The UN-REDD Programme for conserving tropical rainforests in Papua New Guinea

Abstract

Global climate action identifies conserving forests a policy priority because deforestation contributes largely to global emissions. Papua New Guinea (PNG), the custodian of world's third largest tropical rainforest, is experiencing rapid deforestation. Global environment policies are vital in reducing deforestation, but their effectiveness depends largely on stakeholder participation. This paper investigates the effectiveness of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD), a forest-based climate change mitigation approach, in PNG. We use a difference-in-differences with multiple treatment periods of Callaway and Sant'Anna (2021) on a balanced panel of 22 provinces over the period 2001-2021. We found that, on average, stakeholder engagement in UN-REDD has no significant impact on reducing deforestation or associated emissions in PNG. However, compared to 2010, provinces with stakeholder engagement in 2014 show a strong reduction in both deforestation and associated emissions. Understanding these heterogeneous impacts allow for more nuanced policy evaluation and design.

Keywords: UN-REDD; Dynamic Treatment Effects; Variation in Treatment Timing; Deforestation; Emissions; Stakeholder Engagement

JEL classification: O13, O19, O50, Q23, Q50

1. Introduction

Unprecedented increase in greenhouse gas emissions calls for immediate and deep emission reductions across all sectors of the economy for effective global climate action (IPCC, 2022). Deforestation is the second major cause for climate change and tropical deforestation alone accounts for eleven percent of global GHG emissions. Conservation of forests is considered a natural climate solution for climate change[1] as it helps to increase carbon storage or absorb greenhouse gas emissions (Bronson, et al., 2017). Better managed forests absorb 7 billion metric tonnes of emissions annually (Alliance, 2022). Therefore, conservation of tropical forests is considered a major policy strategy in combating climate change in developing countries (Skutsch & Turnhout, 2020; Dawson, et al., 2018; Amelung, 1993). In addition, the importance of forests in maintaining ecological sustainability become prominent as the recent COVID-19 outbreak is presumed to be a resultant of deforestation (Platto, Zhou, Wang, & Wang, 2021; Carrington, 2020). Furthermore, since the governments were not successful in supporting its citizens during the pandemic, forest exploitation as a source of subsistence livelihoods has increased in developing countries (Rahman, Alam, & Salekin, 2021; Golar, et al., 2020). Conservation of forests is therefore, significant in climate change mitigation.

Pacific islands are extremely vulnerable to climate change (Salem, 2020). The largest pacific island, Papua New Guinea (PNG) is ranked amongst world's 20 most vulnerable countries to climate change and owns the world's largest intact tropical rainforest. PNG's forests are of truly global significance and makes country a custodian of an international public good. However, PNG shows high rate of deforestation mainly due to increased industrial logging, conversion of forests for agriculture and mining. As a result, loss of biodiversity, habitat degradation and modified climate are threatening the ecosystem sustainability of the country. Climate change impacts are already being felt in PNG and the country has reported the world's first climate refugees. In this context, PNG has pledged to end deforestation by 2030 at the Global UN Climate Summit 2021.

In reducing deforestation, the national policies alone are inadequate and coupling them with international agreements is vital. The United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) is a global initiative that focuses on reducing the impact of climate change through curtailed deforestation and forest degradation. The UN-REDD programme mobilizes funds from developed countries to establish mechanisms to mitigate climate change in developing countries. The success of the UN-REDD programme largely depends on the engagement of indigenous peoples, local communities and other relevant stakeholders (Mahanty & McDermott, 2013). Awareness on operative mechanism and benefits of carbon payments of the UN-REDD programme ensures meaningful participation. The stakeholders however, willingly participate in forest conservation only when they are aware about the projects or programmes implemented by the government (Soe & Yeo-Chang, 2019). With increased stakeholder participation, forests are better conserved even amidst higher rates of deforestation (Agarwal, Sairorkham, Sakitram, & Lambin, 2022; Minang, et al., 2014). The UN-REDD in PNG however, has been criticized for emphasising more on carbon accounting and valuation rather than the community engagement (Melick, 2010).

[1] Natural climate solutions are defined as conservation, restoration, and improved land management actions that increase carbon storage and/or avoid greenhouse gas emissions across global forests, wetlands, grasslands, and agricultural lands (Bronson, et al., 2017). For instance, conservation of tropical rainforests and climate-smart agriculture are some of the common natural climate solutions. Natural climate solutions reduce emissions by 37 percent (Alliance, 2022).

