

Are Carbon Offset Projects an Effective Vehicle for Carbon Emission Reduction?

Evidence from Global Geo-data

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Motivation

- Reducing carbon emissions has been a top priority for governments and firms globally
- The **carbon offset market** is one of many endeavors, projected to surge to \$250 billion by 2050 (Morgan Stanley, 2023)
- The **effectiveness** of this burgeoning market, however, lacks a thorough investigation



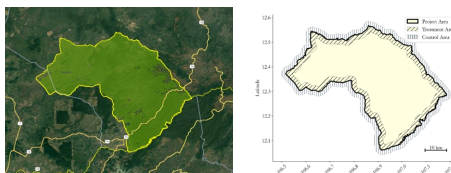
This Paper

- Focuses on REDD+ projects in voluntary carbon offset market
 - Projects aiming to reduce emissions from deforestation
- Constructs a **novel dataset** that includes
 - All available REDD+ projects
 - Time-series of forest coverage in 600 x 600 m² land units
- Evaluates the effectiveness of projects in reducing emissions
 - Employs a **Difference-in-Differences (DID)** approach
 - Finds most of the projects have **nearly zero effect** of slowing down deforestation

Data

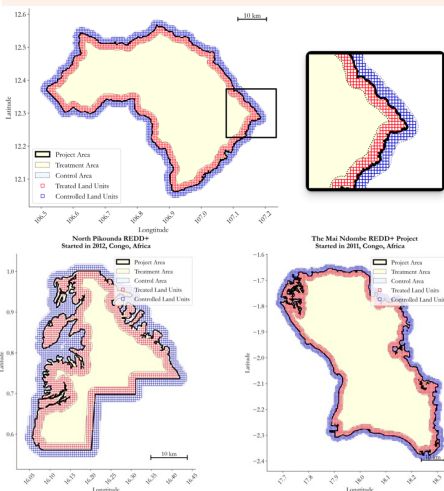
- Carbon offset project data** from the public registry
 - Issuance and retirement, project area, corporate buyers
 - Forest loss data** from Hansen et al. (2013)
 - Global forest changes analyzed using Landsat images
 - High resolution grid cells of approx. 30 x 30 m²
- Forest coverage dataset
 - Cross-sectional snapshot of year 2000
 - Percentage range from 0 to 100
 - Year of forest loss event dataset
 - Cross-sectional data per grid cell
 - Convertible to a panel dataset, annually from 2001-2022

Empirical Design

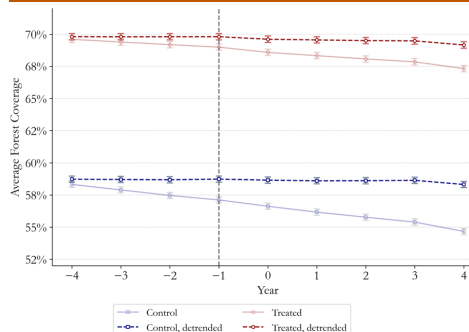


- Construct a panel dataset comprising 2 million observations
 - 68 **projects** (p) (All REDD+ Projects up to 2024)
 - 3,000 individual 600 x 600 m² **land units** (i) per project (p)
 - 9-year time-series data (t) per land unit (i)
- Employ a DID approach, nested within a RDD framework
 - Treatment group:** Individual land units located 2 kilometers **within** the project boundary
 - Control group:** Individual land units located 2 kilometers **outside** the project boundary
- The baseline regression I estimate is as follows

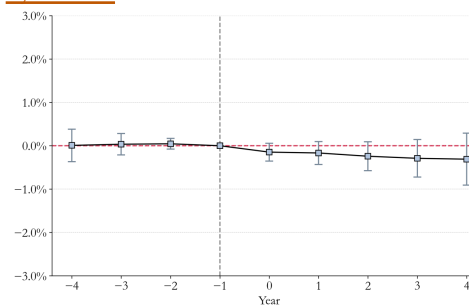
$$ForestCoverage_{ipt} = \beta(Treat_{ip} \times Post_{tp}) + FE_s + \epsilon_{ipt}$$
- The following figures display the land units and some projects



Main Results



Dynamic DID

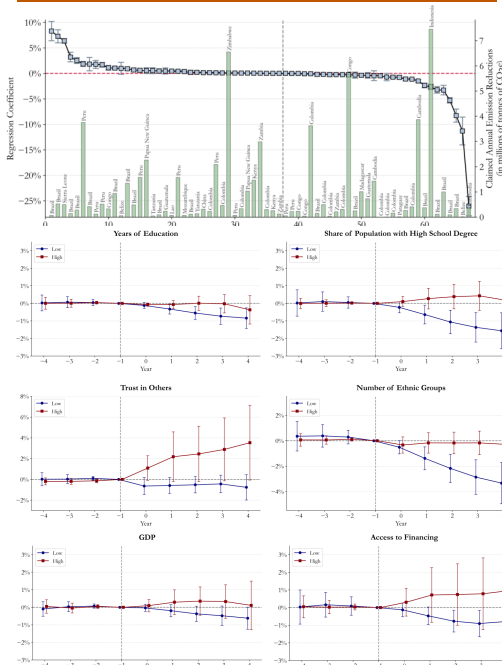


Baseline Regression

	Detrended ForestCoverage		
	(1)	(2)	(3)
$Treat \times Post$	-0.0019 (0.0023)	-0.0019 (0.0023)	-0.0025 (0.0022)
Project FE		✓	
Land Unit FE			✓
Project-Year FE			✓
Observations	1,945,575	1,945,575	1,945,575
R^2	0.0206	0.7168	0.9903
Mean of Dep. Var.	0.6387	0.6387	0.6387
Std of Δ Dep. Var.	0.0284	0.0284	0.0284

Project-clustered standard-errors in parentheses

Heterogeneous Effects



Conclusion

- This paper
 - Examines the effectiveness of projects in preserving forest
 - Documents a precisely estimated **nearly zero effect** of slowing down deforestation
- Finds **culture** and **education** are important factors for project success
- Future research
 - Look into the carbon offset transactions and buyers
 - Investigate the mechanism and reason why these projects are noneffective

Are Carbon Offset Projects an Effective Vehicle for Carbon Emission Reduction?^{*}

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Abstract

This paper investigates the effectiveness of carbon offset projects in reducing carbon emissions, focusing specifically on REDD+ projects, which aim to reduce emissions from deforestation and have the highest carbon offset issuance. I build a novel dataset that includes all available REDD+ projects worldwide and high-resolution forest coverage data. Specifically, I define control and treatment regions based on grid locations within and outside project boundaries. Using a difference-in-differences design, I find that these projects have a nearly zero effect on slowing deforestation. Using subnational region data, I show that projects in regions with access to finance, higher education levels, greater trust, or more ethnic diversity tend to perform better, indicating that cultural and educational factors are crucial for the success of carbon offset projects.

JEL classification: G18, G23

keywords: Carbon Offset, Deforestation, Carbon Emission, Climate Finance

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I. Introduction

In recent years, there has been a growing emphasis on environmental sustainability and the need to mitigate climate change through various means. Carbon offset program is one of the efforts, which enable individuals and businesses to counterbalance their carbon emissions by financially supporting projects that mitigate or eliminate an equal amount of greenhouse gases from the environment. According to [Morgan Stanley \(2023\)](#), the voluntary carbon offset market is expected to grow from \$2 billion in 2020 to around \$250 billion by 2050. However, many concerns have emerged regarding the integrity of carbon offset markets, particularly with respect to fraudulent practices.¹

This paper investigates the voluntary carbon offset market and examines the effect of carbon offset projects on the reductions of deforestation rates. As an emerging market, voluntary carbon offsets have attracted corporate companies and individuals seeking ways to neutralize their carbon footprints². Organizers of carbon offset projects initiate and manage interventions aimed at reducing or eliminating greenhouse gas emissions. A significant fraction of these interventions involves REDD+ projects (Reducing Emissions from Deforestation and Forest Degradation). REDD+ projects focus on forest conservation and the potential of such conservation efforts to reduce carbon emissions. These projects represent a tangible commitment to environmental preservation, and yet, their effectiveness has been a topic of debate. Some argue that these initiatives have played pivotal roles in forest conservation, while skeptics raise concerns over potential over-reporting or misrepresentations of their impacts.

In this paper, I investigate whether voluntary carbon offset projects effectively reduce deforestation rates using a difference-in-differences (DiD) methodology. By defining the treated areas as land within 2,000 meters of the project boundaries and control areas as land situated 2,000 meters outside these boundaries, I leverage the staggered implementation of REDD+ projects to identify causal impacts. Using high-resolution annual forest loss data, I carefully account for pre-existing deforestation trends through detrending techniques, estimating and removing linear pre-project trends separately for treated and control areas. After this detrending adjustment, the rigorous DiD analysis includes

¹A relevant article from the Guardian can be found [here](#).

²See Figure [IA.1](#) for twenty big corporate buyers of carbon offsets.

project-year fixed effects to control for time-varying shocks at the project level and land-unit fixed effects to account for time-invariant geographic characteristics. Standard errors are clustered at the project level. The results reveal precisely estimated effects around zero, indicating that treated areas lose forests at a similar rate as untreated control areas. These findings challenge the claimed effectiveness of many carbon offset projects, suggesting limited measurable impacts on reducing deforestation.

Next, I explore heterogeneity in project outcomes by conducting individual DiD analyses for each project separately. This detailed examination reveals substantial variation in effectiveness, with most projects showing no statistically significant impacts. While a few projects demonstrate meaningful positive outcomes, several others perform substantially worse than their control counterparts, losing forests at even greater rates. Importantly, many ineffective projects claim large annual emission reductions, raising concerns about potential misrepresentations or inaccuracies in carbon credit issuance within voluntary markets.

