The Long Run Effects of Forest Incentives in Guatemala*

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October 2025

Abstract

Forest incentives are a commonly used tool to promote conservation and restoration efforts. However, while there is a large literature studying their effectiveness, it focuses mostly on the effects of small-scale programs designed to promote forest conservation. In this paper, we evaluate the effects of three of the largest and longest running forest incentive programs in the world – Guatemala's three forest incentive programs (PINFOR, PINPEP, and PROBOSQUE) – designed to offer incentives for forest conservation and restoration efforts. We assemble data on environmental outcomes of more than 80,000 plots that participated in these programs for a period of more than two decades. We then use difference-in-difference techniques to document that they had positive effects on tree cover and above- and below-ground biomass carbon, with effects increasing with the length of exposure to the programs and being quite heterogeneous depending on the purpose of the incentives and plot characteristics. Nevertheless, because the effects are modest (4-6% increase in the outcome of interest) and the programs are generous, cost-benefit calculations indicate that costs exceed environmental benefits for most plots. These results highlight the need for improving targeting and calibrating incentives to enhance the environmental gains of large-scale forest incentive programs.

Keywords: Conservation, Carbon Sequestration, Forest Incentives, Public Policies.
JEL: Q23, Q28, Q51, O13, H23

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*We thank Ines Angulo, Tuukka Castren, Philippe Dardel, Paul Jonathan Martin, Stefano Pagiola, David Treguer, and Rene Zamora for their comments and suggestions. We also thank Julia Morato for excellent research assistance. The views expressed here do not necessarily reflect those of the World Bank or their member countries. All errors are our own.

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1 Introduction

Promoting the conservation and restoration of tropical forests is key to mitigate climate change, protect biodiversity, and ensure the provision of key eco-system services for communities (Dasgupta, 2021; IPCC, 2022). Forest incentives are a popular tool used by governments to promote conservation and restoration efforts (Wunder et al., 2020). However, while there is a large literature studying their effectiveness, it focuses mostly on the effects of small-scale programs designed to promote forest conservation.

This paper investigates the long-term effects of three large-scale forest incentive programs (PINFOR, PINPEP, and PROBOSQUE) in Guatemala designed to promote forestry, agro-forestry, forest restoration, and forest conservation. Guatemala – a major agricultural exporter – has experienced significant deforestation over the last decades driven mainly by agricultural expansion (Inter American Development Bank, 2020). PINFOR, PINPEP, and PROBOSQUE were designed to mitigate these trends by offering generous payments for various land management practices (Cristales et al., 2022). This study evaluates the long-term effectiveness of these payments both in aggregate and by modality (forestry, agro-forestry, conservation etc.).

Our analysis proceed in four steps. First, we construct a geo-referenced database containing information on over 80,000 plots enrolled in the incentive programs provided by the Guatemalan National Institute of Forests (INAB) ("treatment" plots) with data from over 400,000 randomly generated 100-meter radius (3.1-hectare) plots located elsewhere in Guatemala ("control" plots). Second, we use satellite information (Landsat 7 and MODIS) and other types of GIS information to calculate forest cover, forest height, and vegetation indices, and above- and below-ground biomass carbon, elevation, slope, distance to cities and rivers both for treatment and control plots.[1] Third, we use propensity score matching (PSM) to create comparable treatment and control groups according to initial plot charac-

[1]We use a random forest model to predict annual above- and below-ground biomass carbon for periods where data was unavailable.

teristics. Fourth, we use difference-in-differences (DID) estimators to compute the effects of the programs.

The results indicate positive but modest effects of forest incentive programs on tree cover and carbon storage. Tree cover increased by 2.6 percentage points while carbon storage increases by 2.7 tC/ha (9.2 tCO2eq/ha) after one decade – these numbers represent a 4-5% increase relative to the baseline. These results are robust to the matching procedure as well as to the differences-in-differences estimator used. There is significant variation across programs and project types. Across programs, PINFOR and PROBOSQUE showed larger effects than PINPEP, suggesting that incentives for large-holders were more effective than incentives for small-holders. Across modalities, we find that incentives for forestry plantations had the highest effects while incentives for conservation had the lowest. Impacts of incentives for agro-forestry were in between. Across initial characteristics, we find that plots with initially poorer forest conditions showed greater responsiveness to the incentives.

We monetize the benefits of Guatemala's forest incentive programs in terms of ecosystem services and carbon storage to perform a cost-benefit analysis. While the programs had positive environmental impacts, their generous payments and relatively modest effects lead to cost-benefit below 1 for most project types. This result aligns with existing literature, which indicates that large-scale projects can often yield low cost-benefit ratios due to factors such as inadequate targeting and weak policy design (McElwee and Nghi, 2021).

The findings contribute to the existing literature on forest incentives by providing a comprehensive long-term evaluation of large-scale programs that provide financial incentives not only to forest conservation but also to forest restoration. This contrasts with the focus on forest conservation of most existing literature (see Jayachandran et al. (2017) for seminal work in this area and Börner et al. (2020) for a review of the effects of programs designed to provide incentives for forest conservation).[2] Our findings show that financial incentives also induce forest restoration (even more than forest conservation). However, while the programs studied here do not create incentives for replacing high quality native forests for low quality planted forests as documented in other settings (e.g., Heilmayr, Echeverría and Lambin (2020)), the effects are not large enough to cover their relatively high costs. This has important implications for global debates on forest restoration – highly regarded as one of the most effective ways of removing GHG from the atmosphere (e.g., Bastin et al. (2019) and Baumbach et al. (2023)). The heterogeneity of the results confirms previous findings from programs designed to promote conservation that their effects depend fundamentally on the opportunity costs of different land uses.

Our findings are closely related to the findings of Patrick, Butsic and Potts (2023) who also evaluate Guatemala's forest incentive programs. Our work differs from theirs in two dimensions. First, we use more comprehensive data – our data covers more plots, contains information on their size, encompass more measures of vegetation cover, and includes information on carbon stocks (above- and below-ground). Second, exactly because our data is more comprehensive, we are able to use an empirical framework that explores the timing of entry and exit of the plots into the forest incentive programs. This enables us to rule out that our results are driven by improvements in the environmental outcomes that were occurring before the enrollment of the plots in the forest incentive programs – the key issue in their analysis. It also enables us to better understand the dynamics of the effects (and their persistence).

Taken together, these dimensions enables us to draw new insights regarding Guatemala's forest restoration programs. Moreover, our methods and findings offer a valuable refer-

[2] A literature review by Börner et al. (2020) was able to identify 136 estimates with counterfactual based treatment effects of conservation mechanisms. The statistical methods and forest indicators used to assess the effectiveness of these programs vary considerably. According to the authors, most studies estimated the average treatment effect on the treated using some type of covariate matching (111 out of 136 studies), followed by matching combined with difference-in-difference (DID) (11 out of 136 studies). Some of the most used forest indicators include forest cover, deforestation, and normalized difference vegetation index (NDVI) (Börner et al., 2020; Wunder et al., 2020).

ences for policymakers in other countries aiming to develop or reform similar forest incentive initiatives. In particular, the ability to isolate causal effects and estimate dynamic effects provides a practical model for improving program effectiveness and long-term sustainability in numerous settings

The rest of this paper is organized as follows. Section 2 presents a brief description of Guatemala's forest incentive programs. Section 3 describes the data and the methods used in the analysis. Section 4 reports and discusses the results. Section 5 concludes and discusses policy recommendations.

2 Forest Incentive Programs in Guatemala

2.1 Background

The preservation and restoration of Guatemala's forests are prioritized within the nation's legal framework. The 1985 Constitution (Article 126) highlights the importance of forest conservation and restoration.[3] Subsequently, the National Institute of Forests (*Instituto Nacional de Bosques*, INAB) was established by the forest law (Decree 101/1996). INAB introduced three forest incentive programs (PINFOR, PINPEP, and PROBOSQUE) furthering Guatemala's commitment to its forests.

PINFOR (*Programa de Incentivos Forestales*) was the first forest incentives program established in Guatemala. It was established in 1996 (Decree 101/1996) to promote productive forests with a focus of simultaneously providing ecosystem services and stimulating economic growth. Initially, 80% of PINFOR funds were allocated to reforestation or natural regeneration, and 20% to natural forest conservation. Beneficiaries needed a minimum of

[3]Even before the constitutional recognition of the importance of forest conservation and restoration, Guatemala already had incentives for forest-related activities. Decree 58/1974 created an incentives system aimed to stimulate the development of a robust commercial forestry industry. This legislation allowed the deduction for a period of ten years of the costs invested in restoration and forest plantations of over than 5 hectares of income and vehicles taxes. Companies – mostly large ones – were allowed to deduct up to 50% of their tax burden. See Larrazábal Melgar et al. (2009) for details.

two hectares of land to participate in the program – excluding 45% of landowners from the program. Over time, some small beneficiaries, supported by their municipalities, successfully enrolled in PINFOR. However, most of the funds (75.7% between 1998 and 2016) were allocated to large private landowners or companies, rather than smallholders (see vonHedemann (2020) for details).

PINPEP (*Programa de Incentivos para Poseedores de Pequeñas Extensiones de Tierras de Vocación Forestal o Agroforestal*) was created to provide forest incentives to smallholders who were not able to access PINFOR. It was established in 2010 (Decree 51/2010) with a focus of providing ecosystem services, stimulating economic growth, and inducing rural development. Its creation aimed to increase smallholders access to forest incentives with the program focusing on properties with less than 15 hectares. PINPEP is largely based on a program funded by the Dutch government created in 2006 and absorbed by the Guatemalan government in 2010.

In 2016, PROBOSQUE (*Programa de Incentivos para establecimiento, recuperación, manejo, producción y protección de bosques en Guatemala*) was created to replace PINFOR. PROBOSQUE was established by Decree 02/2015 — this decree shifted the program's focus to emphasize the provision of ecosystem services as its key objective, included agroforestry in the program, and reduced the minimum area requirement to 0.5 hectares. Furthermore, the decree changed the land titling requirements — PROBOSQUE accepts not only formal titles as PINFOR but also ancestral titles of indigenous communities' land. Guatemala's forest incentive programs are among the longest running and largest scale forest incentives programs in the world. More than USD 700 million have been invested in Guatemala's forest incentive programs since 1996, two thirds in PROBOSQUE and PINFOR and one third in PINPEP. These resources have supported conservation and restoration activities in more than 400,000 hectares.

2.2 Payments and Enrollment

To participate in Guatemala's forest incentive programs, landholders must submit a management plan to INAB. If the plan is approved, INAB will evaluate the enrolled parcels periodically. The available streams are management of natural forests for production, management of natural forests for protection, forest plantations, restoration of degraded forests, and agro-forestry systems. Landholders must provide evidence of their right to the parcels enrolled in forest incentive programs—requirements in terms of land titles are different across programs with PINPEP accepting informal land titles and the other programs requiring formal land titles.

The forest incentive programs in Guatemala provide different amounts and durations of support depending on the activity. The structure of the support provided by the current programs is summarized as follows:

In PINPEP, the annual payments are currently the following:

- USD 398 per hectare for managing natural forest for production for plots between 0.1 and 5 hectares and USD 1,991 for the first 5 hectares plus USD 111 for each additional hectare for plots over 5 hectares. Payments are made for a period of 10 years.
- USD 372 per hectare for managing natural forest for protection for plots between 0.1 and 5 hectares and USD 1,861 for the first 5 hectares plus USD 96 for each additional hectare for plots over 5 hectares. Payments are made for a period of 10 years.
- USD 296-394 per hectare for forestry plantations, with smaller amounts for larger plantations. Payments are made for a period of 6 years.
- USD 148-197 per hectare for agroforestry systems, with smaller amounts for larger systems. Payments are made for a period of 6 years.

In PROBOSQUE, the annual payments are currently the following:

- USD 181-322 per hectare for managing natural forest for production, depending on the type of production, with additional amounts for plots larger than 15 hectares. Payments are made for a period of 10 years.
- USD 350 per hectare for forest protection. Payments are made for a period of 10 years.
- USD 490- 578 for forestry plantations, depending on their destination. Payments are made for a period of 5-6 years.
- USD 290-320 for restoring degraded forests, depending on their type. Payments are made for a period of 10 years.
- USD 211-320 for agro-forestry systems, depending on the original forest density (lower density receives lower amounts). Payments are made for a period of 6 years.

