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

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Abstract

We evaluate the poverty impacts of the Philippines' National Greening Program, a large-scale tree planting initiative that generated hundreds of thousands of jobs. Exploiting the program's staggered roll-out, a dynamic difference-in-differences strategy reveals significant gains in tree cover and reductions in poverty between 2011 and 2018. Poverty reduction is channeled through labor market shifts reducing agricultural work while increasing unskilled and service jobs, in turn generating gains in income, consumption, and assets. While payments have short-term effects, combining them with income-generating forest assets yields longer-lasting effects, highlighting how nature-based, multifaceted interventions can support rural economies.

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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 (United Nations, 2015).[1] Designing and implementing effective policies that provide incentives for sustainable land use and management, including tree planting, has become ever more important (Seymour and Harris, 2019), especially in light of potential synergies between conservation and poverty alleviation (Alix-Garcia *et al.*, 2015; Jayachandran *et al.*, 2017; Ferraro and Simorangkir, 2020). Implemented at scale across the world in recent decades, tree planting is uniquely positioned to address both environmental and poverty concerns.[2]

In this paper, we examine the potential of tree planting schemes to reduce poverty. It is well-known that forests directly contribute to local well-being through, for example, fuel wood, fodder, timber, and watershed protection (Alix-Garcia *et al.*, 2013). Yet, these are potential long-term benefits that are typically only generated once the plantation, or forest asset, has matured. Our study focuses on that critical early phase in which incentives are needed on the ground to help establish and maintain plantations and hence, ensure that the forest asset reaches maturity sufficient to generate both private and social returns.

We analyze the poverty implications of the National Greening Program (NGP), a large-scale tree-planting scheme, administered by the Department of Environment and Natural Resources (DENR) in the Philippines. Launched in 2011, the NGP is a reforestation program with the goal of planting 1.5 billion trees on 1.5 million hectares across the country as a means of reaching multiple policy objectives, including poverty reduction. The NGP provides three years of payments to village organizations, known as People's Organizations (PO), to establish forestry plantations, covering seedling production, site preparation, and maintenance. After this three-year period, PO assume full managerial control of the forest assets and retain all associated revenues, in principle, for reinvestment in the forest assets. Since the program began, the NGP has reportedly planted billions of trees across millions of hectares of land, directly and indirectly generating hundreds of thousands, if not millions, of jobs across the Philippines.

[1]These goals are reinforced by the 2021-2030 UN Decade on Ecosystem Restoration, which draws on the conclusions of the Dasgupta Review (Dasgupta, 2021), stressing the critical need to preserve and restore biodiversity and ecosystem services for the transition to sustainable economic development.

[2]Photosynthetic carbon capture by trees is critical for limiting the increase in global CO_2 concentrations (Griscom *et al.*, 2017; Lewis *et al.*, 2019) and hence, forest restoration is viewed as an effective nature-based solution for climate change mitigation (Bastin *et al.*, 2019). Over 50 percent of the signatories to the Paris Agreement list land use and forest as a priority area to achieve CO_2 emissions reductions (UNFCCC, 2022), and tree planting is an important part of almost all proposed pathways to 'net zero' emissions (Grosset *et al.*, 2023). Forests offer many other environmental benefits, including habitats for biodiversity, maintenance of soil fertility, pollution control, stabilization of hydrological flows, flood mitigation, and the prevention of soil erosion (Pattanayak and Butry, 2005; Bhattacharjee and Behera, 2017; Alix-Garcia and Wolff, 2014).

Using data from 2000 to 2018, and drawing on information from more than 102,000 plantation sites, we link NGP projects to two measures of poverty, official small area poverty estimates and a novel measure of economic deprivation based on the proportion of built settlements lacking nighttime luminosity. The NGP was administered in a staggered manner, implying that the dynamic treatment effects may be heterogeneous across treated cohorts. Since a traditional two-way fixed effects event-study estimator would be unable to recover the true causal effects of the program, we leverage its phased roll-out and implement a dynamic difference-in-differences (DID) estimator, following Callaway and Sant'Anna (2021). Our main empirical strategy, applied to both municipality- and village-level data, compares the pre-planting and post-planting periods between treated NGP units and a pool of untreated units.

Our results suggest that the NGP increased tree cover by 4 percent and reduced poverty, measured through both traditional and remotely-sensed indicators. Treated municipalities experience a 6-percentage point decline in poverty and an 8-percentage point reduction in the share of unlit settlements. An event-study framework, applied to trace out the dynamic impact of the NGP over time, indicates an immediate reduction in poverty in the first year of the program, the magnitude of which remains unchanged before further declining after the end of the three-year payment period. In other words, the impact on poverty is not only sustained over time but is greater in the long run than in the short run, that is, in the absence of payments.

Village-level results reinforce our main findings. Treated villages experience a 10 to 11-percentage point reduction in unlit settlements compared to control villages. To examine potential spillover effects (among villages), we adapt the dynamic DID estimator in a novel way. Specifically, we compare control villages with a neighbor treated earlier by the NGP against villages with neighbors that had not yet been treated by the time of the program implementation, and control villages with a treated neighbor against villages with neighbors that were never treated. Indicative of a positive (average) spillover effect, neighboring control villages experience a 5-percentage point reduction in unlit settlements when an adjacent village receives the tree planting program, relative to those without a treated neighbor.

We next explore how and why the NGP reduced poverty. Returning to the design of the NGP, fixed per ha payments are transferred to PO for the establishment and maintenance of plantations in the first three years of each project. Given the payments are made conditional on completion of such activities, the NGP could be characterized as a kind of payment for ecosystem services (PES) scheme (Alix-Garcia *et al.*, 2015; Wilebore *et al.*, 2019; Jayachandran *et al.*, 2017).[3] However, what sets the NGP apart from other PES programs is that the DENR, via the payments,

[3]PES attempt 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 ecosystem services (Jack *et al.*, 2008). 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.

directly invests in plantation establishment and maintenance, creating jobs. As such, the NGP could also be defined as a kind of 'conditional cash transfer for work', or public works program, but with the caveat that the NGP was not motivated by the existence of surplus labor as in other settings (for a recent review, see Alik-Lagrange and Imbert, 2024). The sheer scale of the NGP implies that reductions in poverty could be materializing via shifts in the structure of local labor markets, as beneficiaries move from the agricultural sector to potentially higher-productivity jobs generated by NGP projects.[4]

To assess potential channels and mechanisms, we first examine structural changes in local labor markets induced by the NGP, focusing on sectoral reallocation and shifts in labor supply. We find that treated municipalities experience a decline in the share of individuals employed in agriculture. There is also evidence of increases in unskilled manual labor, services and in those not working, but no evidence that the NGP affected the labor supply through population changes or migration. Taken together, this supports the notion that the NGP created economic activity, as opposed to economic activity being created through shifts in the labor supply or induced migration. With these changes to local labor markets, the reductions in poverty imply that NGP beneficiaries allocated their private incomes to consumption and the acquisition of durable assets, which is confirmed in our data. Our results show significant increases in income and non-food expenditures at the village scale, as well as increases in electricity consumption, television, and refrigerator ownership at the municipality scale.

That the reductions in poverty induced by the NGP are not only sustained beyond the three-year payment period but also increase in magnitude implies a role for the forest asset in poverty reduction. Although this is plausible given the observed increase in tree cover, these assets, transferred to communities after the third year of payments, are not all immediately productive, generating returns that could be reinvested in support of jobs and, potentially, the creation of new ones. Some trees, such as coffee and rubber, typically reach maturity within 3–8 years, while others, including bamboo and rattan, require over 15 years to mature (USAID, 2018). Thus, payments could continue to play a role in reducing poverty through the acquisition of private assets in the first three years of the NGP. To differentiate the effects on poverty arising from the payments versus those generated by the forest asset, we classify individual sites using project records and explicit provisions in the NGP guidelines delineating production and protection zones. Sites with income-generating species, such as fruit-bearing or predominantly fast-maturing trees, are classified as productive, while degraded sites targeted for restoration and the planting of slow-maturing indigenous or endemic species are classified as protection. We then estimate event studies for village sub-samples of each site type and find that in the first three years both productive and protection villages exhibit comparable declines in the share

[4] Besley and Coate (1992) show theoretically the conditions under which public works programs better target the poor compared to unconditional cash transfers when governments lack information on precisely who is poor.

of unlit settlements, consistent with the distribution of payments. However, after the payments end, the pace of poverty reduction slows considerably in protection villages, bottoming out in year four before trending towards zero. Productive villages, by contrast, continue to experience steady and statistically significant declines in poverty, with the average difference between the two sub-samples, that is, the implied effect on poverty due to returns on the forest asset, reaching 5.5 percentage points.

To our knowledge, we provide the first quantitative evidence of the possible effects of large-scale tree planting on poverty. As such, given the use of conditional payments to incentivize tree planting, our study contributes to a large body of economic research that seeks to determine the causal impact of conservation programs on forest protection and the generation of ecosystem services (Pattanayak *et al.*, 2010; Ferraro *et al.*, 2012), in particular, that which examines the relationship between PES and poverty alleviation (Bulte *et al.*, 2008; Samii *et al.*, 2014). It also contributes to a literature on public works programs and their welfare and labor market effects (Alik-Lagrange and Imbert, 2024). Our results are consistent with, for example, Muralidharan *et al.* (2023), who show that the income gains from India's National Rural Employment Guarantee Scheme (NREGS) were largely allocated toward consumption or asset acquisition. Similarly, Egger *et al.* (2022) document substantial direct effects of cash transfers on household outcomes, including increases in consumption expenditures and durable asset ownership 18 months after the initiation of the transfers.[5]

This paper also contributes to an emerging body of literature that seeks to integrate structural change and growth with micro-level data and analysis (Gollin and Kaboski, 2023). A central focus is on identifying policies that enable structural transformation away from low productivity agriculture (Banerjee and Newman, 1998; Bryan *et al.*, 2014; Bustos *et al.*, 2016; Gollin *et al.*, 2021; Asher *et al.*, 2023). 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, such as in agroforestry, and through moving surplus labor to other sectors in the economy. Closest to our study is previous research on China's Grain for Green program, one of the largest tree-planting programs in the world. One unintended effect of this program was a relaxation of liquidity constraints for participating households, leading to increased off-farm employment in sectors not directly treated by the program (Uchida *et al.*, 2009; Groom *et al.*, 2010; Kelly and Huo, 2013). By contrast, the NGP is shown to influence localized structural transformation, reallocating labor from agriculture to unskilled manual and service sector work created within the NGP.

Given the focus of the NGP in creating new natural assets, our study relates to the

[5]Notably, more than half of the increase in asset ownership reported by Egger *et al.* (2022) derives from non-productive items such as radios and televisions, while smaller gains are observed in productive agricultural tools and potentially productive assets like motorcycles and solar systems.

nascent literature on multi-faceted interventions that grant productive assets alongside cash transfers. There is relatively little evidence on the building of potentially valuable assets in public works programs, showing how these assets contribute to poverty reduction (Alik-Lagrange and Imbert, 2024). Yet, multi-faceted approaches, combining cash payments, asset transfers, or training, have emerged as a leading strategy to achieve sustained improvements in income and other measures of well-being in the medium to long term (Banerjee *et al.*, 2015; Bandiera *et al.*, 2017; Banerjee *et al.*, 2021). A growing debate questions whether cash or in-kind transfers alone are sufficient to sustain impacts after programs end, underscoring the need to identify components most essential for generating significant benefits (Sedlmayr *et al.*, 2020). Work by Banerjee *et al.* (2015) and Bandiera *et al.* (2017) suggests 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 beneficiaries. Balboni *et al.* (2022) show that large transfers, to create jobs for the poor, are an effective means of getting people out of poverty traps. Overall, the evidence suggests that adding complementary components to cash transfers, such as training or productive investments, can amplify outcomes and deliver greater benefits (Banerjee *et al.*, 2022; Bossuroy *et al.*, 2022; Macours *et al.*, 2022; Sedlmayr *et al.*, 2020). Our findings contribute to this emerging literature, demonstrating that combining payments for plantation establishment with the transfer of productive forest assets is a sustainable pathway for long-term, economically-meaningful impacts.

In the remainder of the paper, we first present background to the NGP, in Section 2, followed by a description of our data, in Section 3. The methods applied to these data are shown in Section 4, the results of which are presented in Section 5. We then analyze the channels and mechanism underlying our results in Section 6 before discussing our results and concluding, in Section 7.

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 declined from 17.8 million ha, or about 60 percent of total land area, in 1934 to about 7.2 million ha or 23.9 percent in 2011 (Department of Environment and Natural Resources, 2011). In 2000, the Philippines ranked among the top ten deforestation countries (Food and Agriculture Organization of the United Nations, 2005), and since has lost a further 1.42 million ha of tree cover, equivalent to a 7.6 percent decrease, or 848 $MtCO_2$ emissions (Global Forest Watch, 2023). Yet between 2001-2022, the country's forests were a net carbon sink, emitting 38.5 $MtCO_2$ while removing 96.9 $MtCO_2$ per year.

The 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 (∼$710m), the NGP sought to plant 1.5 billion seedlings on 1.5 million ha of land from 2011-2016 (Calderon, 2016). This is equivalent to a 11.4 percent increase on the 2010 forest stock, or the replanting of an area of land exceeding the 1.42 million ha of forest cover lost between 2001-2021. In 2015, the program expanded through Executive Order No. 193 (2015), which extended its coverage from 2016-2028, setting the goal of rehabilitating all remaining unproductive, denuded and degraded forest lands, estimated at 7.1 million ha, or around 53 percent of the country's total forested area (Department of Environment and Natural Resources, 2019; Global Forest Watch, 2023). Table A.1 outlines the program's reported accomplishments between 2011-2022, including the planting of over two million hectares, the direct employment of nearly one million people, and the generation of almost six million jobs (Department of Environment and Natural Resources, 2022).[6]

Designed primarily as a reforestation program, the NGP restores vegetation cover as a means of meeting multiple policy objectives, including biodiversity conservation and poverty reduction.[7] Tree planting projects were established in village (*barangays*) territories across the Phillipines via partnerships formed between the DENR and PO, initially prioritizing PO with formal tenure to plantation sites.[8] Planting mostly took place on degraded or deforested lands, but also included protected areas, ancestral domains, urban areas, and inactive and abandoned mining sites (Executive Order No. 26, 2011). In the first three years of each project, the DENR transferred a series of fixed per ha conditional payments to PO (Department of Environment and Natural Resources, 2019). These payments followed a schedule to incentivize the preparation of sites (strip brushing, hole digging, and staking the target areas), planting of seedlings, and implementation and maintenance of protective measures (weeding/brushing, fertilizer application, and creating fire breaks or green breaks).[9]

[6]The NGP provided jobs to various program participants such as members of PO, extension officers and laborers. There is no information on whether this labor participation is full-time or part-time, nor are there other details that could provide a better picture of the employment contribution of the NGP (Israel and Arbo, 2015).

[7]Explicit provisions in the implementation of the NGP include: 1) utilizing a forest and landscape restoration 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 also targets poverty reduction, food security, environmental stability, biodiversity conservation, and the enhancement of climate change mitigation and adaptation.

[8]PO are community-based organizations with formal recognition established by village communities to address community concerns and share the benefits from collective activities. Initially, the DENR gave priority to PO holding tenure, specifically, those with existing CBFMA/PACBRMA agreements, as they were formally acknowledged as the current occupants and cultivators of 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. These agreements offer a (renewable) 25-year term, providing tenurial security and incentives for the development, utilization, and management of forest lands. An insufficient number of PO with such agreements led to the DENR allowing PO without tenure to participate in the NGP (Commission on Audit Performance Report, 2019).

[9]A uniform strategy was applied across all tree planting sites. There were standard unit costs for reforestation species (categorized by commodity) to be planted with their equivalent density

The DENR oversaw the provision of nursery establishment, seedling production, site identification, technical support, and program monitoring, while PO were responsible for preparing the sites, planting seedlings, and maintaining and protecting the trees (Commission on Audit Performance Report, 2019). After 2013, seedling production became the duty and responsibility of PO, which were encouraged to establish their nurseries near or adjacent to planting sites to minimize hauling stress and costs. Profits generated from seedling production and tree plantations are directed towards the implementing PO.

To assist NGP coordinators in implementing the program, the DENR hired extension officers to provide technical assistance to PO. Additionally, the NGP promoted the planting of indigenous species as well as species found naturally growing in targeted areas.[10] The NGP aimed to achieve a yearly seedling survival rate of 85 percent. Between 2011-2015, the national annual survival rate was 82-83 percent (Israel, 2016). To ensure compliance with the program's standards, the PO were monitored. The DENR monitored compliance 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 PO or private suppliers. The reports were generated by extension officers who visited each site to check whether the plantations achieved the survival rate target, taking geo-tagged photos as proof of compliance. Once the IAC approved each report, the PENRO enables processing and release of payments. 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.1 for an example).

3. Data

Our main analysis is based on a municipality-by-year panel 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; (3) remotely-sensed data, comprised of several variables measured at the 1km x 1km grid cell level (0.083x0.083 arc-degrees), and; (4) remotely-sensed tree cover data from the European Space Agency (ESA-CCI, 2017). Table A.2 provides summary statistics at the municipality level (Table A.3 at the village level) for each of the variables used in the analysis.

per hectare. Appendix B further outlines the standard template payment structures for seedling production, site preparation, and site maintenance.

[10] 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) purposes for which they are planted; 3) availability of planting materials, and; 4) market for commercial potential. Each PO could plant their preferred species on condition that they were compatible with site conditions.

National Greening Program (NGP): Annual data on the NGP, between 2011-2018, are sourced from the DENR. The dataset includes information on 102,572 individual tree planting projects. Information is also provided on the villages that were treated, the number of hectares planted, and the commodity or species planted. Figure A.2 plots the distribution of tree planting sites by hectares. The average tree planting site has an area of 15 ha, with the majority of projects on sites of less than 20 ha. Furthermore, in Figure A.3, we classify each tree planting site as a reforestation, agroforestry, mixed agroforestry/reforestation or urban reforestation site. The majority of 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 1 shows the frequency of municipalities by treatment pool as the NGP was rolled out. Around 16 percent of municipalities are never treated by the NGP, and 77.5 percent of remaining 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. Figures A.4 and A.5 demonstrates the spatial variation of the program based on the cumulative number of tree planting projects and the cumulative number of hectares planted per municipality. Treatment intensity appears to be a fairly evenly distributed throughout the Philippines.