Lastly, I investigate which regional characteristics are associated with project effectiveness to understand factors that may facilitate successful carbon offset interventions. Using detailed subnational data covering geographic, economic, and social characteristics, I examine how these factors correlate with project outcomes through a triple-interaction DiD approach, incorporating event-time and project fixed effects. The results identify several key characteristics associated with positive project outcomes. Specifically, regions with higher access to finance, greater educational attainment, higher trust among local populations, and higher ethnic diversity experience significantly better results. Conversely, other regional attributes such as access to land, local GDP, and government predictability appear to have limited influence. These findings provide critical insights for policymakers and project designers, highlighting specific regional conditions that enhance the effectiveness and integrity of carbon offset programs.

Related Literature. This research is primarily related to two strands of literature. First, the potential findings would speak to the growing concern about the carbon offset markets. [Badgley, Freeman, Hamman, Haya, Trugman, Anderegg, and Cullenward \(2022\)](#) investigate California's forest carbon offsets program and find that its design systematically over-credits carbon offsets, leading to the issuance

of credits that do not reflect real climate benefits. [West, Börner, Sills, and Kontoleon \(2020\)](#) study the impacts of deforestation projects in the Brazilian Amazon and find that these projects' crediting baselines assumed higher deforestation than what was observed. [West, Wunder, Sills, Börner, Rifai, Neidermeier, and Kontoleon \(2023\)](#) study 27 forest conservation projects across six countries and find that most of these projects have not effectively reduced deforestation, and those that did showed reductions significantly lower than claimed. [Calel, Colmer, Dechezleprêtre, and Glachant \(2021\)](#) find that a significant portion of carbon offsets in India was allocated to projects that would have proceeded regardless, leading to wasted resources and increased global carbon dioxide emissions. [López-Vallejo \(2021\)](#) discover that non-additionality, overestimated supply, and double counting are prominent quality concerns in Mexico's offset market. This paper contributes to the prior works by proposing a novel identification strategy and conducting a comprehensive study of all registered REDD+ projects. Leveraging the high-resolution annual forest loss dataset cross-referencing, this paper identifies the effect of REDD+ projects on the reduction of deforestation rates.

Second, in a broader view, this study relates to a growing literature of corporate greenwashing. [Marquis, Toffel, and Zhou \(2016\)](#) find that firms with greater environmental impact, especially those in countries with increased scrutiny and exposure to global norms, are less likely to engage in selective disclosure of benign environmental impacts. [Ferrés and Marcet \(2021\)](#) find that firms involved in price fixing schemes increase their CSR initiatives when they become targets of antitrust investigations. [Li, Lou, and Zhang \(2022\)](#) argue that commercial ties between ESG rating agencies and their clients lead to inflated ESG ratings. Lastly, [Lyon and Montgomery \(2015\)](#) synthesize the literature on greenwashing and emphasize the need for further research to identify, catalog, and model the mechanisms and impacts of various forms of misleading environmental communication. This paper contributes to the previous studies by systematically examining the carbon offset market and providing a novel angle to measure corporate greenwashing.

The remainder of this paper is structured as follows: Section II offers an overview of the carbon offset market. In Section III, I outline data sources and provide pertinent summary statistics. Section IV demonstrates the empirical methodology. Section V presents the test results, and Section VI

explores regional factors driving the project outcomes. Finally, Section VI concludes.

II. Carbon Offset Market Overview

This section provides the institutional background of the carbon offset market, a tool for reducing greenhouse gas emissions through carbon credit transactions. The market consists of two sectors: compliance and voluntary. This paper primarily focuses on the voluntary market.

A. Compliance Carbon Offset Market

The compliance market is part of a regulatory system, often a cap-and-trade system. These systems set a cap on total emissions and issue a limited number of emission allowances that can be bought, sold, and traded by companies. If a company emits more than its allocated allowances, it must purchase more allowances or offset credits to comply with the regulations. These purchases often happen in organized exchanges and are tracked by regulatory bodies. Over time, the cap is gradually lowered, reducing the total amount of emissions.

B. Voluntary Carbon Offset Market

In voluntary carbon market, carbon offset is a voluntary mechanism designed to mitigate greenhouse gas emissions by investing in projects that offset or reduce carbon emissions. Carbon credits are purchased as units of carbon dioxide removed from the atmosphere or prevented from being released. Carbon offset transactions are tracked by independent registries. There are four major registries — American Carbon Registry (ACR), Climate Action Reserve (CAR), Gold Standard, and Verra (VCS). They claim to provide a transparent system for tracking and verifying the issuance, ownership, and retirement of carbon offset credits. The registries require projects to undergo a rigorous process of measurement, monitoring, and third-party verification to ensure the credibility and accuracy of carbon offsets. Panel A of Figure 1 shows the amount of issuance and retirements of carbon credits over time. There are 287 million carbon credits issued in 2022, while 146 million retired.

Projects that generate carbon credits have many categories, such as renewable energy, energy efficiency, and forestry or land-use changes. Given the vast disparities in methodologies and impacts

among various carbon credit projects, this paper narrows its lens to primarily explore REDD+ projects. Figure 1 shows the amount of carbon offsets retired in each year by a few top project types. Among all project types, REDD+ projects stand out, accounting for the largest share of retired carbon credits, further justifying this paper’s emphasis on them.

REDD+ Projects. REDD stands for “Reducing Emissions from Deforestation and Forest Degradation,” with the ‘plus’ encompassing conservation, sustainable forest management, and enhancement of forest carbon stocks. Given the threats to tropical forests from various activities, REDD+ projects are mostly implemented in these regions, especially in developing nations. They provide financial incentives to landowners to maintain their forests rather than converting them for other uses. The emission reductions from these projects, representing carbon that would have been released if the forest was destroyed, are quantified into tradable carbon credits. The number of credits is determined through a methodology that involve counterfactual baseline emission calculations — representing emissions that would have occurred in the absence of the REDD+ project — and the actual emissions observed after project implementation. The difference between the two provides the net carbon emissions mitigated by the project.

III. Data and Summary Statistics

In this section, I introduce the data sources that I use for my studies and show the summary statistics.

A. Carbon Offset Project Data

This study utilize publicly available carbon offset data from four main carbon offset registries — American Carbon Registry (ACR), Climate Action Reserve (CAR), Gold Standard, and Verra (VCS) — in the United States. They keep track of carbon credit projects and cover most of the projects globally. One can find detailed documents for each registered project on the registry’s official website. These four registries generate almost all of the world’s voluntary market offsets and provide valuable insights into carbon offset projects, project developers, and the issuance and retirement of various types of carbon credits.

Issuance and Retirement. I use the Voluntary Registry Offsets Database from [So, Haya, and Elias' \(2023\)](#) Berkeley Carbon Trading Project. [So, Haya, and Elias \(2023\)](#) collect and organize the cross-sectional project information, such as project ID, credit issuance, credit retirement, reported emission reduction, location, project start date, and etc. The dataset contains all carbon offset projects listed globally by four major voluntary offset project registries. As mentioned previously, Figure 1 provides the amount of carbon credit issuance and retirement over the year.

Project Area. The official public registry website provides detailed information for each project, most of the times including a KML file detailing the border of the project. I scrape the project description file for each REDD+ project in the registry. I collect all registered REDD+ projects that are started between 2005 and 2018. As I provide more details about the forest data later, I choose 2005 and 2018 so that my annual forest coverage data can have at least four years of both pre- and post-treatment periods.³ I drop the projects that are too small or didn't provide project area data. In total, I collect 68 projects from all over the world. Panel B of Figure 1 shows the countries that the projects are implemented. The darker the color, the more projects are implemented in this country. Brazil has the most REDD+ projects implemented (22 of them). The left panels of Figure 2 are satellite images that show the border of a project in Cambodia, called REDD in Keo Seima wildlife sanctuary. Figure IA.3 provides details for another project in Congo, called North Pikounda REDD+.

Panel A of Tabel 1 provides the summary statistics on the project level. We can see that 75% of the projects started between 2010 and 2014. The average area is 207,486 hectares. The average estimated annual emission reduction is 893,909 tonnes of CO_2e .

Corporate Buyers. In the public registry data, approximately 50% of the retirement transactions also provides an one-sentence summary of the retirement details in the notes section. Using textual analysis, I extract the corporate buyers of corresponding carbon offset transaction. Figure IA.1 shows 20 companies that heavily involves in purchasing the carbon credits. The circles are sized by the amount of carbon credits retired by corresponding company. Some of the big corporate buyers are Shell, Delta, Disney, and Volkswagen.

³There are only 5 projects started either before 2005 or after 2018.

B. Forest Loss Data

I utilize Global Forest Change data provided in the study by [Hansen, Potapov, Moore, Hancher, Turubanova, Tyukavina, Thau, Stehman, Goetz, Loveland, Kommareddy, Egorov, Chini, Justice, and Townshend \(2013\)](#), which examines global forest changes using time-series Landsat images. The data covers the entire globe and has a resolution of squares approximately 30 meters wide at the equator. In my research, I focus on the tree canopy cover for the year 2000 dataset and the year of gross forest cover loss event dataset.

Tree canopy cover for year 2000 dataset. This dataset captures tree cover in 2000, detailing canopy closure for all vegetation taller than 5 meters. This dataset is represented as a percentage for each grid cell, indicating the proportion of canopy cover.