3 Data and Methods

We estimate the dynamic effects of Guatemala's forest incentives on four different outcome variables following five-step procedure outlined below:

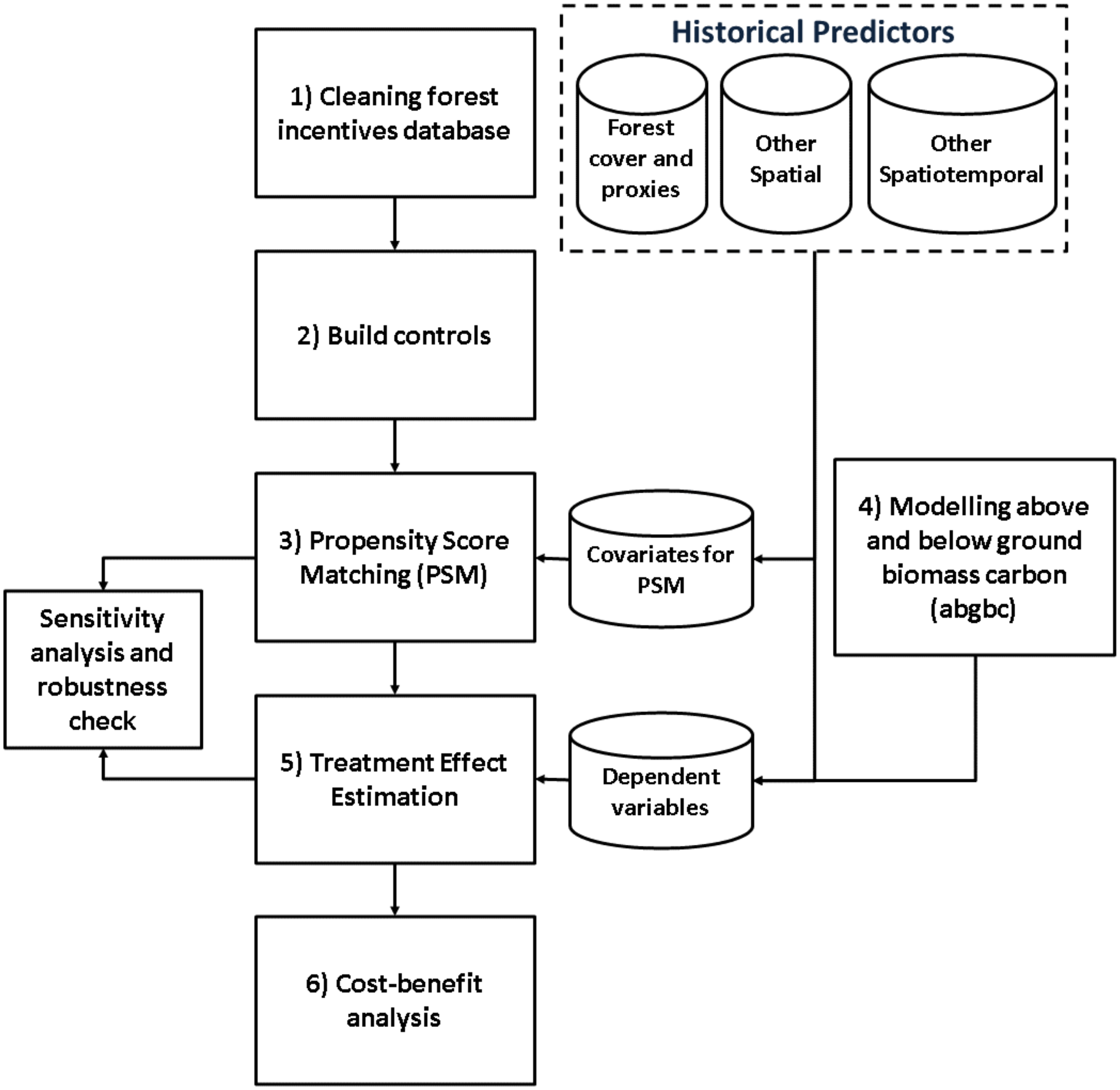
1. We cleaned a forest incentives database obtained from INAB containing GIS information of the plots enrolled in the three forest incentive programs ("treatment" plots).
2. We created a dataset of 3.1 ha (100m radius) random plots located in areas without forest incentives and outside protected areas across Guatemala ("control" plots).
3. We extracted covariates for treated and untreated plots and used propensity score matching (PSM) to construct a dataset with comparable groups of treated and untreated plots.
4. We calculated the treatment effect of forest incentive programs on the following out-

comes: tree cover, above and below ground biomass carbon (ABGBC), fractional vegetation cover (FVC), and normalized difference vegetation index (NDVI) using a number of differences-in-differences (DID) estimators.

5. We performed a cost-benefit analysis to compare the environmental benefits (carbon storage and eco-system services) of Guatemala's forest incentives programs with its economic costs (USD/ha currently paid by the programs). We evaluated the overall cost-benefit of the forest incentive programs as well as the effects by program and project type.

Figure 1 presents a schematic presentation of the five-step process used in the analysis. The following subsections discuss each step in more detail. Appendices A, B, C, and D provide more details on the data and methods used.

Figure 1: Schematic diagram showing the modeling framework used to estimate the impact of forest incentives programs in Guatemala



3.1 Treatment Plots

The main source of data used throughout this paper is geo-referenced data on the plots enrolled in Guatemala's forest incentive programs – treatment plots – obtained from INAB.[4] For each treatment unit, this database contains information on the program (PINFOR,

[4]It contains information from the beginning of each program up to August 2023.

PINPEP or PROBOSQUE), the project type (e.g., restoration, conservation, agro-forestry), the type of owner (individual, municipality, business, NGO, etc.), location (region, department, municipality), and the period it received financial incentives (different phases for each project, with first year and last year for each one of them).

We cleaned this dataset using the following procedures:

1. We checked if there were any relevant overlaps between plots. If overlapping area between two plots was small (<1% on area of plots), these plots remained in the database. Otherwise, plots were flagged and assessed further for exclusion in the analysis.

2. We checked consistency of reported location and geo-spatial information, mainly, the assigned Department within Guatemala. We flagged those plots with wrong Department and excluded from our analysis.

3. We extracted predictors to apply the propensity score matching algorithm, but flagged those plots with missing data and excluded from our analysis.

It should be noted that some plots were flagged more than once (i.e., wrong department and overlap of at least 1%, or wrong department and missing data).

The original INAB dataset contained information of 83,677 plots (434,184 hectares). There is some overlap in 30,696 plots (roughly 37% of the plots). However, the typical intersection is small – only 1,064 plots (25,417 hectares) had an overlap of more then 1% of the plot area and were excluded from the analysis. Other 3,035 plots (15,071 hectares) which had the wrong department assigned and 609 plots (10,030 hectares) with missing data on covariates or outcomes were also excluded from the analysis. The final dataset of treatment plots had 79,156 plots (94.6% of original number of plots) with a total of 394,636 hectares (90.6% of original area).

Table 1 reports some descriptive statistics of the final dataset. The most common program is PINPEP (52,515 plots), followed by PROBOSQUE (16,902 plots), and PINFOR (9,739 plots). However, in terms of area, the largest program is PINFOR (mean = 10.6 ha, SD = 88.4 ha), followed by PROBOSQUE (mean = 7.9 ha, SD = 35 ha), and PINPEP (mean = 3 ha, SD = 2.9 ha). This is coherent with the characteristics of each of the programs. For example, the mean area is highest for PINFOR and lowest for PINPEP as is the minimum area required in each case (i.e., 2 ha for the former and 0.1 ha for the latter). The average treatment plot has 5 hectares and received payments for an average of 4.8 years.

Table 1: Descriptive statistics by program

Program	**Legal period**	**Legal minimum area**	**Number of plots**	**Area* (hectares)**	**Time active* (years)**
PINFOR	1996-2005	2 ha	9,739	10.6 (88.4)	6 (2.4)
PINPEP	2010-present	0.1 ha	52,515	3 (2.9)	5.2 (2.7)
PROBOSQUE	2016-present	0.5 ha	16,902	7.9 (35)	2.9 (1.8)
TOTAL			**79,156**	**5 (35.2)**	**4.8 (2.7)**

* mean (standard deviation)

3.2 Control Plots

INAB's dataset only contains information of plots that enrolled in Guatemala's forest incentive programs. Thus, we created our own control units. To do this, we randomly created 100 meters (100m) radius plots located outside protected areas[5] (and outside forest incentives programs areas) throughout Guatemala. In total, we were able to create 500,663 plots (roughly six times the number of original treated plots). Appendix B further describes this procedure. Prior to applying the propensity score matching, we also excluded control plots with missing data, ending up with a total of 494,087 potential control plots.

[5]There are 349 protected areas covering 32% of the Guatemalan territory according to the *Sistema Guatemalteco de Área Protegidas (SIGAP)*

3.3 Propensity Score Matching

To ensure that control plots were comparable to treatment plots, we used propensity score matching (PSM). We used a series of variables in our PSM algorithm to characterize baseline conditions (i.e., conditions before the forest incentive programs began). Elevation, aspect, and slope were obtained from the NASA Shuttle Radar Topographic Mission (SRTM) digital elevation data (Jarvis et al., 2008). Forest cover and forest height for 2000 were obtained from the Global Land Analysis and Discovery lab (GLAD) (Potapov et al., 2022). Travel time to cities with a population larger than 20k was obtained from (Nelson et al., 2019). Distance to rivers and streams was obtained from the HydroSHEDS dataset (Lehner and Grill, 2013). Finally, mean annual precipitation, mean annual temperature, and precipitation during the driest month were obtained from the Worldclim dataset (Hijmans et al., 2005). Appendix C presents the details of the estimation of the propensity score, the matching procedure used, more details on the matching variables, and the various sensitivity analysis performed.

Figure 2 shows the spatial distribution of treated (panel A) and untreated (panel B) plots. PSM seems to match plots adequately. Figure 2 show the means of selected variables used in the procedure are adequately balanced between treated and untreated plots. This can be further observed in Figure B.1 which reports the region of common support between treatment and control plots before and after the matching as well as an estimate of the standardized mean difference and the Kolmogorov-Smirnov statistic before and after matching.

Figure C.2 shows the annual mean values for the four outcome variables for treated and matched untreated plots. It provides suggestive evidence that outcomes were improving more in treatment plots than in control plots. Table C.1 provides descriptive statistics of the outcome variables in 2001 and 2023 for treatment and control plots. It reinforces the result that outcomes improved more in treatment plots than in control plots in the period under analysis. The key shortcoming with these descriptive statistics is that they do not enable us to test whether the relative increases in outcomes of interest in the treatment plots were occurring before these plots enrolled in the forest incentive programs – a limitation of previous work on these programs like Patrick, Butsic and Potts (2023). By exploring the timing of enrollment in detail, our treatment effects estimation deals with this issue.

Figure 2: Location (distribution) of (A) selected treated and (B) untreated plots

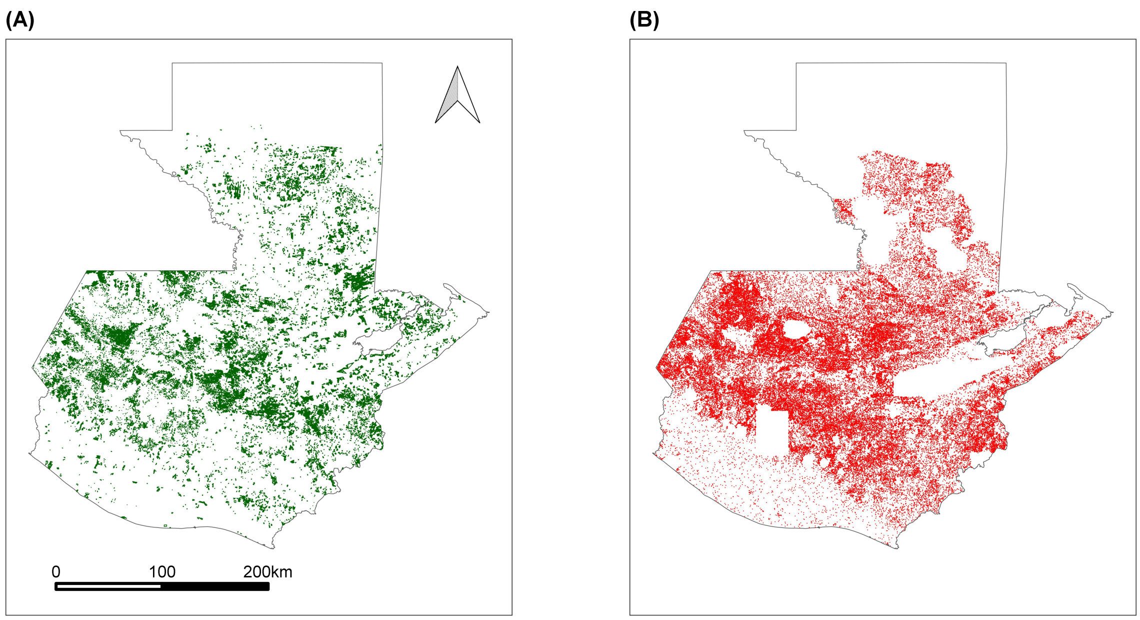


Table 2: Descriptive statistics for selected variables

	Treated*				Untreated*
Variable	**All**	**PINFOR**	**PINPEP**	**PROBOSQUE**	**All**
Space					
MODIS Tree cover 2001 (%)	44.7 (20.2)	44.4 (21.2)	42.8 (20)	51 (18.9)	45.1 (18.8)
Spawn et al. (2020) - Above and below ground biomass carbon 2000 (MgC/ha)	62.5 (29.8)	55.7 (32.7)	63.1 (28.9)	64.4 (30.4)	61.7 (29.7)
GLAD Forest cover 2000 (share)	0.9 (0.2)	0.8 (0.3)	0.9 (0.2)	0.9 (0.3)	0.9 (0.2)
GLAD Forest height 2000 (meters)	13.4 (7.2)	11.3 (7.1)	13.5 (7)	14.4 (7.5)	13.2 (6.4)
Threat					
Orientation of slope (degrees 0 to 360)	15.3 (8.5)	11.2 (8.8)	17.2 (7.9)	11.8 (8.2)	15.4 (9)
Travel time to cities with population above 20k (mins)	83.8 (98.7)	78.1 (89.9)	76.4 (93.2)	110.2 (114.4)	80.8 (104.4)
Distance to rivers and streams 2010 (meters)	255.8 (470.7)	320.7 (529.7)	256.3 (467.1)	216.6 (440.4)	248.4 (493.8)

* mean (standard deviation) for treated and matched untreated plots

3.4 Treatment Effects

To estimate the effects of Guatemala's forest incentive programs, compute a 2×2 differences-in-differences estimator comparing the difference in outcomes in period 0 (before all plots were treated) and from 10 years before to 10 years after each plot was treated between treatment and control groups. This estimator identifies the effects of the forest incentive programs under hypotheses of parallel trends and no anticipation. We also explore if there are any differences when comparing the difference in outcomes with period -1 (instead of 0). We control for all covariates that were previously used in the matching procedure.