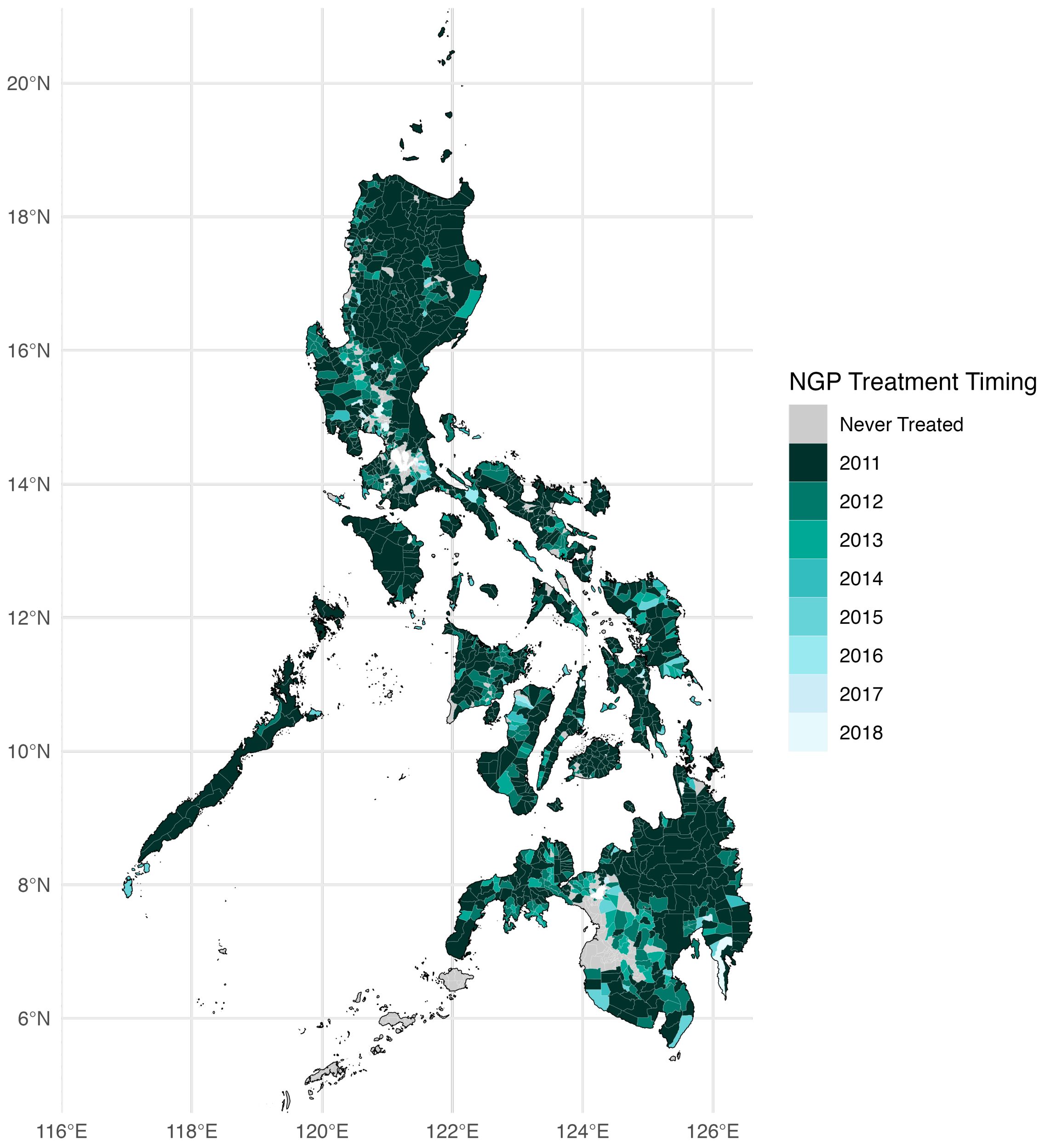
Table 1: NGP Timing by Treatment Pool

Treatment Timing	Frequency	Percent	Cumulative
Never Treated	264	16.0	16.0
2011	890	54.0	70.1
2012	289	17.5	87.6
2013	99	6.0	93.6
2014	30	1.8	95.4
2015	44	2.7	98.1
2016	9	0.5	98.7
2017	10	0.6	99.3
2018	12	0.7	100.0
Total	1649	100.0	

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 official estimates of poverty incidence from the Philippine Statistics Authority (PSA), based on national data sources and food price information. These small area poverty estimates are updated every three years from 2000 to 2018 and are

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.

expressed as a percentage of households that fall below the poverty threshold.[11] Second, we create a remotely-sensed proxy for poverty by calculating the percentage of unlit settlements at the municipality and village level, expanding on McCallum *et al.* (2022).[12] This indicator allows us to overcome well-known problems connected with the use of night-time lights (NTL) as a predictor of economic activity in low income countries, where NTL are sparse and only loosely correlated with income and wealth, especially at the left tail of their distributions (Neal *et al.*, 2016).[13] The unlit settlements percentage indicator is constructed by combining data on NTL, which we retrieve from Li *et al.* (2020), with newly released data on building footprints. The latter are obtained from the Global Human Settlement Layer (GHSL) 1 km GHS-SMOD product, available at 5-year intervals between 2000 and 2015.[14] 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 NTL 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 1 km^2 pixels of the unlit building footprint raster and divide them by the total building footprint to obtain the percentage of unlit settlements, as follows:

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

where $j = 1, ..., J$ are the 1 km^2 pixels contained in administrative unit (municipality or village) i.[15] Subscript s denotes that, e.g., building footprint constructed at $s = 2000$ is used to construct $Unlit_{it}$ for $t = 2000, 2001, 2002, 2003, 2004$.

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 footprints, 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 re-

[11] Figure A.6 is a map of pre-NGP small area poverty estimates at the municipality level for the year 2010.

[12] Figure A.7 is a map of pre-NGP estimates for the share of unlit settlements at the municipality level in 2010.

[13] Previous studies have shown a correlation between NTL and economic activity (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.

[14] Li *et al.* (2020) produce a time-consistent time series of NTL observations by intercalibrating DMSP-OLS and VIIRS values, thereby acknowledging concerns with the year-on-year intercalibration of satellites' sensor settings. These may render the NTL time series inconsistent and prone to measurement error, especially in light of our treatment switching on in 2011.

[15] 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.

trieve monthly observations of maximum and minimum temperature, precipitation accumulation, and wind speed at 10m, at a 0.1° scale.[16] 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 NTL.

Tree Cover: To test whether the NGP was successful at increasing tree cover, we utilize land cover data from the European Space Agency (ESA-CCI, 2017), where pixels are classified at a spatial resolution of 300m^2 on an annual basis from 1992 until 2020. We aggregate all discrete land cover classes corresponding to tree cover, requiring canopy cover exceeding 15 percent of the surface of a pixel. This includes pixels classified as having either open (15-40 percent) or closed (>40 percent) canopy cover in our tree cover definition.

4. Identification and Empirical Strategy

The principal concern, in the causal identification of the effects of the NGP on poverty reduction, is the differential timing of program roll-out among Philippine municipalities, which could yield heterogeneous treatment effect dynamics. A standard econometric specification in such cases is the two-way fixed effects (TWFE) event-study estimator, with treatment indicator variables 'switching on' the participation status for treated municipalities as soon as NGP projects are established. Yet, under staggered treatment implementation and in the presence of a never treated group, TWFE is only able to recover the true causal effect of the program when treatment effects are homogeneous across treatment cohorts.[17] In our setting, we are unable to determine *ex ante* whether the impact of the NGP roll-out on poverty outcomes is homogeneous across municipalities treated at different time periods. Traditional TWFE methods could then give rise to severely biased treatment effect estimates. Also, using coefficient leads as a way to assess parallel trends could be fraught with imprecision (Sun and Abraham, 2021).

To address these potential shortcomings, we implement the dynamic DID estimator (CS-DID) proposed by Callaway and Sant'Anna (2021), among other new DID estimators robust to heterogeneous treatment effects. This setup applies to staggered designs in which treatment can 'switch on' at different time periods and units do not forget about their treatment experience. 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 treated in the NGP. We further contrast these estimates with more canonical dynamic settings in which treated municipalities are compared to 'never treated' municipalities. To address concerns due to the limited sample size for later treated

[16] Approximately 5km at the equator.

[17] Additionally, all feasible leads and lags of the treatment variable are included, omitting one extra period in addition to -1 to avoid multicollinearity issues (Borusyak *et al.*, 2024).

cohorts at the municipality level, we focus on aggregated treatment effect parameters rather than group-time average treatment effects (Callaway and Sant'Anna, 2021). We also perform the analysis at the village level where the number of treated and control units is substantially higher and more uniformly distributed across time.

By estimating treatment effects for each treatment cohort at any time period included in the analysis, the CS-DID estimator causally identifies the effect of the NGP on each cohort of treated municipalities under the following identifying assumptions. The first is the irreversibility of treatment assumption, which is ensured by the program design: once a municipality receives a forestry plantation, it is extremely unlikely to reverse its course. To validate this assumption, in Section 5 we estimate our main CS-DID specification using our tree cover data as the outcome. Second, the CS-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 that have yet to receive the program 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 potential for selection bias. Notably, pre-tests based on group-time average treatment effects in the framework of the CS-DID estimator are robust to concerns about selective treatment timing (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021). 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 'not yet treated' observations in the control sample provide a useful indication in this regard, that municipalities treated at a later stage are plausibly 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 analysis is based on a municipality-by-year panel dataset. To estimate the impact of the NGP, let G_m represent the period when a municipality m is treated. Municipality m is in treatment cohort g if the NGP happens at $G_m = g$. The effect of the NGP, or the average treatment effect on the treated (ATT) for cohort g in year t, can be expressed as:

$$ATT(g,t) = E[Y_{m,t}(g) - Y_{m,t}(0) \mid G_m = g] \tag{2}$$

where $Y_{m,t}(g)$ is estimated separately for tree cover[18], small area poverty estimates and the percentage of unlit settlements for municipality m, in time t in treatment cohort g. $Y_{m,t}(0)$ represents the outcome of interest for municipality m at time t when in the control group. Throughout the analysis, we implement doubly robust

[18]We estimate treatment effects using both the inverse hyperbolic sine of tree cover pixels, and the number tree cover pixels in levels.

standard errors based on Sant'Anna and Zhao (2020) and cluster the error term at the municipality level.

An event study-type effect with ϕ periods of exposure following staggered adoption is estimated as:

$$ES(\phi) = \sum_{g \in Cohort} \mathbb{1}(g + \phi \leq T) \Pr(G = g | G + \phi \leq T) ATT(g, g + \phi) \tag{3}$$

where ϕ represents the elapsed time between the initial treatment time g and the current year, and T represents the maximum number of time periods observed in the sample. Following Callaway and Sant'Anna (2021), the base year in pre-treatment years is the immediate preceding year.

4.2. Village-level Analysis

To reinforce the main analysis, we conduct a village-level analysis. This analysis examines both the direct impact of the NGP at the village level and the distribution of the municipality-level effect, that is, within municipalities. We apply the same empirical strategy as the municipality-level analysis but leverage variation in the NGP's roll-out at the village level. Table 2 shows the frequency with which villages become treated as the NGP was phased in, while Figure A.8 illustrates the spatial and temporal variation of treated and control villages.

Table 2: Village-level NGP Timing by Treatment Pool

Treatment Timing	Frequency	Percent	Cumulative
Never Treated	31449	75.0	75.0
2011	2693	6.4	81.4
2012	2536	6.0	87.5
2013	1883	4.5	92.0
2014	751	1.8	93.7
2015	1296	3.1	96.8
2016	384	0.9	97.8
2017	606	1.4	99.2
2018	335	0.8	100.0
Total	41933	99.9	

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.

For the village-level analysis, we estimate the following specification:

$$ATT(g, t) = E[Y_{v,t}(g) - Y_{v,t}(0) \mid G_v = g] \tag{4}$$

where $Y_{v,t}(g)$ is estimated for the percentage of unlit settlements for village v, in time t in treatment cohort g. $Y_{v,t}(0)$ represents the outcome of interest for village v at time t when in the control group. 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.

The dynamic effect with ϕ periods of exposure following staggered adoption can be expressed as:

$$ES(\phi) = \sum_{g \in Cohort} \mathbb{1}(g + \phi \leq T) \Pr(G = g | G + \phi \leq T) ATT(g, g + \phi) \qquad (5)$$

where ϕ represents the elapsed time between the initial treatment time g and the current year, and T represents the maximum number of time periods observed in the sample.

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). Villages in the Philippines are interconnected through complex socio-economic networks including kinship ties, trade relationships, and communal governance structures such as PO, which facilitate collaboration and resource-sharing across villages (Porio and Roque-Sarmiento, 2019; Balisacan and Hill, 2007). Additionally, individuals may participate in PO from neighboring villages or in PO that span multiple villages, fostering inter-village collaboration, resource sharing, and strengthened connections that contribute to collective efforts toward community development (Tuaño, 2011).

Whether the NGP led to economic spillovers in surrounding villages is explored by taking advantage of our high resolution village-level data. We follow Ferraro and Simorangkir (2020) regarding their methodology for assessing the spillover effects of Indonesia's national anti-poverty program, tailoring this approach to fit within the context of our dynamic DID framework. Here, we focus on the 31,449 never-treated villages and exploit the timing of when a village's neighbor was treated by the NGP, using queen contiguity as a criterion. We compare pre-planting and post-planting periods across: (1) control villages which experienced a neighbor treated by the NGP relative to a pool of control villages that never had a neighbor treated by the NGP, and; (2) control villages which experienced a neighbor treated by the NGP in earlier years compared to a pool of control villages that experienced a neighbor treated by the NGP in later years. Table 3 shows the frequency with which control municipalities were treated by the NGP. There are 16,876 control villages (or 53.7 percent) that never had a treated neighbor for the duration of the panel, while 16.5 percent of control villages had at least one neighbor that was treated by the NGP in 2011.

To identify spillover effects, we estimate:

Table 3: Control Village Neighbor's NGP Timing by Treatment Pool

Treatment Timing	Frequency	Percent	Cumulative
No Neighbor Treated	16876	53.7	53.7
2011	5176	16.5	70.1
2012	4159	13.2	83.3
2013	2255	7.2	90.5
2014	652	2.1	92.6
2015	1112	3.5	96.1
2016	322	1.0	97.1
2017	514	1.6	98.8
2018	383	1.2	100.0
Total	31449	100.0	

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 that never had a neighbor treated by the NGP in the duration of the panel.

$$ATT(g,t) = E[Y_{n,t}(g) - Y_{n,t}(0) \mid G_v = g] \tag{6}$$

where $Y_{n,t}(g)$ is estimated for the percentage of unlit settlements for neighbor village n which has a neighbor treated by the NGP, in time t in treatment cohort g. $Y_{n,t},(0)$ represents the outcome for neighbor village n at time t when it is in the control group and has no neighboring village treated by the NGP. As before, we employ doubly robust standard errors and cluster at the municipality level. In addition, we estimate event study-type effects for control villages following exposure to a treated neighbor's staggered adoption, similar to Equation 5.

5. Results

This section first provides evidence on whether the NGP was effective at increasing tree cover. Next, we present our main results on the poverty reduction effects of tree planting.[19] We then test for various potential threats to identification and perform multiple robustness checks. Finally, we show results from the village-level analysis to complement the main analysis as well as estimate spillover effects.

5.1. Impact of the NGP on Tree Cover

Figure 2 shows that NGP municipalities experience a steady increase in tree cover each year after the implementation of the program. On average, tree cover increases

[19] We also aggregate the estimated treatment effects in two different ways. First, we aggregate the treatment effects into cohort level event studies (Figure A.9 - Figure A.12). Second, we aggregate the results into an average cohort effect of the NGP (Figure A.13 - Figure A.16).

by 4 percent (Table 4). We further analyze the dynamic effect by each cohort (Figure A.9) to show that this increase is mainly driven by the 2011 to 2013 cohorts, as well as show that, on average, all cohorts (besides 2014) experience a positive increase in tree cover (Figure A.13). This evidence implies that the program was effective in its main objective of reforestation and acts as a check on the dynamic DID assumption of treatment irreversibility: once a municipality is treated by the program, the treatment does not switch off. If, in the short term, 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 tree cover persistently and significantly increases, without any reversal towards zero, up to seven years after the first NGP roll-out, this possibility is ruled out. We then scale our estimated treatment effects and compare them to the NGP accomplishment report for 2011–2018, and find that our estimates capture about 30 percent of the area reported as planted by the program over this period.[20]

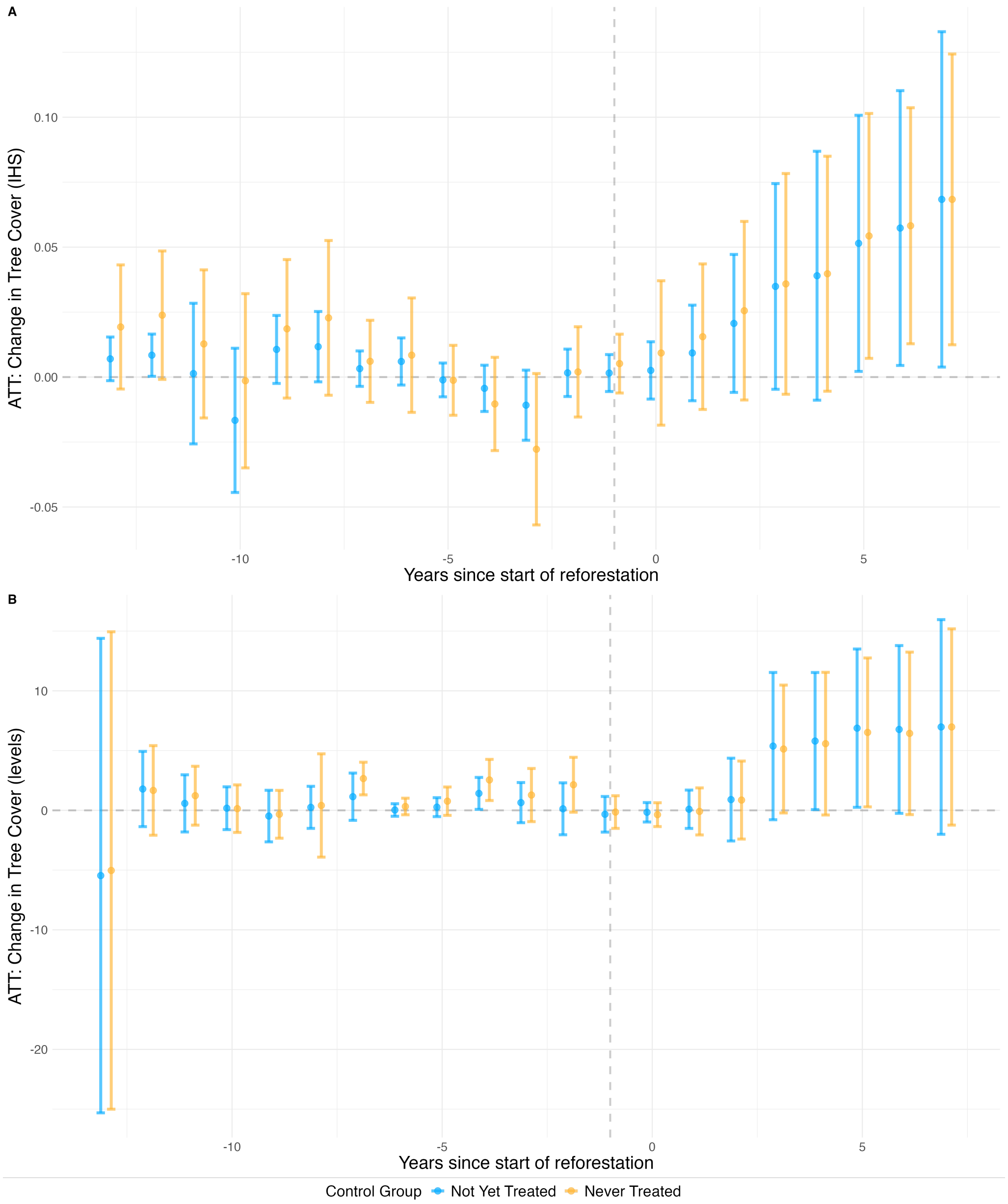
Table 4: Impact of NGP on Tree Cover

	Tree Cover (IHS)		Tree Cover (Levels)	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated
NGP	0.035***	0.038***	4.078***	3.882**
	(0.013)	(0.015)	(1.497)	(1.679)
Observations	29646	29646	29646	29646

Notes: This table presents estimates for the effect that the NGP had on the inverse hyperbolic sine (IHS) of tree cover, and on tree cover in levels (pixels) 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 *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[20] Specifically, we aggregate effects at $t = 2018$ using the inverse hyperbolic sine outcome transformation. For each treatment cohort, we take the cohort–time treatment effect in 2018 and transform it into an implied change in tree cover in levels using the cohort mean tree cover in the last pre-treatment year as the baseline. We then scale the cohort-level change by the number of treated municipalities in the cohort and convert pixels to hectares multiplying by pixel area (9 ha). We report details about this procedure in Appendix C. To retrieve the estimated change in tree cover, we sum across cohorts and obtain an implied total increase of 592,325 ha. According to the National Greening Program Accomplishment Report in Table A.1, the NGP reports having planted 1,992,498 hectares between 2011 and 2018 (2011-2016 + 2017 + 2018). Notably, our scaled-up tree cover change is a lower-bound estimate. Because the ESA-CCI Land Cover product classifies tree cover based on canopy cover, non-mature or sparsely distributed plantations may remain classified as non-forest until canopy cover exceeds 15 percent at the $300m^{2c}$ pixel scale. Moreover, the administrative figure of 1.99 Mha does not take into account plantations' failure rates, reported to be around 17-18 percent.

Figure 2: Impact of NGP on Tree Cover



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the inverse hyperbolic sine of tree cover (Panel A) and on tree cover in levels (pixels, Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

5.2. Impact of NGP on Socio-Economic Measures

Figure 3 shows that treated and control municipalities exhibit similar pre-NGP trends, providing evidence in support of the parallel trends assumption. The confidence intervals of pretreatment trends generally include zero, sufficient to rule out substantial selection between treatment and control municipalities.

Municipalities that receive the NGP experience reductions in poverty, measured through both traditional and remotely-sensed indicators. Table 5 columns 1 and 2 show that NGP municipalities experience a reduction in poverty incidence of 6- to 7-percentage points. This is equivalent to an 18-20 percent reduction over the sample mean. To put into context, Muralidharan *et al.* (2023) found a 7.4-percentage point or 26 percent reduction in poverty in India's NREGS. Second, from columns 3 and 4, the program led to a decrease in the percentage of unlit settlements, with municipalities that received a tree planting project experiencing a 7- to 8-percentage point decrease, or a 18-20 percent reduction over the sample mean.[21]

In Figure 3, we illustrate the dynamics of the NGP's impact on small-area poverty estimates and the percentage of unlit settlements. Panel A shows an initial reduction in poverty incidence followed by a plateau and then further reductions. A similar pattern is observed for the percentage of unlit settlements in Panel B, with a one-year delay preceding the initial decline, followed by a continued gradual reduction.[22] Additionally, both figures suggest persistent effects, which are still significant and without any reversal toward zero, in terms of levels, seven years after the first year of implementation. This further underscores the program's ability to sustain poverty reduction even after the payment phase has concluded.