This study investigates the effectiveness of the UN-REDD programme in PNG in the presence of wider stakeholder engagement. The main aim of this study is to examine whether the UN-REDD programme has been able to reduce deforestation and associated emissions in PNG. The findings are useful to implement sensible climate change mitigation policies for PNG. The effectiveness of the UN-REDD programme in PNG is evaluated by employing the difference-in-differences (DID) with multiple time periods approach proposed by Callaway & Sant'Anna (2021). Majority of the existing impact evaluation studies on the UN-REDD have employed qualitative approaches or show limited use of quantitative policy techniques (Bayrak & Marafa, 2016; Agung, Galudra, Van Noordwijk, & Maryani, 2014). The use of DID technique of Callaway & Sant'Anna (2021) in evaluating the UN-REDD programme is therefore, significant and has several advantages over the previous literature. First, it allows quantification of the impact of UN-REDD over multiple time periods, which is not possible in the standard DID setting. Second, it allows for the variation in treatment timing and could be employed for settings when the "parallel trends assumption" holds potentially only after conditioning on observed covariates. Third, the accuracy and comparability of spatial data on deforestation is vital, as new information is often revealed by the choice of good data (Zabala, 2018). The lack of good quality data is a common issue in forest literature. In this study, the satellite data is used to advance the quality of the research findings which improves the existing knowledge on tropical forest dynamics. To the best of my knowledge, this is the first study that employs contemporary programme evaluation econometric technique to investigate the effect of a global environment policy in PNG.

Results suggest, on average, stakeholder engagement in UN-REDD shows no significant impact on reducing deforestation or associated emissions in PNG. However, compared to 2010, provinces with stakeholder participation in 2014 show a significant reduction in both deforestation and associated emissions. In particular, reduction approximates to 40% for both deforestation and emissions over the post-policy period. Strong follow-up consultations that facilitate strong interchange of information among provincial stakeholders is a key reason for this success (WCS, 2018). Hence, it is evident that continuous stakeholder engagement is significant for the effectiveness of the UN-REDD programme. Understanding these heterogeneous impacts allow for more nuanced policy evaluation and design.

Overall, the research findings of this study are in line with the PES literature, which states that the effectiveness of PES depends on transaction costs and these upfront costs are often higher for developing countries (Alston & Andersson, 2011). The transaction costs includes negotiation, monitoring (verification) and enforcement costs between forest users, governments, and donors (Corbera, 2012). The existing institutional structures of developing countries make limited PES performance inescapable. In such cases, PES is ineffective as a conservation strategy. The results indicate that the later the PNG is exposed to the policy; the policy effect is stronger. This supports the belief that over the years, the UN-REDD incentives might have overridden transaction costs to deliver a positive policy effect (Libecap, 2014). Clearly, understanding and minimising the transaction costs in policy implementation is critical for the success of the UN-REDD.

In addition, success of the PES depends on various factors including pre-programme compliance, opportunity cost of participation and property rights. The inclusion of risk-integrated payments, robust monitoring and enforcement programmes ensures environmental effectiveness (Scullion, Thomas, Vogt, Perez-Maqueo, & Logsdon, 2011). Moreover, PES is different from traditional policy instruments that are abide by legal regulations, sanction mechanisms or taxes (Börner, et al., 2017). Careful design of UN-REDD policy could thus

deliver the expected outcomes effectively. However, PES schemes are implemented in a policy-mix, thus, interaction with pre-existing policies is inevitable. Future research on disentangling the true impact of the UN-REDD programme from other policies is paramount in order to assess its real effectiveness.

The remainder of the study is organised as follows. Section 2 introduces the status of tropical deforestation and describes the UN-REDD programme. Section 3 describes the data and the variables, and Section 4 details the empirical strategy. Section 5 discusses the empirical findings and some robustness checks present in Section 6. Section 7 concludes the paper.

2. Tropical Deforestation and the UN-REDD Programme

Tropical deforestation

Greenhouse gas emissions have increased to levels unprecedented in the past few decades (IPCC, 2022). Anthropogenic greenhouse gas emissions are the leading cause of the earth's rapidly changing climate. The burning of fossil fuels is the primary source of human-induced emissions. The second major source is deforestation, contributing to 20 percent of global emissions. Of which, tropical deforestation and forest degradation alone accounts for 11 percent of these emissions, which is a larger contribution than the entire global transport sector. Forests are the most cost effective and immediate solution to climate change. Reducing emissions from tropical forests, therefore substantially helps reducing the impacts of climate change.

In 2010, the world's tree cover of 3,900 million hectares (million ha) has declined by 25.3 million ha and released 10.1 gigatonnes of carbon dioxide to the atmosphere in 2021 (Table 2.1). Between 2001 and 2021, the rate of deforestation (or tree cover loss) in developing countries ranked highest, at 11.2 million ha per annum, twice as large as developed countries. In developing countries, the Latin America and the Caribbean region has the highest annual rate of deforestation (5.2 million ha) followed by the Asia-Pacific region (3.4 million ha).

Table 2.1: Deforestation and emissions trends, 2001-2021

Region	Deforestation (million ha)		CO_2 emissions (gigatonnes)		Annual average deforestation (2001-2021)	
	2001	2021	2001	2021	million ha	Share (%)
World	**13.3**	**25.3**	**4.7**	**10.1**	**20.78**	**100**
Developed countries	4.2	6.5	1.1	2.3	5.9	28
Economies in transition	1.9	6.7	0.3	1.0	3.7	18
Developing countries	7.2	12.1	3.2	6.8	11.2	54
Latin America & Caribbean	4.2	5.2	1.7	3.0	5.2	46
Africa	1.4	3.7	0.6	2.0	2.6	23
Asia-Pacific	1.7	3.2	0.9	1.7	3.4	30
Papua New Guinea	0.04	0.1	0.03	0.1	0.1	3

Source: Global Forest Watch (GFW, 2022)

PNG's natural forest extends over 93 percent of the country's land area in 2010. Most forests are under customary ownership and vital as a source of subsistence livelihoods. Deforestation is increasing owing to logging, agriculture (commercial and small-scale) and mining. On average, PNG's tree cover loss during 2001-2021 is 0.1 million ha per year while Manus and

Western provinces lost more than 50 percent of its tree cover. The island provinces experience the highest tree cover loss between 2014 to 2018.