As a sensitivity analysis, we use the event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024). This estimator generalizes event study estimators robust to heterogeneity in treatment timing such as Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020) to settings in which treatment might be reversed.[6] It is thus ideal to our setting as farmers/ranchers enter in forest incentives programs at different moments and exit forest incentives programs after some time. The event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024) has the same identification hypotheses of the differences-in-differences estimator described earlier. In our application, these hypotheses imply that outcome of interest should have evolved comparably between treatment and control units in the absence of the forest incentive programs and that farmers/ranchers should not have made changes because they expected to enroll in forest incentives programs in the future.

We estimated the forest incentives' programs overall effects as well as their effects by program (PINFOR, PINPEP, PROBOSQUE), project type (Agroforestry, Forestry plantations, NFM Production, NFM Protection), and location (regions, ecoregions, and departments). We further evaluated whether the forest incentives' effects changed according to the following initial plot conditions: slope, area, distance to cities, and the initial values of the outcomes of interest. For each variable, we estimate the effects separately above and below the median of the variable.

We considered four outcomes of interest. Our main analysis focuses mainly on the impact of forest incentives programs on tree cover and above and below ground biomass carbon (a proxy for carbon stock). These results will help us perform an analysis of the costs and benefits of these programs. To assess how our results change when using spatial data with a finer spatial resolution, we explore the impact of these programs on two other variables: Landsat 7 fractional vegetation cover (FVC) and normalized difference vegetation index (NDVI). For all variables, we extracted annual mean values for each plot (treated and untreated) for the years 2001-2023.

[6] De Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021) introduce consistent estimators for the ATT(g,t) – the treatment effects for cohort g and period t – for setting in which there is heterogeneity of treatment time. They also show how these estimators can be aggregated to compute the dynamic effects of policies. However, these estimators do not allow for the case in which treatment is reversed.

To estimate tree cover, we used the MOD44B Version 6.1 Vegetation Continuous Fields (Dimiceli, Sohlberg and Townshend, 2022) which has a spatial resolution of 250m. To estimate annual above and below ground biomass carbon, we obtained above and below ground biomass carbon (abgbc) density (MgC/ha) for the year 2010 at a 300m spatial resolution from Spawn et al. (2020). We then developed a random forest model to predict abgbc for other years (i.e., 2001 to 2009, 2011 to 2023), based on a series of spatial and spatio-temporal predictors. Appendix D presents the details on model development and performance. To compute annual fractional vegetation cover (FVC) and normalized difference vegetation index (NDVI), we use the Google Earth Engine algorithm developed by (Ermida et al., 2020). FVC represents the ratio between the vertical projected area of above-ground green vegetation and the total vegetation area (Yang et al., 2017). Values of FVC range from 0 (no green vegetation) to 1 (only green vegetation). NDVI is a vegetation index with values that range from -1 to 1. Values indicate: below 0, water and other non-vegetated features, between 0 and 0.3, no vegetation cover; between 0.3 and 0.6, sparse vegetation cover; between 0.6 and 0.9, dense and healthy vegetation cover; above 0.9, very dense vegetation as rainforest. In our analysis, FVC was calculated at 30m spatial resolution while NDVI was calculated at 100m spatial resolution.

3.5 Cost-benefit analysis

We use the estimates obtained in the previous sections to monetize the benefits of Guatemala's forest incentive programs in terms of ecosystem services and carbon storage. We convert changes in tree cover into changes in ecosystem services using data from Bank (2021). This data reports that a typical hectare of forests in Guatemala generates USD 32.7 per year in benefits from the production of non-timber forest products, USD 24.1 per year in benefits from watershed protection, and USD 319.5 per year in benefits from recreation, hunting, and fishing. We monetize changes in carbon storage assuming a price of USD

20 / tCO2eq and a discount rate of 5%.[7] We assumed that benefits were permanent (consistent with our findings for the period under analysis). We calculated the project costs based on payments from the different programs and project types reported in section 2. We performed the analysis for the typical plot enrolled in the programs, for typical plot enrolled in each program per program, and for the typical plot of each program / project type.

4 Results

4.1 Treatment Effects

Figure 3 shows the dynamics of tree cover and above and below ground biomass carbon in treated/untreated plots over time, with a window of 10 years before and after the treatment. Here, we focus on the overall effects (all programs), and can see how before treatment there were minor differences (treated vs. untreated) in trends, at least up to 5 years pre-treatment. After treatment, both tree cover and above and below ground biomass carbon begin to increase in treated plots relative to untreated 1-2 years after enrollment in the forest incentive programs. Figure 3 also shows how these dynamics change when using a different reference point (i.e., the year chosen as the last period before treatment change), with consistent patterns for year 0 and -1. The results show a consistent increase in treatment effect for both outcomes reaching more than 2.5 p.p. (p-value<0.001) for tree cover and almost 2.7 (MgC/ha) (p-value<0.001) for above and below ground biomass carbon.

Figure E.1 in the appendix shows these results for all four outcome variables. The chosen reference year does not seem to have a big influence in these results, and although all four present different patterns before treatment - particularly Landsat 7 FVC and NDVI compared to tree cover and above and below ground biomass carbon - in all cases a consistent

[7] It is also possible to convert changes in tree cover directly into changes in carbon storage using data on carbon storage in Guatemala's forests. We find similar results using this approach.

increase in treatment effect is observed until 10 years after treatment.

As discussed previously (subsection 3.4), we also used an event study design to investigate the dynamics of land use in treated/untreated plots in more detail. Figure E.2 shows how results compare when using DID w/matching vs. event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024). Some differences are observed when comparing results estimated using DID w/matching compared to the event study estimator, particularly for years further away (before and after) from treatment, but increasing trends in time are consistent in all cases after treatment. Differences in magnitudes are likely due to not controlling for matching covariates with the event study estimator as we did with DID w/matching. Table E.1 in appendix shows a summary of treatment effects for the four outcome variables, 5 and 10 years after treatment, when using DID w/matching and the event study estimator.

Figure 3: The dynamic effects of Forest Incentives on Tree Cover(%) and Above and Below Ground Biomass Carbon (MgC/ha)

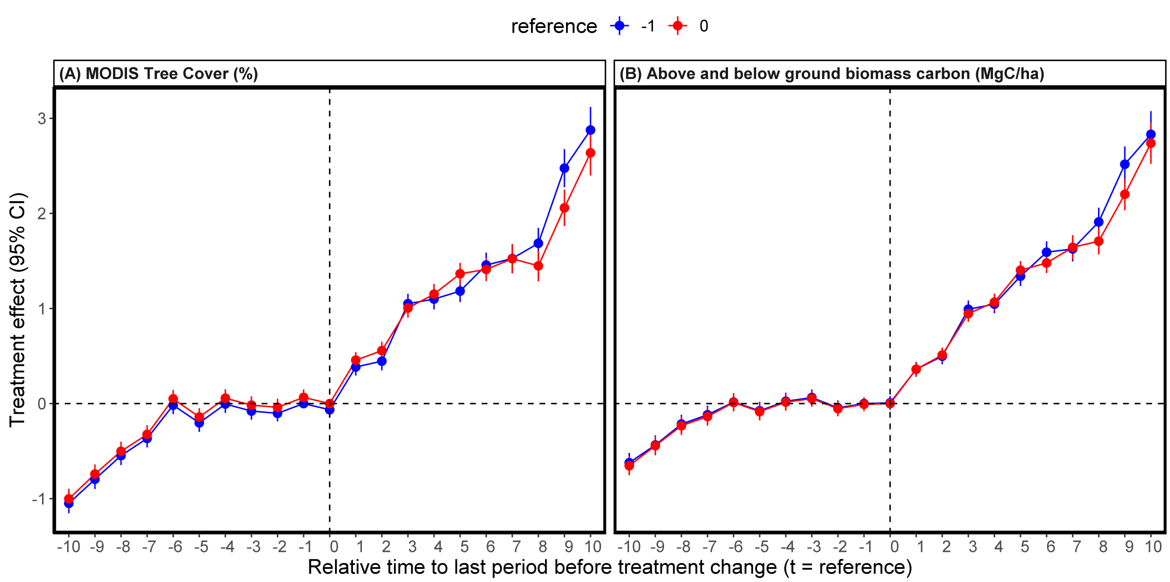


Table 3 reports the numerical estimates of effects of forest incentives on tree cover and above and below ground biomass carbon, 5 and 10 years after treatment, using differences-in-differences with matching. We estimate that forest incentives increase tree cover by 1.37

p.p. (95% CI, 1.25 - 1.48) after 5 years of treatment and by 2.64 p.p. (95% CI, 2.4 - 2.88) after 10 years of treatment. These are relatively modest impacts – an average increase of 5.9% in tree cover (2.64 over 44.7%) and 4.3% in carbon storage (2.74 over 63 MgC/ha abgbc) relative to the baseline across all programs. This translates into a Cohen d – a measure of effect size – of 0.13. As a comparison, the studies of the impacts of PES programs reviewed by Wunder et al. (2020) had an average Cohen d of 0.19. Although the impacts are modest, the alignment of the results for tree cover and above and below ground biomass carbon across all estimates suggest that the programs do not create incentives for replacing high-quality native forests for low quality planted forests as documented in other settings (see Heilmayr, Echeverría and Lambin (2020)). There is also no evidence that the effects revert after the forest incentives end – the effects continue increasing up to 10 years although most plots stop receiving after 5 years.

There is considerable heterogeneity in the effects of Guatemala's forest incentive programs. The 10-year effect of PINPEP is 1.69 p.p. (95% CI, 1.4 - 1.98) while the 10-year effect of PINFOR is 4.34 p.p. (95% CI, 3.86 - 4.81). PROBOSQUE, which has been active for less time, has a 5-year effect of 3.16 (95% CI, 2.64 - 3.68). The relative magnitudes of the treatment effect estimates for above and below ground biomass carbon are largely comparable to those for tree cover. The 10-year effect for PINPEP and PINFOR is of 1.58 (95% CI, 1.33 - 1.84) and 4.87 (95% CI, 4.42 - 5.31) (MgC/ha) respectively, while the 5-year effect for PROBOSQUE is of 2.2 (95% CI, 1.77 - 2.62). Heterogeneity across programs is largely explained by differences in the activities supported by each of them. A larger proportion of projects (31.9%) in PINFOR and PROBOSQUE are forestry plantations compared to PINPEP (12.3%), which is the project type with one of the highest treatment effects.

There is also substantial heterogeneity depending on the location of beneficiaries and their characteristics. All regions (Figure 4) show positive treatment effects for tree cover (%) 10 years after treatment with effects ranging from 1.4% (95% CI, 0.79-2.01) in the Northeast to 5.52% (95% CI, 3.10-7.93) for Guatemala. There seems to be higher heterogeneity in

Table 3: Effects on Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha): DID w/ matching

Program/ Project type	**Years since treatment**	**Tree cover (%)**	**Above and below ground biomass carbon (MgC/ha)**
All	5	1.37 (1.25 - 1.48)***	1.4 (1.31 - 1.5)***
	10	2.64 (2.4 - 2.88)***	2.74 (2.52 - 2.96)***
Program			
PINPEP	5	0.62 (0.49 - 0.76)***	0.83 (0.72 - 0.93)***
	10	1.69 (1.4 - 1.98)***	1.58 (1.33 - 1.84)***
PINFOR	5	2.17 (1.86 - 2.49)***	2.85 (2.56 - 3.14)***
	10	4.34 (3.86 - 4.81)***	4.87 (4.42 - 5.31)***
PROBOSQUE	5	3.16 (2.64 - 3.68)***	2.2 (1.77 - 2.62)***
Project type			
Agroforestry	5	0.76 (0.3 - 1.23)**	1.2 (0.85 - 1.55)***
	10	1.95 (0.96 - 2.94)***	1.74 (0.92 - 2.55)***
Forestry plantations	5	2.89 (2.58 - 3.19)***	3.75 (3.49 - 4.02)***
	10	4.96 (4.45 - 5.47)***	5.5 (5.02 - 5.99)***
NFM Production	5	1.6 (0.74 - 2.45)***	2.01 (1.15 - 2.87)***
	10	-0.66 (-2.04 - 0.72)	0.06 (-1.41 - 1.53)
NFM Protection	5	0.8 (0.65 - 0.94)***	0.47 (0.34 - 0.59)***
	10	1.18 (0.88 - 1.49)***	0.71 (0.43 - 0.99)***
Other	5	0.83 (-0.82 - 2.48)	3.07 (1.76 - 4.38)***
	10	10.02 (7.76 - 12.27)***	11.53 (9.83 - 13.24)***

Notes: *** $p<0.01$; ** $p<0.05$; * $p<0.10$.

point estimates by departments and ecoregions (Figure E.5 and E.6) although it is often not possible to rule out that estimates are equal due to the wide confidence intervals of most estimates.[8]

We also explored how these estimates varied by different initial plot conditions (Figure 5). Plots with relatively more "negative" characteristics (e.g., lower forestation rate, lower tree cover prior to treatment, further away from cities, etc.) tend to show higher treatment effects (more than double) compared to those plots with more "positive" characteristics.