Year of gross forest cover loss event dataset. This dataset provides information on forest loss from the year 2000 to 2022. Specifically, it captures instances when forest areas underwent significant changes, transitioning from a forested to a non-forested state. The data is encoded in a manner where a value either signifies no loss, or it represents the particular year between 2001 and 2022 when the loss predominantly occurred.

Using two datasets above, I am able to observe the forest coverage for year 2000 and pinpoint the year of forest loss for roughly every 30x30 meters of the earth's surface. Subsequently, I construct a panel dataset for areas measuring 600x600 meters. I refer to each of these 600x600 meter squares as a land unit. Panel B of Table 1 offers summary statistics at the land unit level. Land units in the control (treatment) group have average forest coverage of 68.99% (80.27%) in the year prior to the project implementation.

IV. Empirical Methodology and Results

In this section, I first outline the development of research questions and related hypotheses. Next, I present the step-by-step empirical design and clarify the validity of the construction of each test.

A. Hypothesis Development

The effectiveness of carbon offset projects stands as a pivotal inquiry in the arena of environmental economics and corporate responsibility. On one hand, rising concerns about global warming have driven many companies to adopt environmentally responsible practices. One popular strategy involves purchasing carbon credits generated by carbon credit projects, under the belief that these efforts genuinely reduce carbon emissions. In acquiring these offsets, companies not only demonstrate their commitment to the environment but also aim to enhance their *green* reputation. This widespread corporate behavior indicates a general consensus regarding the positive impact of carbon offsets. However, skepticism exists. Several media outlets have raised concerns, suggesting that there exists carbon offsets that lack additionality, are subject to double-counting, or are non-existent.⁴ These critiques further highlight the potential for firms that may overlook due diligence, leading them to invest in questionable carbon offsets.

Despite the contention, limited research has systematically investigated the carbon offset market to provide a rigorous measure of the effectiveness of the credits. To bridge this gap, this paper constructs an comprehensive dataset encompassing all publicly registered REDD+ projects. With granular annual forest coverage data, I examine the real-world effects of these carbon offset projects. Since REDD+ projects' primary objective is forest preservation, it is crucial to determine if forests within these project areas truly remain protected. Considering the voiced concerns about the carbon offset market, the null hypothesis is:

H.0 *Carbon offset projects have no effect on the deforestation rates within their areas.*

On the other hand, given the significant corporate investment in carbon offsets, the alternative hypothesis suggests:

H.1 *Carbon offset projects lead to a significant reduction in deforestation rates within their areas.*

⁴Relevant Bloomberg articles can be found [here](#) and [here](#).

B. Empirical Design

To investigate the effect of carbon offset projects on deforestation rates within their designated areas, I employ a difference-in-differences (DID) methodology. I demarcate both control and treatment regions in proximity to the project boundaries. Specifically, the control region covers land located 2000 meters outside the project boundary, while the treatment region spans land 2000 meters within the boundary. Panel A of Figure 2 provides a visual representation of these control and treatment zones for a sample project. Within these delineated areas, I segment the land into units, each measuring 600x600 meters. Notably, each of these units comprises 20 squares of 30x30 meters from the [Hansen et al. \(2013\)](#) dataset. This is further depicted in Panel B of Figure 2. The basic regression I estimate is as follows:

$$ForestCoverage_{ipt} = \beta (Treat_{ip} \times Post_{tp}) + Distance_{ip} + \alpha_{ip} + \delta_{tp} + \epsilon_{ipt}, \quad (1)$$

where the dependent variable $ForestCoverage_{ipt}$ is the percentage of forest in land unit i in project p in year t . The main explanatory variable $Treat_{ip} \times Post_{tp}$ takes the value of 1 for the four years following a land unit i that is preserved by a project p , and a value of 0 in the four years prior to a project implementation. I implement the regression discontinuity approach, by adding $Distance_{ip}$ as a control variable. It measures the closest distance between land unit i and the area of project p in terms of meters.

This identification strategy allows me to employ a difference-in-differences methodology that exploits the staggered implementation of REDD+ projects over time. The first difference is the change in forest coverage before and after the start of a REDD+ project. The implicit control group at time t consists of land units located in areas without a REDD+ project. The change in forest coverage within this control group is the second difference captured in my tests. The effect of REDD+ projects on land-unit-level forest coverage is estimated as the difference in those two differences. The regression discontinuity approach provides evidence that the test is not simply capturing any effect driven by the characteristics of the land, which is far away from the project area, which coincides with but is unrelated to the implementation of REDD+ projects.

V. Results

In this section, I present the main empirical findings of the paper. I first show baseline results and then present the heterogeneous effects.

A. Baseline Results

I start the analysis by examining project performance around the boundary to explore the potential effects of REDD+ project implementation. Figure 3 displays the change in forest coverage four years after project implementation as a function of distance from the project boundary using a binscatter plot. Each dot represents the average forest coverage change within equally sized distance bins, where negative distances indicate the treated area (red circles) and positive distances represent the control area (blue triangles). The vertical dashed line at zero marks the project boundary. The y-axis indicates the percentage change in forest coverage post-implementation. The fitted curves, estimated using the underlying unbinned data, represent second-order polynomial trends. The figure reveals a clear discontinuity at the project boundary, with notably less forest loss inside the project boundary compared to outside. This seems to suggest an initial positive association between project implementation and forest preservation.

However, a rigorous evaluation of project effectiveness requires considering pre-project trends in forest coverage. Figure 4 addresses this issue. Panel A of Figure 4 plots average forest coverage over time separately for treated and control areas. The lightly shaded lines represent the raw data, showing that both treated and control areas were experiencing forest loss even before project implementation. Importantly, the control area was losing forest at a slightly faster rate than the treated area. Given these differing pre-trends, it is insufficient to interpret the lower forest loss observed within project boundaries in Figure 3 as clear evidence of project effectiveness.

To formally address this issue, I follow recent literature and implement a detrending procedure (Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018; Freyaldenhoven, Hansen, and Shapiro, 2019; Gruber, Jensen, and Kleven, 2021). Specifically, using data from the pre-project period, I estimate separate linear time trends in forest coverage for the treated and control groups. I then remove these

estimated trends from both the pre- and post-project period data for each group. Detrending in this context is reasonable because the treated and control regions might naturally exhibit different long-run forest-loss trends due to varying climate conditions. After this adjustment, as illustrated by the darker dashed lines in Panel A, the pre-trends for treated and control areas become parallel, supporting the parallel trend assumption necessary for a valid difference-in-differences analysis. With parallel pre-trends established, it is now appropriate to directly compare how the treated area performs relative to the control group after project implementation.

To formally evaluate the project's effectiveness, Panel B of Figure 4 presents a dynamic difference-in-differences (DiD) analysis. Specifically, the figure plots the estimated coefficients of interaction terms between treatment status and event-time indicators, capturing the differential forest coverage change in treated relative to control areas over time. The regressions include project-year fixed effects to control for any time-varying shocks at the project level and land-unit fixed effects to account for time-invariant characteristics at the local geographic level. Standard errors are clustered at the project level. Overall, the dynamic DiD estimates reveal no statistically significant positive effects on forest preservation. Notably, the estimated coefficients are precisely estimated around zero, indicating that treated areas are losing forest coverage at a similar rate as control areas. Table 2 presents the static regression results and confirms the same results. The absence of a kink or clear change in slope for the treated group's line in Panel A at the time of project implementation further supports the finding of no measurable impact on reducing deforestation.

B. Heterogeneous Effects across Projects

Although collectively the REDD+ projects show no significant effect on preventing deforestation, it is valuable to examine individual projects to determine whether some are effective or if ineffectiveness is widespread. Thus, I conduct a separate DiD analysis for each individual project. Figure 5 presents these estimated DiD coefficients, ordered from the most positive to the most negative. Each point represents the DiD coefficient of a single project, with error bars displaying 95% confidence intervals. A positive coefficient indicates that the treated area experienced less forest loss relative to its control

group, while a negative coefficient suggests greater forest loss relative to controls. The vertical dashed line at zero distinguishes projects with positive effects from those with negative effects.

The figure reveals that the majority of projects cluster around zero, showing no statistically significant difference in deforestation rates between treated and control areas. This indicates that most treated areas, purportedly protected by project developers, were losing forest at similar rates to their controls, suggesting these areas were not genuinely at high risk of deforestation. Only a small number of projects demonstrate significant effectiveness in reducing forest loss, while several exhibit substantially worse outcomes, losing forest coverage at higher rates than their control counterparts. Furthermore, the green bars in the figure represent the claimed annual emission reductions associated with each project. Notably, many of the ineffective projects claimed substantial volumes of emission reductions, implying that these credits were inaccurately or unjustifiably issued according to the DiD results.

VI. What Drives Project Success?

Given the heterogeneity across REDD+ projects—with some projects effective and others ineffective—it is valuable to understand which regional characteristics are associated with successful outcomes. Such an analysis has important policy implications and can inform future carbon project design aimed at effectively reducing emissions. Since most REDD+ projects are concentrated in a limited set of countries, particularly in South America, I leverage subnational data obtained from [Gennaioli, La Porta, Lopez-de Silanes, and Shleifer \(2013\)](#) to capture region-specific variation. The authors compile an extensive cross-country dataset at the second-level administrative regions, encompassing numerous geographic, economic, social, and cultural characteristics for over 1,500 subnational units globally. Knowing precise project locations allows me to match each project to its corresponding subnational region and utilize detailed regional attributes. Figure [IA.4](#) visually demonstrates these subnational administrative regions across countries hosting REDD+ projects, illustrating the granularity of the data.