Table 5: Impact of NGP on Socio-Economic Measures

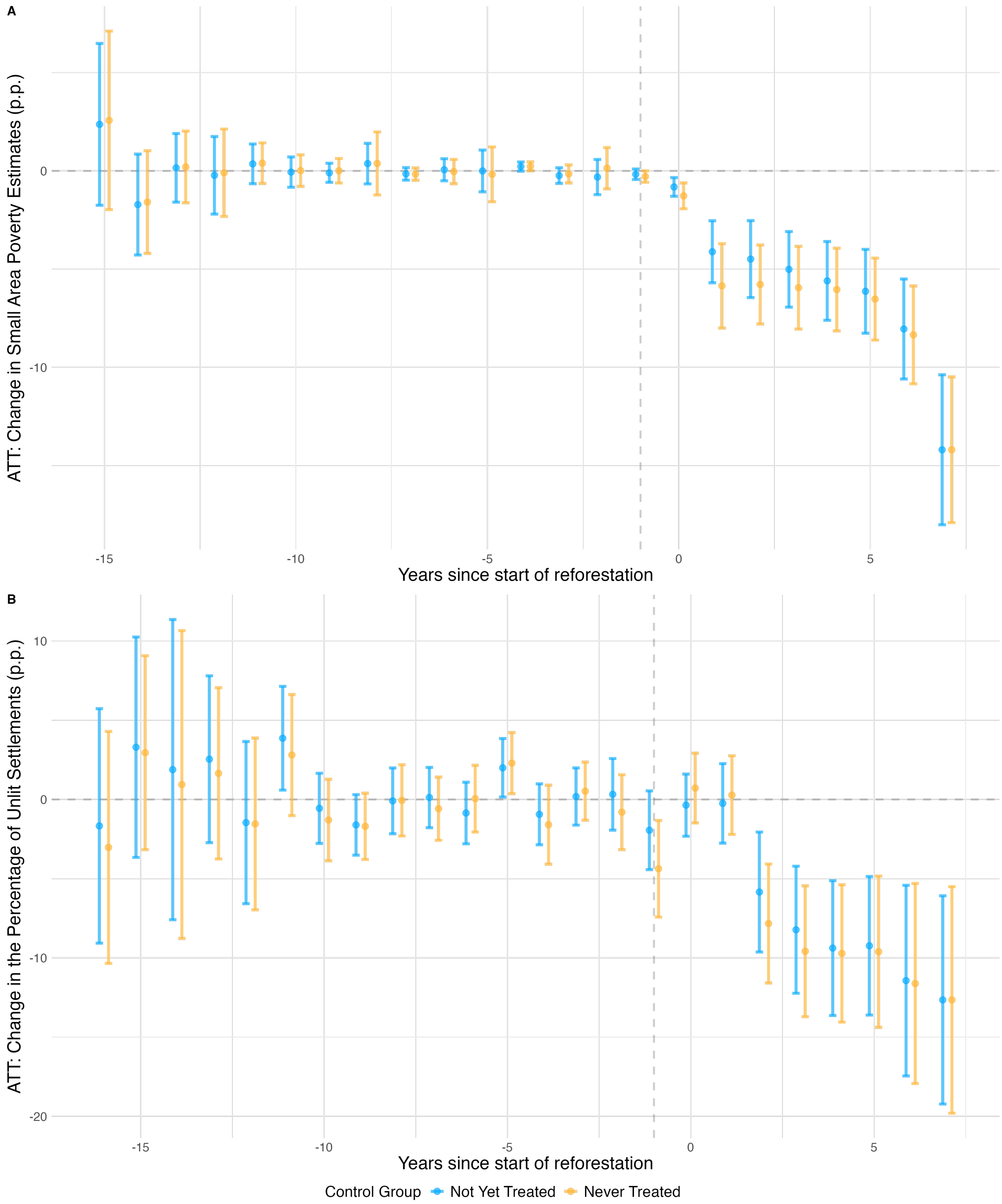
	Small Area Poverty Estimates		Percentage Unlit Settlements	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated
NGP	-6.045***	-6.739***	-7.172***	-7.502***
	(0.681)	(0.751)	(1.110)	(1.197)
Observations	28350	28350	24462	24462

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.

[21] We present results from a standard two-way fixed effect (TWFE) estimation in Table A.4 and Figure A.17, where the results (compared to the never treated) are slightly underestimated though qualitatively similar to our CS-DID specifications.

[22] Regarding the dynamic effects by cohort, Figure A.10 shows that the effects on small area poverty estimates accumulate over time, with the point estimates for the 2011 and 2012 cohorts declining each year following the implementation of the NGP. Similarly, Figure A.11 demonstrates a sustained decrease in the percentage of unlit settlements.

Figure 3: Impact of NGP on Socio-Economic Measures



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.

We further analyze heterogeneity in the NGP's impact based on different levels of baseline poverty and unlit settlements. To do so, we split the sample at the median, comparing high-poverty and low-poverty groups. The results are presented in Table A.5 and Figure A.18, where we find differential effects between the two groups. Both groups experience a reduction in poverty, but the effect is mostly concentrated in poorer municipalities, with a reduction in poverty of around 11-percentage points. In terms of unlit settlements, the results are again driven mostly by poorer municipalities. Municipalities with an above median level of unlit settlements experience a 7-percentage point decrease in remotely-sensed poverty, which appears to level off after two years.

5.2.1. Threats to Identification

We next check the robustness of our main analysis, by restricting the dataset in different ways and re-estimating Equations 2 and 3, with respect to the impacts of land tenure, Typhoon Haiyan, internal conflict, and a conditional cash transfer scheme. The results are shown in Figure 4 for small area poverty estimates (Panel A) and unlit settlements (Panel B).[23]

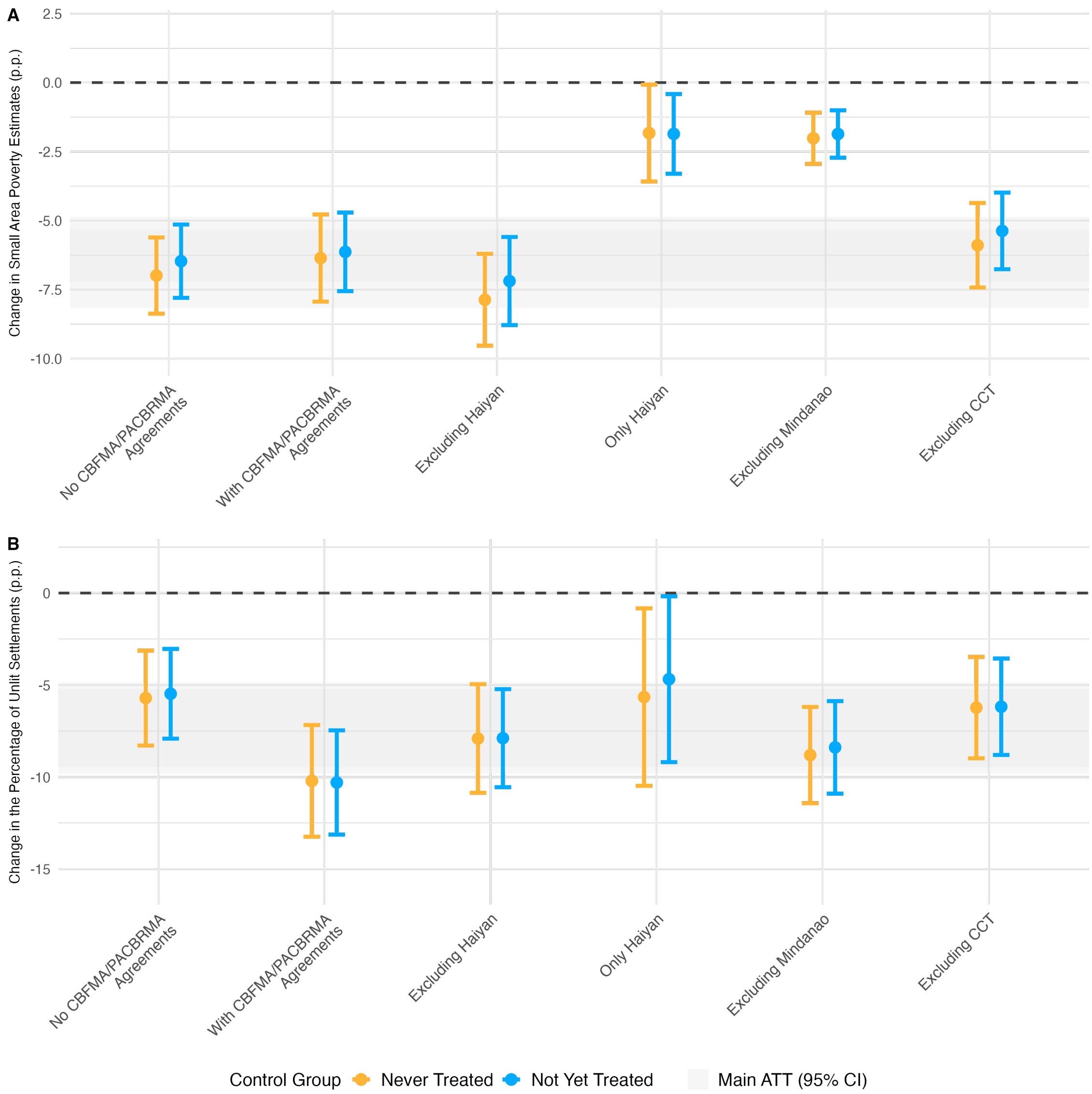
Although the roll-out of the NGP was primarily determined by environmental objectives, concerns regarding selection bias may still arise. The NGP initially prioritized PO with existing tenurial agreements (CBFMA or PACBRMA; see footnote 8), which are potentially better organized and positioned to receive funds, and implement the program more effectively, than PO without tenure. To assess this possibility, we first restrict the treated sample to municipalities with PO lacking tenure, finding similar effects for small area poverty estimates and slightly lower effects for the percentage of unlit settlements. We next restrict the treated sample to municipalities with PO that had tenure and find similar estimates for small area poverty estimates as well as slightly higher effects for the percentage of unlit settlements.

Second, Typhoon Haiyan made landfall in 2013 over Eastern Samar in Visayas region.[24] It affected different ecosystems as well as livelihoods, poverty incidence, and economic activity. To ensure that our main results are not biased due to this typhoon, we exclude municipalities affected by it. Our results remain quantitatively similar. It could also be argued that the typhoon made the program less effective, or that the program had a protective effect against typhoons. To investigate this angle, we restrict the sample to typhoon-affected municipalities only. We find that

[23] The ATT results for tenurial agreements are presented in Table A.6, while the other robustness results for small area poverty estimates and unlit settlements are presented in Table A.7 and A.8, respectively.

[24] This category 5 typhoon is considered one of the strongest tropical cyclones ever recorded globally, generating sustained winds of 315 kph and a 5-meter storm surge. Affecting 591 municipalities, it left 6,300 people dead, 1,061 missing, and 28,689 injured (National Disaster Risk Reduction and Management Council, 2013). The total estimated cost of damage to physical assets, including public and private assets, was PhP424 billion or 3.7 percent of GDP (National Economic and Development Authority, 2013). Figure A.19 presents a map of the affected municipalities.

Figure 4: Impact of NGP accounting for threats to identification



Notes: This figure presents estimates from all event study specifications for the effect the NGP had on small area poverty estimates (Panel A) and the percentage of unlit settlements (Panel B), accounting for the threats to identification described in this section, namely: the existence of CBFMA or PACBRMA tenurial agreements, the impact of Typhoon Haiyan, conflict on the island of Mindanao, and the 4Ps CCT program. All point estimates are plotted with their 95% confidence intervals. The grey shading represent the 95% confidence intervals for the main specifications of Table 5.

the NGP continues to significantly reduce poverty and unlit settlements, though the magnitude is muted compared to the main results in Table 5. These findings suggest that the program might also mitigate the negative welfare impacts of extreme weather shocks.

Third, the southwestern provinces on the island of Mindanao have been affected 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, 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. We find a reduction in the main effect on small area poverty estimates, where NGP municipalities experience a 2-percentage point reduction in poverty, but the effect on remotely-sensed deprivation remains quantitatively similar.

Fourth, the Aquino administration implemented a conditional cash transfer program targeting poor families prior to the NGP, called the Pantawid Pamilyang Pilipino Program (4Ps). The main aim of 4Ps was to provide cash-grants to families with children suffering from chronic hunger and provides incentives to access schooling and healthcare.[25] The program was piloted in 2007 and launched on a wider scale, starting in 2008, before reaching the full country in 2011 with an annual budget of PHP 21 billion (∼$481m) (Fernandez and Olfindo, 2011). Figure A.20 presents a map of how the 4Ps program was rolled-out from 2008-2010.[26] When we exclude municipalities that received the program prior to the introduction of the NGP, the results remain quantitatively similar to our main results.

Finally, we conduct several additional checks on the robustness of our main findings. First, in Appendix A.1.4 we re-estimate the effects using alternative specifications that include both time-varying and time-invariant controls in Table A.9. Additionally, we apply alternative estimators proposed by Sun and Abraham (2021) in Table A.10 and De Chaisemartin and d'Haultfoeuille (2024) in Table A.11.[27] Last in Appendix D, we replicate the main analysis using two alternative outcome variables: nighttime lights and the share of the population living in unlit areas.

[25]On average, 4Ps beneficiaries received a monthly grant of $2.72 per person. The average household (of six members) received $16.36 per month, or $196 for the full year of 2013 (Acosta and Velarde, 2015). Impact evaluations show that 4Ps 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 enrollment and attendance in school, and did not disincentivize 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, by 6.5 percentage points (Acosta and Velarde, 2015).

[26]We find a weak or negligible correlation of 0.15 between municipalities treated under the 4Ps program and the NGP.

[27]Figure A.17 presents event study estimates of the NGP's impact on small area poverty (Panel A) and unlit settlements (Panel B), using the Callaway and Sant'Anna (2021) estimator with and without controls, Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2024).

5.3. Impact of NGP on Socio-Economic Outcomes and Spillovers: Village-level

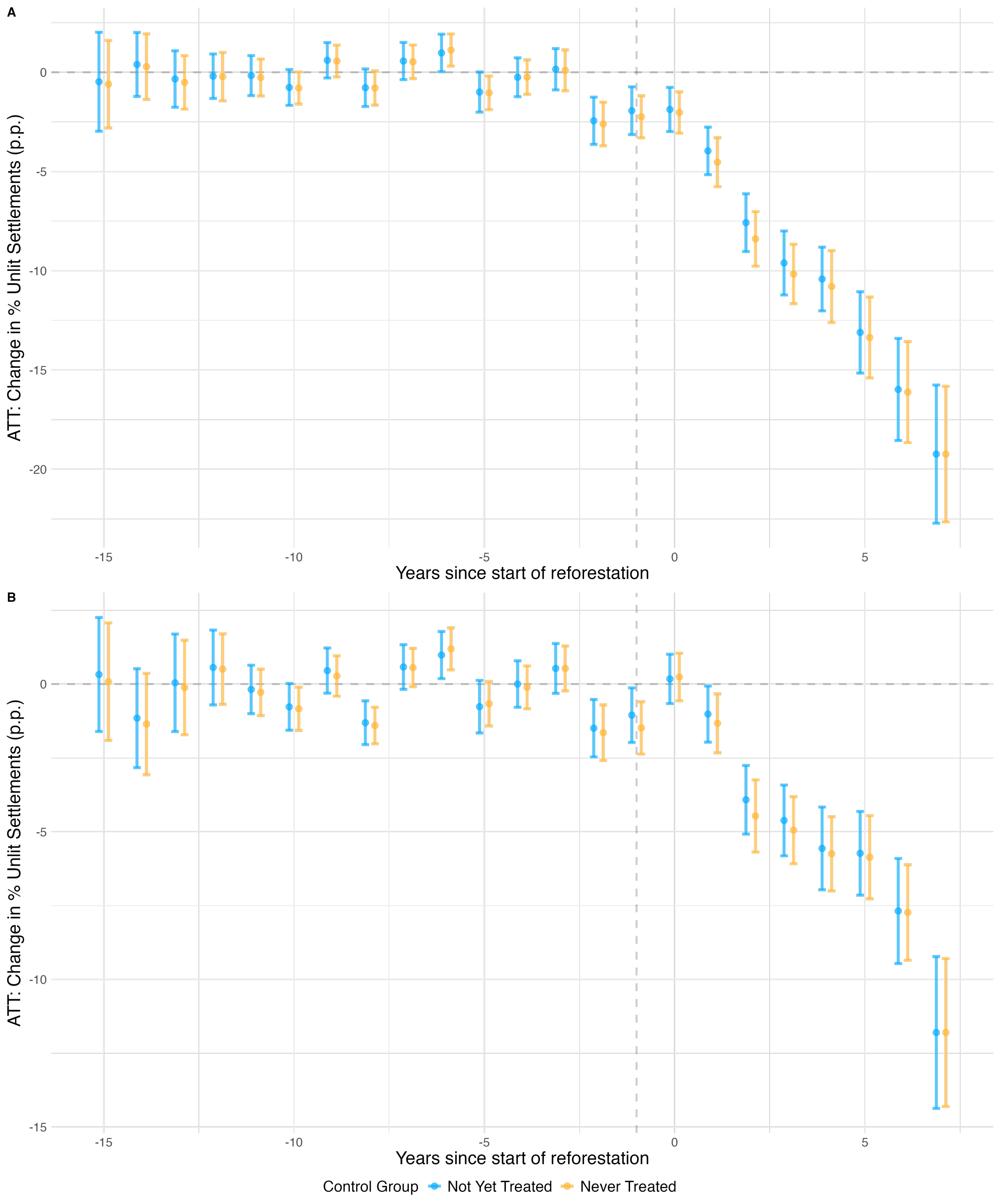
Next, we present the results from the village-level analysis in Table 6, to reinforce the findings shown in Table 5. Columns 1 and 2 indicate that treated villages experience an 8-percentage point reduction in the share of unlit settlements relative to control villages. However, these estimates do not account for potential policy-induced spillovers from treated to neighboring villages. When policies are implemented at the administrative level, their effects may cross administrative boundaries, leading to contamination of control units and potential bias in standard estimation approaches. This violates the Stable Unit Treatment Value Assumption (SUTVA), as the outcomes of control units may be influenced by exposure to nearby treated units (Butts, 2023).

To address this concern, we follow a modified version of the approach proposed by Butts (2023), removing immediate neighbors of treated villages from the sample and re-estimating the main regression using a comparison group located farther away from the treated units. The modified sample, shown in columns 3 and 4 of Table 6, reveals a 10- to 11-percentage point reduction in unlit settlements among treated villages, which is slightly larger than the main results in Table 5. Figure 5, Panel A, further shows parallel pre-trends between treated and control villages, with effects emerging within one year of program implementation. These effects persist over time and remain statistically significant up to seven years after treatment.[28]

We then explore whether the NGP generated positive externalities for neighboring control villages. As described in Section 4.2.1, we implement two identification strategies similar to Ferraro and Simorangkir (2020): (1) comparing control villages with at least one treated neighbor to control villages with neighbors that were never treated; and, (2) comparing villages with neighbors treated in earlier years to villages with neighbors that were treated later. Results are presented in columns 5 and 6 of Table 6, and Panel B of Figure 5. We find evidence of economic spillovers, in which control villages with treated neighbors experience a 5-percentage point decline in the share of unlit settlements relative to villages without treated neighbors.

[28]Appendix Figures A.12 and A.16 provide further cohort-specific breakdowns, showing consistent declines in unlit settlements.

Figure 5: Impact of NGP on Unlit Settlements at the Village Level



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 6: 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	-8.214***	-8.406***	-10.221***	-10.577***	-5.019***	-5.205***
	(0.458)	(0.470)	(0.468)	(0.466)	(0.386)	(0.360)
Observations	466906	466906	324330	324330	369949	369949

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. Channels and Mechanism

6.1. Channels: Labor Reallocation and Household Well-being

After establishing that the NGP reduced poverty, did it do so as a type of public works scheme, in which the transfers are invested in the creation of new jobs? If so, did these jobs generate income sufficient to lead to asset accumulation among beneficiary households? This subsection explores the potential channels through which the NGP reduced poverty, focusing on sectoral reallocation and labor supply dynamics, followed by changes in household incomes, food and non-food expenditures, energy use and durable asset ownership.

6.1.1. Sectoral Changes

We first analyze whether the NGP led to broader sectoral changes in the distribution of employment as a form of localized structural change. To explore how different sectors changed as a result of the NGP, we geolocate individual's household data from the Philippines Demographic and Health Surveys (DHS) in 2008 and 2017.[29] We use repeated cross sections of individual-level data aggregated to the municipality level to estimate the following two-period DID model:

$$Y_{i,m,t} = \beta_0 + \beta_1 NGP_{m,t} + \tau_t + \gamma_m + \epsilon_{m,t} \tag{7}$$

where $Y_{i,m,t}$ is estimated separately for the percentage of individuals who do not work, work in services, agriculture, unskilled manual labor or skilled labor for municipality m, in time t.[30] Time and municipality fixed effects are denoted as τ_t, and γ_m, respectively, and standard errors are clustered at the municipality level.