[8]Figure E.7 reports of the typical estimates for tree cover (%) by Region, Department and Ecoregion.

Figure 4: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Region - 10 years since treatment

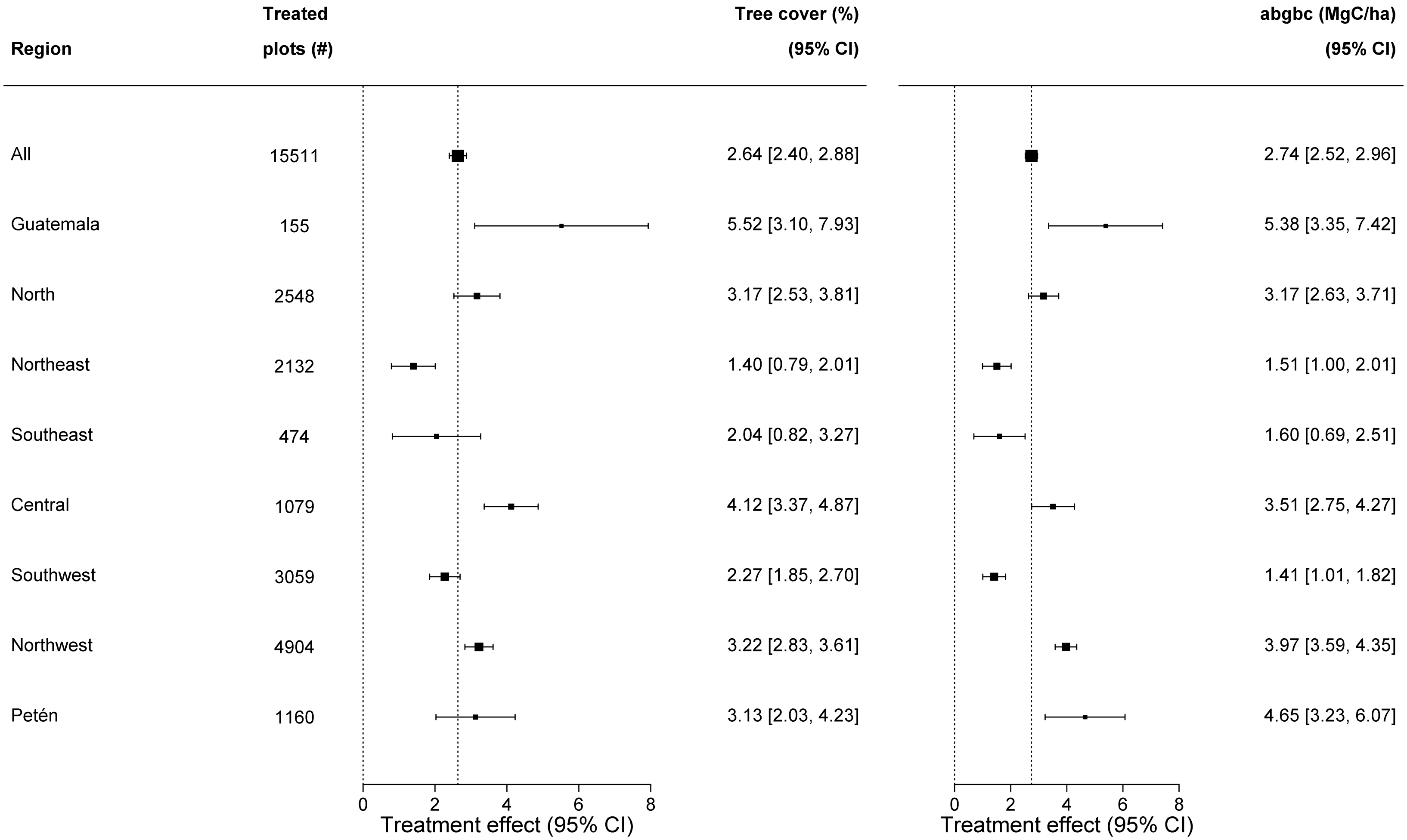
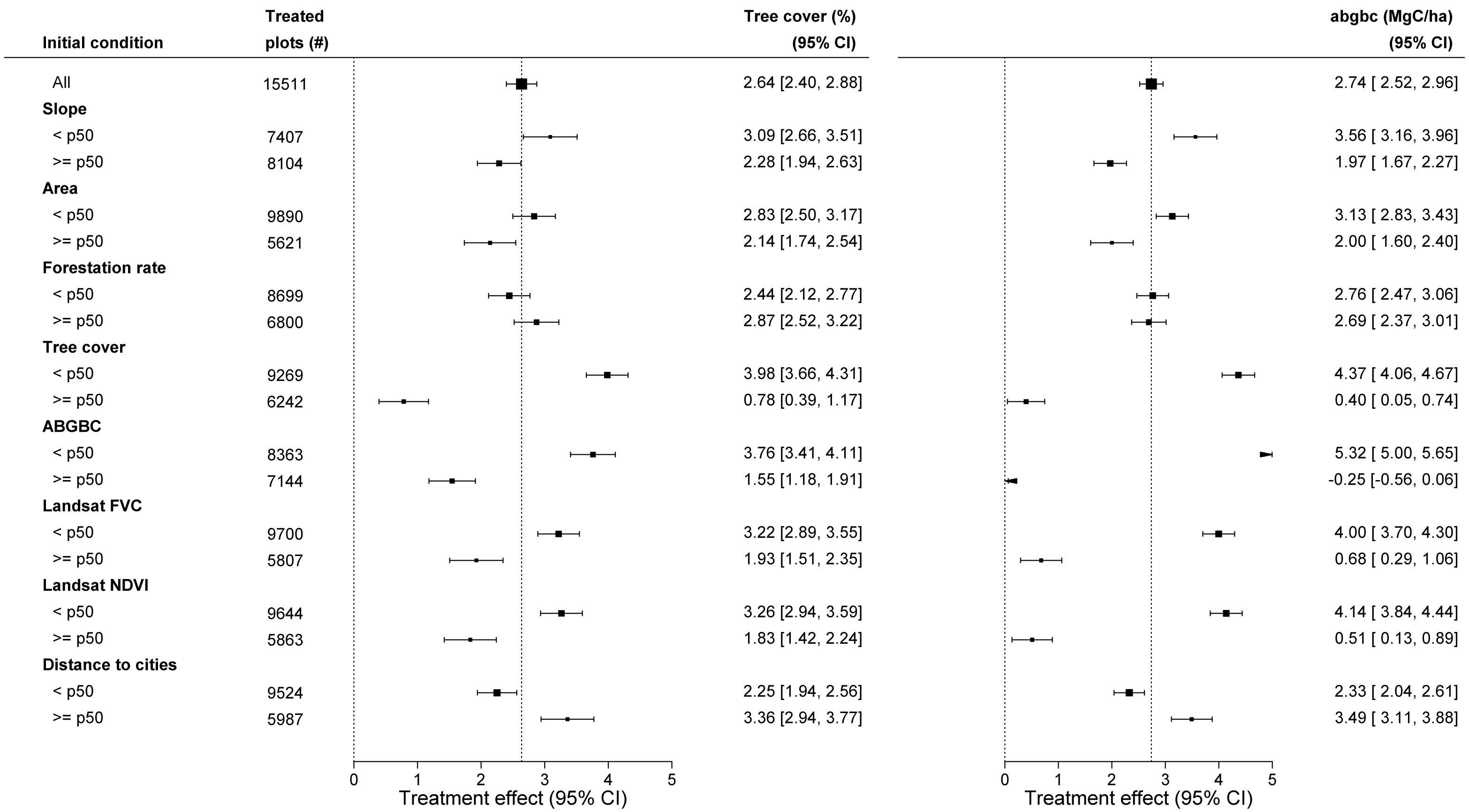


Figure 5: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by initial plot conditions - 10 years since treatment



4.2 Cost-benefit analysis

Table 4 reports the results of the cost-benefit analysis. Assuming permanence of benefits (benefits do not disappear over time), our results indicate a total benefit (ecosystem services and carbon) of 565-659 USD/ha for all projects combined, 330-390 USD/ha for PINPEP and 996-1150 for PINFOR/PROBOSQUE. By project type, forestry plantations (1,126-1,302 USD/ha] and restoration projects (2,352-2,707 USD/ha) have higher benefits per hectare. These environmental benefits are lower than the costs for all types of projects except one with an average cost-benefit ratio of 0.31-0.36. These numbers reflect two features of Guatemala's forest incentive programs: these programs are quite generous (as generous as the most generous programs in the region, see Cristales et al. (2022)) and their effects are slightly lower than the effect of comparable programs (see Wunder et al. (2020)).

Table 4: Cost-benefit analysis

	Benefits					
	Eco-system services		Carbon	Total	Costs	Ratio
	Low	High				
All	62	156	503	[565, 659]	1818	[0.31, 0.36]
PINPEP	40	100	290	[330, 390]	1617	[0.2, 0.24]
PROBOSQUE	102	256	894	[996, 1,150]	1,949	[0.51, 0.59]
PINPEP, Agroforestry	46	115	319	[365, 434]	715	[0.51, 0.61]
PINPEP, Forestry	117	293	1,009	[1,126, 1,302]	1,430	[0.79, 0.91]
PINPEP, NFM (Production)	-16	-39	11	[-5, -28]	2,086	[0, -0.01]
PINPEP, NFM (Protection)	28	70	130	[158, 200]	1,656	[0.1, 0.12]
PROBOSQUE, Agroforestry	46	115	319	[365, 434]	501	[0.73, 0.87]
PROBOSQUE, Forestry	117	293	1,009	[1,126, 1,302]	2,312	[0.49, 0.56]
PROBOSQUE, NFM (Production)	-16	-39	11	[-5, -28]	1873	[-0.03, -0.15]
PROBOSQUE, NFM (Protection)	28	70	130	[158, 200]	1,933	[0.08, 0.1]
PROBOSQUE, Restoration	236	591	2,116	[2,352, 2,707]	1,831	[1.28, 1.48]

5 Conclusion

This paper studies the environmental effects of forest incentive programs in Guatemala, one of the largest and longest running forest incentive programs in the world. Using differences-in-differences with matching, we document that forest incentives have a positive impact on tree cover and carbon storage. The effects become more pronounced over time and do not revert after incentives end. Albeit significant, the results are quantitatively modest: the three programs evaluated increase tree cover and carbon storage between 4-6%. Because the programs are quite generous, environmental benefits are not enough to cover the programs' costs. These mean effects hide considerable heterogeneity – we find higher effects (although not sufficient to cover costs) for projects focused in forestry or agro-forestry (and lower for conservation projects) located in regions with more deforestation pressure.

Our analysis has important implications for the redesign of Guatemala's forest incentive programs as it shows that there is substantial scope for improving these benefits. First, monitoring should be enhanced by establishing clear and quantifiable indicators for each of the programs' objectives. This is imperative to ensure they respond to changing conditions and outcomes. Second, our results reveal heterogeneous effects across regions and property types, underscoring the need for improved targeting. Tailoring program design to reflect this heterogeneity can increase both equity and cost effectiveness. Finally, we find that the environmental effects of incentives for different activities are quite different. Therefore, adjusting payment structures to better reflect the relative environmental value of these activities represents a critical opportunity to improve overall program performance.

As the most generous forest incentive programs in Latin America and the Caribbean (LAC), Guatemala's initiatives provide valuable insights for broader policy contexts. Despite their scale, our analysis points to low cost-effectiveness, a challenge that can be addressed through policy actions such as improved targeting and monitoring mechanisms. Other countries considering or implementing similar programs can learn from both the strengths and limitations of Guatemala's approach, using this experience to design more efficient and sustainable forest conservation policies. In conclusion, our work contributes to both the empirical and policy literatures by demonstrating how high-resolution spatial data and dynamic program evaluation methods can inform environmental policy design at a global level. Future research is needed to understand the economic and environmental effects of these programs in broader policy contexts, as well as their effects on people's well being.

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Appendix to “The Long Run Effects of Forest Incentives on Forest Cover and Carbon Storage”

Table of Contents

A Datasets and variables used

Table A.1 summarizes the datasets and variables used in our analysis for propensity score matching and to model above and below-ground biomass carbon density. Table C.1 presents descriptive statistics for the four outcome variables used in this assessment (tree cover, above and below ground biomass carbon, Landsat 7 FVC, and Landsat 7 NDVI) for treated and matched untreated plots.