UN-REDD Programme in Papua New Guinea

Launched in 2008, the UN-REDD programme is the first global joint UN initiative on climate change and deploys the support of three agencies: The Food and Agriculture Organization of the United Nations (FAO), the United Nations Development Programme (UNDP) and the United Nations Environment Programme (UNEP). The overall development goal of the UN-REDD programme is to enhance carbon stocks in tropical forests while contributing to national sustainable development. The UN-REDD, therefore, aims to determine national deforestation reference levels, develop monitoring systems and promote the adoption of national strategies for programme implementation (Davis, Daviet, Nakhooda, & Thuault, 2009). In addition, it encourages the establishment of good governance, which is a pre-requisite for the sustainable use of forest resources. This includes clarity on tenure on forest lands, enforcement of forest laws and empowerment of forest-dependent communities to participate in forest management. For their efforts in implementing REDD+, participating countries receive results-based payments complemented by technical assistance, capacity building and policy advice. Over the period 2009-2018, 62 developing countries adopted this policy. Of those, more than 30 countries have advanced their national REDD+ strategies or action plans, 40 countries were supported in developing national forest monitoring systems, and 15 countries developed country approaches to meet the social and environmental safeguards requirements of the United Nations Framework Convention on Climate Change (UNFCCC) (UN-REDD, 2022).

The unsustainable exploitation of natural resources is inevitable in the context of using ecosystem services for human well-being. The introduction of payment schemes for ecosystem services curbs the loss of tropical forests (Pistorius, 2012) and success at the local and national level encourages the scaling up of these ecosystem payment schemes to the international level. The UN-REDD programme, negotiated under the UNFCCC, is such an international financial mechanism. The mandate of this convention frames the loss of forests as a climate mitigation issue. Thus, the implementation of an international compensation mechanism for developing countries that succeed in reducing their forest sector emissions slows down climate change. Despite the belief that UN-REDD is a promising option for addressing the depletion of forests, the modalities for participation and compensation payments remain unclear. The programme goes beyond a simple compensation mechanism and entails technical and political complexities with the main concerns over the establishment of developing countries' emission targets and accounting responsibilities. Consequently, the opportunity for the UN-REDD to become the future climate agreement under the convention is at stake. As such, the positive incentives of UN-REDD will encourage voluntary participation only if they do not impair countries' development ability.

PNG is a leading proponent of the UN-REDD programme. However, poor governance conditions in the country have frustrated efforts to create an enabling environment for the UN-REDD progress (Babon, 2011). Majority of the PNG's land (97 percent) is held under customary ownership by kinship groups, not by the state. Without the involvement of customary landholders, beginning at the community level with sustainable land use planning, effective, efficient and equitable REDD+ is unlikely and the permanence of emission reductions is tenuous. PNG's logging industry has been subject to chronic allegations of illegal and unsustainable logging practices for decades (Lawson, 2014; Trends, 2006). Since inception, the government of PNG has received substantial criticism about a lack of stakeholder

and community consultation in the UN-REDD policy development. This has led to a lack of national ownership of the UN-REDD strategies, including within implementing agencies. Without major governance and institutional reforms capable of getting the machinery of government moving in the same direction, effective, efficient and equitable UN-REDD in PNG is uncertain.

The UN-REDD is the world's largest payments for environmental services (PES) scheme. Yet, the success of the UN-REDD programme has been widely debated among economists and scientists. Country-specific impact assessments on the UN-REDD pilot projects that offer PES schemes in Brazil (Simonet, Subervie, Ezzine-de Blas, Cromberg, & Duchelle, 2019) and in Uganda (Jayachandran, et al., 2017) provide strong evidence in support of the positive impact of the UN-REDD. Insecure and poorly defined community forest tenure in developing countries however, makes it difficult to obtain benefits of UN-REDD programme (Bluffstone, Robinson, & Guthiga, 2013). There is a risk that the UN-REDD becomes another contingency-based aid like structural adjustment programme rather than a cost effective carbon sequestration mechanism. Despite increased country participation, the effectiveness and the integrity of the programme is at risk (Pistorius, 2012). The complexities in forest governance and the absence of clear implementation and funding modalities have stalled the achievement of the intended targets of UN-REDD. Therefore, despite the increasing number of countries joining the UN-REDD, the ambiguity of its performance could jeopardise its fate as an effective global environmental policy (Reinecke, Pistorius, & Pregernig, 2014).