Table 7 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 7.9 percentage points in NGP municipalities relative to non-NGP municipalities. On the other hand, the percentage of individuals working in unskilled manual labor increased by 2.6 percentage points and services by 3.7 percentage points. Together both results provide support that individuals moved out of agriculture and some of this surplus labor likely moved into unskilled manual labor and service sector labor, but not to skilled labor. We also note that the percentage of individuals not working increased by 5.7 percentage points.

[29] 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.

[30] 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.

There are three limitations to this part of the analysis. First, how the NGP influences the sectoral reallocation of labor is only suggestive of the types of jobs created by the program. Second, 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, e.g. potentially higher-productivity agroforestry. Third, since we only have data from two periods before and after the implementation of the NGP, we are unable to investigate the dynamics of how sectoral employment varies over time.

Table 7: Impact of NGP on Employment in Different Sectors

	Not Working	Services	Agriculture	Unskilled	Skilled
NGP	0.057*	0.037**	-0.079***	0.026*	-0.007
	(0.034)	(0.019)	(0.018)	(0.014)	(0.012)
Observations	1160	1160	1160	1160	1160
R^2	0.856	0.832	0.898	0.823	0.834
Control mean (2008)	0.514	0.050	0.063	0.041	0.032

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.

6.1.2. Changes in Labor Supply

We next investigate whether the NGP led to broader changes in labor supply. One could argue that the estimated impacts on poverty alleviation might be the result of changes to labor supply through either population growth or migration. To investigate, 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 A.21, 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 by inducing migration.

6.1.3. Poverty, Income, Food and Non-Food Expenditures

We next examine the impact of the NGP on income and expenditures at the village level using an alternative data source. Specifically, we use the Family Income and Expenditure Survey (FIES), a nationally representative household survey conducted in 2009, 2012, and 2015, covering 8,500 villages across the Philippines. The FIES is the primary source of information on household income, consumption, and spending patterns in the country. It estimates cash and in-kind family income and expenditures, and records consumption by detailed itemized expenditure categories. To improve comparability between treated and control villages, we implement nearest-neighbor propensity-score matching at the baseline (2009).[31] The final dataset is a balanced village-year panel after merging by village identifier and year. We estimate the following DID model:

$$Y_{i,v,t} = \beta_0 + \beta_1 NGP_{v,t} + X_{v,t}\delta + \delta_{v,t} + \epsilon_{v,t} \tag{8}$$

where $Y_{i,v,t}$ is estimated separately for small area poverty estimates, total income, agricultural income, non-agricultural income, food expenditure and non-food expenditure for village v, in time t. We additionally control for the total NGP payment transferred to each village, captured by $X_{v,t}\delta$. Municipality-by-year fixed effects are denoted as $\delta_{v,t}$ and standard errors are clustered at the village level.

The results are presented in Table 8. We find that the NGP led to a 5.4-percentage point reduction in village-level poverty, which is closely aligned with the municipality-level estimates shown in Table 5. In terms of income, treated villages saw an overall increase in total income or a 14 percent increase over the control mean. Breaking down income, we find that consistent with the sectoral results in Table 7, there is a decline in agricultural income (10 percent) and a rise in non-agricultural income (18 percent). Finally, we examine changes in consumption. We find no evidence of a significant change in food expenditures. However, non-food expenditures increased by 19 percent over the control mean, further indicating improvements in household welfare.

6.1.4. Household Energy Use and Durable Assets

Having established that the NGP led to the sectoral reallocation of labor, as well as changes in incomes and non-food expenditures, we now analyze the impact of the NGP on household energy sources and durable asset ownership, which serve as key indicators of how the program improved household welfare in treated municipalities. We again use the DHS repeated cross sections of individual-level data aggregated to

[31] In Appendix A.1.5 and Figure A.22 we provide pre and post matching diagnostics. The propensity score is estimated using a logistic regression, as a function of pre-treatment covariates capturing socioeconomic conditions and geographic/environmental features: night-time lights, population, slope, elevation, NDVI, temperatures (max/min), flooded area, deforestation, precipitation, and tree cover. Treated units are matched to control units using nearest-neighbor propensity score matching, enforcing exact matching within regions.

Table 8: Impact of NGP on Poverty, Income, and Consumption

	(1) Small Area Poverty Estimates	(2) Total Income	(3) Ag. Income	(4) Non-ag. Income	(5) Food exp.	(6) Non-food exp.
NGP	-0.054**	27352.79*	-3018.46*	30371.25**	3715.439	17586.097**
	(0.022)	(14442.27)	(1638.34)	(14936.37)	(2389.006)	(8945.304)
Controls	✓	✓	✓	✓	✓	✓
FE	MxY	MxY	MxY	MxY	MxY	MxY
Observations	2002	2002	2002	2002	2002	2002
Adj. R^2	0.179	0.181	0.114	0.185	0.227	0.185
Control mean (2009)	0.55	193679.2	29499.38	164179.8	70994.15	93250.82

Notes: This table presents estimates for the effect that the NGP has on village-level small area poverty estimates, income, and consumption (expenditures) as measured in the FIES data, identified using a DID based on whether a village received the NGP program or not. Regressions control for the total cash transfers received by each village. Municipality-by-year fixed effects are included in every regression. Standard errors are clustered at the village level. Significant at * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the municipality level and re-estimate Equation 8, modifying the dependent variable to separately examine the percentage of households using wood for cooking fuel and specific household amenities, including electricity, television, radio, refrigerator, and motorcycle ownership for municipality m, in time t.

The results, presented in Table 9, indicate a significant positive impact on the acquisition of consumer durables in treated municipalities. Specifically, television and refrigerator ownership increase by 7 and 8.1 percentage points, respectively. Additionally, we find evidence of an increase in households with electricity of 5.6 percentage points, which provides support to the main findings regarding reductions in unlit settlements.

Table 9: Impact on Household Energy Use and Durable Assets

	Wood Cooking Fuel	Electricity	Television	Radio	Refrigerator	Motorcycle
NGP	-0.049	0.056**	0.070**	0.002	0.081**	0.053
	(0.042)	(0.027)	(0.031)	(0.039)	(0.037)	(0.036)
Observations	1160	1160	1160	1160	1160	1160
R^2	0.912	0.895	0.915	0.879	0.883	0.894
Control mean (2008)	0.452	0.803	0.691	0.666	0.421	0.213

Notes: This table presents estimates for the effect that the NGP has on household energy use and durable assets, 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.

6.2. Mechanism: Payments and Forest Assets

The NGP led to a reduction in poverty and unlit settlements, but why? The temporal dynamics in Figure 3 suggest that the initial decline is likely driven by financial payments that were invested to establish and maintain the new forest assets. Subsequent reductions are more plausibly attributed to the returns generated by the forest assets once they have reached maturity. Yet, it is also possible that long-term reductions occurred, at least partially, as a consequence of private investments made by the NGP's beneficiaries in the first three years of the program. In the following, we attempt to disentangle the effects of the payments to PO, for establishing and maintaining tree plantations, from the impacts due to the forest assets. This will allow us first, to identify the key components of the bundled intervention that contribute to poverty reduction and second, to estimate the differential trajectories of the returns generated by both productive and non-productive natural assets.

Although the forest assets are transferred to communities after the third year of the program, they are not all immediately income-generating or fully matured. Their productivity depends on the species planted and the time required for these species to mature. A report by USAID (2018) further details the life cycle of species planted in the Philippines. Fuelwood and fruit-bearing trees, such as coffee, cacao, rubber, jackfruit, lanzones, mango, and rambutan typically reach maturity within three to eight years. By contrast, medium- and slow-growing timber species, along with bamboo and rattan, by contrast require more than 15 years to become productive. Furthermore, explicit provisions in the NGP guidelines delineated production and protection zones during the planning phase and matched specific species to the sites. Typically slow-growing indigenous and endemic species were required in strict protection areas while income-generating species, like fruit-bearing trees and fast-growing timber, were permitted only in designated production or multiple-use zones (DENR, 2012).[32] Non-productive sites were designated as such to restore degraded forestland within the protected zones and thus, by definition, are not expected to generate direct economic returns. Any poverty reduction observed in these areas is most likely to be attributed to the payments, with any sustained decline in poverty after the payment period representing the residual impact of these payments. In contrast, sustained reductions in productive areas beyond year three are more likely to reflect the emerging returns from forest assets, in addition to any residual impact of the payments. The divergence in trajectories between the two groups therefore provides a means to approximate the contribution of forest assets to long-term poverty reduction.

To conduct the analysis, we first classify plantation sites (Figure A.23) using project records as either productive, protection (non-productive), or mixed, where sites contain both productive and protection plantings.[33] We then define productive villages as those that planted only productive sites, and protection villages as those that

[32] In 2011, a DENR memorandum directed that premium and indigenous species be planted to restore degraded forestlands and protected zones, whereas fast-growing and fruit-bearing species were allocated to agroforestry, production areas, and multiple-use zones (DENR Memorandum Circular No. 2011-01, 2011).

[33] Protection sites are defined narrowly as areas where the planted species do not yield direct financial returns to participating communities. However, we acknowledge that these sites likely generate important indirect benefits, including watershed protection, erosion control and biodiversity conservation.

planted only protection sites. Villages that planted both productive and protection sites or mixed sites are excluded from the analysis to avoid conflating the returns from productive and protective assets. With this classification, we re-estimate Equations 2 and 3 separately for two subsamples: one consisting of productive villages and never treated villages, and another of protection villages and never treated villages.

The event study (Figure 6) and average treatment effects (Table 10) allow us to compare outcomes across villages exposed to different natural asset profiles. In the first three years following the start of the NGP, both productive and protection villages exhibit comparable declines in the share of unlit settlements, consistent with the distribution of financial payments during this period. Since there are no returns to productive or protection assets in the first three years, the impacts are driven by the standardized payment component of the program.

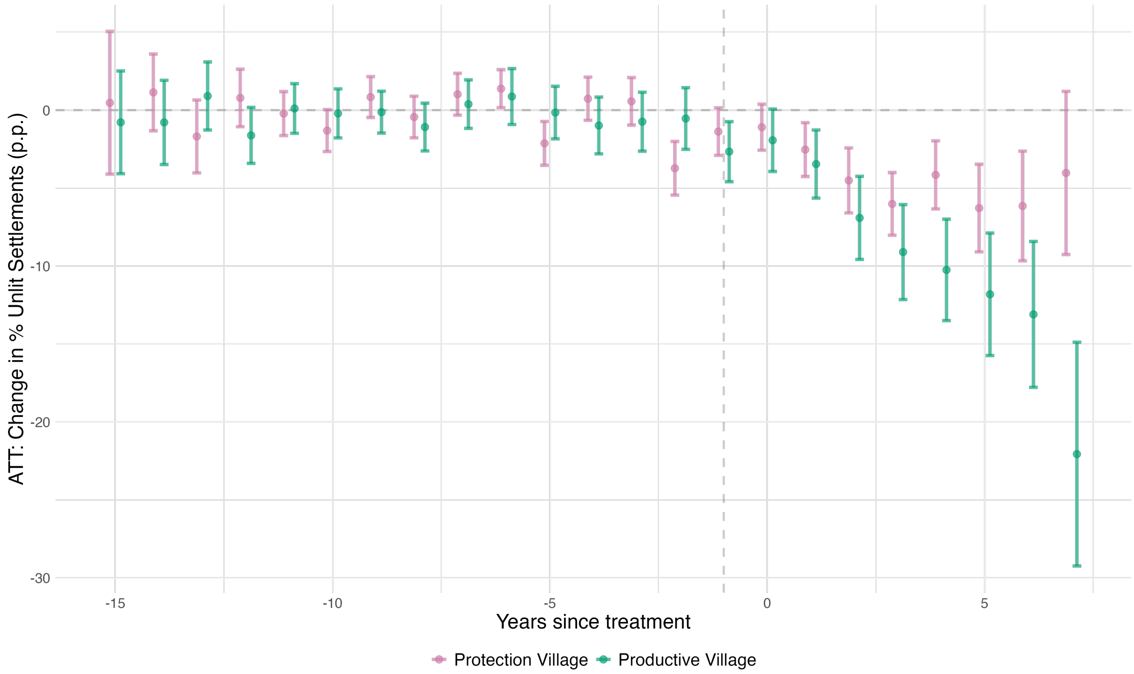
Starting in year four, after the end of the payment period, a clear divergence emerges. In protection villages, the pace of poverty reduction slows considerably, bottoming out in year four before trending toward zero. Since protection sites are not designed to generate economic returns, any persistent effects are likely the residual impact of the payments. In contrast, productive villages continue to experience steady and statistically significant declines in unlit settlements. The sustained divergence between the two groups suggests that productive assets are driving continued reductions in unlit settlements after the payment period ends. By the end of the observation period, the average difference between the two groups is 5.5 percentage points.

Table 10: Impact of Productive vs. Protection Assets

	Percentage of Unlit Settlements	
	(1) Productive Village	(2) Protection Village
NGP	-9.83***	-4.346***
	(0.878)	(0.594)
Observations	398221	413725

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. 'Productive Village' compares NGP villages which only planted productive plantations relative to a pool of control villages who are never treated during the duration of the panel. 'Protection Village' compares NGP villages which only planted non-productive plantations relative to a pool of control villages 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.

Figure 6: Impact of Productive vs. Protection Natural Assets



Notes: This figure presents estimates from an event study specification for the effect the NGP had on the percentage of unlit settlements. 'Productive Village' compares NGP villages which only planted productive plantations relative to a pool of control villages who are never treated during the duration of the panel. 'Protection Village' compares NGP villages which only planted non-productive plantations relative to a pool of control villages who are never treated during the duration of the panel. Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

7. Conclusions

Global enthusiasm around tree planting as a means of addressing development and environmental challenges has raised questions about the optimal design of such projects. In this paper, we studied the poverty implications of the National Greening Program, which planted billions of trees in the Philippines from 2011-2018. We implemented a dynamic difference-in-differences identification strategy that compared the pre- and post-planting periods between earlier treated NGP municipalities and a pool of municipalities that had either 'not-yet' been treated by the time of the program implementation, or were never treated in the duration of the panel.

Our main results found that the NGP led to a reduction in traditionally-measured poverty, of 6-percentage points, and a decline in the percentage of unlit settlements, of 7-percentage points. The program operated as a hybrid PES-public works program that, via financial transfers, invested in the creation of new jobs dedicated to the establishment and maintenance of forest assets. Once created, these assets, in turn, were to continue to support jobs while potentially generating new ones. As evidence of the channel through which the NGP reduced poverty, specifically through job creation, we showed that the program led to a decline in agricultural labor and a corresponding increase in unskilled manual and service sector employment. Although our data are limited to two survey rounds, these results implied changes to the structure of local labor markets that could, in the event of forest assets generating long-term returns, become permanent. Also, the economic activity generated by the NGP was unlikely to result from changes in labor supply. We next assessed the extent to which changes in local labor markets, due to the NGP, impacted on incomes, non-food expenditures and private assets. Consistent with previous research on public works programs, such as those in Kenya (Egger *et al.*, 2022) and India (Muralidharan *et al.*, 2023), we found positive effects on income and non-food expenditures, as well as increases in electricity, television, and refrigerator ownership.

Yet, what sets the NGP apart from public works programs in other settings is the standardized drive to create durable natural assets, as a means of sustaining development benefits from the program after the payments ended. Payments and forest assets played complementary roles in reducing poverty. Alone, the payments reduced poverty for another three years after the end of the transfers, before this residual effect appeared to dissipate, but not reverse. Payments, in combination with the creation of natural assets designed to generate tangible, long-term economic returns, appeared to reduce poverty even more and to longer-lasting effect. These results contribute to the evidence base on the impacts of multi-faceted approaches to poverty reduction, specifically the idea that adding complementary components to cash transfers, such as training or productive investments, can amplify outcomes and deliver even greater benefits (Banerjee *et al.*, 2022; Bossuroy *et al.*, 2022; Macours *et al.*, 2022; Sedlmayr *et al.*, 2020). Whether cash or in-kind transfers alone are sufficient to sustain impacts after programs end underscores the need to identify the components of policies responsible for generating benefits (Sedlmayr *et al.*, 2020). In our case, payments are shown to be critical for generating short- and, via incentivizing the creation of forest assets, long-term benefits. Although not a focus of our analysis, we also note the program's design, particularly the engagement of the DENR with PO during the planning and implementation phases, in addition to the continued monitoring of plantations, as a likely critical factor contributing to the program's success.

Productive plantations appeared to generate tangible returns, feeding into sustained reductions in poverty, at least seven years after establishment. Future research could evaluate these effects beyond our limited study period yet these results are suggestive of growing and durable natural assets. That forest cover grew, and did not reverse during our study period reinforces this point. The 'permanence' of the tree plantations, and indeed forest carbon stocks (MacKenzie *et al.*, 2012), as well as the implications of tree planting for other ecosystem services (Grosset *et al.*, 2023), are important subjects for further study. Environmental impacts aside, the continued durability of forest assets is likely to be important for sustaining the success of the NGP in creating jobs and reducing poverty. When designing tree planting projects, our study has shown that such programs can be powerful tools for economic development in rural areas.

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A. Appendix

A.1. Additional Tables

A.1.1. Descriptives and Summary Statistics

Table A.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).

Table A.2: Summary Statistics at the Municipality Level

Variable	Mean	SD	Min	Max	N
Small Area Poverty Incidence	33.3	18	0.28	97.5	29290
Unlit Settlements (%)	38.1	36.7	0	100	27714
Nighttime lights (DN)	3.15	5.89	0	48.3	29646
Forest Cover (ha)	675	1345	0	18776	29646
Number of NGP projects	16.1	43.5	1	746	6348
Extent of NGP projects (ha)	243	464	0.000814	18522	6348
Population count	57284	118104	0	2898835	29646
Precipitation (mm)	235	70.5	87.1	640	29322
Maximum temperature (°C)	30.6	1.41	20.1	33.6	29322
Minimum temperature (°C)	22.8	1.47	12.6	25.7	29322
Wind speed (m/s)	1.95	0.502	0.451	3.87	29322
Slope	7.3	5.07	0.367	25.1	29610
Elevation	233	270	2.32	1899	29610
Unemployment (%)	0.456	0.168	0	1	1160
Agricultural employment (%)	0.123	0.155	0	1	1160
Services employment (%)	0.0837	0.0753	0	0.407	1160
Unskilled manufacturing empl. (%)	0.0329	0.0625	0	0.667	1160
Skilled manufacturing empl. (%)	0.0487	0.0719	0	1	1160
Access to highways	19.5	13.8	1	168	28674
Access to markets	4.45	4.75	1	78	26838
Commercial establishments (2010)	299	594	0	14545	29232
Manufacturing establishments (2010)	42.9	106	0	3105	29232
Bank establishments (2010)	11	45.1	0	1184	29232
Affected by typhoon Haiyan (%)	0.381	0.486	0	1	29646
Received CCT (%)	0.356	0.479	0	1	29646
Located in Mindanao province (%)	0.233	0.422	0	1	29646

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

Table A.3: Summary Statistics at the Village Level

Variable	Mean	SD	Min	Max	N
Unlit Settlements (%)	27.9	39.1	0	100	633381
Nighttime lights (DN)	1.66	2.9	0	37.7	796727
Number of NGP projects	18.5	42.1	1	835	20527
Extent of NGP projects (ha)	75.4	147	0.0000271	4788	20527
Population count	2235	5775	0	269881	796727
Precipitation (mm)	231	69.7	68.2	662	789488
Maximum temperature (°C)	30.9	1.23	18.4	34	789488
Minimum temperature (°C)	23.1	1.31	11	25.8	789488
Wind speed (m/s)	1.96	0.52	0.417	3.92	789488
Slope	5.02	5.08	0	32.7	796727
Elevation	152	248	-1.02	2203	796727

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

A.1.2. Supplementary Results

Table A.4: Impact of NGP on Socio-Economic Measures: Standard TWFE-DID

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
DID_{TWFE}	-4.517***	-3.789***	-7.051***	-4.750***
	(0.4707)	(0.4409)	(0.8877)	(0.9384)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	29,290	26,443	27,714	25,138
Adjusted R^2	0.82235	0.83120	0.79461	0.80180

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

	Small Area Poverty Estimates		Percentage of Unlit Settlements	
	(1)	(2)	(3)	(4)
	Above Median	Below Median	Above Median	Below Median
NGP	-11.203***	-1.477**	-6.939***	-4.15***
	(1.210)	(0.577)	(2.177)	(0.685)
Observations	14382	13968	10350	14112

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 *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1.3. Additional Robustness Check Results

Table A.6: Impact of NGP with Different Samples Depending on CBFMA/PACBRMA Agreements

	No CBFMA/PACBRMA Agreements				Only CBFMA/PACBRMA Agreements			
	Small Area Poverty Estimates		Percentage Unlit Settlements		Small Area Poverty Estimates		Percentage Unlit Settlements	
	(1) Not Yet Treated	(2) Never Treated	(3) Not Yet Treated	(4) Never Treated	(5) Not Yet Treated	(6) Never Treated	(7) Not Yet Treated	(8) Never Treated
NGP	-6.469***	-6.989***	-5.472***	-5.707***	-6.131***	-6.355***	-10.292***	-10.205***
	(0.706)	(0.715)	(1.248)	(1.402)	(0.676)	(0.799)	(1.412)	(1.447)
Observations	19224	19224	17028	17028	13302	13302	11268	11268

Notes: Note: This table presents estimates for the effect of the NGP on small area poverty estimates and the percentage of unlit settlements, using a DID approach based on the roll-out of the NGP. 'Not Yet Treated' compares earlier treated NGP municipalities to municipalities that have 'not-yet' been treated by the time of treatment. 'Never Treated' compares NGP municipalities with tree planting to control municipalities never treated during the panel duration. Columns 1-4 restrict the treated sample to municipalities without CBFMA/PACBRMA agreements, while columns 5-8 restrict the treated sample to municipalities with these agreements. 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 A.7: Impact of NGP on Small Area Poverty Estimates: Robustness

	Excluding Haiyan		Only 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	(7) Not Yet Treated	(8) Never Treated
NGP	-7.187***	-7.866***	-1.859**	-1.828**	-1.862***	-2.017***	-5.372***	-5.891***
	(0.782)	(0.815)	(0.728)	(0.904)	(0.430)	(0.496)	(0.705)	(0.779)
Observations	17280	17280	11070	11070	22104	22104	18180	18180

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. '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. Columns 1 and 2 exclude municipalities affected by Typhoon Haiyan, while columns 3 and 4 only include municipalities affected by Typhoon Haiyan. Columns 5 and 6 exclude municipalities in the region of Mindanao, and columns 7 and 8 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.8: Impact of NGP on Unlit Settlements: Robustness

	Excluding Haiyan		Only 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	(7) Not Yet Treated	(8) Never Treated
NGP	-7.884***	-7.903***	-4.682**	-5.653**	-8.385***	-8.804***	-6.177***	-6.226***
	(1.355)	(1.466)	(2.360)	(2.387)	(1.303)	(1.271)	(1.261)	(1.277)
Observations	14724	14724	9738	9738	19350	19350	16182	16182

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. '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. Columns 1 and 2 exclude municipalities affected by Typhoon Haiyan, while columns 3 and 4 only include municipalities affected by Typhoon Haiyan. Columns 5 and 6 exclude municipalities in the region of Mindanao, and columns 7 and 8 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.1.4. Conditional Parallel Trends and Alternative Estimators

While the main CS-DID estimates are well identified, as shown by unconditional parallel trends between treatment and control cohorts in the pre-intervention periods, we investigate the robustness of our results to conditioning the CS-DID estimator on a set of characteristics which might influence poverty. We deal with potential selection issues by re-running Equation (1) and condition on several time-varying characteristics (population, precipitation, and maximum temperature) as well as 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 banks).[34] The results are presented in Figure A.17 (Table A.9), where we show effect sizes that are slightly smaller than the main results in Table 5.