Table A.1: Summary of data used for modelling

Name	Concept	Units	Time coverage	Spatial resolution	Data source
agbc	Above ground biomass carbon	MgC/ha	2010	300m	Spawn et al. (2020)
bgbc	Below ground biomass carbon	MgC/ha	2010	300m	Spawn et al. (2020)
y	y coordinate of plot centroid	degrees	-	-	Calculated with R based on data provided by INAB
x	x coordinate of plot centroid	degrees	-	-	Calculated with R based on data provided by INAB
landsat_ndvi	annual mean normalised difference vegetation index (NDVI)	-	2001-2023	100m(*)	Ermida et al. (2020)
landsat_lst	annual mean land surface temperature	Kelvin	2001-2023	100m(*)	Ermida et al. (2020)
landsat_fvc	annual mean fractional vegetation cover	fraction	2001-2023	100m(*) 30m(**)	Ermida et al. (2020)
landsat_em	annual mean emissivity	fraction	2001-2023	100m(*)	Ermida et al. (2020)
glad_forest_cover	mean forest cover	fraction	2000, 2020	30m	Potapov et al. (2022)
glad_forest_height	mean forest height	meters	2000, 2020	30m	Potapov et al. (2022)
elevation	distance above sea level	meters	-	90m	Jarvis et al. (2008)
slope	measure of steepness	degrees	-	90m	Jarvis et al. (2008)
aspect	orientation of slope in degrees from 0 to 360	degrees	-	90m	Jarvis et al. (2008)
modis_perc_tree	tree cover	%	2001-2023	250m	Dimiceli, Sohlberg and Townshend (2022)
modis_perc_nontree_veg	non-tree cover	%	2001-2023	250m	Dimiceli, Sohlberg and Townshend (2022)
modis_perc_nonveg	non-vegetation cover	%	2001-2023	250m	Dimiceli, Sohlberg and Townshend (2022)
ttc_20k	Travel time to cities with a population larger than 20k	minutes	-	100m	Nelson et al. (2019)
dist_to_river_2010	Distance to rivers and streams	meters	2010	-	Lehner and Grill (2013)
annualPrecip	Mean annual precipitation	mm	average 1970-2000	100m	Hijmans et al. (2005)
annualMeanTemp	Mean annual temperature	°C	average 1970-2000	100m	Hijmans et al. (2005)
precipDriestMonth	Precipitation during driest month	mm	average 1970-2000	100m	Hijmans et al. (2005)

(*) Original resolution at 30m, but calculated at 100m due to resource restriction
(**) additionally calculated at 30m to estimate treatment effect

B Building Controls

Following methods used by Patrick, Butsic and Potts (2023) we created 500,663 non-overlapping 100m radius (3.1ha) potential control plots using the Open Source Geographic Information System QGIS (version 3.22.8-Białowieża) (QGIS Development Team, 2024). We used the following procedure:

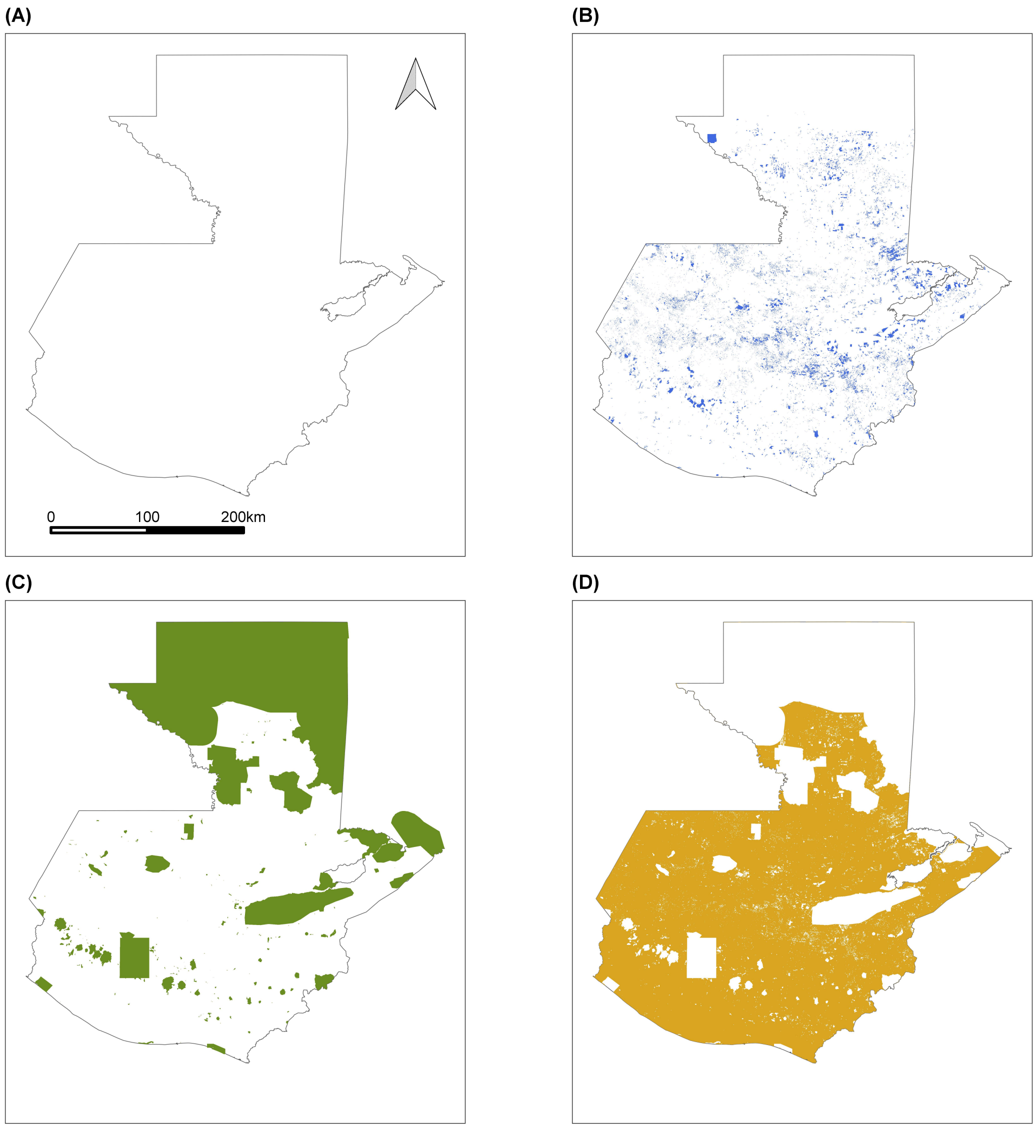
1. We identify the area within Guatemala that doesn't contain any forest incentive projects (INAB's database) nor any protected areas (UNEP-WCMC, 2024). We do this by using the "Difference" algorithm in combination with the country, forest incentives and protected areas shapefiles.

2. We generate a 350m x 350m grid using the "create grid" algorithm (rectangle) for the extent of the area identified in 1). A total of 1,607,148 grid cells were generated.

3. We use the "Extract by location" algorithm to extract grid cells from 2) that 'are within' the area identified in 1). A total of 500,663 grid cells are extracted.

4. We use the "Geometry by expression" algorithm to generate circular plots of 100m radius (3.1 hectares) centered on grid cells extracted in 3).

Figure B.1: Maps of (A) Guatemala, (B) INAB's forest incentives, (C) Protected Areas, and (D) Search area for controls



After this, we used propensity score matching to select one control plot for each treated plot. This procedure is detailed in appendix C.

C Propensity Score Matching (PSM)

We used propensity score matching to select 1 control for each treated plot. The process we used, adapted from Hui, Ma and Hübner (2023), is as follows:

1. **Choose relevant covariates**: following methods used by Patrick, Butsic and Potts (2023) we selected the following covariates: (1) elevation, (2) aspect, (3) slope, (4) GLAD forest cover 2000, (5) GLAD forest height 2000, (6) travel time to cities with a population larger than 20k, (7) distance to rivers and streams, (8) mean annual precipitation (mean of 1970-2000), (9) mean annual temperature (mean of 1970-2000), and (10) precipitation of driest month (mean of 1970-2000).

2. **Extraction of covariates**: we used the 'exact_extractr' function from the 'exactextracr' R package (Daniel Baston, 2020) to extract the mean values for the selected covariates for each of the treated and untreated (or control) plots. After this process, we dropped all plots (treated and untreated) that had missing data, ending up with 79020 treated plots and 489061 potential control plots.

3. **Estimate the propensity score**: We modelled the propensity score using the MatchIt package (Ho et al., 2011) in the R statistical software (R Core Team, 2018). Treated plots were assigned a value of 1 while control plots were assigned a value of 0. For our main analysis, we used a logistic regression with no replacement and all controls (489,061 controls with complete data on covariates). We performed the following sensitivity analyses:

   (a) *function for calculating the propensity score* - we used the following alternative functions or methods to calculate the propensity score: probit, gam, lasso, ridge, glmnet, bart, and randomforest.

   (b) *replacement of controls* - we calculated with and without replacement of controls.

   (c) *number of potential controls* - we tested allowing the algorithm to select from the following number of controls: 97800, 195600, 293400, 391200, or 489061 (all potential controls).

4. **Match treated and untreated**: After modelling, we used the 'match.data' function from the MatchIt package, which matches treated and untreated plots minimising the distance between them (i.e., the propensity score).

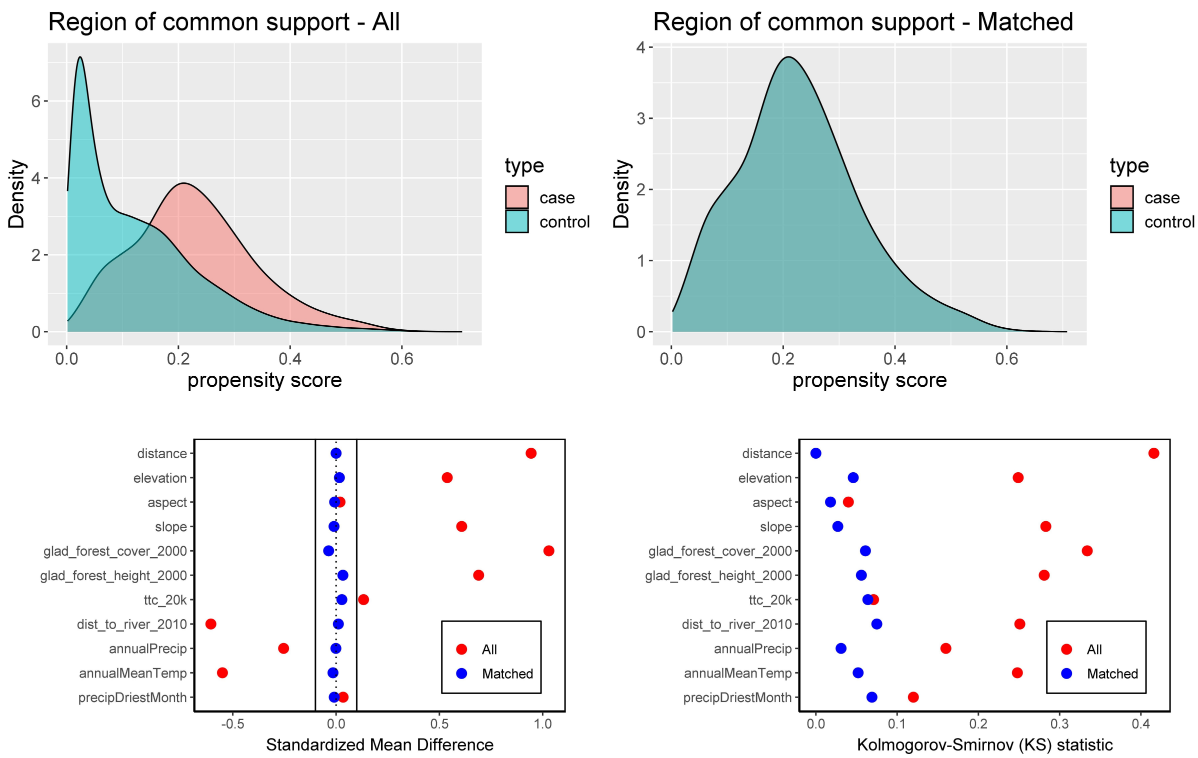
5. **Evaluate matches**: We evaluate our matching procedure using different methods:

   (a) *visual inspection*: we look at the region of common support before and after matching, and different density plots to check covariate balance.

   (b) *t-test*: we calculate t-test to test for differences in means between treated and untreated plots after matching

   (c) *Kolmogorov–Smirnov test*: we apply the Kolmogorov-Smirnov Goodness of Fit Test (K-S test) to compare if covariates from treated and untreated plots have the same distribution.