Figure [6](#) explores several regional factors and their correlation with project outcomes, estimated

through a dynamic DiD specification. Specifically, I introduce a triple interaction term combining the treatment indicator, event-time indicators, and an indicator for whether the region is in the top 30% for the respective characteristic ("High"). This allows me to differentiate the project impacts in regions with high versus low values of each characteristic. All regressions include event-time fixed effects and project fixed effects to account for common time shocks and time-invariant project characteristics, and standard errors are clustered at the project level.

Results indicate that access to finance, education, trust, and ethnic diversity significantly correlate with project effectiveness. Regions with high access to finance exhibit more positive outcomes, likely because financial resources enable consistent implementation of forest protection measures. Conversely, in regions with limited access to finance, implementers might face greater difficulty obtaining external funding when cash-constrained, forcing them to prematurely abandon or compromise conservation commitments. Education also emerges as important, with higher education levels correlating with better project performance, possibly reflecting greater local awareness and responsiveness to conservation goals. Trust levels within the population similarly associate positively with successful project outcomes, likely because trust fosters greater local cooperation and adherence to agreed-upon forest management practices. Lastly, projects in regions with a low number of ethnic groups tend to perform worse, indicating that diversity can help facilitate collective action and engagement, which improves the likelihood of project success. In contrast, access to land and local GDP appear to have little impact on project outcomes according to Figure 6. Figure IA.5 further examines additional factors such as government predictability, which also seem to play a limited role in determining project effectiveness.

VII. Conclusion

The rigorous examination of the carbon offset market is of great importance, particularly given the rising concerns, skepticism, and limited existing research on its actual environmental impact. This study posed a fundamental question: do carbon offset projects significantly slow down deforestation within their designated areas? To address this, I employ a difference-in-differences (DiD) framework, defining treated regions as land within 2,000 meters of project boundaries and control regions as land

2,000 meters outside. The analysis leverages high-resolution forest loss data, applies detrending to account for pre-existing differences in deforestation trends, and incorporates project-year and land-unit fixed effects, with standard errors clustered at the project level to ensure robust inference.

The results show that, on average, REDD+ projects have no measurable effect on reducing deforestation. Treated areas lose forests at rates similar to their control counterparts, and most projects fail to achieve statistically significant impacts. A small subset of projects shows modest success, while some perform worse than comparable areas. Importantly, many of the ineffective projects are associated with substantial claimed emission reductions, highlighting potential misrepresentation and raising questions about the credibility of voluntary carbon markets.

Finally, I examine regional characteristics that correlate with project success. Projects located in regions with better access to finance, higher education levels, stronger local trust, and greater ethnic diversity are more likely to succeed, while factors such as access to land, local GDP, and government predictability appear to matter less. These findings underscore the need for careful project design and rigorous oversight in voluntary carbon markets. Strengthening the credibility of these markets will require both stricter validation of claimed credits and attention to local conditions that enhance the likelihood of meaningful forest preservation.

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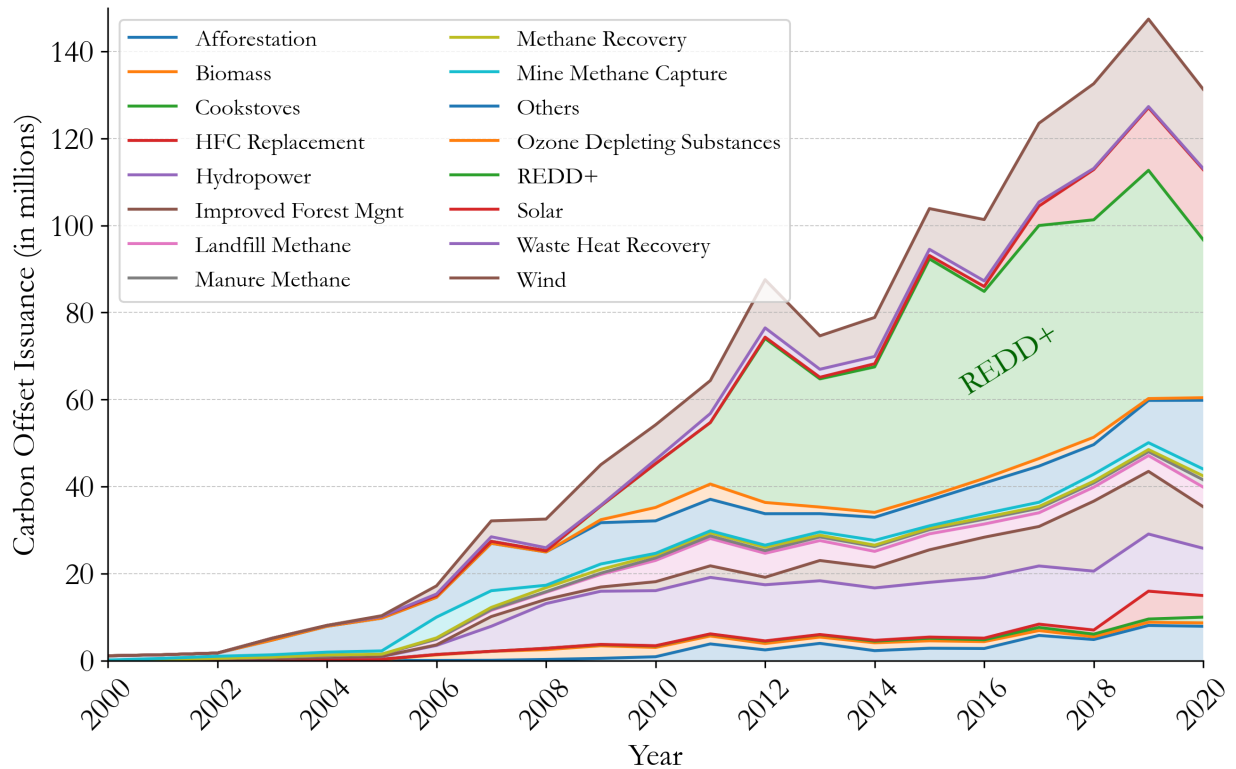
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Figure 1: Carbon Offset Issuance and REDD+ Project Overview

This figure presents an overview of carbon offset issuance by type and the geographical distribution of REDD+ projects globally. Panel A illustrates the annual volume of carbon offsets issued across various project categories from 2000 to 2020. The y-axis quantifies carbon offset issuance in millions. The stacked areas, each distinguished by color, represent different carbon offset types, with REDD+ highlighted. Panel B displays the worldwide distribution and concentration of REDD+ projects between 2005 and 2018. The map uses varying shades of green to indicate the number of REDD+ projects implemented in each country, with a darker shade signifying a higher project count. In total, 68 REDD+ projects are represented in this panel. Project information for this panel is sourced from the carbon offset public registry.

Panel A: Annual Carbon Offset Issuance by Project Type



Panel B: Geographic Distribution of REDD+ Projects

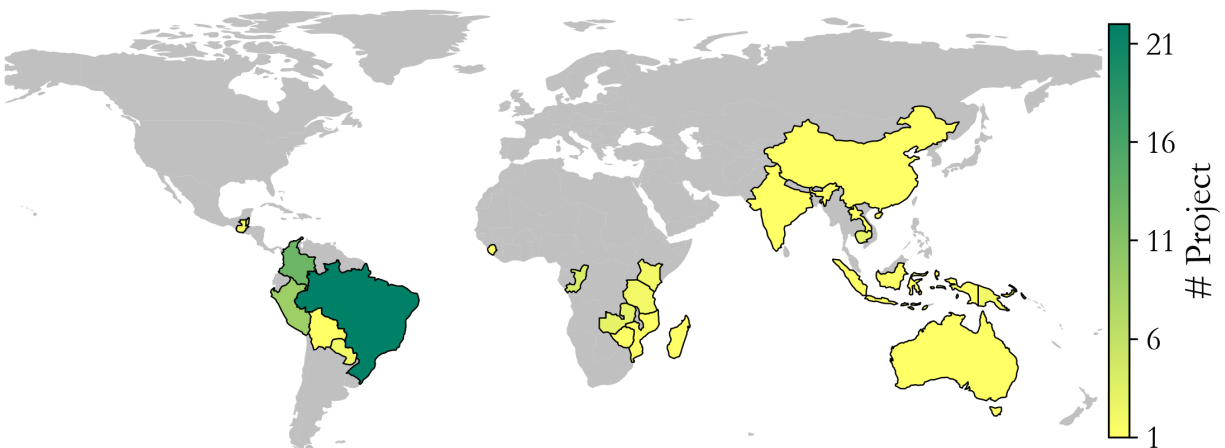
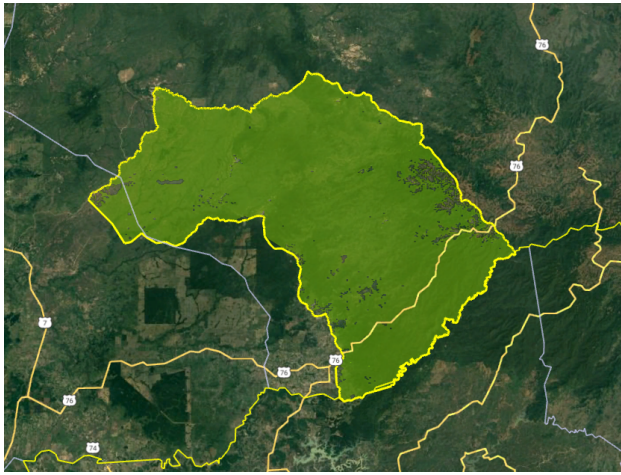