Table A.9: 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	-3.475***	-4.339***	-6.513***	-7.554***
	(0.691)	(0.952)	(2.064)	(2.088)
Controls	✓	✓	✓	✓
Observations	25596	25596	22212	22212

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 *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we re-run the main analysis following Sun and Abraham (2021), which is very similar to Callaway and Sant'Anna (2021), but corrects for the possibility that coefficients on a given lead or lag could be contaminated by the effects from other periods. Further, we employ the De Chaisemartin and d'Haultfoeuille (2024) staggered DID

[34] 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.

Table A.10: 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}	-7.103***	-6.737***	-7.147***	-5.771***
	(0.6815)	(0.7094)	(1.202)	(1.344)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	29,290	26,443	27,714	25,138
Adjusted R^2	0.82721	0.83566	0.79858	0.80452

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.

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. The results, presented in Figure A.17 (Table A.10 and Table A.11 respectively), remain qualitatively similar to Table 5.

Table A.11: 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_{CDH}	-5.366***	-4.509***	-6.390***	-4.588***
	(0.5584)	(0.5445)	(1.066)	(1.124)
Controls		✓		✓
Municipality FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	12166	12007	11412	10165

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.

A.1.5. Channels and Mechanism: FIES Sample

Table A.12: Baseline (2009) differences: Treated vs Control — pre-matching

	Control	Treated	Diff	p-value
Nighttime lights	1.010	0.476	-0.535***	0.000
Population	1,742.060	1,761.563	19.502	0.898
Slope	5.474	9.624	4.150***	0.000
Elevation	123.772	272.431	148.659***	0.000
Vegetation index (NDVI)	0.891	0.912	0.021***	0.000
Max temperature	30.263	29.534	-0.730***	0.000
Min temperature	23.184	22.259	-0.925***	0.000
Flooded	0.005	0.018	0.013	0.263
Deforestation	19,800.385	72,360.190	52,559.806***	0.000
Tree Cover	439,656.628	1,510,491.376	1,070,834.748***	0.000
Precipitation	271.861	292.929	21.068***	0.000

Notes: This table presents baseline differences between treated and control villages prior to matching. Standard errors are clustered at the village level. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Table A.13: Baseline (2009) differences: Treated vs Control — post-matching

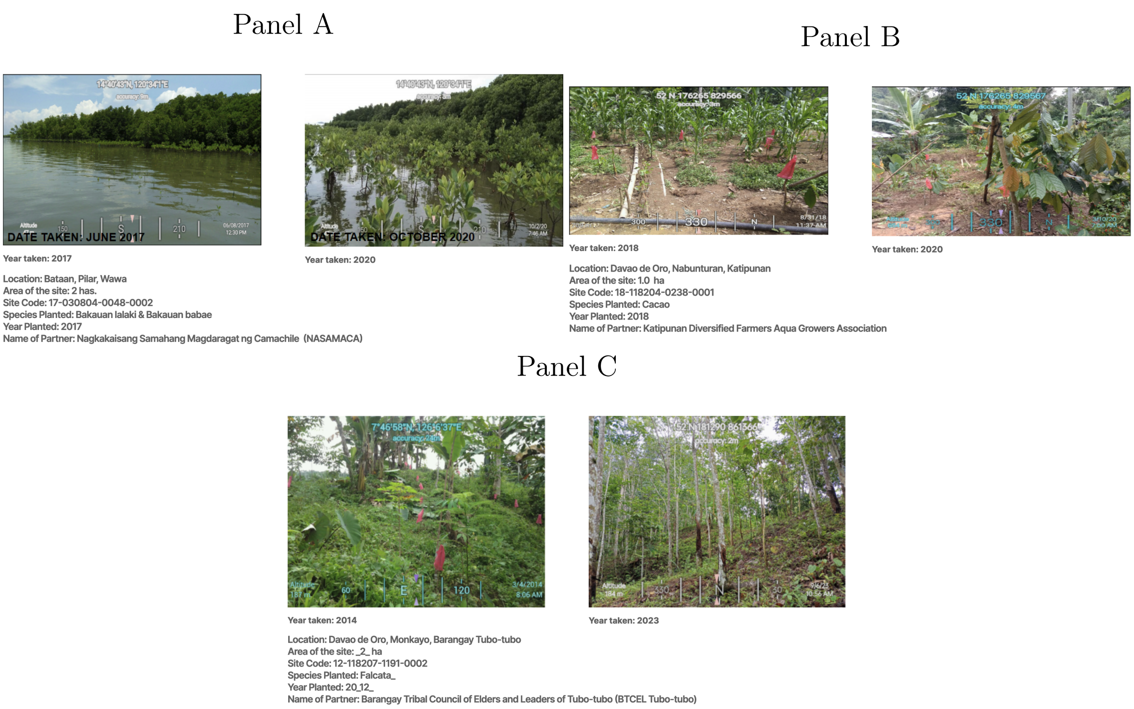
	Control	Treated	Diff	p-value
Nighttime lights	0.538	0.487	-0.051	0.572
Population	1,968.150	1,774.138	-194.012	0.657
Slope	9.803	9.653	-0.150	0.725
Elevation	272.281	277.511	5.231	0.789
Vegetation index (NDVI)	0.913	0.914	0.001	0.830
Max temperature	29.587	29.530	-0.056	0.597
Min temperature	22.305	22.257	-0.048	0.689
Flooded	0.007	0.006	-0.001	0.684
Deforestation	71,688.898	74,374.692	2,685.794	0.880
Tree Cover	1,432,194.920	1,538,627.736	106,432.816	0.656
Precipitation	292.552	292.709	0.156	0.967

Notes: This table presents baseline differences between treated and control villages post matching. Standard errors are clustered at the village level. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

A.2. Additional Figures

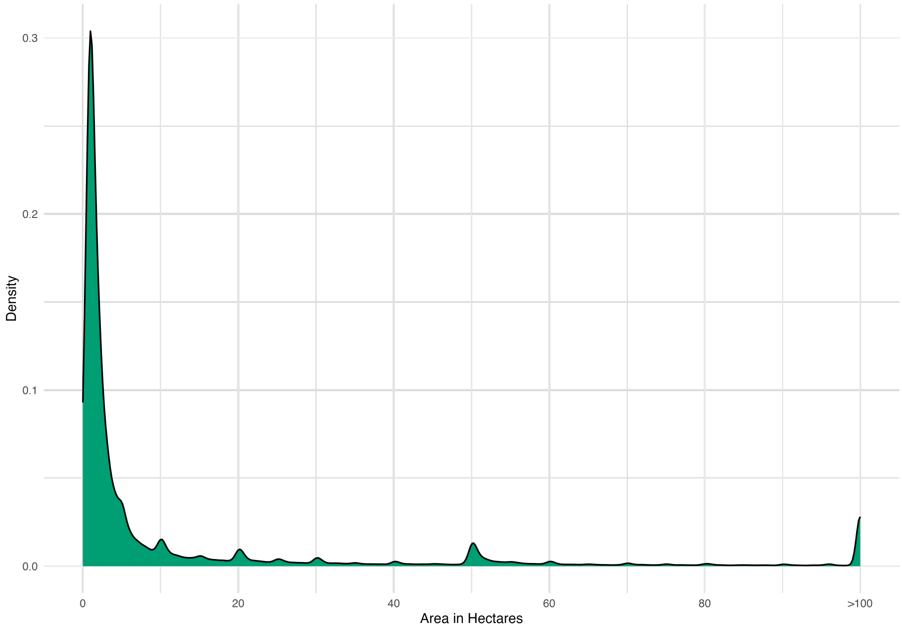
A.2.1. Descriptives, Summary Statistics and Identifying Assumptions

Figure A.1: Before and After Geo-tagged Photos of NGP Plantations



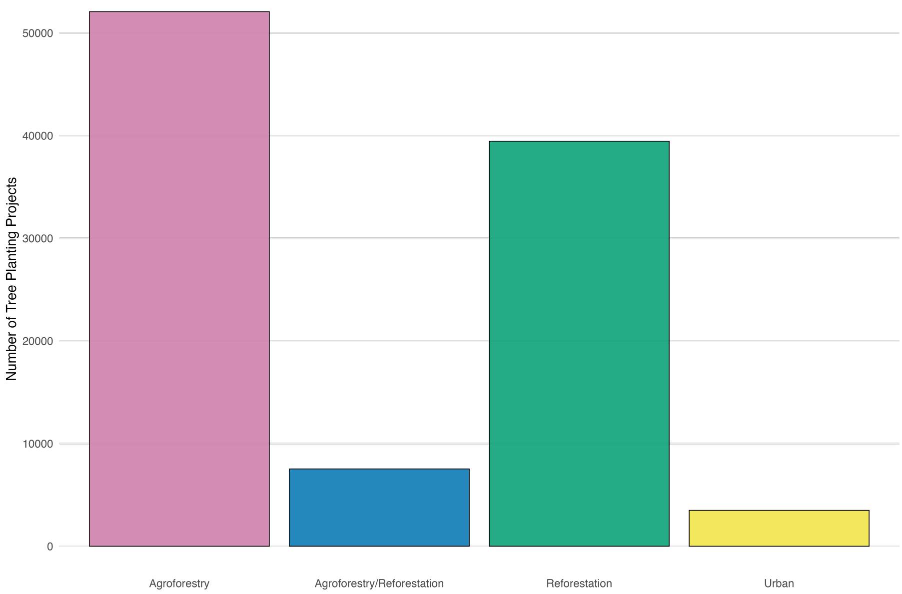
Notes: This figure shows three before and after geo-tagged photos of NGP plantations. Photos taken by the National Greening Program Coordinating Office, Forest Management Bureau.

Figure A.2: Distribution of Tree Planting Sites by Hectares



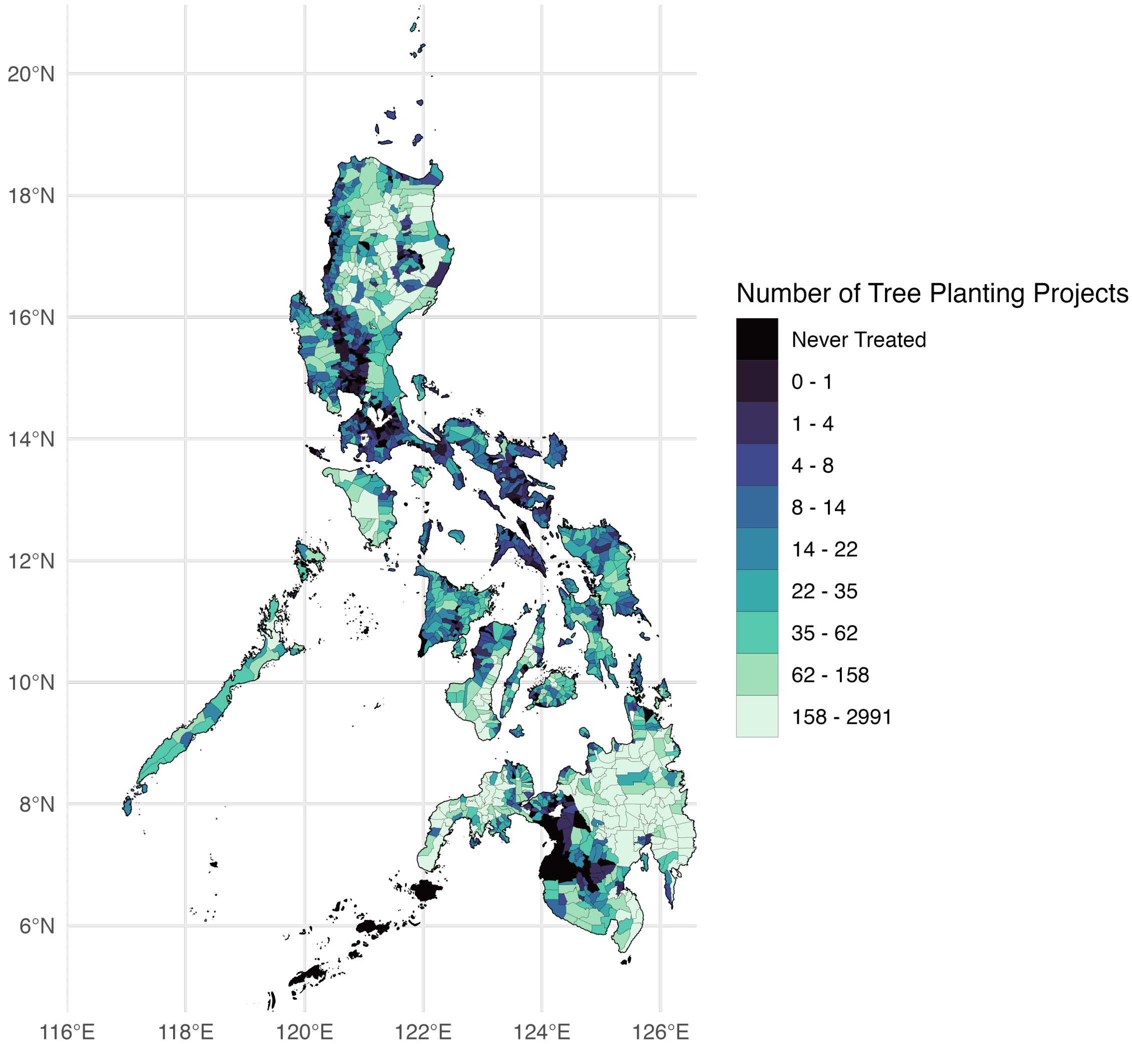
Notes: This figure plots the distribution of each tree planting site's area in hectares. The average tree planting site is 15 hectares.

Figure A.3: Classification of Tree Planting Sites



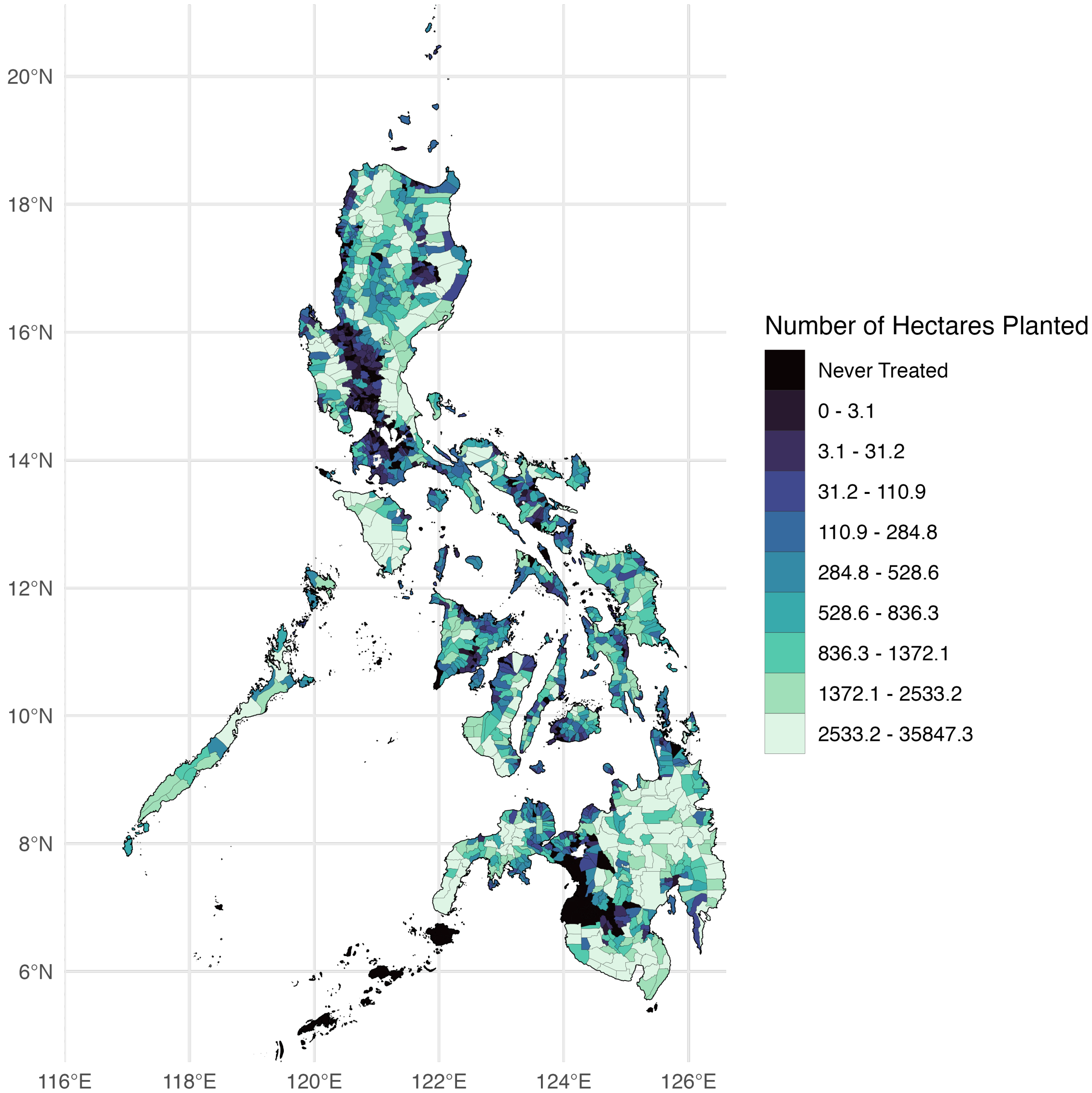
Notes: This figure classifies the number of tree planting projects into agroforestry, agroforestry/reforestation, reforestation and urban reforestation.