3. Data

The UN-REDD programme was launched in 2008. From 2009 to 2021, 62 developing countries adopted the programme. PNG, a founding member of the UN-REDD programme, recognizing the importance of stakeholder engagement for the success of the UN_REDD implementation, have conducted awareness programmes or have developed stakeholder engagement plans in seven pilot districts in 2010 and in 2014. These plans are province-specific and formulated considering the social and cultural constructs, norms and practices (WCS, Stakeholder engagement mapping and analysis report, 2018). The seven pilot provinces are the East Sepik, West Sepik, Manus, Milne Bay (in 2010) and East New Britain, Madang, and West New Britain (in 2014), the treated group. The remaining provinces with no stakeholder engagement programmes/plans are in the control group (Table A.1 in the Annex). The study period is from 2001–2021. The study focuses on deforestation and emissions in provinces where UN-REDD stakeholder engagement programmes conducted and/or plans developed during a time period from 2001-2021.

The data on two outcome variables – deforestation and associated emissions – were obtained from the Global Forest Watch web platform (GFW, 2022). This data set includes tree cover, tree cover loss, CO_2 emissions and biomass loss at the country-level and at first and second sub-national levels. The analyses use the data at first sub-national, the provinces. The tree cover data were produced by the University of Maryland's Global Land Analysis and Discovery (GLAD) laboratory in partnership with Google (GLAD, 2022). The above-ground biomass loss estimates are based on the collocation of above-ground live woody biomass density values for the year 2000 (Baccini, et al., 2012) and annual tree cover loss data (Hansen, et al., 2013). The carbon dioxide emissions data quantify the amount of CO_2 emissions to the atmosphere based on above-ground biomass loss. All values are presented at different percentage canopy cover levels (10%, 15%, 20%, 25%, 30%, 50% and 75%). This analysis uses a 30% canopy cover threshold following the Global Forest Watch website. Here, "tree cover" includes all vegetation

over five meters in height and may take the form of natural forests or plantations across a range of canopy densities. The study considers annual tree cover loss as a proxy for deforestation. Hence, deforestation is defined as the hundred thousand hectares of tree cover loss – removal or mortality of tree cover – at the province level by 30% canopy cover. Emissions are measured per gigatonnes of carbon dioxide release to the atmosphere as a result of above-ground biomass loss, at the province level by 30% canopy cover.

Accuracy in quantifying of global forest cover change is vital in forest ecosystem studies. Spatially and temporally detailed information on global-scale forest change does not exist and previous efforts have been either sample-based or employed coarse spatial resolution data (Hansen, et al., 2013; Hansen, Stehman, & Potapov, 2010; Hansen & DeFries, 2004). Using the Earth observation satellite data (Hansen, et al., 2013), the study improves on existing knowledge of global forest cover changes. These data are spatially explicit, quantify gross forest loss and gain, and provide annual loss information, and are derived through an internally consistent approach. In contrast, the widely used forestry data of the FAO suffer from several limitations, thus making comparability an issue: the FAO quantifies deforestation according to land use instead of land cover; forest area changes are reported only at net values, although forest definitions have changed over time. The use of this new data set offers a unique level of precision on forest losses and is therefore, a significant contribution of this study to the literature.

Data on explanatory variables were extracted from the PNG's National Population & Housing Census 2000, 2011 (NSO, 2003; NSO, 2013) and Global Data Lab Web Platform (GDL, 2022) The choice of selection variables follows existing literature on direct and underlying causes of deforestation (Barbier & Burgess, 2001; Barbier, Burgess, & Grainger, 2010; Bhattarai & Hammig, 2001; Foster & Rosenzweig, 2003). Population pressure and impact of education are thus considered as important drivers of deforestation in PNG.

Considering the role of population pressure on the tropical deforestation process, **population**, is used as an explanatory variable in the analysis. Through this approach, the impact of overall population on deforestation is controlled. It is hypothesised that an increase in population leads to an increase in deforestation in tropical forests. Growing population leads to migration to the forests by peasants seeking land to clear for subsistence farming. Larger population also increases the collection of fuel wood, which removes nutrients from forests. If nutrient loss is sufficiently intense, the result is slowed regeneration and degradation of forest cover. Increasing population is associated with deforestation but the effect is not immediate (Deacon, 1994). To control for the impact of **education**, school attendance as a percentage of population aged between 5-29 years is used.

Summary statistics, for treated and never-treated (control) groups are in Table A.2 in the Annex. Deforestation and emissions are on average higher for the treated provinces. Among the treated group, the higher rate of deforestation and emissions is in 2014 group. In addition, although the population pressure is lower in the treated group, they are highly educated compared to the 2010 group.

4. Empirical Strategy

To identify the effect of UN-REDD policy adoption (or UN-REDD stakeholder consultations), the study employs a difference-in-differences (DID) setup with multiple time periods proposed by Callaway and Sant'Anna (2021). The effect of stakeholder consultations on deforestation

and associated emissions is examined investigating the variation in timing of such stakeholder consultations across provinces. In some provinces, stakeholder engagement programmes conducted and/or plans developed – the treatment groups. In particular, groups defined as a treatment group when a province first receive a stakeholder consultation. Other provinces did not have stakeholder mapping – the untreated or control group.