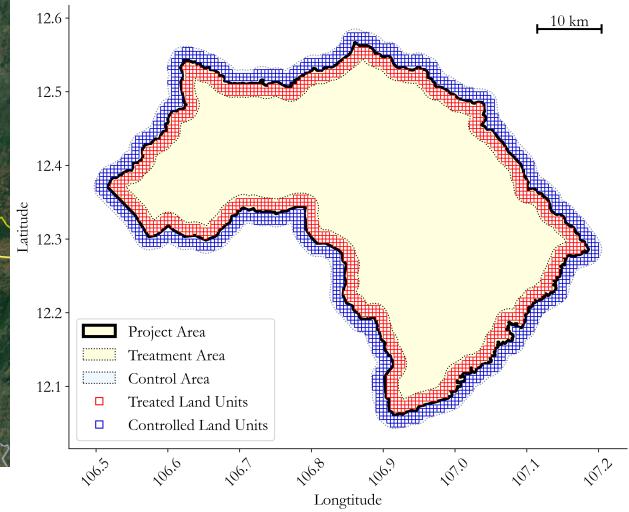
Figure 2: Empirical Design of the DiD method

This figure illustrates the empirical design of the difference-in-differences (DiD) method using two projects. The top panels show the REDD Project in the Keo Seima Wildlife Sanctuary in Cambodia, and the bottom panels show the North Pikounda REDD+ Project in Congo. The left panels display satellite images of the project areas, and the right panels depict the delineation of treated and control areas. The treatment area, outlined in red, is defined as land within 2,000 meters of the project boundary, and the control area, outlined in blue, is land beyond 2,000 meters outside the project boundary. Each grid cell on the maps represents a land unit measuring 600×600 meters, located either in the treated or control area.

Panel A: Keo Seima Project Area



Panel B: Keo Seima Treated & Control



Panel C: North Pikounda Project Area



Panel D: North Pikounda Treated & Control

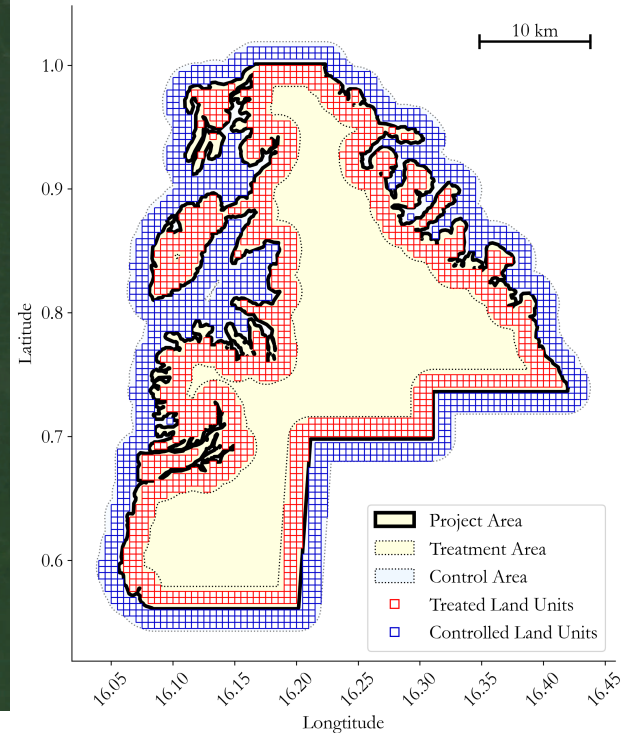


Figure 3: Post-Project Change in Forest Coverage

This figure is a binscatter plot illustrating the change in forest coverage four years after project implementation, relative to the distance from the project boundary. The x-axis represents the distance from the project boundary in meters, with negative values indicating the Treated Area (red circles) and positive values indicating the Control Area (blue triangles). The dashed vertical line at zero marks the project boundary. The y-axis shows the post-project change in forest coverage. The lines are second-order polynomials fitted using the underlying data points for both the Treated and Control areas.

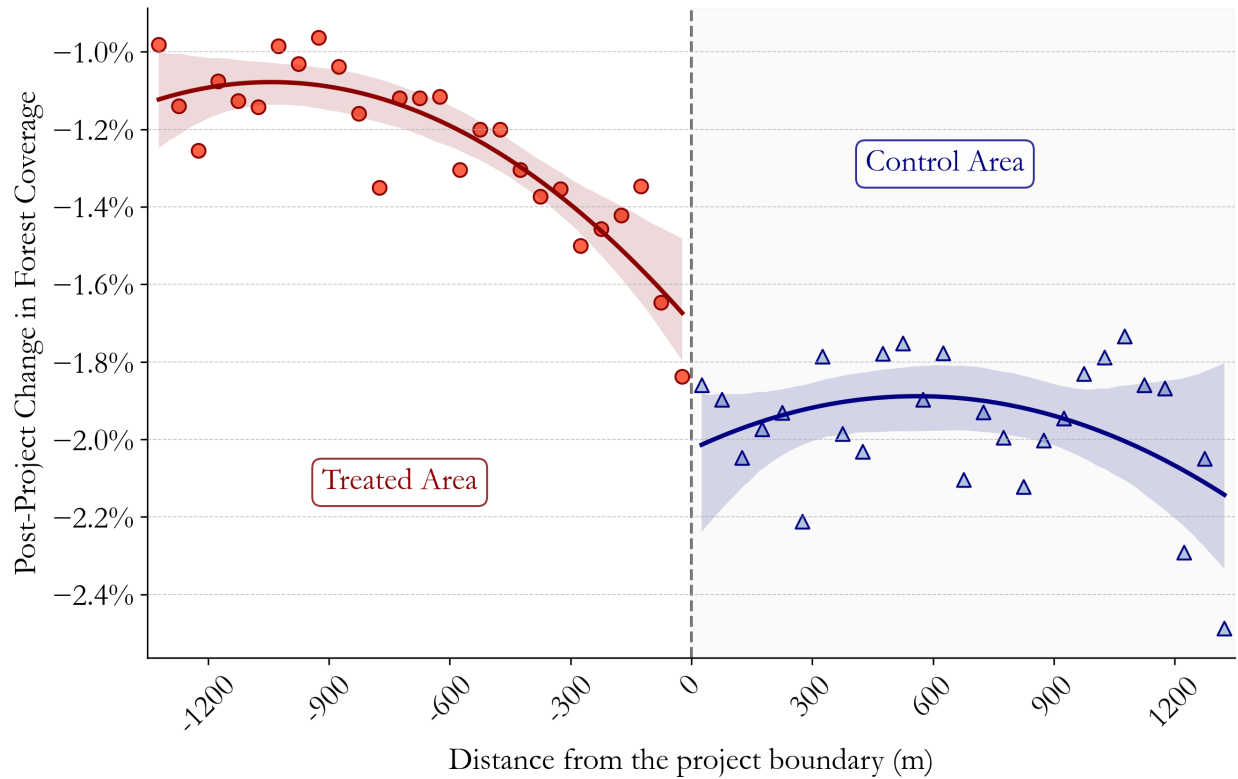
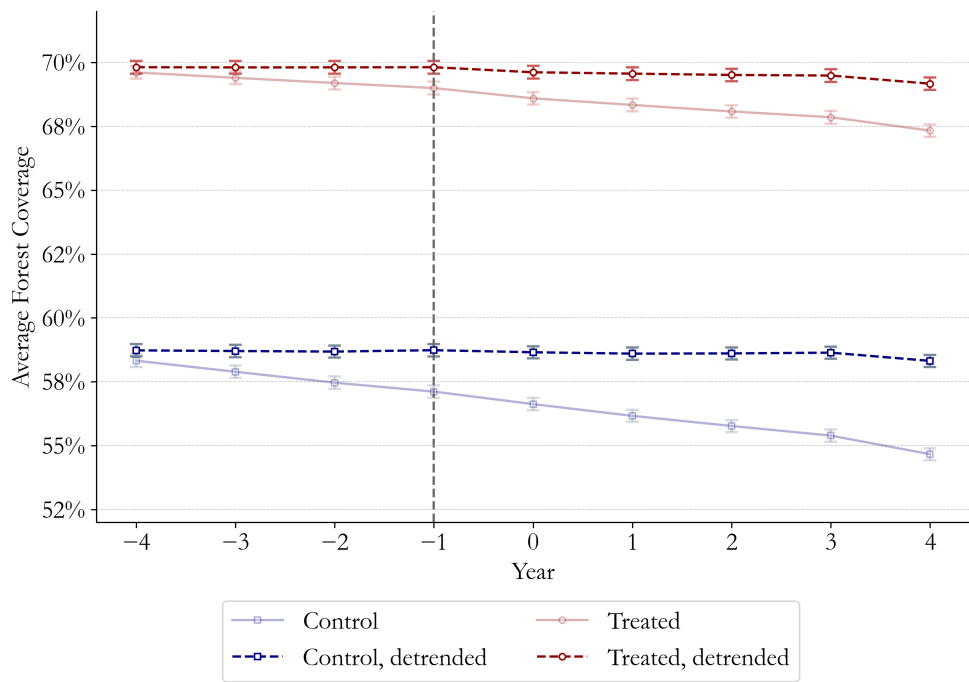


Figure 4: Effects of REDD+ Projects on Forest Coverage

This figure illustrates the effects of REDD+ projects on forest coverage, comparing treated and control areas within a Difference-in-Differences (DiD) framework. Treated areas are defined as land within 2000 meters of the project boundary, while control areas consist of land 2000 meters outside the project boundary. The unit of observation is a 600x600 meter square land unit. Panel A displays the average forest coverage over time for both treated (red dashed line) and control (blue dashed line) groups, along with their detrended counterparts, all accompanied by confidence intervals. Detrending is performed by estimating a linear time trend using pre-period data and removing this trend from the observed outcomes. Panel B presents the dynamic Difference-in-Differences estimates, which capture the differential change in forest coverage between the treated and control areas before and after project implementation. The analysis utilizes the full sample of all REDD+ Projects. All regressions include event-time fixed effects and project fixed effects, and standard errors are clustered at the project level.