Figure A.4: Number of Tree Planting Projects per Municipality, 2011-2018



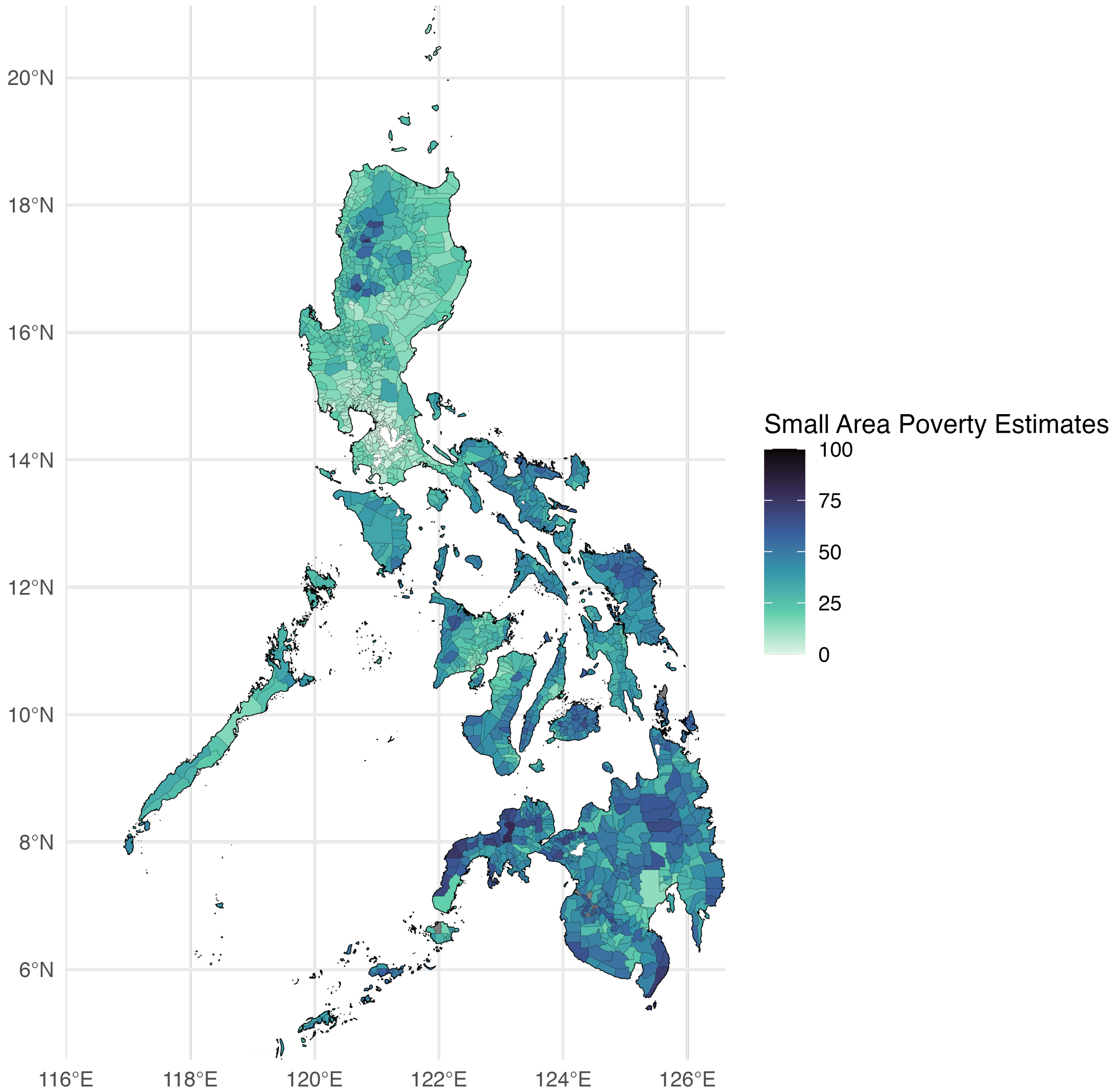
Notes: This figure presents the cumulative number of tree planting projects implemented in each municipality from 2011-2018. *Source*: Author's own calculations.

Figure A.5: Number of Hectares Planted per Municipality, 2011-2018



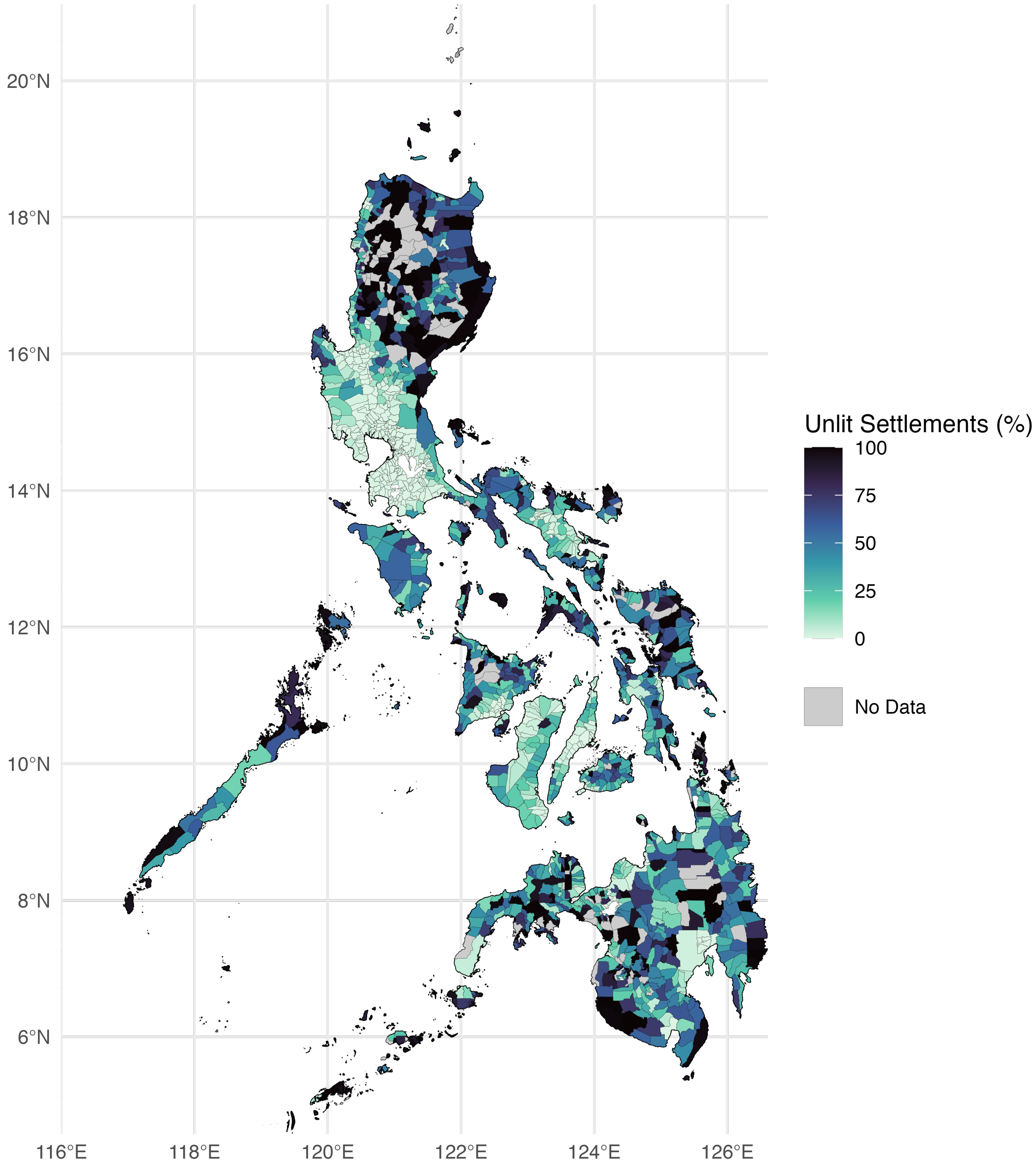
Notes: This figure presents the cumulative number of hectares planted in each municipality from 2011-2018. *Source*: Author's own calculations.

Figure A.6: Small Area Poverty Estimates, 2010



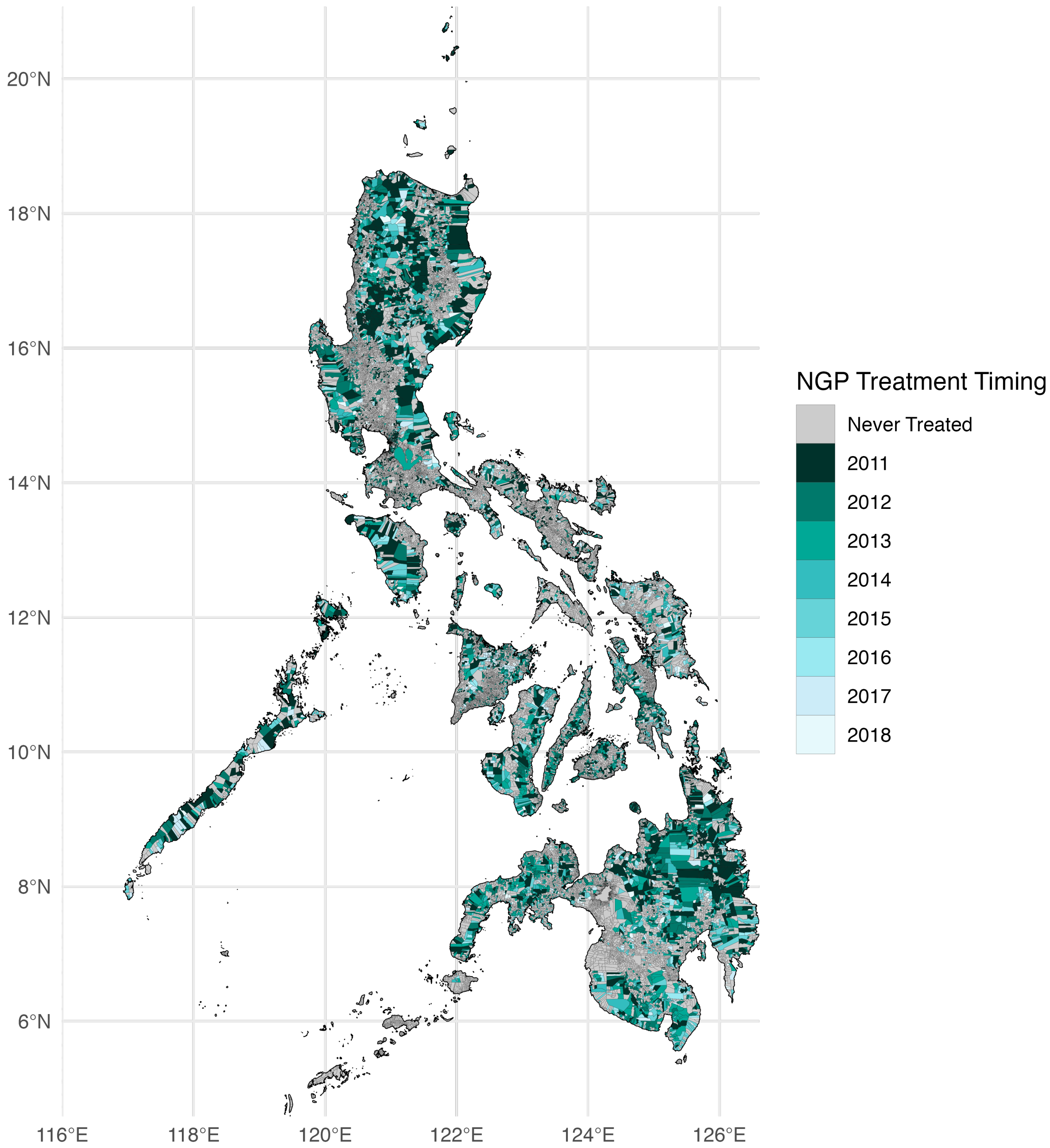
Notes: This figure presents the small area poverty estimates in 2010. *Source*: Author's own calculations.

Figure A.7: Percentage of Unlit Settlements, 2010



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

Figure A.8: Village-level NGP Timing by Treatment Pool



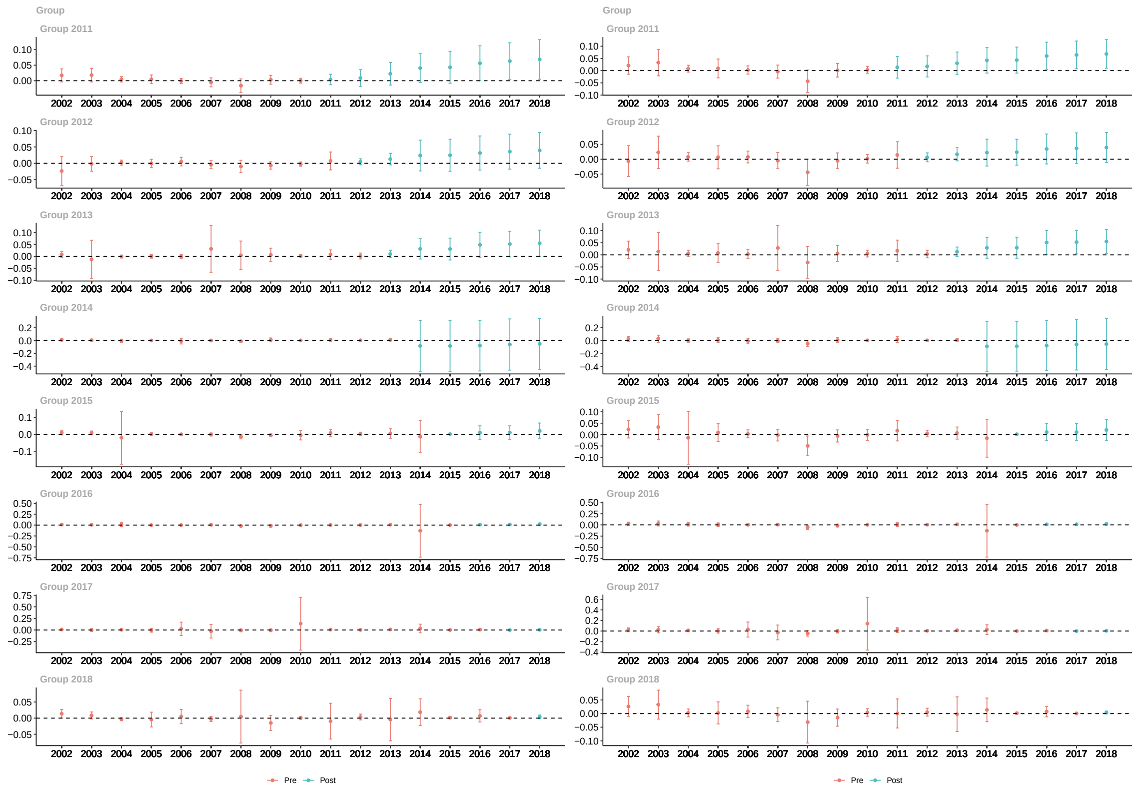
Notes: This figure presents identifying variation for the year in which villages first received an NGP project. *Source*: Author's own calculations.

A.2.2. Dynamic Effects By Cohort

Event studies by cohort

Figure A.9: Dynamic Impact of NGP on Forest Coverage

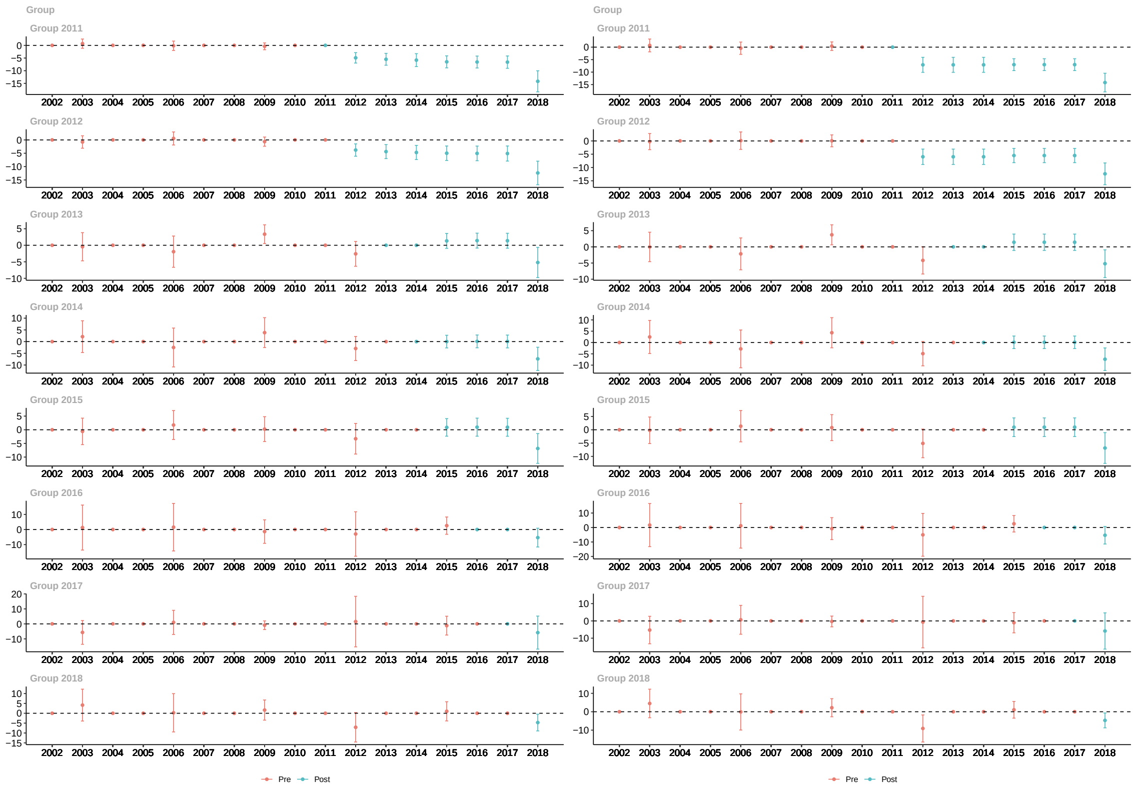
Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



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.10: Dynamic Impact of NGP on Small Area Poverty Estimates

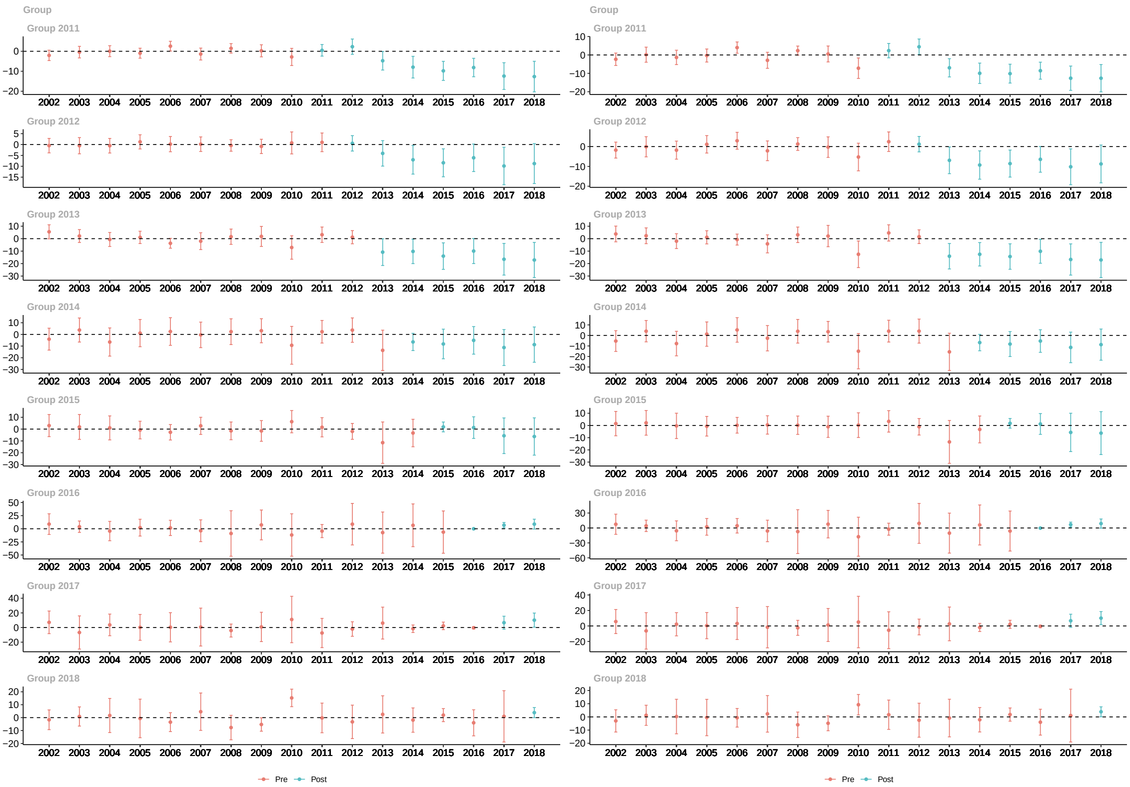
Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



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.11: Dynamic Impact of NGP on Unlit Settlements