Callaway and Sant'Anna (2021) DID approach allows estimation of causal parameters allowing for arbitrary treatment effect heterogeneity and dynamic effects as oppose to the standard two-way fixed effects (TWFE) regressions (Athey & Imbens, 2022; Sun & Abraham, 2021). This approach uses a disaggregated causal parameter – group-time average treatment effect, i.e. the average treatment effect for group g at time t, where a "group" is defined by the time period when units are first treated. The canonical DID setup has two periods and two groups and the parameter of interest reduce to ATT. Group-time average treatment effects allow heterogeneity in observed covariates, the period in which units are first treated, or the evolution of treatment effects over time. Hence, these are useful in learning treatment effect heterogeneity.

In the canonical DID setup with two time periods, the treatment effect parameter is the average treatment effect on the treated:
$ATT = \mathbb{E}\,[Y_{\mathbf{2}}(2) - |Y_{\mathbf{2}}(0)|G_{\mathbf{2}} = 1]$

In Callaway and Sant'Anna (2021) DID approach, a natural generalization of the ATT is used to setups with multiple treatment groups and multiple time periods. The average treatment effect for units who are members of a particular group g at a particular time period t, denoted by below specification. The main building block of Callaway and Sant'Anna (2021) is this group-time average treatment effect parameter:
$ATT_{g,t} = \mathbb{E}\,[Y_{\boldsymbol{t}}(g) - |Y_{\boldsymbol{t}}(0)|G_{\boldsymbol{g}} = 1]$

To identify $ATT(g,t)$, few assumptions used: limited treatment anticipation; conditional parallel trends based on 'never-treated' group' and overlap in multiple groups/periods (Callaway & Sant'Anna, 2021). So that, $ATT(g,t)$ is identified by restricting treatment anticipation behaviour and imposing a conditional parallel trends assumption. Though, $ATT(g,t)$ highlights treatment effect heterogeneity across different groups g, at different points in time t, and across different lengths of treatment exposure, $e = t - g$, it is required to combine these different $ATT(g,t)$'s to form more aggregated causal parameters. The aggregation schemes used by Callaway and Sant'Anna (2021) is as follows:

$$\theta = \sum_{g \in \mathrm{G}} \sum_{t=2}^{\tau} w\,(g,t).\,ATT(g,t)$$

where $w(g,t)$ are carefully-chosen (known or estimable) with specific weighting functions such that θ can be used to address a well-posed empirical/policy question. Difference choices of $w(g,t)$ allows researchers to highlight different types of treatment effect heterogeneity.

The static TWFE linear regression:
$Y_{i,t} = \alpha_t + \alpha_g + \beta D_{i,t} + \varepsilon_{i,t}$ --------(4.1)

The dynamic TWFE linear regression:

$$Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{2} \delta_k^{anticip} D_{i,t}^{e} + \sum_{e=0}^{L} \beta_e D_{i,t}^{e} + v_{i,t} \text{---------(4.2)}$$

where α_t time fixed effect, α_g is a group fixed effect, $\varepsilon_{i,t}$ and $v_{i,t}$ are error terms, $D_{i,t}^{e} = 1\{t - G_i = e\}$ is an indicator for unit i being e periods away from initial treatment at time t and K and L are positive constants. The parameter of interest in the static TWFE specification is β, which, in applications, is typically interpreted as an overall effect of participating in the treatment across groups and time periods. In the dynamic TWFE specification, practitioners usually focus on the $\beta_e, e \geq 0$, and these parameters are typically interpreted as measuring the effect of participating in the treatment at different lengths of exposure to the treatment.

Accordingly, the aggregations to highlight treatment effect heterogeneity is specified in equation 4.3 and aggregations into overall treatment effect parameters is specified in equation 4.4. below:

Aggregations to highlight treatment effect heterogeneity

Let e denote event-time, i.e., $e = t - g$ denotes the time elapsed since treatment was adopted. G denotes the time period that a unit is first treated. Thus, a way to aggregate the $ATT(g,t)$'s to highlight treatment effect heterogeneity with respect to e is

$$\theta_{es}(e) = \sum_{g \in \mathrm{G}} 1\{g + e \leq \tau\} P(G = g | G + e \leq \tau) ATT(g, g + e) \text{ ----------(4.3)}$$

This is the average effect of participating in the treatment e time periods after the treatment was adopted across all groups that are ever observed to have participated in the treatment for exactly e time periods. Here, the "on impact" average effect of participating in the treatment occurs for $e = 0$. $\theta_{es}(e)$ is the natural target for event study regressions and it completely avoids the pitfalls associated with the dynamic TWFE specification in (4.2).

Aggregations into overall treatment effect parameters

This is obtained by simply averaging all of the identified group-time average treatment effects together; i.e., to consider the parameter 4.4 below.

$$\theta_W^O = \frac{1}{K} \sum_{g \in \mathrm{G}} \sum_{t=2}^{\tau} 1\{t \geq g\} ATT(g,t) P(G = g | G \leq \tau \text{ ----------(4.4)}$$

where $K = \sum_{g \in \mathrm{G}} \sum_{t=2}^{\tau} 1\{t \geq g\} ATT(g,t) P(G = g | G \leq \tau$ (which ensures that the weights on $ATT(g,t)$ in the second term sum up to one). θ_W^O is a weighted average of each $ATT(g,t)$ putting more weight on $ATT(g,t)$'s with larger group sizes. Unlike β in the TWFE regression specification (4.1), this simple combination of $ATT(g,t)$'s immediately rules out troubling issues due to negative weights; as a particular example, when the effect of participating in the treatment is positive for all units, this aggregated parameter cannot be negative.