Figure C.1: Summary for main matching model



	Means Treated	Means Control	Std. Mean Diff.	t_stat	p_value_t	ks_stat	p_value_ks
distance	0.23	0.23	0	0	0.9977	0	1
elevation	1336.9	1322.14	0.016	3.37	0.0008	0.046	0
aspect	177.72	178.32	-0.007	-1.45	0.1471	0.018	0
slope	15.31	15.4	-0.01	-1.9	0.0574	0.027	0
glad_forest_cover_2000	0.89	0.9	-0.036	-7.66	0	0.061	0
glad_forest_height_2000	13.45	13.22	0.033	6.79	0	0.056	0
ttc_20k	83.89	81.1	0.028	5.45	0	0.064	0
dist_to_river_2010	255.17	250.16	0.011	2.06	0.0396	0.075	0
annualPrecip	1902.57	1903.35	-0.001	-0.18	0.8569	0.031	0
annualMeanTemp	19.92	20	-0.015	-3.19	0.0014	0.052	0
precipDriestMonth	36.64	36.95	-0.009	-1.68	0.0925	0.069	0

Figure C.2: Annual means for outcome variables for treated and matched untreated plots

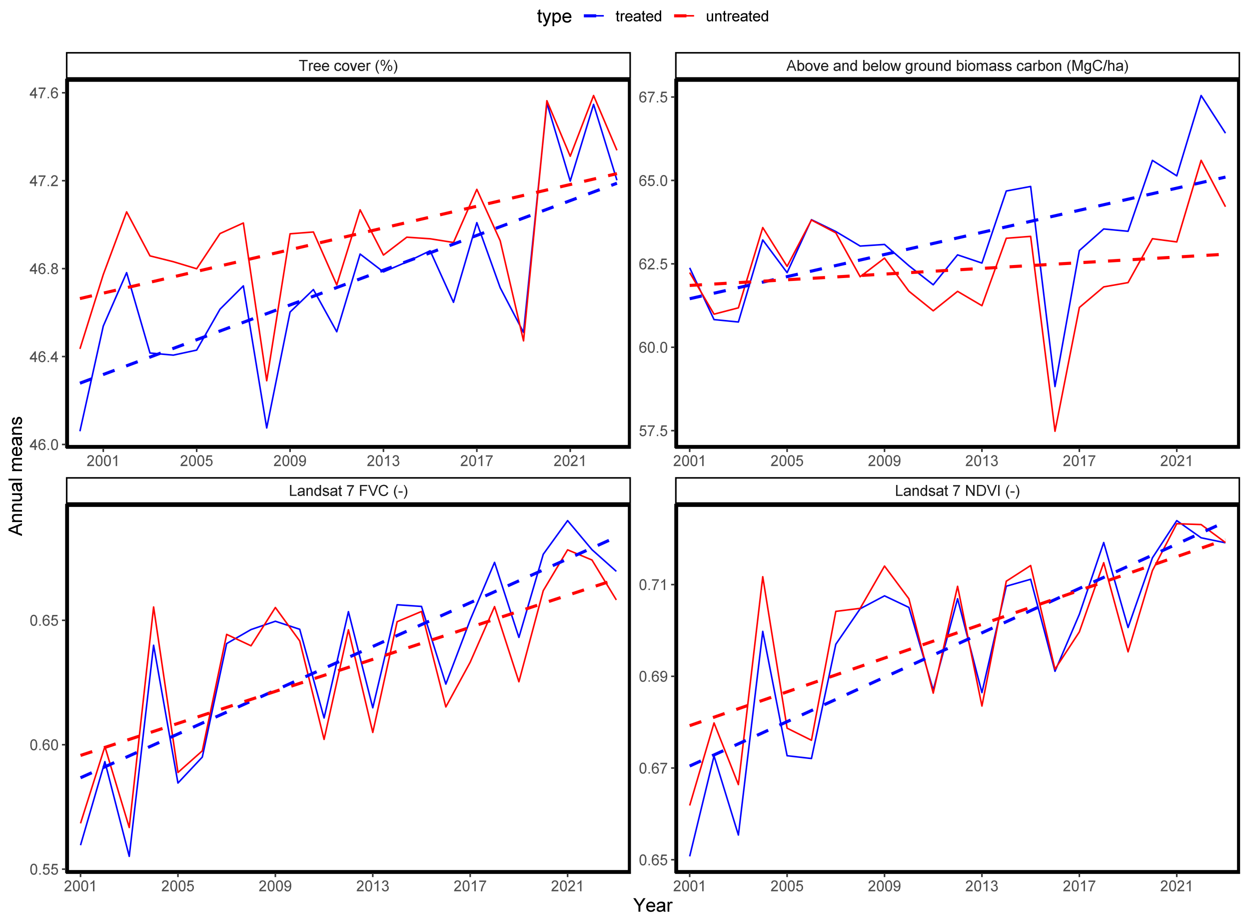


Table C.1: Descriptive statistics for outcome variables (2001, 2023, and change)

	Treated				Untreated*
Variable	**All**	**PINFOR**	**PINPEP**	**PROBOSQUE**	**All**
Tree cover (%)					
2001	44.7 (20.2)	44.4 (21.2)	42.8 (20)	51 (18.9)	45.1 (18.8)
2023	48.2 (18.9)	47.4 (18)	46.9 (19.1)	52.9 (18)	46.6 (18)
Δ 2003-2001	3.5 (11.4)	3 (14)	4.1 (10.4)	1.8 (12.5)	1.5 (12.9)
abgbc (MgC/ha)					
2001	61.9 (24.5)	57.5 (27.8)	61.7 (23.8)	64.9 (24.2)	61.4 (23)
2023	66.4 (21.4)	62.9 (22.4)	67 (21.3)	66.6 (21)	64.2 (21.4)
Δ 2003-2001	4.5 (10.8)	5.4 (14.8)	5.3 (9.3)	1.6 (11.8)	2.8 (12.2)
Landsat 7 FVC (-)					
2001	0.56 (0.238)	0.583 (0.263)	0.519 (0.223)	0.674 (0.229)	0.568 (0.231)
2023	0.67 (0.186)	0.694 (0.171)	0.648 (0.191)	0.723 (0.166)	0.658 (0.172)
Δ 2003-2001	0.11 (0.184)	0.11 (0.191)	0.129 (0.18)	0.049 (0.176)	0.09 (0.19)
Landsat 7 NDVI (-)					
2001	0.651 (0.137)	0.672 (0.138)	0.628 (0.132)	0.71 (0.13)	0.662 (0.134)
2023	0.719 (0.103)	0.734 (0.089)	0.707 (0.108)	0.748 (0.091)	0.719 (0.094)
Δ 2003-2001	0.068 (0.111)	0.062 (0.101)	0.079 (0.11)	0.037 (0.112)	0.057 (0.113)

* mean (standard deviation) for treated and matched untreated plots

D Modeling Above and Below-Ground Biomass Carbon Density

We trained a random forest model to predict above and below ground biomass carbon (abgbc) density for years 2001-2009 and 2011-2023. We modelled abgbc as a function of: (1) x coordinate, (2) y coordinate, (3) elevation, (4) aspect, (5) slope, (6) GLAD forest cover (mean of 2000 and 2020), (7) GLAD forest height (mean of 2000 and 2020), (8) mean annual precipitation (mean of 1970-2000), (9) mean annual temperature (mean of 1970-2000), and (10) precipitation of driest month (mean of 1970-2000), (11) MODIS tree cover (%), (12) MODIS non-tree vegetation cover (%), (13) MODIS non-vegetation cover (%), (14) LANDSAT land surface temperature, (15) LANDSAT fractional vegetation cover, (16) LANDSAT emissivity, (17) LANDSAT NDVI. In our model, the independent variable was abgbc for 2010 from Spawn et al. (2020), which was calculated as the sum of above- and below-ground biomass carbon density. A full dataset for 2010 was used to train our model. Variables (1)-(10) were kept constant for all years, while MODIS (11-13) and LANDSAT (14-17) variables varied each year.

To develop our model we first split our dataset (2010 data) into a training (90% of dataset) and a validation set (10% of dataset). We tested the performance of our model with the out-of-bag (OOB) R-squared and the R-squared calculated on the validation set (unseen data). Our model obtained similar performance values for OOB and validation with an R-squared of 81.5% and a root mean squared error (RMSE) of 13.8. Figure D.1 shows a scatter plot of predicted vs. original values from (Spawn et al., 2020) for the validation set (i.e., 10% of left out data).

The top 5 most important variables (Figure D.2) were: (1) GLAD forest height, (2) GLAD forest cover, (3) MODIS tree cover, (4) MODIS non-tree vegetation cover, and (5) LANDSAT FVC.

Figure D.1: Predicted vs. (Spawn et al., 2020) above and below ground biomass carbon density: (A) out-of-bag, (B) validation set

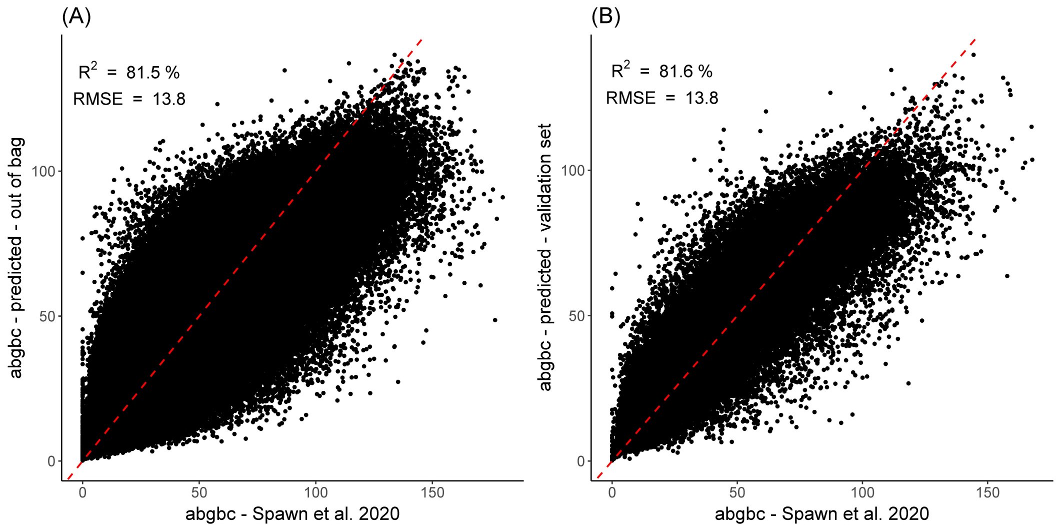
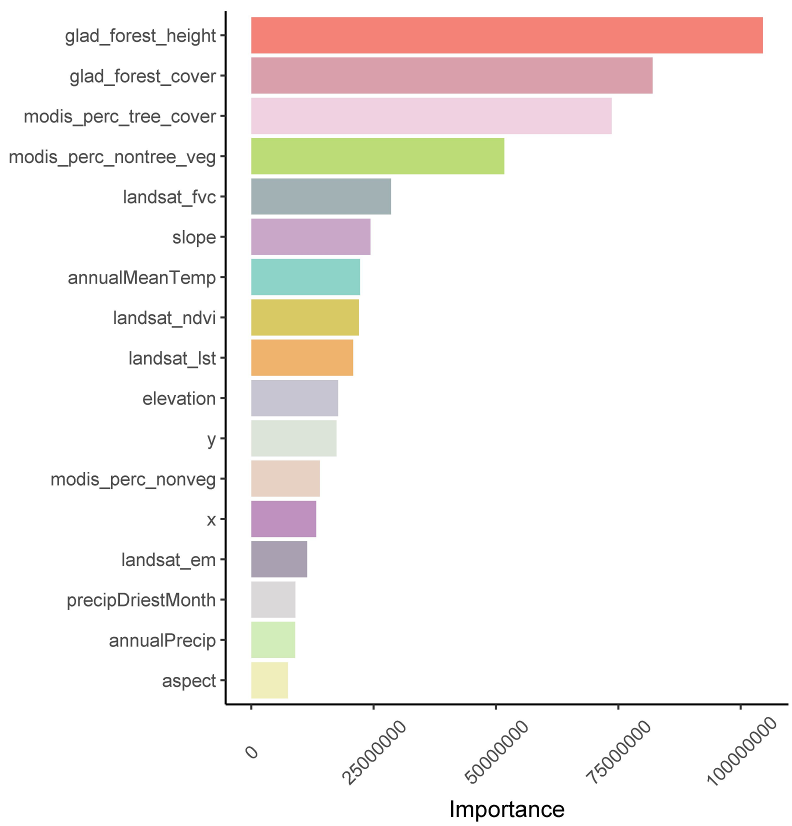


Figure D.2: Variable importance of random forest model



E Additional Results

Figure E.1: The Effects of Forest Incentives on tree cover (%), abgbc (Mg/ha), FVC (-), and NDVI(-): DID w/matching