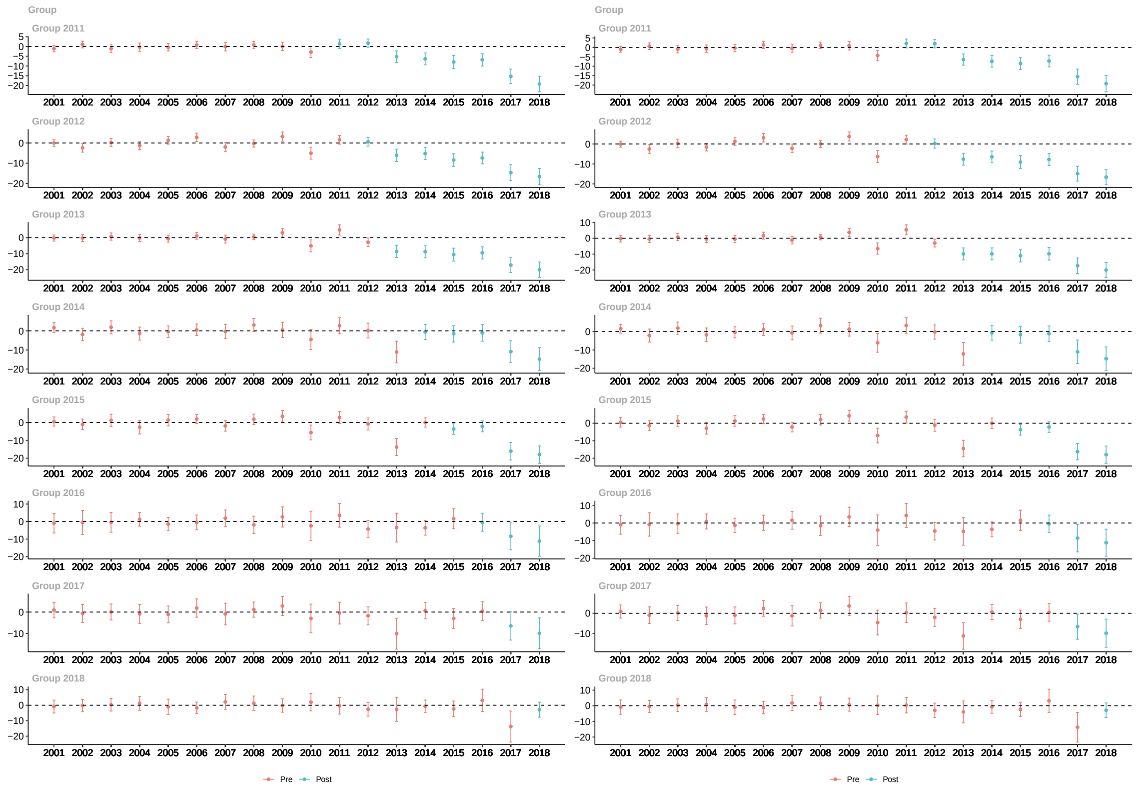
Panel A: Treatment vs. Not Yet Treated   Panel B: Treatment vs. Never Treated



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

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

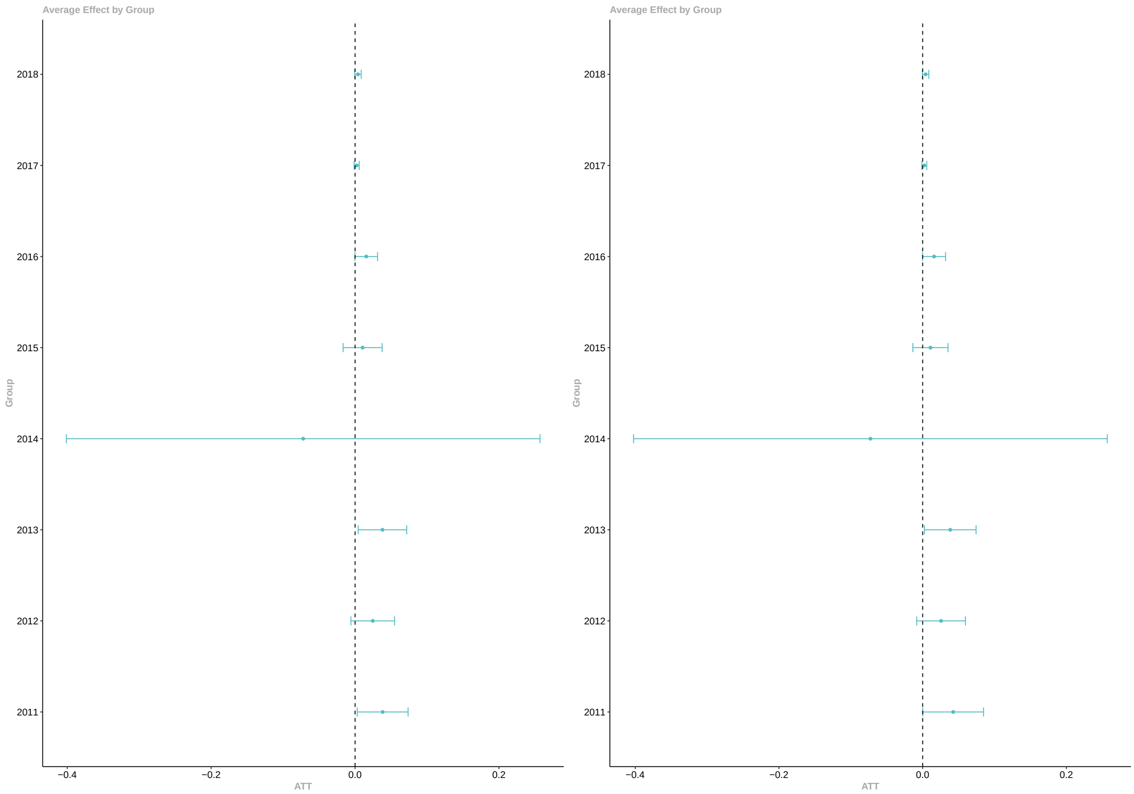


Notes: This figure presents estimates from an event study specification for each cohort effect the NGP had on the percentage of unlit settlements at the village level using the modified sample. Panel A presents estimates for treated cohorts versus not yet treated cohorts and Panel B presents estimates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

Average Treatment Effect by Cohort

Figure A.13: Average Cohort Impact of NGP on Forest Coverage

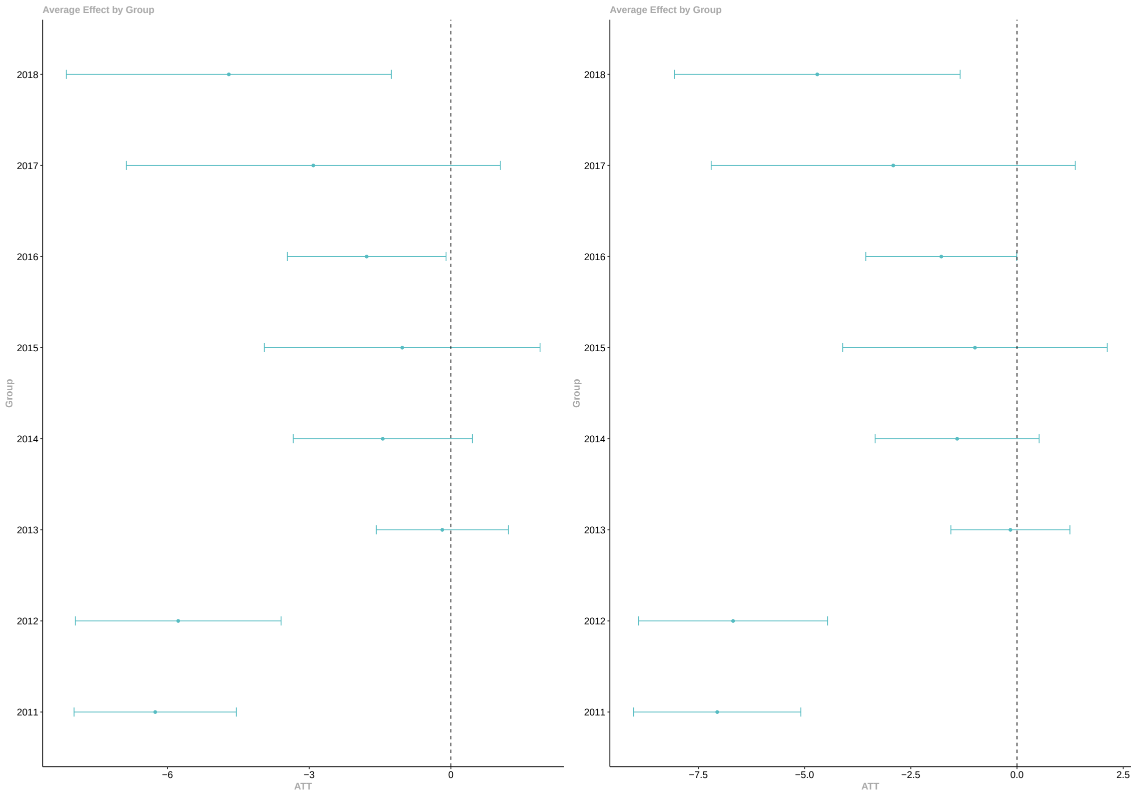
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



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.14: Average Cohort Impact of NGP on Small Area Poverty Estimates

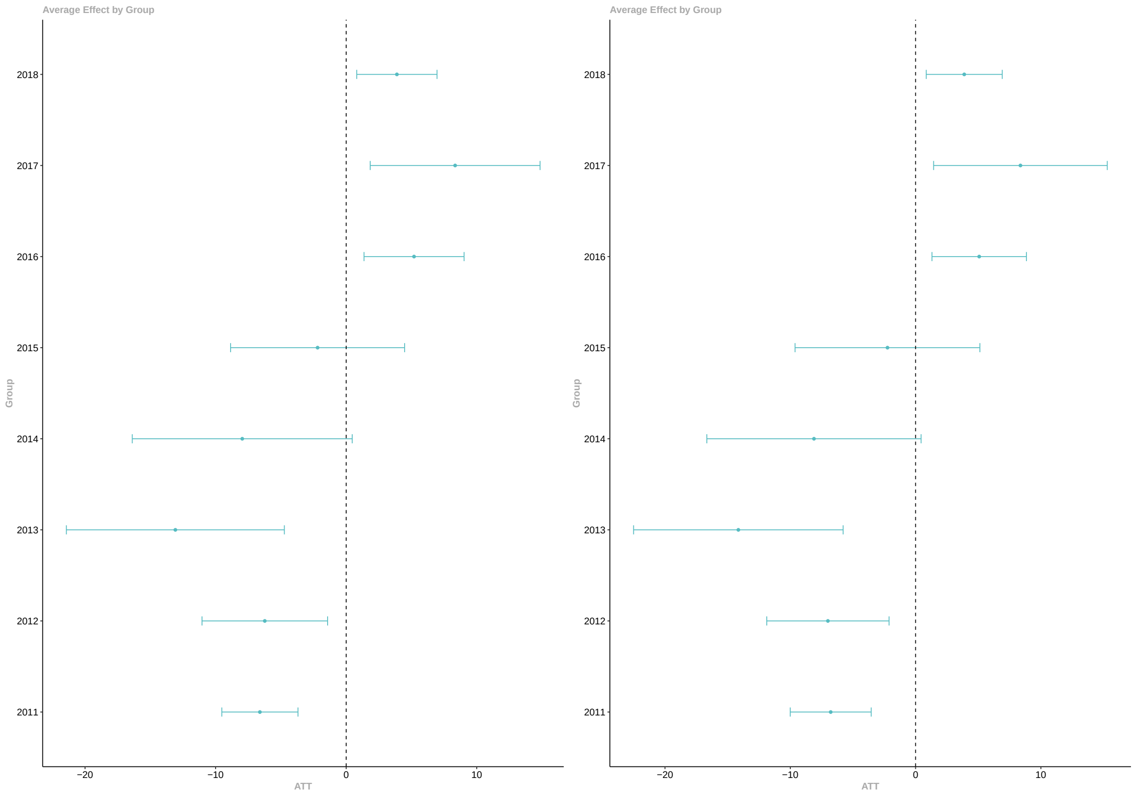
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



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.15: Average Cohort Impact of NGP on Unlit Settlements

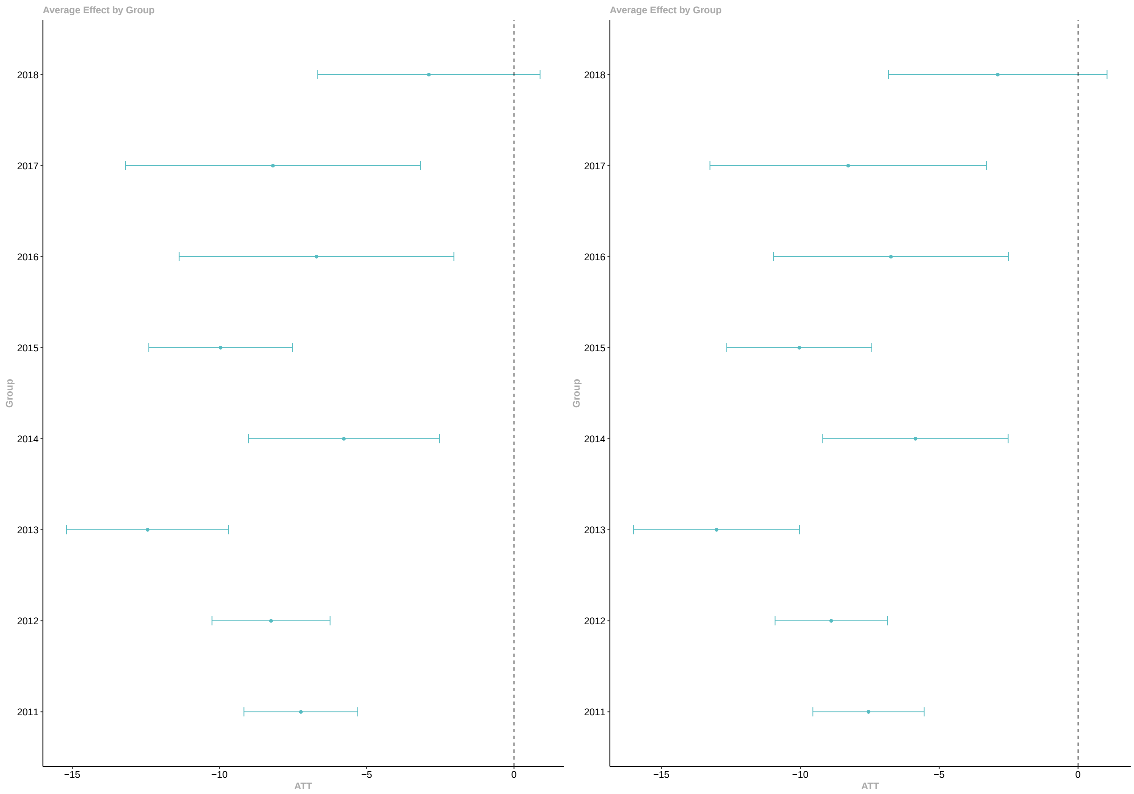
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



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.16: Average Cohort Impact of NGP on Unlit Settlements at the Village Level

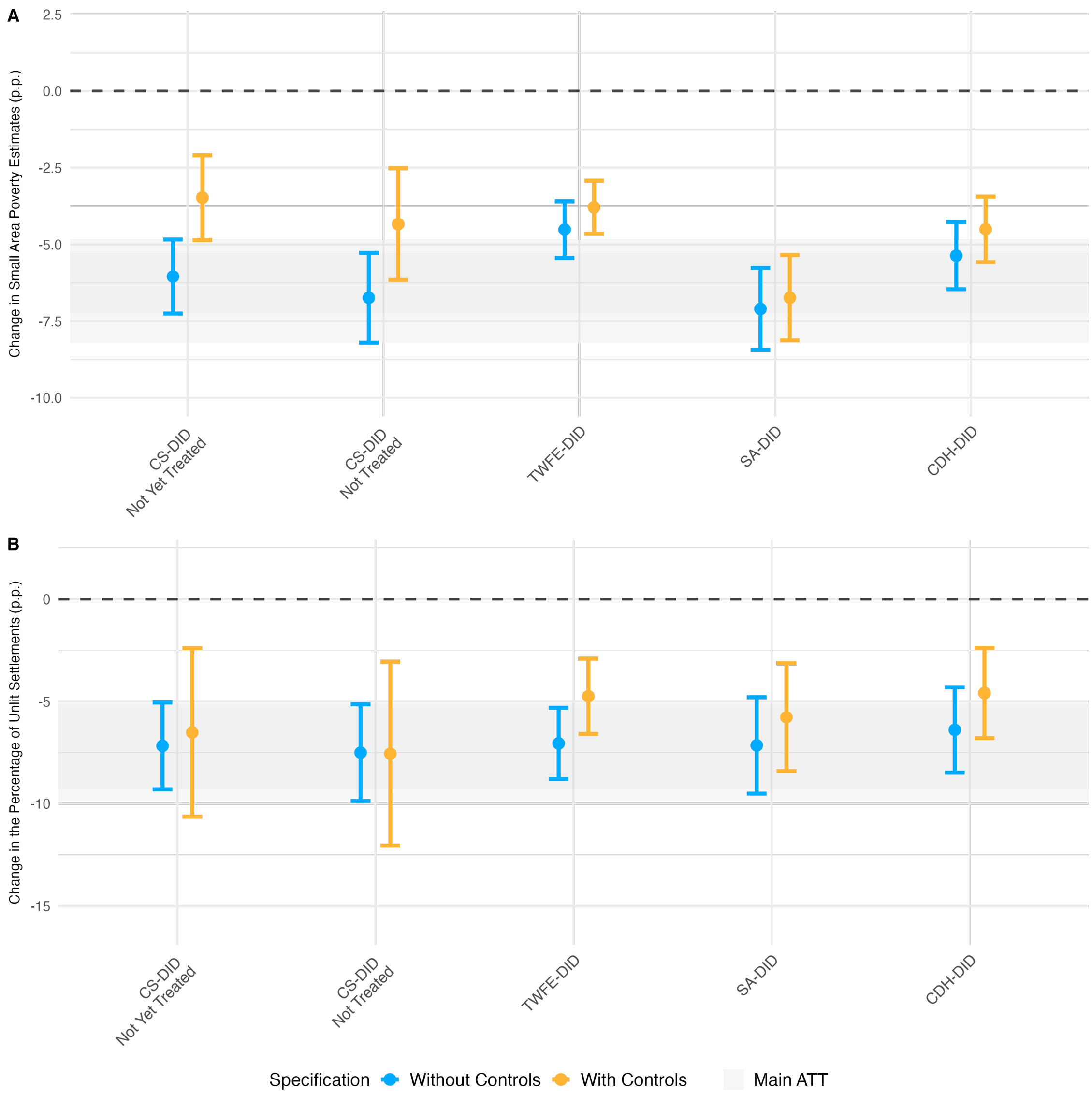
Panel A: Treatment vs. Not Yet Treated Panel B: Treatment vs. Never Treated



Notes: This figure presents the average cohort effect that the NGP had on the percentage of unlit settlements at the village level for the modified sample. 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.2.3. Supplementary Results

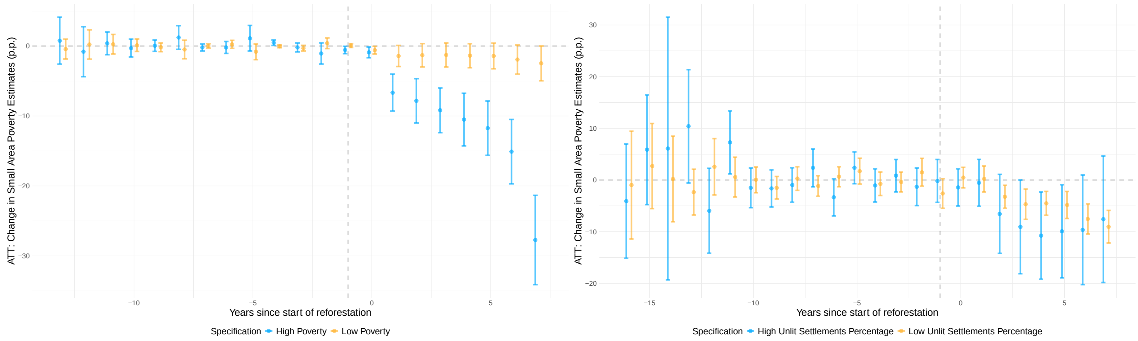
Figure A.17: Impact of NGP across different estimators



Notes: This figure presents estimates from all event study specifications for the effect the NGP had on small area poverty estimates (Panel A) and the percentage of unlit settlements (Panel B), employing different estimators, with and without conditioning on control variables. We use the CS-DID estimator from Callaway and Sant'Anna (2021) (using the not yet treated and never treated groups as controls, respectively), a simple staggered TWFE-DID, the SA-DID estimator from Sun and Abraham (2021), and the CDH-DID estimator from De Chaisemartin and d'Haultfoeuille (2024). All point estimates are plotted with their 95% confidence intervals. The grey shading represents the 95% confidence intervals for the main specifications of Table 5.