5. Results and Discussion

This section presents the aggregated treatment effects over different time periods for deforestation and emissions in treated provinces. Two conditions are assumed in the estimation: the parallel trends would hold unconditionally and when it holds only after controlling on observed characteristics X. In this analysis, never-treated provinces are the comparison group and has not allowed for anticipation effects (i.e. $\delta = 0$). First, the results using conditional parallel trends to estimate the effect of UN-REDD stakeholder engagement is shown. The estimates of deforestation and associated emissions are in Table 5.1. (Table A.3 and A.4 in the Annex present the group-time average treatment effects for deforestation and emissions. Figure A.1 and A.2 illustrates the same graphically).

Table 5.1: UN-REDD aggregated treatment effect estimates

TWFE	Group-Specific Effects		Event Study		Calendar Time Effects	
			(A) Deforestation			
Single Parameters						
-0.251	-0.274			-0.253		-0.240
(0.224)	(0.199)			(0.251)		(0.243)
Partially aggregated						
	g=2010	-0.172	*e*=0	-0.206 (0.183)	*t*=2010	-0.048 (0.264)
		(0.306)	*e*=1	0.087 (0.319)	*t*=2011	0.058 (0.441)
	g=2014	-0.411***	*e*=2	-0.546* (0.315)	*t*=2012	-0.569 (0.386)
		(0.156)	*e*=3	-0.384 (0.326)	*t*=2013	-0.131 (0.467)
			e=4	-0.132 (0.233)	*t*=2014	-0.159 (0.167)
			e=5	-0.032 (0.277)	*t*=2015	0.291 (0.271)
			e=6	-0.377 (0.308)	*t*=2016	-0.421 (0.315)
			e=7	-0.399 (0.309)	*t*=2017	-0.551* (0.287)
			e=8	-0.444 (0.439)	*t*=2018	-0.406 (0.334)
			e=9	-0.242 (0.242)	*t*=2019	-0.408** (0.159)
			e=10	-0.049 (0.285)	*t*=2020	-0.205 (0.191)
			e=011	-0.309 (0.382)	*t*=2021	-0.333 (0.227)
			(B) Emissions			
Single Parameters						
-0.288	-0.308			-0.288		-0.279
(0.229)	(0.201)			(0.261)		(0.249)
Partially aggregated						
	g=2010	-0.220	*e*=0	-0.253 (0.184)	*t*=2010	-0.127 (0.256)
		(0.320)	*e*=1	0.064 (0.316)	*t*=2011	0.031 (0.437)
	g=2014	-0.425***	*e*=2	-0.570* (0.331)	*t*=2012	-0.599 (0.409)
		(0.165)				
			e=3	-0.432 (0.314)	*t*=2013	-0.207 (0.449)
			e=4	-0.175 (0.229)	*t*=2014	-0.190 (0.162)
			e=5	-0.080 (0.271)	*t*=2015	0.240 (0.275)
			e=6	-0.400 (0.308)	*t*=2016	-0.457 (0.295)
			e=7	-0.453 (0.313)	*t*=2017	-0.594** (0.295)
			e=8	-0.463 (0.466)	*t*=2018	-0.430 (0.340)
			e=9	-0.248 (0.253)	*t*=2019	-0.415** (0.167)
			e=10	-0.068 (0.290)	*t*=2020	-0.209 (0.202)
			e=011	-0.384 (0.408)	*t*=2021	-0.391 (0.251)

Notes: The Table reports aggregated treatment effect parameters under the conditional parallel trends assumptions and with clustering at the province level. The estimates in Panel (A) is for Deforestation and (B) for emissions. The column "TWFE" reports the coefficient on a post-treatment dummy variable from a two-way fixed-effects regression. The column "Group-Specific Effects" summarizes average treatment effects by the timing of the stakeholder engagement: here, *g* indexes the year that a province is first treated. The column "Event Study" reports average treatment by the length of the exposure to the stakeholder engagement; here *e* is the length of exposure to the treatment. The column "Calendar Time Effects" reports average treatment effects by year; here, *t* is "year".

The results for group-time average treatment effects are in Figure A.1 and A.2 along with a uniform 95% confidence band. All inference procedures use clustered bootstrapped standard errors at the province level, and account for the autocorrelation of the data. The figure contains pre-treatment estimates that can be used to “pre-test" the parallel trends assumption as well as treatment effect estimates in post-treatment periods.