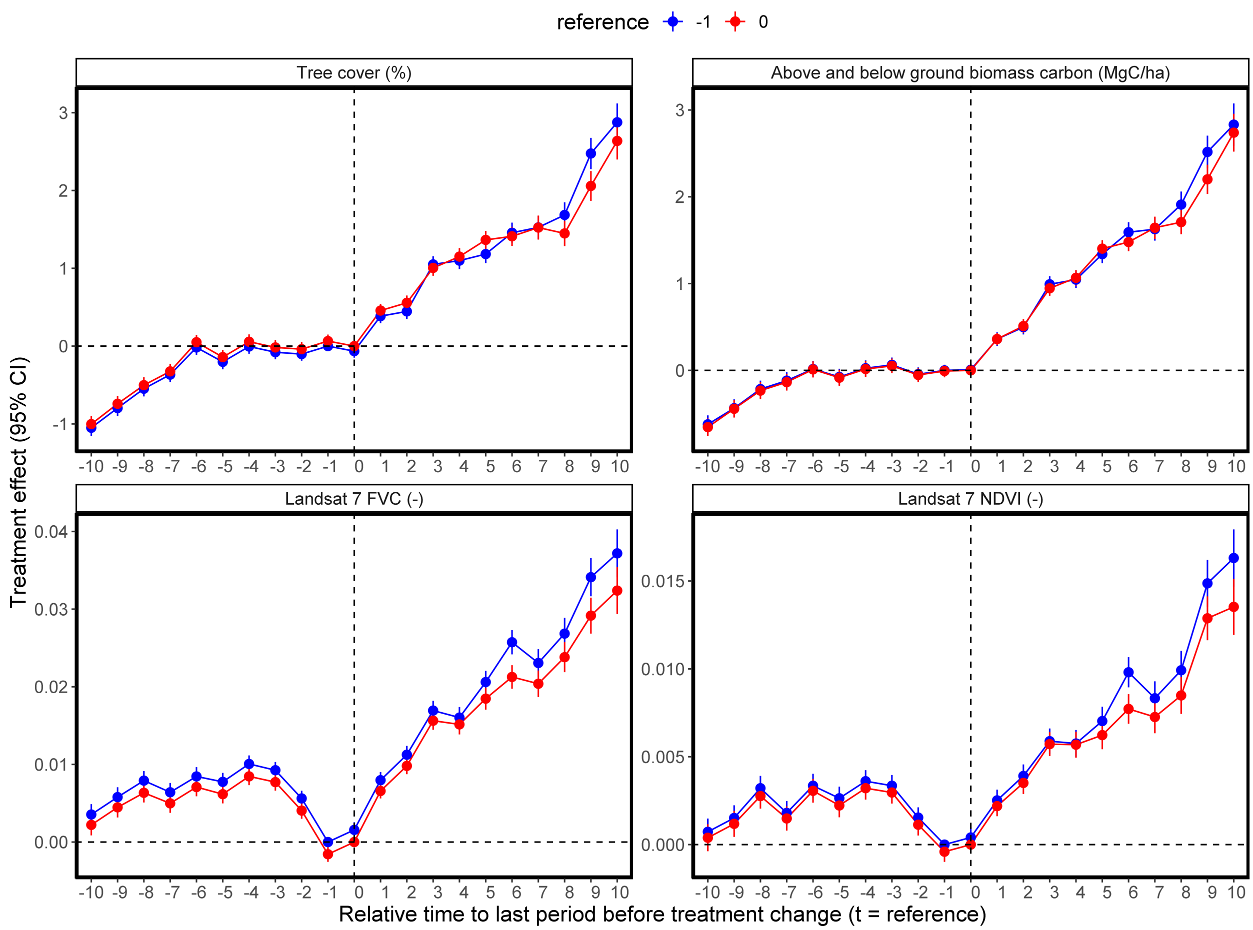


Figure E.2: The Effects of Forest Incentives on tree cover (%), abgbc (Mg/ha), FVC (-), and NDVI(-): DID w/matching vs. event study

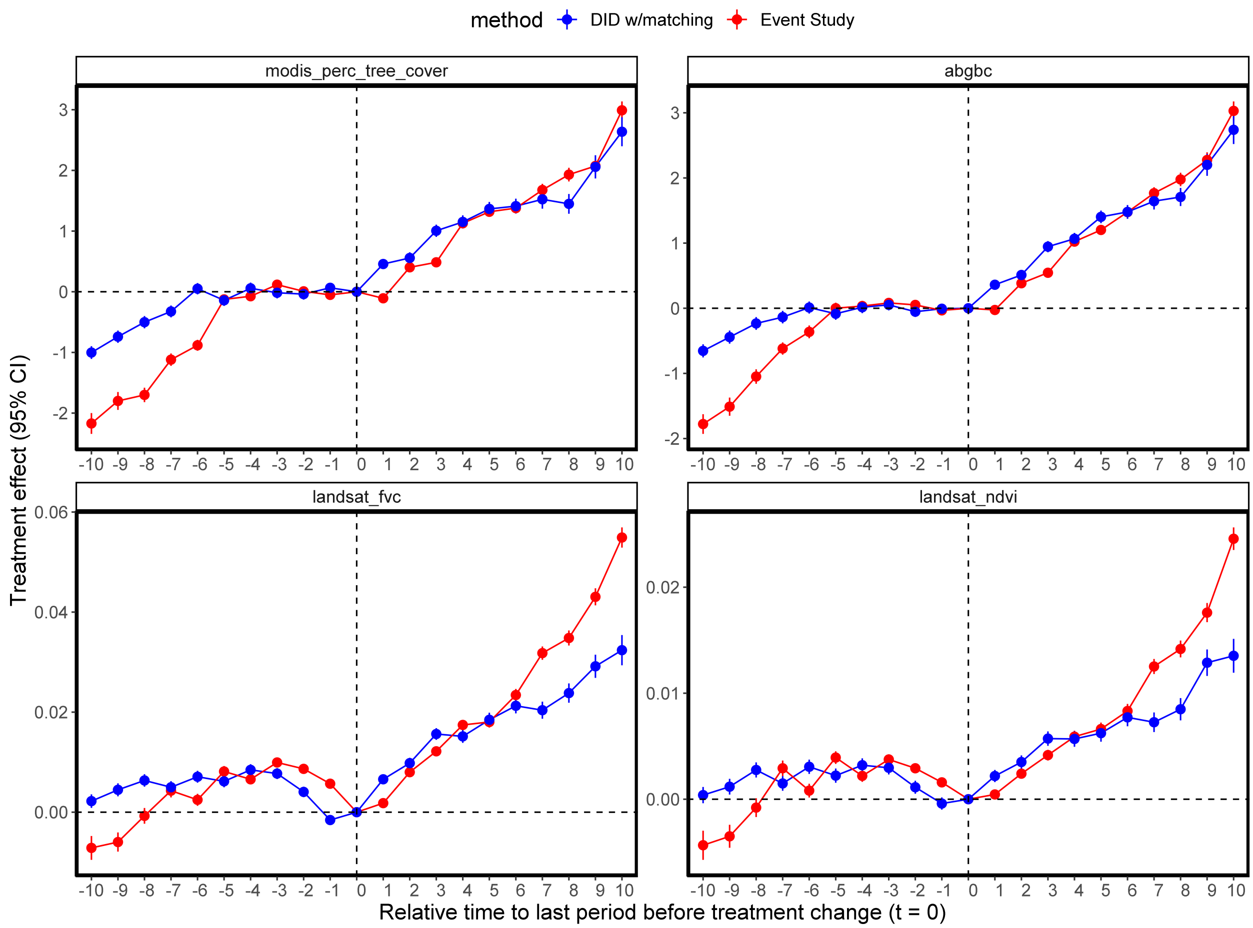


Table E.1: Treatment effect by outcome variable and assessment method

Outcome variable	**Years since treatment**	**DID w/matching**	**Event study estimator**
Tree cover (%)	5	0.81 (0.69 - 0.92)***	1.32 (1.23 - 1.4)***
	10	2.51 (2.27 - 2.76)***	2.99 (2.84 - 3.14)***
Above and below ground biomass carbon	5	1.01 (0.91 - 1.11)***	1.2 (1.13 - 1.28)***
	10	2.69 (2.46 - 2.92)***	3.03 (2.88 - 3.17)***
Landsat 7 FVC	5	0.02 (0.02 - 0.02)***	0.02 (0.02 - 0.02)***
	10	0.03 (0.03 - 0.04)***	0.05 (0.05 - 0.06)***
Landsat 7 NDVI	5	0.01 (0.01 - 0.01)***	0.01 (0.01 - 0.01)***
	10	0.01 (0.01 - 0.02)***	0.02 (0.02 - 0.03)***

Notes: *** p<0.01; ** p<0.05; * p<0.10.

Figure E.3: Treatment effect by program and years of treatment (DID w/matching) - Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha)

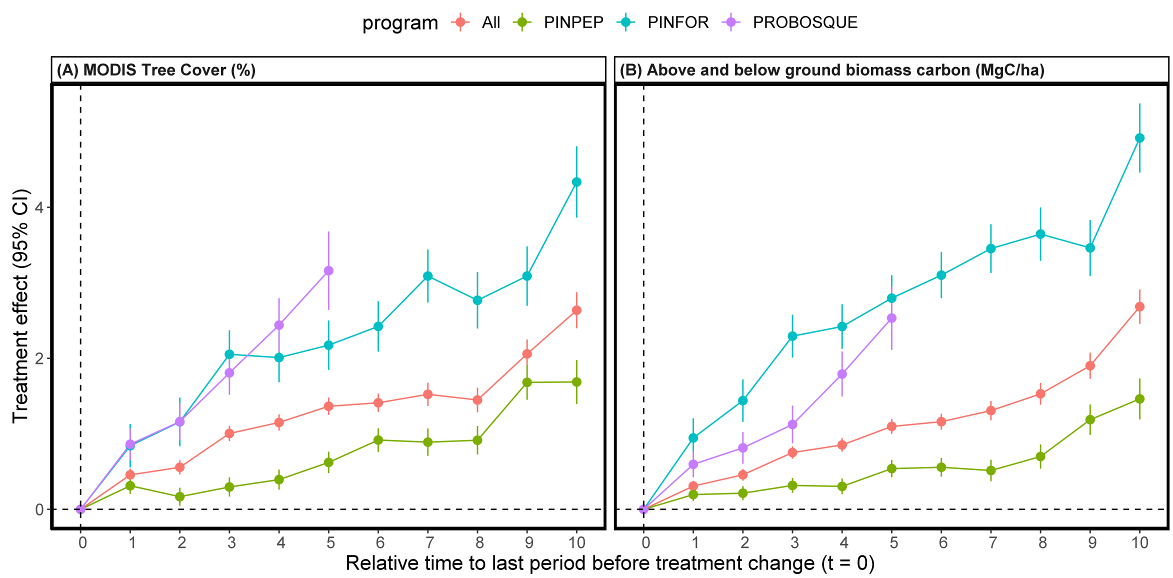


Figure E.4: Treatment effect by project type and years of treatment (DID w/matching) - Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha)

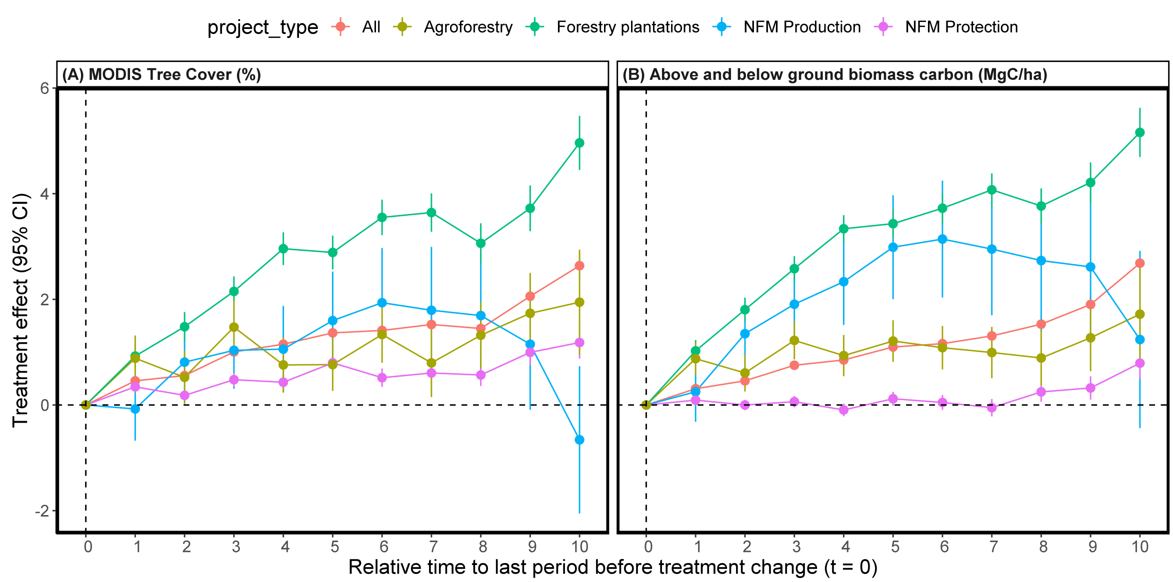


Figure E.5: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Department - 10 years since treatment