Figure A.18: Heterogeneous Impact of NGP on Socio-Economic Measures

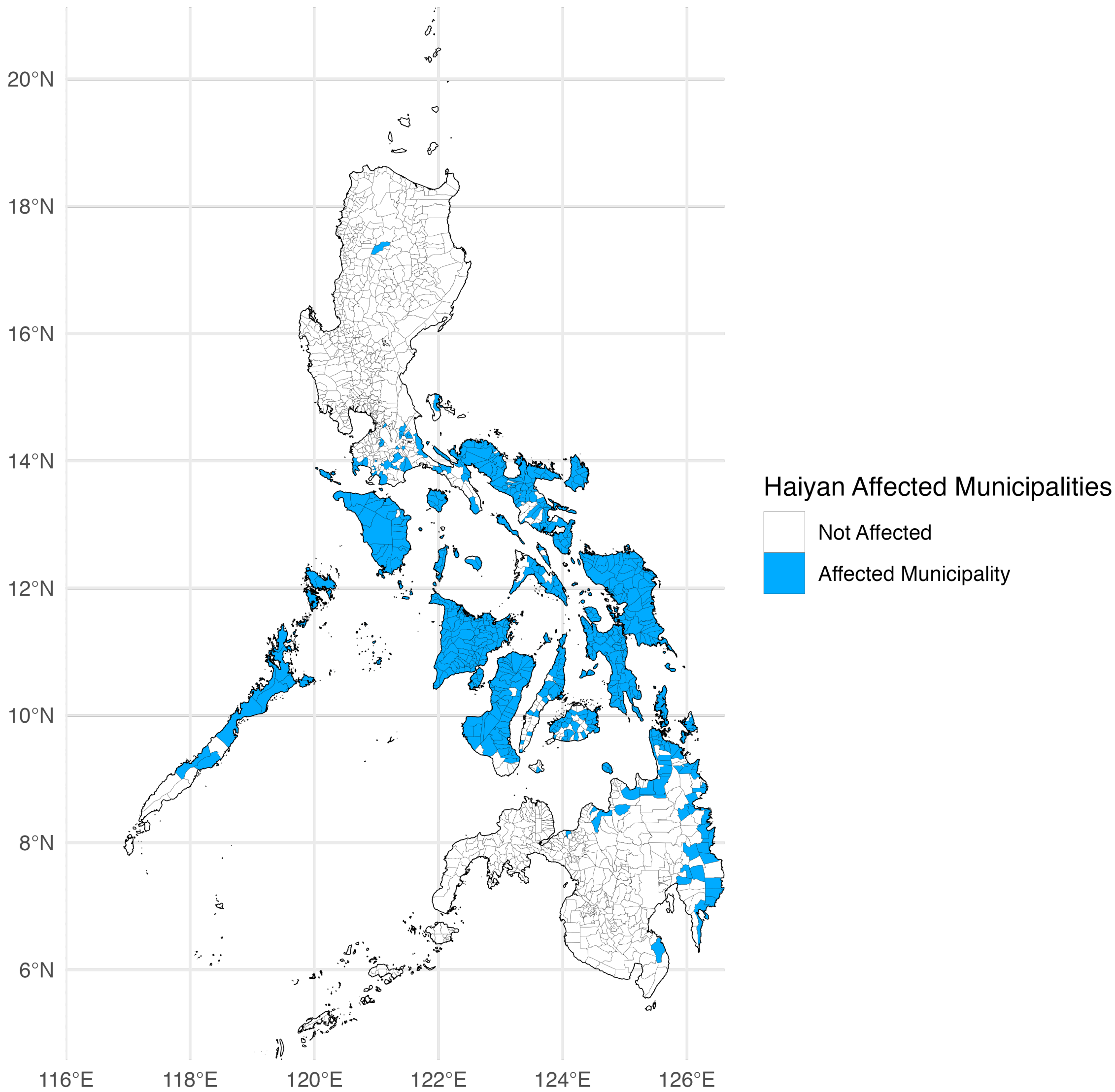
Panel A Panel B



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.

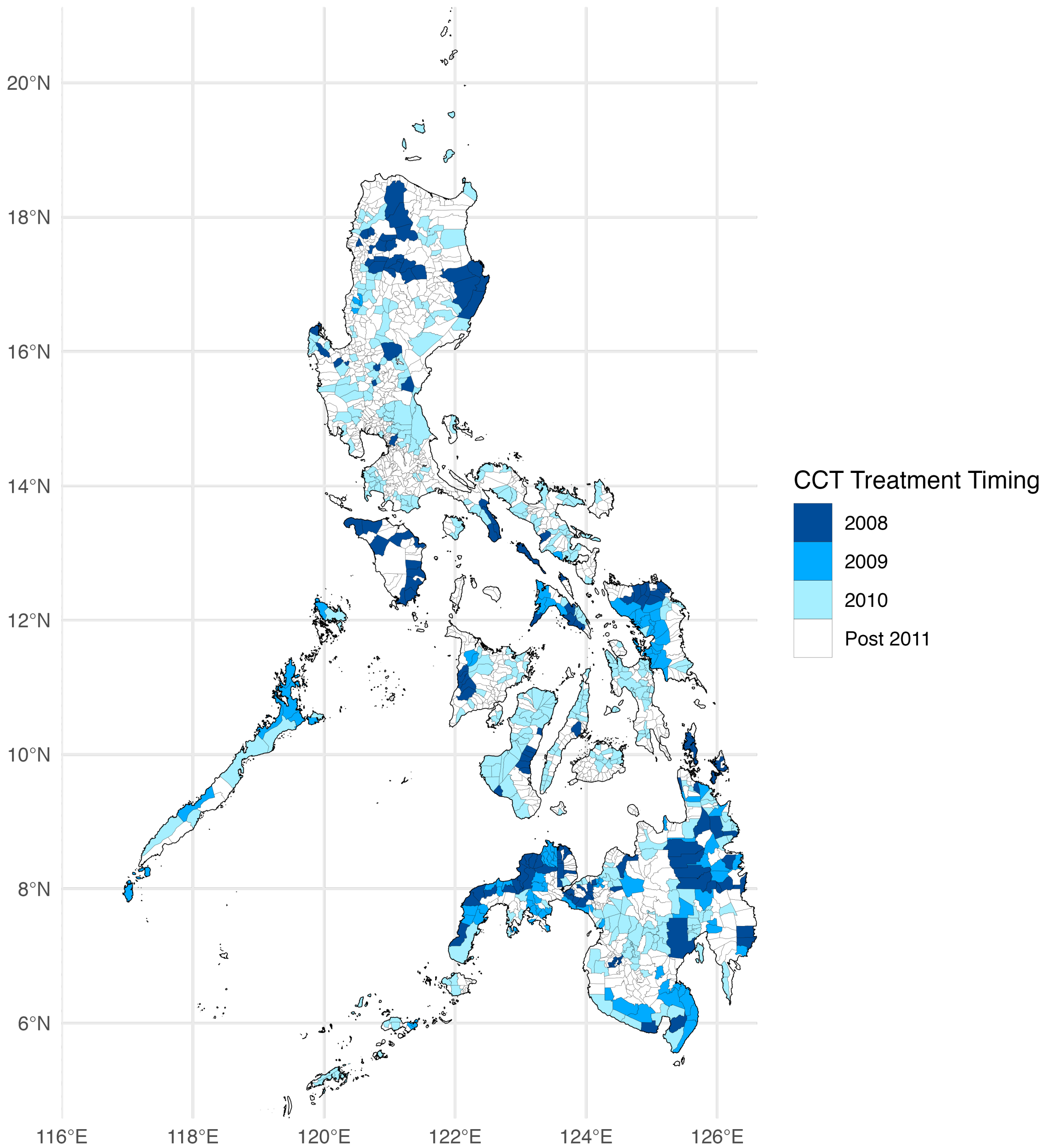
A.2.4. Additional Robustness Check Results

Figure A.19: 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.20: 4Ps CCT Timing by Treatment Pool

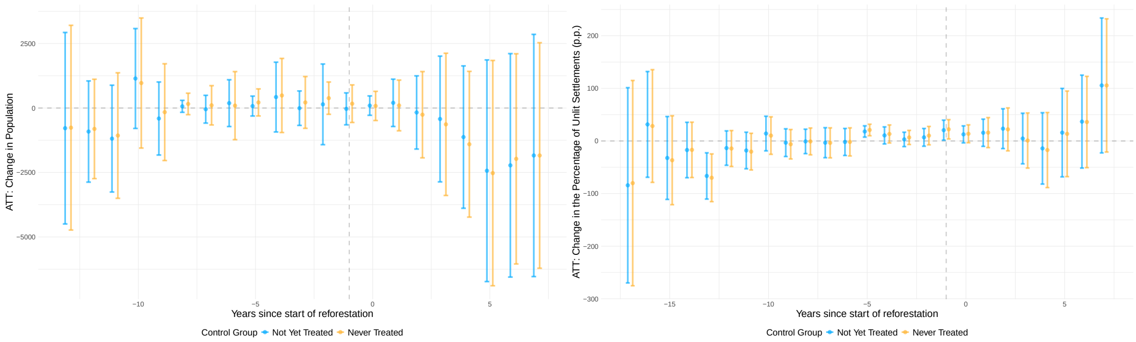


Notes: This figure presents identifying variation for the year in which municipalities first received the 4P's CCT program. *Source*: Author's own calculations based on data from Fernandez and Olfindo (2011).

A.2.5. Supplementary Channels and Mechanism Results

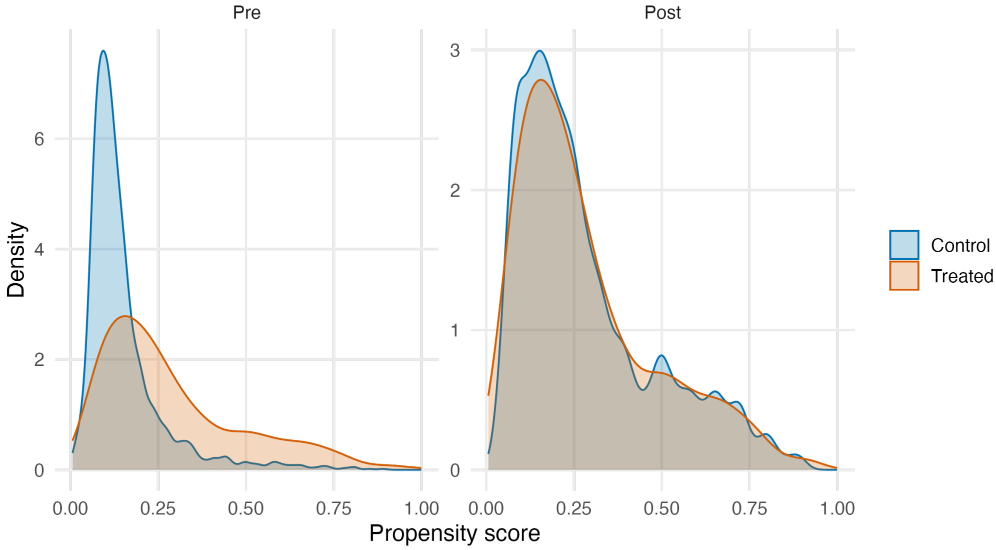
Figure A.21: Impact of NGP on Population

Panel A | Panel B



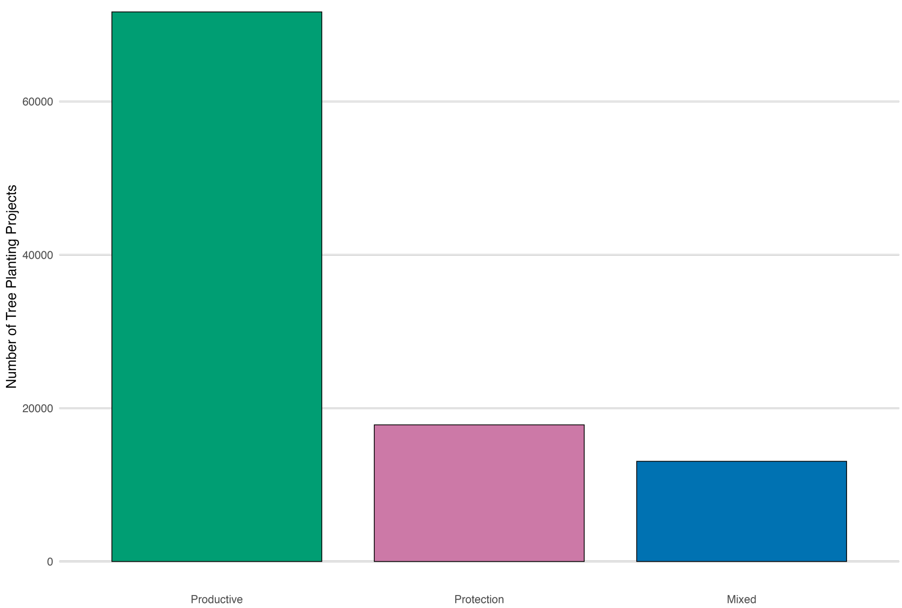
Notes: This figure presents estimates from an event study specification for the effect the NGP had on population at the municipality level (Panel A) and at the village level (Panel B). Doubly robust standard errors are clustered at the municipality level. Confidence intervals are set at 95 percent.

Figure A.22: Distribution of Propensity Scores: pre- and post-matching



Notes: This figure plots the distribution of propensity scores pre and post matching.

Figure A.23: Classifying the Productivity of Tree Planting Sites



Notes: This figure classifies tree planting sites as either productive, protection or mixed. Mixed are plantation sites that have both productive and protection tree species.

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) 50 percent upon completion of strip brushing, hole digging, and staking according to the agreed density and planting standards, 2) 40 percent upon completion of hauling and planting of seedlings according to agreed density and planting standards and 3) 10 percent upon planting the target number of seedlings.
- Payments for maintenance follow: 1) 50 percent upon completion of at least 70 percent of total target on maintenance and protection activities, 2) 40 percent upon completion of at least 30 percent of total target on maintenance and protection activities and 3) 10 percent upon accomplishing the total target for the maintenance and protection as well as attaining an 85 percent survival rate.[35]

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

Notes: This table outlines the three-year payment schedule for site preparation and maintenance activities, along with the standardized unit cost per hectare (in Philippine Pesos) for each component.

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

C. Estimating the Impact of the NGP on Afforestation

We evaluate the implied increase in tree cover by aggregating staggered difference-in-differences estimates at the 2018 endpoint using the inverse hyperbolic sine (IHS) outcome transformation. Let $Z_{it} = \operatorname{asinh}(Y_{it})$, where Y_{it} denotes tree cover in municipality i and year t (measured in pixels). The CS-DID estimator yields cohort–time effects:

$$ATT(g,t) = \mathbb{E}[Z_{it}(1) - Z_{it}(0) \mid G = g,\ t]$$

where $G = g$ denotes the cohort first treated in year g. To retrieve the aggregate tree cover at the endpoint year $T = 2018$, we back-transform the IHS effects using a cohort-specific baseline level $\bar{Y}_0(g)$, defined as the mean of tree cover Y_{it} in the last pre-treatment year ($t = g - 1$) among municipalities in cohort g:

$$\bar{Y}_0(g) = \mathbb{E}[Y_{i,g-1} \mid G = g]$$

We then recover the implied 2018 change for cohort g as:

$$\Delta Y(g,T) = \sinh\big(\operatorname{asinh}(\bar{Y}_0(g)) + ATT(g,T)\big) - \bar{Y}_0(g).$$

Finally, we multiply by the number of treated municipalities in each cohort, N_g, and convert pixels to hectares using pixel area (9 hectares for 300x300m pixels):

$$\Delta Forest_{2018} = \sum_{g \le T} N_g \cdot \Delta Y(g,T) \cdot 9 \text{ ha}$$

Our aggregation is thus consistent with interpreting satellite-derived tree cover as a stock outcome (tree cover at time T) and ensures comparability across municipalities with different initial levels of tree cover.

D. Nighttime Lights and Percentage of Unlit Population

This section repeats the 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, 2024; Alesina *et al.*, 2016).[36]

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 and VIIRS satellites' sensor settings, plus the retirement of DMSP-OLS in 2013 in favor of VIIRS, may render the NTLs time series inconsistent and prone to measurement error.[37]

Given the roll-out of the NGP started 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 Harmonized 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.[38] 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 is not a problem in our setting as the descriptive statistics show the maximum coded value of nighttime light emitted is 48.3, out of a maximum possible digital number of 63.

Additionally, we construct a measure for the share of population living in unlit areas at the municipality and village levels. Following the method developed by Smith and Wills (2018), we combine high-resolution nighttime light imagery with remotely sensed population data from LandScan, available at a 30 arcsecond resolution (Sims *et al.*, 2023). This method exploits the relationship between nighttime radiance and population density to estimate the proportion of individuals residing in areas without artificial lighting. While similar in construction to the share of unlit settlements used

[36]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.

[37]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.

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

in the main analysis (McCallum *et al.*, 2022), this measure differs from standard nighttime lights metrics by focusing specifically on extreme rural poverty. Rather than using light intensity as a proxy for economic activity, it captures the number of people living in complete darkness at night.

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 2000-2018, 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 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.

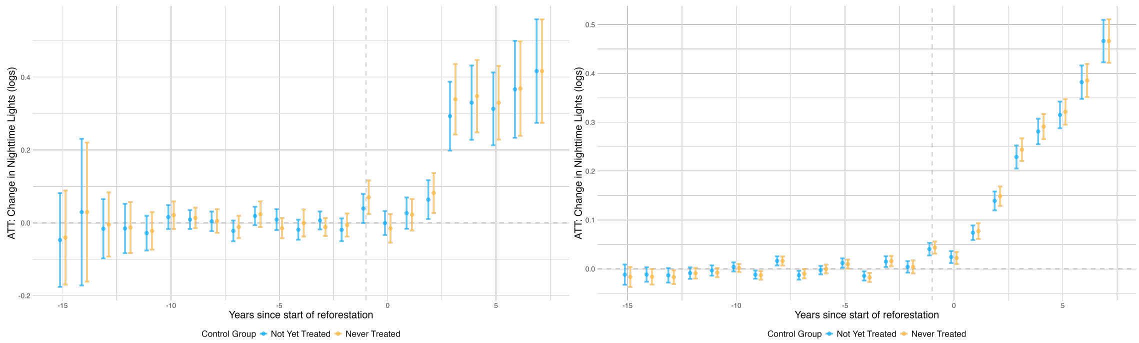
$$Unlit_{it}^{share} = \frac{1}{Pop_{it}} \sum_{j=1}^{J} NTL_{jt}\bigg|_{NTL_{jt}=0} \cdot Pop_{jt} \tag{9}$$

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

We re-estimate equation 2 and 3 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 led to an increase in economic activity, with municipalities that received a tree planting project experiencing an increase in nighttime luminosity of 23- to 24 percent or an increase of 0.2 standard deviations over the pre-treatment nighttime light mean. Figure C.1 Panel B further confirms the results at the village level and shows that the effect is persistent in that seven 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 17 percent. In Table C.2 and Figure C.2, we observe similar results for the percentage of unlit population as the main results. 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 7.5 percentage points, with similar effects (11 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

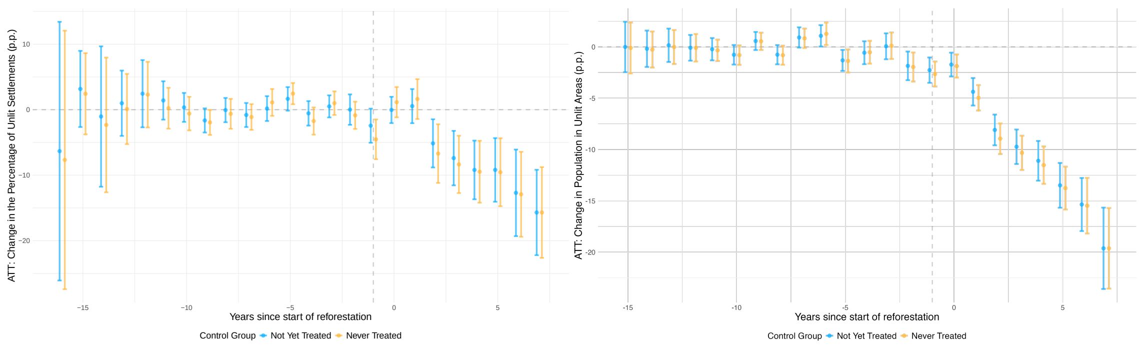
Panel A Panel B



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	0.226***	0.237***	0.239***	0.245***	0.165***	0.168***
	(0.023)	(0.024)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	29646	29646	537035	537035	597531	597531

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 Percentage of Unlit Population

	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	-7.353***	-7.491***	-10.441***	-10.815***	-4.741***	-4.92***
	(1.191)	(1.337)	(0.523)	(0.517)	(0.370)	(0.392)
Observations	22050	22050	286862	286862	334153	334153

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 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.