Panel A: Average and Detrended Forest Coverage



Panel B: Dynamic DID Estimates

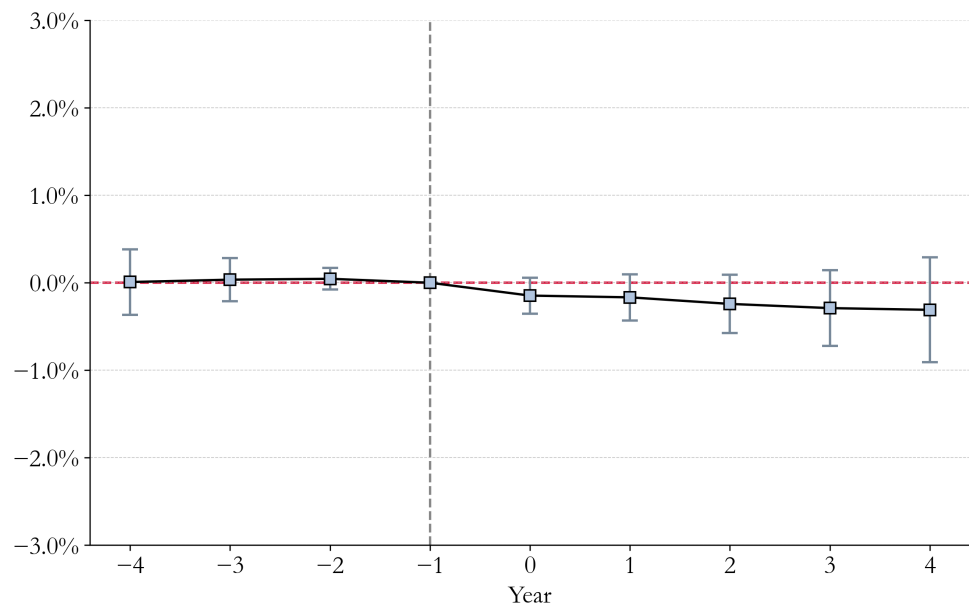


Figure 5: Heterogeneous Effects and Emission Reductions Across Projects

This figure shows the estimated Difference-in-Differences (DiD) regression coefficients for individual REDD+ projects, alongside their claimed annual emission reductions. The x-axis represents individual projects, ranked by their regression coefficient. The left y-axis indicates the Regression Coefficient, with the red dashed line at 0% marking no effect. The vertical dashed line at zero highlights where the coefficient is zero, with projects to the left having a positive coefficient and projects to the right having a negative coefficient. The coefficients are displayed as points with error bars, representing confidence intervals. The right y-axis indicates claimed annual emission reductions and is represented by green bars for each project.

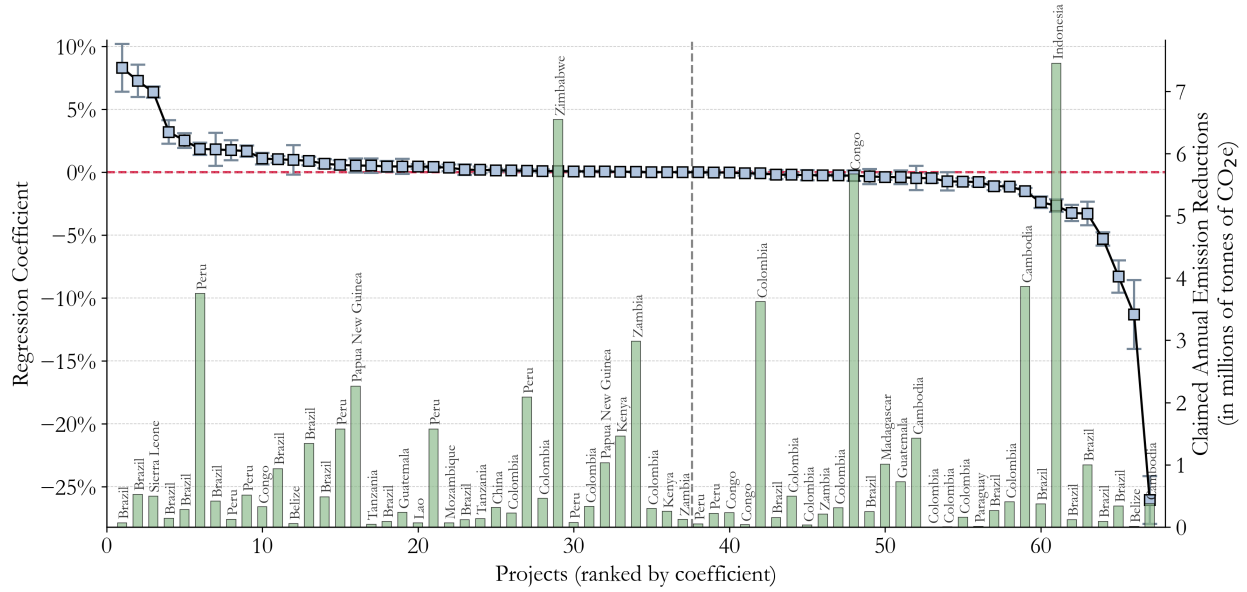


Figure 6: Subnational Characteristics and Project Outcomes

This figure examines how subnational characteristics are associated with project outcomes over time. The characteristics, measured at the second-level administrative divisions (e.g., states or provinces), are obtained from [Gennaioli et al. \(2013\)](#). Each panel reports the results of a dynamic Difference-in-Differences (DiD) specification, interacted with an indicator for whether the region is in the top 30% for the respective characteristic. All regressions include event-time fixed effects and project fixed effects, and standard errors are clustered at the project level. Confidence intervals at the 95% level are shown for all estimates.

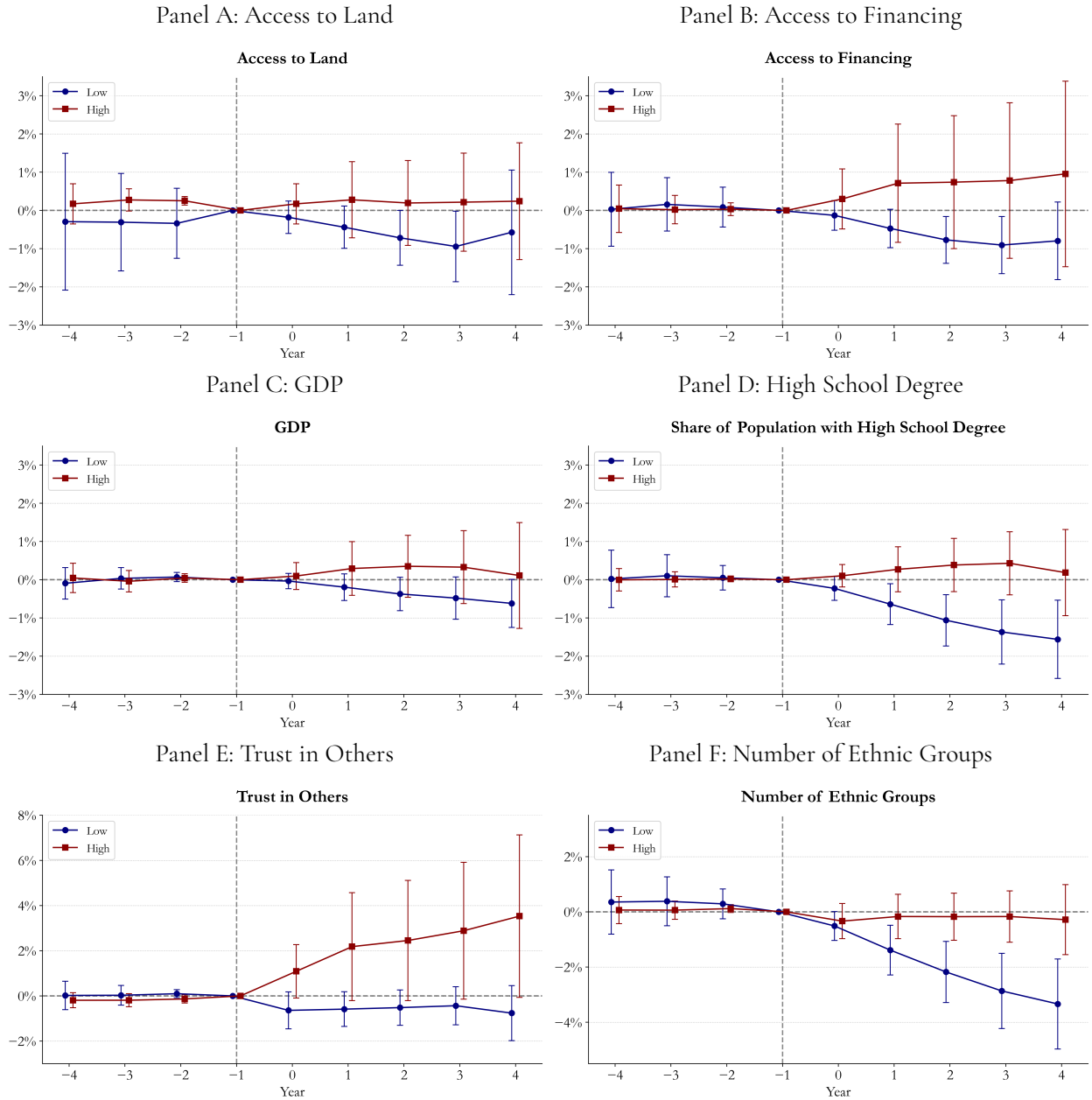


Table 1: Summary Statistics

This table presents summary statistics for various metrics. Panel A provides statistics at the project level, whereas Panel B details metrics at the land unit level. In Panel A, the project's area is quantified in hectares. The forest coverage is calculated as a percentage (ranging from 0 to 1) and represents the coverage in the year preceding the project's implementation ($t - 1$). Emission reductions refer to the estimated annual emission reductions reported by the project, denominated in tonnes of CO_2e . In Panel B, each land unit is a square which has the width of 0.005 degrees (approximately 600 meters). Distance is measured in meters. It represents the closest distance between the land unit and the project area. All forest coverage measures are calculated as a percentage (ranging from 0 to 1).