The group-time average treatment effect estimates provide support for the view that UN-REDD stakeholder engagement has led to a reduction in deforestation or associated emissions. For the 2014 group, there is a clear statistically significant negative effect in group-time average treatment effect on deforestation or associated emissions. The 2010 group is marginally insignificant (and negative). The group-time average treatment effects show 41.1% decline in deforestation and 42.5% decline in emissions. The average effect of UN-REDD stakeholder engagement across all groups is 27.4% decline in deforestation and 20.1% decline in emissions. A two-way fixed effects model with a post treatment dummy variable also provides similar results, indicating 25.1% decline in deforestation and 28.8% decline in emissions to UN-REDD stakeholder engagement. In light of the literature on UN-REDD programme, these results are encouraging, being a founding member of the UN-REDD programme, PNG receives heavy criticism locally and globally on integrity and quality of programme conduct (Babon, 2011).

There is dynamic effect of UN-REDD stakeholder engagement. During 2010-2013, with only four provinces in the treated group (East Sepik, West Sepik, Manus, Milne Bay), deforestation decline is not significant (and negative) and vary from 4.8% in 2010 to 13.1% in 2013. Similarly, the decline in emissions in 2010 and 2013 is 9.1%. The summary parameters aggregated by group and calendar time are consistent with the main purpose of the UN-REDD programme, conserve tropical rainforests as a natural climate solution (Bronson, et al., 2017) .

Overall, the study provides evidence that UN-REDD stakeholder engagement is significant for the provinces that receives the treatment later. As the results support treatment heterogeneity, Callaway and Sant’Ánna’s (2021) DID setting is preferred over the canonical DID setting.

6. Policy Implications and Concluding Remarks

Climate change imposes significant economic and social costs and has the potential to reverse the development gains made in developing economies. Empirical evidence, suggests that investments in climate adaptation enhance economic well-being (Dell et al., 2008, Stern, 2008, Tol, 2009). As resource-constrained economies often seek external financial assistance to overcome their development challenges, this study examines the effectiveness of one such global climate change programme in Papua New Guinea (PNG).

This study investigates the effectiveness of stakeholder consultations of the United Nations programme on reducing emissions from deforestation and forest degradation (UN-REDD) on deforestation and emissions in PNG. The UN-REDD aims to enhance carbon stocks in tropical forests through the provision of results-based payments for member countries’ efforts to avoid deforestation. It has been observed that stakeholder engagement in UN-REDD is a vital attribute in forest conservation.

The study uses a difference-in-differences with multiple treatment periods of Callaway and Sant’Anna (2021) on a balanced panel of 22 provinces over the period 2001-2021. On average, stakeholder engagement in UN-REDD shows no significant impact on reducing deforestation or associated emissions in PNG. However, compared to 2010, provinces with stakeholder

participation in 2014 show a significant reduction in both deforestation and associated emissions. In particular, reduction approximates to 40% for both deforestation and emissions over the post-policy period. Strong follow-up consultations that facilitate strong interchange of information among provincial stakeholders is a key reason for this success (WCS, 2018). Hence, it is evident that continuous stakeholder engagement is significant for the effectiveness of the UN-REDD programme. Understanding these heterogeneous impacts allow for more nuanced policy evaluation and design.

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Annex

Table A.1: Provinces in control and treated groups

Control	Treated	
	Adoption Year*	Province
Bougainville	2010	East Sepik
Central	2010	Manus
Chimbu	2010	Milne Bay
Eastern Highlands	2010	Sandaun (West Sepik)
Enga	2014	East New Britain
Gulf	2014	Madang
Hela	2014	West New Britain
Jiwaka		
Morobe		
National Capital District		
New Ireland		
Oro (Northern)		
Southern Highlands		
Western Highlands		
Western		

Notes: Control group is the provinces (15) with no stakeholder engagement programmes/plans and treated group (7) contains any of those. The adoption year indicates the year in which the stakeholder engagement programmes/plans were held/developed in each province.

Table A.2: Summary statistics

Variable	Description (Source)	Treated Provinces	Untreated Provinces	Diff.	P-val on Diff.
Deforestation	Tree cover loss at national level by 30% canopy cover, in hundred thousand hectares per year (GFW)	5.930	2.463	3.467	0.00
Emissions	Tree cover loss at national level by 30% canopy cover, in hundred thousand hectares per year (GFW)	4.462	1.752	2.710	0.00
Population	Population, in total million (NPHC, GDL)	0.280	0.321	-0.041	0.01
Education	Attending school, percentage of population aged 5-29 years (NPHC, GDL)	33.212	31.730	1.482	0.03

Sources: GFW = Global Forest Watch; GDL = Global Data Lab and NPHC = National Population & Housing Census 2000, 2011