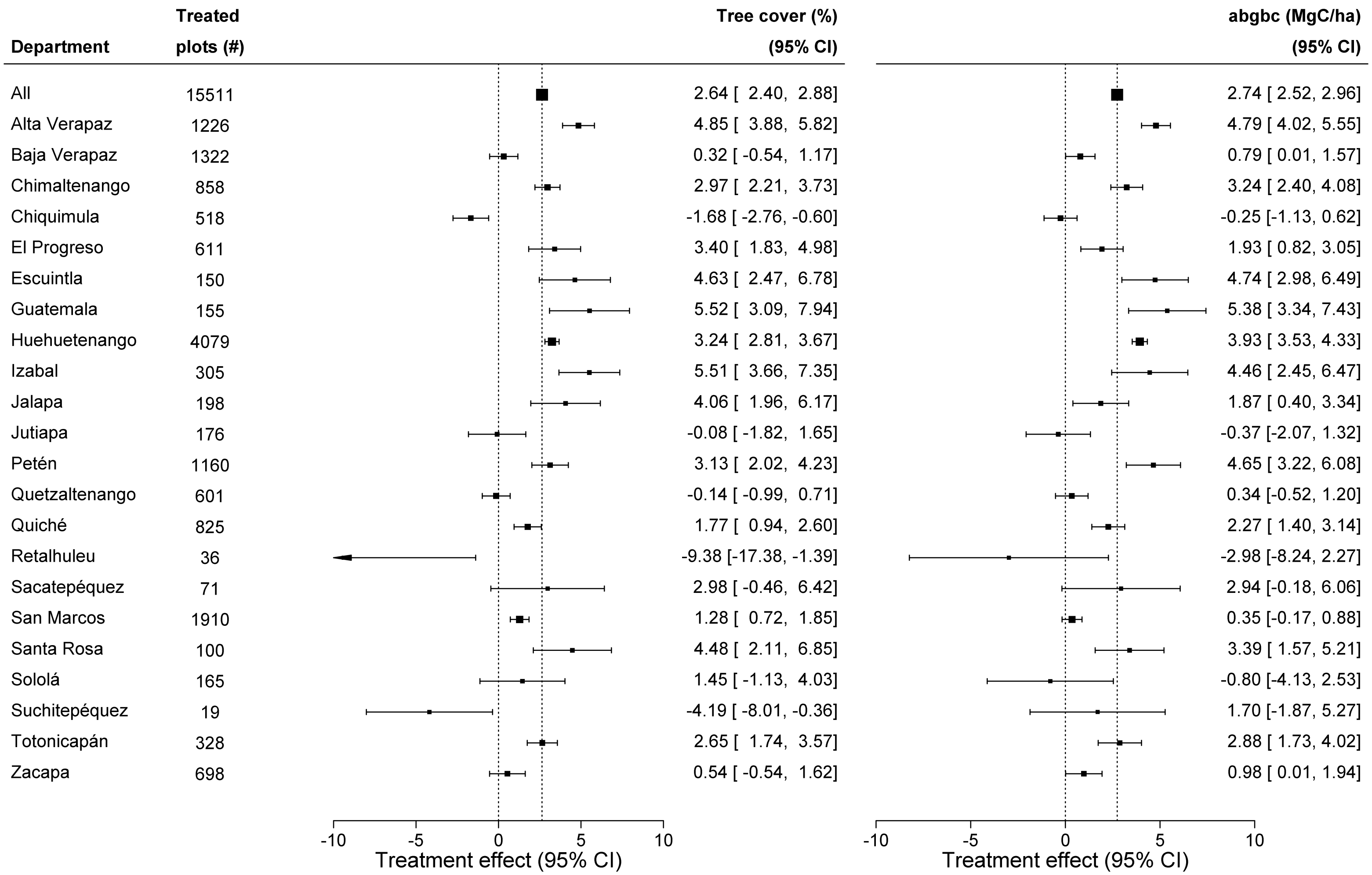
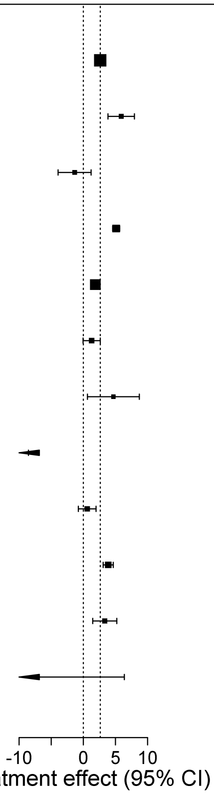


Figure E.6: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Ecoregion - 10 years since treatment

Ecoregion	Treated plots (#)	Tree cover (95% CI)	abgbc (MgC/ha) (95% CI)
All	15511	2.64 [2.40, 2.88]	2.74 [2.52, 2.96]
Central American Atlantic Moist Forests	303	5.89 [3.84, 7.95]	5.35 [3.31, 7.39]
Central American Dry Forests	178	-1.36 [-3.93, 1.21]	0.57 [-1.63, 2.76]
Central American Montane Forests	3147	5.11 [4.56, 5.66]	4.28 [3.81, 4.74]
Central American Pine-Oak Forests	7908	1.88 [1.58, 2.18]	2.02 [1.73, 2.30]
Chiapas Depression Dry Forests	551	1.30 [-0.04, 2.64]	1.80 [0.55, 3.05]
Chiapas Montane Forests	126	4.68 [0.64, 8.72]	7.28 [0.76, 13.80]
Mesoamerican Gulf-Caribbean Mangroves	4	-13.99 [-19.43, -8.54]	-39.60 [-45.01, -34.19]
Motagua Valley Thornscrub	587	0.60 [-0.78, 1.98]	0.86 [-0.18, 1.89]
Petén-Veracruz Moist Forests	2358	3.87 [3.09, 4.66]	4.48 [3.60, 5.35]
Sierra Madre De Chiapas Moist Forests	204	3.34 [1.46, 5.21]	4.04 [2.34, 5.74]
Southern Mesoamerican Pacific Mangroves	3	-13.76 [-33.91, 6.38]	6.72 [-10.86, 24.31]



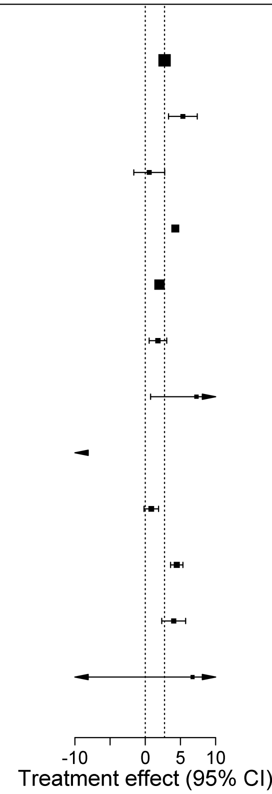


Figure E.7: Treatment effect by (A) Region, (B) Department and (C) Ecoregion (DID w/matching) - Tree Cover (%) - 10 years after treatment

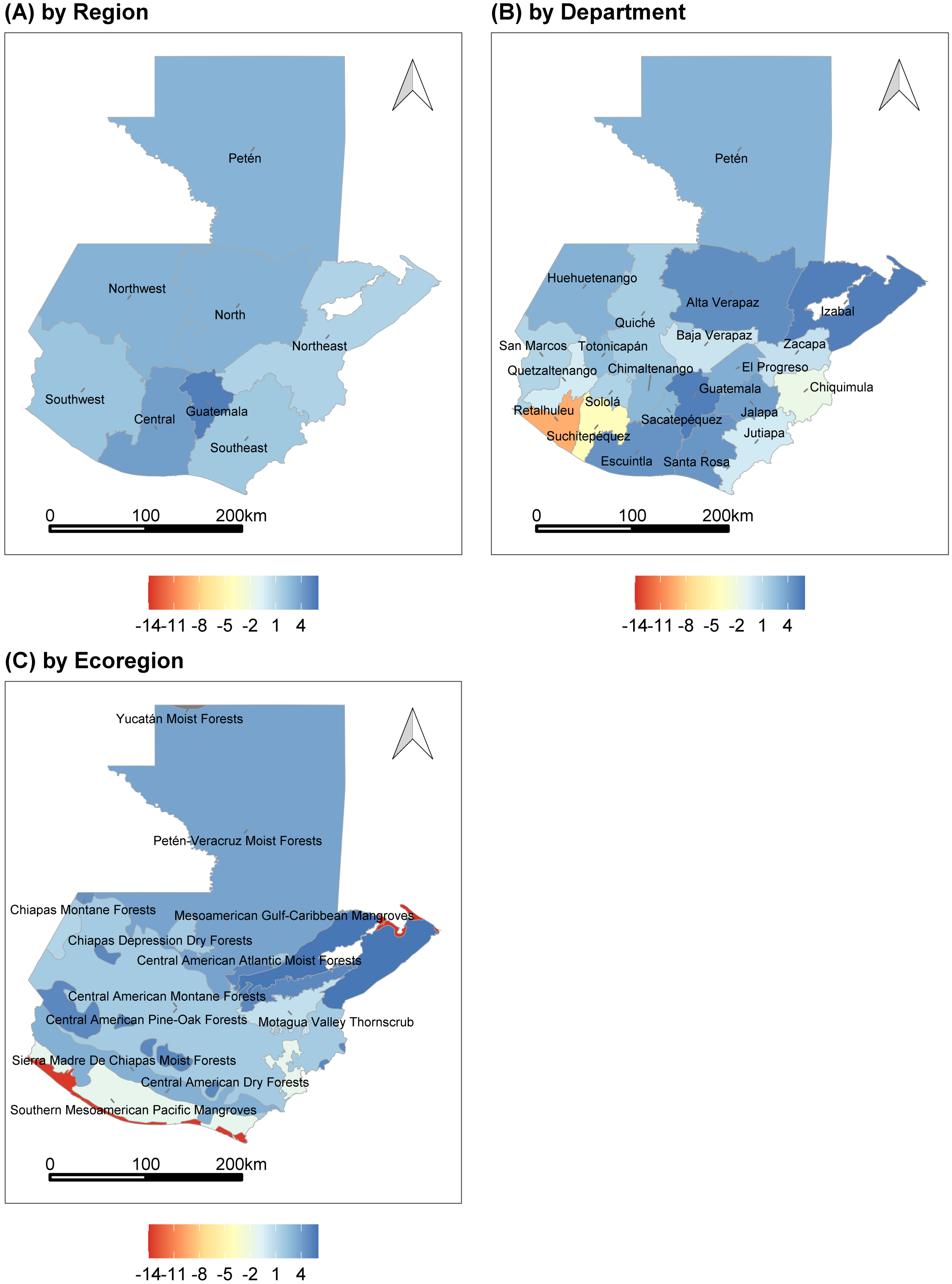


Figure E.8: Treatment effect by initial conditions (10th and 90th percentiles) after 10 years by model used for matching - DID w/matching

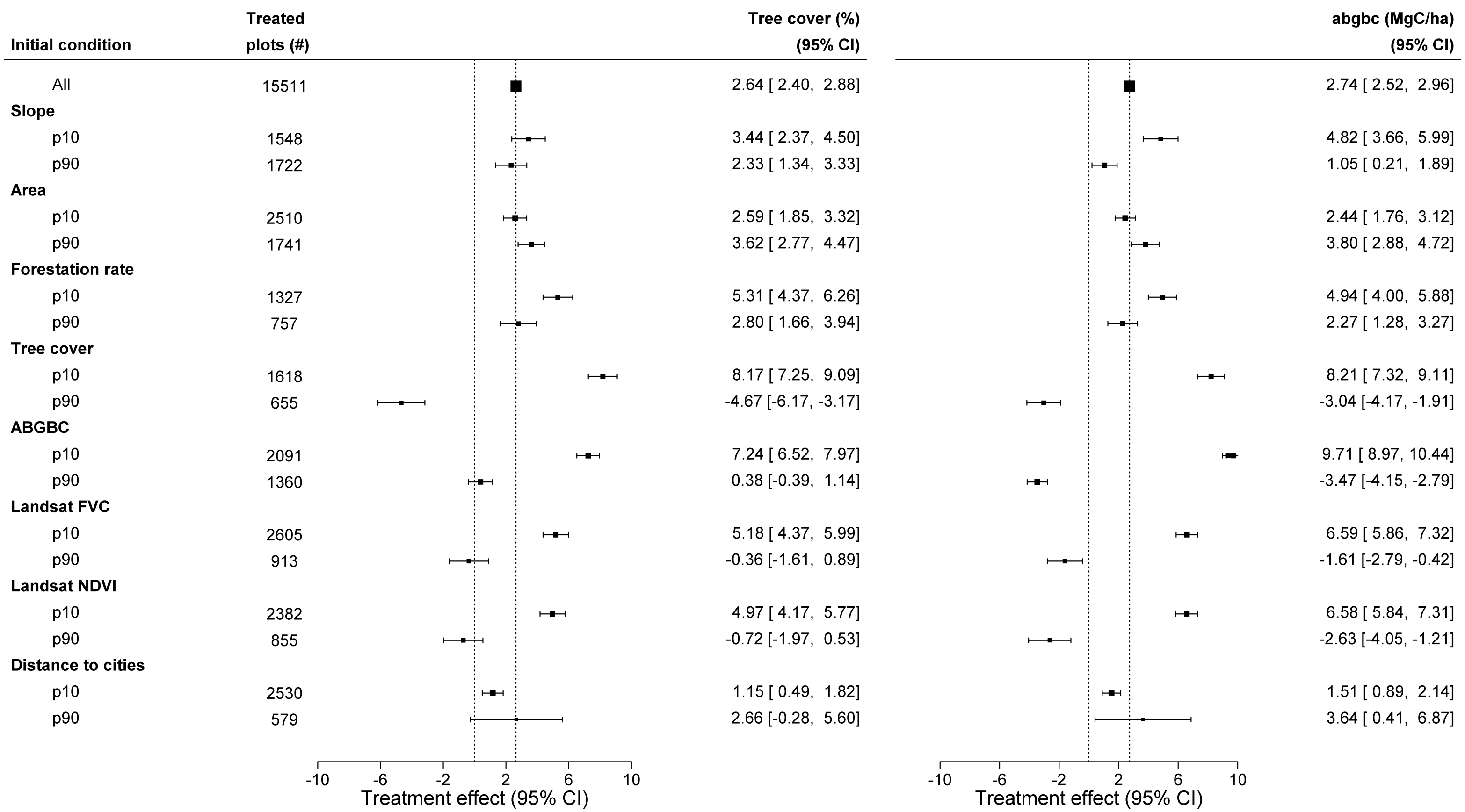


Figure E.9: Treatment effect (all programs) after 10 years by model used for matching - DID w/matching