	Count	Mean	Std	Min	Quartiles			Max
					1st	2nd	3rd	
Panel A: Project Basics								
Start Year	68	2012	3	2005	2010	2012	2014	2018
Area	68	207486	309476	3392	44211	99435	193175	1376474
Emission Reductions	68	893909	1524274	96	118862	304783	952861	7451846
Panel B: Land Units								
<i>Units in the control group</i>								
Distance	113084	644.86	384.91	0.00	310.41	635.07	971.21	1579.30
Coverage2000	113084	61.09	38.55	0.00	19.70	79.04	98.31	100.00
Coverage	113084	57.11	38.86	0.00	16.75	64.16	97.69	100.00
<i>Units in the treatment group</i>								
Distance	103091	617.64	386.31	0.00	278.12	592.90	939.69	1663.27
Coverage2000	103091	70.67	36.09	0.00	28.78	94.74	98.73	100.00
Coverage	103091	68.99	36.55	0.00	26.86	92.60	98.44	100.00

Table 2: Effects of REDD+ projects on Deforestation Reductions

This table examines the effect of REDD+ projects on the reductions of deforestation rates. I estimate the OLS regression of the form:

$$ForestCoverage_{ipt} = \beta (Treat_{ip} \times Post_{tp}) + \alpha_{ip} + \delta_{tp} + \epsilon_{ipt},$$

where the dependent variable $ForestCoverage_{ipt}$ is the percentage of forest in land unit i in project p in year t . The main explanatory variable $Treat_{ip} \times Post_{tp}$ takes the value of 1 for the four years (or eight years) following a land unit i is preserved by a project p , and a value of 0 in the four years prior to a project implementation. $Distance_{ip}$ is a control variable and measures the closest distance between land unit i and the area of project p in terms of meters. Fixed effects are indicated at the bottom of each column. Standard errors are double clustered by year and project and reported in parentheses.

Dep. Variable:	Detrended $ForestCoverage$		$\Delta ForestCoverage$	
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.0019 (0.0023)	-0.0025 (0.0022)	0.0005 (0.0007)	0.0006 (0.0007)
Land Unit FE		✓		✓
Project-Year FE		✓		✓
Observations	1,945,575	1,945,575	1,945,575	1,945,575
R^2	0.0206	0.9903	0.0013	0.2245
Dep. Var. Mean.	0.6387	0.6387	0.0037	0.0037

Standard errors clustered by carbon projects

*** p<0.01, ** p<0.05, * p<0.1

For Online Publication

Internet Appendix for:
“Are Carbon Offset Projects an Effective Vehicle for Carbon Emission Reduction?”

ZIRUI WANG

Figure IA.1: Twenty Corporate Buyers of Carbon Credits

This figure illustrates 20 companies with significant involvement in purchasing carbon credits. Each circle represents a company, and the size of the circle corresponds to the volume of carbon credits the company has purchased and retired. The sample includes all transactions through May 2023 recorded in four primary registries: the American Carbon Registry (ACR), Climate Action Reserve (CAR), Gold Standard, and Verra (VCS). Note that these 20 companies are not necessarily the top 20 corporate buyers.

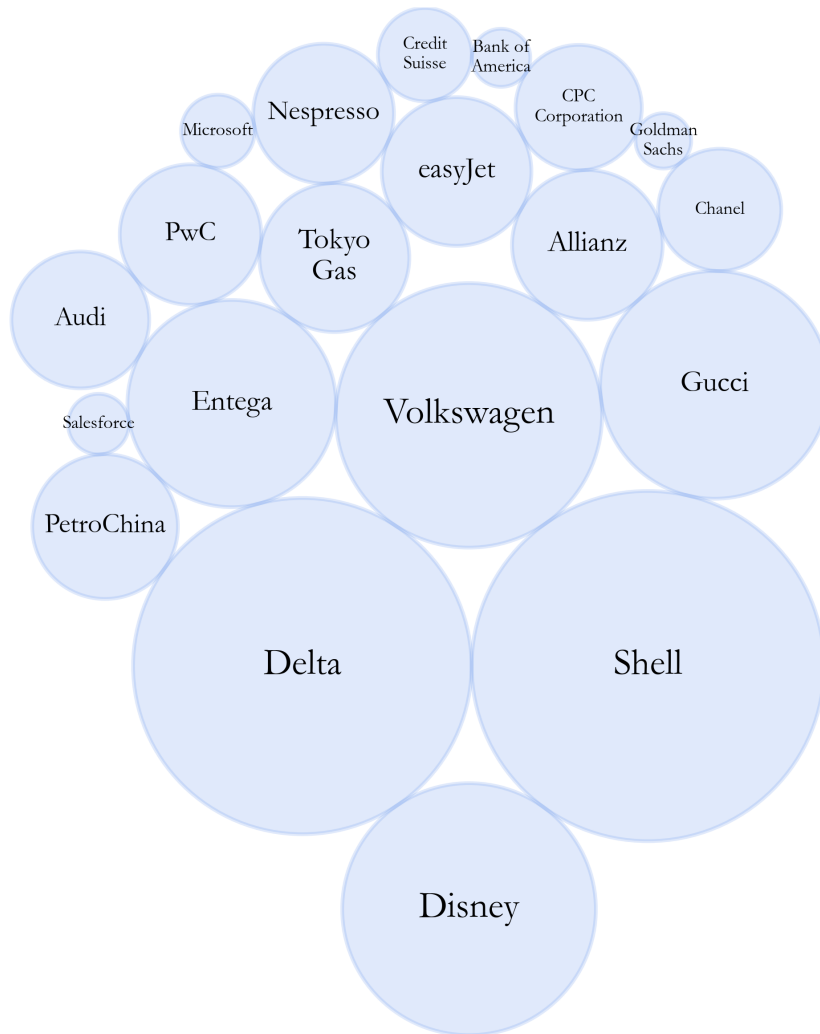
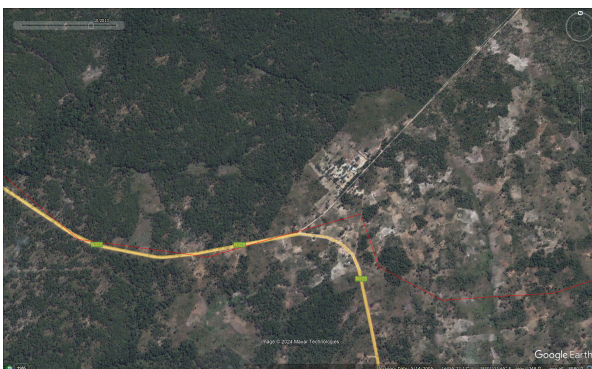


Figure IA.2: Satellite Images of Two Projects

This figure presents satellite images of two carbon credit projects registered in the Verra (VCS) registry. The top panels show the Mozambique project (project ID: vcs1674b) with project boundaries marked in red, and the bottom panels show the Cambodia project (project ID: vcs1689) with project boundaries marked in black. The left panels show the project areas before project implementation, and the right panels show the same areas five years after project implementation.

