by the NGP in earlier years are compared to a pool of control villages who experience a neighbor treated by the NGP in later years while in columns (4) and (6) 'Never Treated' compares control villages which experience a neighbor treated by the NGP relative to a pool of control villages who never have a neighbor treated by the NGP during the duration of the panel. In columns (3) and (4) we further modify the sample by removing all immediate neighbors of treated units from the main sample in order to address possible contamination. Doubly robust standard errors (Sant'Anna and Zhao, 2020) clustered at the municipality level are reported in parentheses. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.