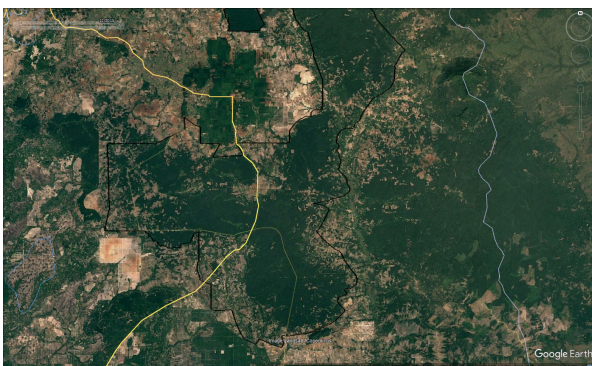
Panel A: Mozambique Project in Oct 2013



Panel B: Mozambique Project in Sep 2018



Panel C: Cambodia Project in Dec 2015



Panel D: Cambodia Project in Dec 2020

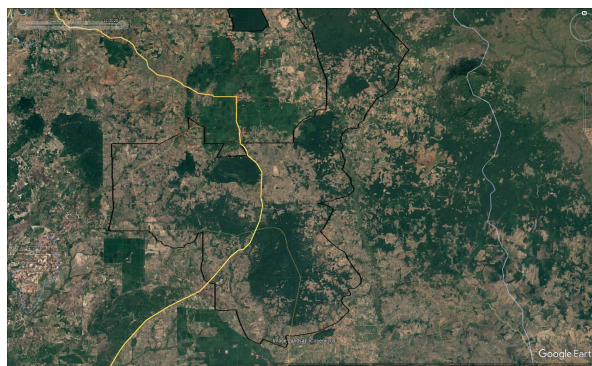
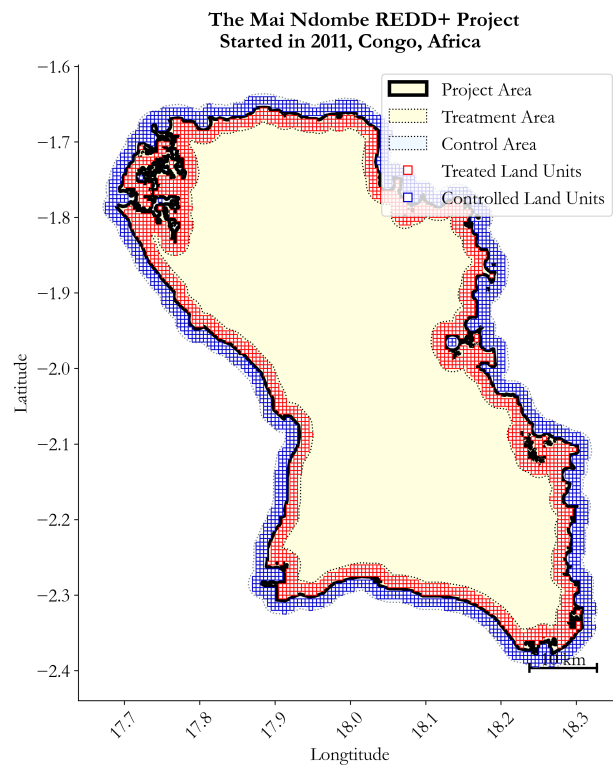


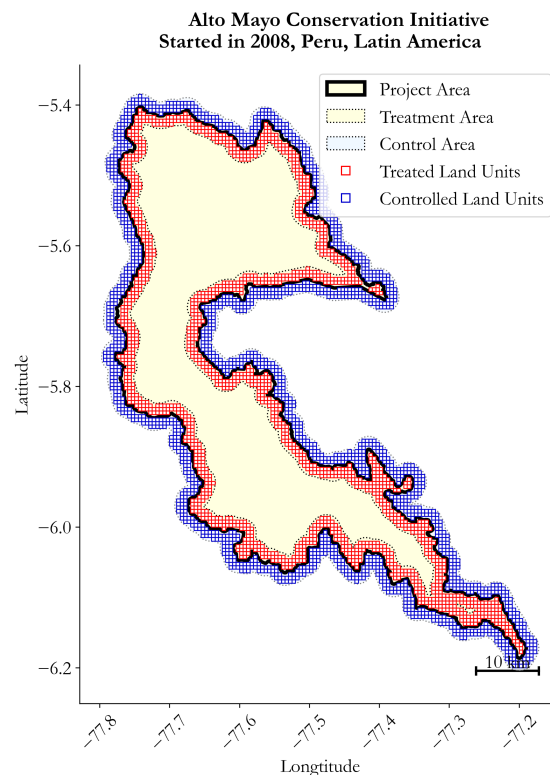
Figure IA.3: Additional REDD+ Project Areas and Treatment-Control Design

This figure shows the geographic delineation of treated and control areas for four additional REDD+ projects used in the difference-in-differences (DiD) analysis. Treated areas, marked in red, include land units within 2,000 meters of the project boundary, while control areas, outlined in blue, include units located beyond 2,000 meters outside the boundary. Each grid cell represents a 600×600 meter land unit assigned to either the treated or control group. Project locations, start years, and country information are indicated in each panel title.

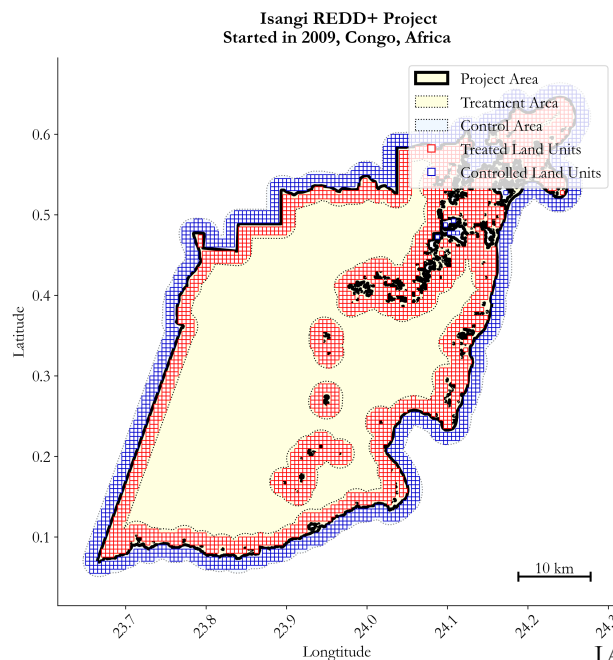
Panel A: Mai Ndombe REDD+ Project in Congo



Panel B: Alto Mayo Conservation Initiative in Peru



Panel C: Isangi REDD+ Project in Congo



Panel D: Mutatá REDD+ Project in Colombia

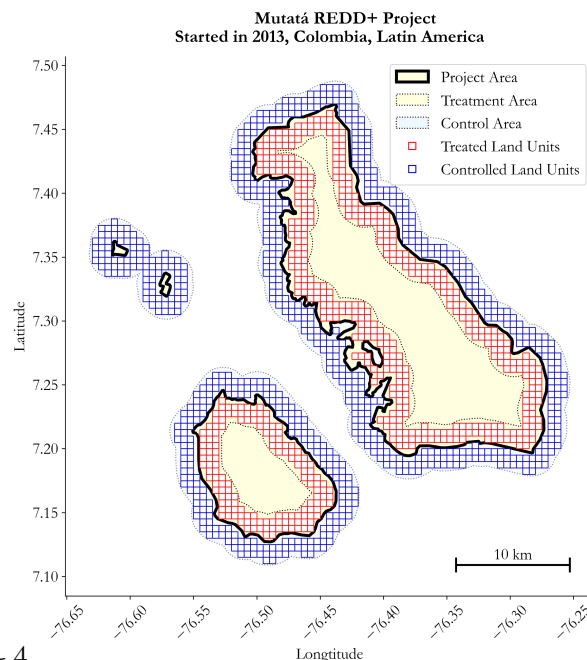
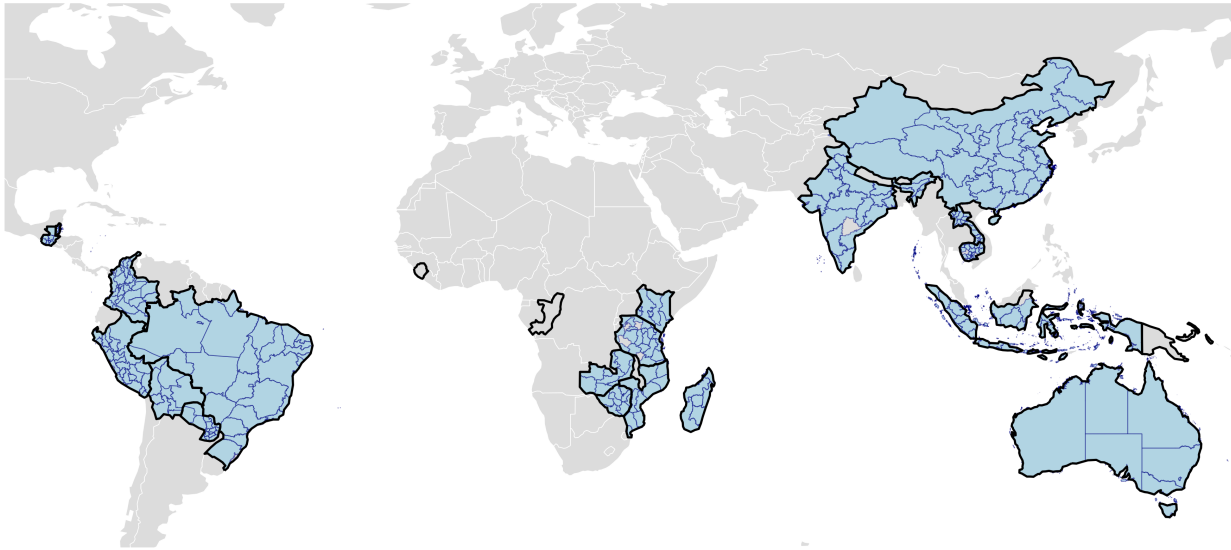


Figure IA.4: Subnational Maps of Project Locations

This figure illustrates the delineation of subnational regions used in the analysis. Panel A maps the subnational regions across countries that host REDD+ projects, while Panel B zooms in on Brazil, showing its subnational regions and marking the project areas with red circles.

Panel A: Subnational Regions Across Countries with REDD+ Projects



Panel B: Subnational Regions and Project Areas in Brazil



Figure IA.5: Additional Subnational Characteristics and Project Outcomes

This figure examines additional two subnational characteristics in relation to project outcomes over time using a dynamic Difference-in-Differences (DiD) design. Subnational characteristics are drawn from the cross-country database in [Gennaioli et al. \(2013\)](#) and are measured at second-level administrative regions (e.g., states or provinces). In each panel, the event-time coefficients are interacted with an indicator for regions in the top 30% of the respective characteristic, with 95% confidence intervals shown. All regressions include event-time fixed effects and project fixed effects, and standard errors are clustered at the project level.