Table A.3: UN-REDD aggregated treatment effect estimates, deforestation

TWFE	Group-Specific Effects		Event Study		Calendar Time Effects	
(A) Unconditional parallel trends						
Single Parameters						
-0.194	-0.274			-0.195		-0.171
(0.195)	(0.199)			(0.226)		(0.199)
Partially Aggregated						
	g=2010	0.085	*e*=0	-0.186 (0.178)	*t*=2010	-0.021 (0.231)
		(0.263)	*e*=1	0.247 (0.208)	*t*=2011	0.330 (0.294)
	g=2014	0.410***	*e*=2	-0.479 (0.276)	*t*=2012	-0.438 (0.428)
		(0.107)	*e*=3	-0.280 (0.282)	*t*=2013	-0.014 (0.414)
			e=4	-0.144 (0.219)	*t*=2014	-0.102 (0.165)
			e=5	-0.009 (0.259)	*t*=2015	0.314 (0.255)
			e=6	-0.301 (0.216)	*t*=2016	-0.366 (0.260)
			e=7	-0.379 (0.288)	*t*=2017	-0.509* (0.285)
			e=8	-0.359 (0.427)	*t*=2018	-0.421 (0.330)
			e=9	-0.202 (0.211)	*t*=2019	-0.381* (0.169)
			e=10	0.005 (0.219)	*t*=2020	-0.162 (0.168)
			e=011	-0.248 (0.305)	*t*=2021	-0.284 (0.208)
(B) Conditional parallel trends						
Single Parameters						
-0.251	-0.274			-0.253		-0.240
(0.224)	(0.199)			(0.251)		(0.243)
Partially Aggregated						
	g=2010	-0.172	*e*=0	-0.206 (0.183)	*t*=2010	-0.048 (0.264)
		(0.306)	*e*=1	0.087 (0.319)	*t*=2011	0.058 (0.441)
	g=2014	-0.411***	*e*=2	-0.546* (0.315)	*t*=2012	-0.569 (0.386)
		(0.156)	*e*=3	-0.384 (0.326)	*t*=2013	-0.131 (0.467)
			e=4	-0.132 (0.233)	*t*=2014	-0.159 (0.167)
			e=5	-0.032 (0.277)	*t*=2015	0.291 (0.271)
			e=6	-0.377 (0.308)	*t*=2016	-0.421 (0.315)
			e=7	-0.399 (0.309)	*t*=2017	-0.551* (0.287)
			e=8	-0.444 (0.439)	*t*=2018	-0.406 (0.334)
			e=9	-0.242 (0.242)	*t*=2019	-0.408** (0.159)
			e=10	-0.049 (0.285)	*t*=2020	-0.205 (0.191)
			e=011	-0.309 (0.382)	*t*=2021	-0.333 (0.227)

Notes: The Table reports aggregated treatment effect parameters under the conditional parallel trends assumptions and with clustering at the province level. The estimates in Panel (A) is for unconditional trends and (B) for conditional trends. The column "TWFE" reports the coefficient on a post-treatment dummy variable from a two-way fixed-effects regression. The column "Group-Specific Effects" summarizes average treatment effects by the timing of the stakeholder engagement: here, *g* indexes the year that a province is first treated. The column "Event Study" reports average treatment by the length of the exposure to the stakeholder engagement; here *e* is the length of exposure to the treatment. The column "Calendar Time Effects" reports average treatment effects by year; here, *t* is "year".

Table A.4: UN-REDD aggregated treatment effect estimates, emissions

TWFE	Group-Specific Effects		Event Study		Calendar Time Effects	
(A) Unconditional parallel trends						
Single Parameters						
-0.231	-0.259		-0.230		-0.211	
(0.199)	(0.169)		(0.229)		(0.208)	
Partially Aggregated						
	g=2010	-0.133	*e*=0	-0.230 (0.168)	*t*=2010	-0.091 (0.223)
		(0.275)	*e*=1	0.214 (0.209)	*t*=2011	0.291 (0.292)
	g=2014	-0.427***	*e*=2	-0.504 (0.321)	*t*=2012	-0.476 (0.445)
		(0.113)	*e*=3	-0.329 (0.285)	*t*=2013	-0.091 (0.402)
			e=4	-0.189 (0.223)	*t*=2014	-0.137 (0.165)
			e=5	-0.062 (0.259)	*t*=2015	0.259 (0.252)
			e=6	-0.338 (0.254)	*t*=2016	-0.405 (0.255)
			e=7	-0.428 (0.307)	*t*=2017	-0.547** (0.275)
			e=8	-0.386 (0.489)	*t*=2018	-0.450 (0.341)
			e=9	-0.198 (0.242)	*t*=2019	-0.387** (0.177)
			e=10	0.000 (0.235)	*t*=2020	-0.165 (0.181)
			e=011	-0.315 (0.339)	*t*=2021	-0.338 (0.209)
(B) Conditional parallel trends						
Single Parameters						
-0.288	-0.308		-0.288		-0.279	
(0.229)	(0.201)		(0.261)		(0.249)	
Partially Aggregated						
	g=2010	-0.220	*e*=0	-0.253 (0.184)	*t*=2010	-0.127 (0.256)
		(0.320)	*e*=1	0.064 (0.316)	*t*=2011	0.031 (0.437)
	g=2014	-0.425***	*e*=2	-0.570* (0.331)	*t*=2012	-0.599 (0.409)
		(0.165)	*e*=3	-0.432 (0.314)	*t*=2013	-0.207 (0.449)
			e=4	-0.175 (0.229)	*t*=2014	-0.190 (0.162)
			e=5	-0.080 (0.271)	*t*=2015	0.240 (0.275)
			e=6	-0.400 (0.308)	*t*=2016	-0.457 (0.295)
			e=7	-0.453 (0.313)	*t*=2017	-0.594** (0.295)
			e=8	-0.463 (0.466)	*t*=2018	-0.430 (0.340)
			e=9	-0.248 (0.253)	*t*=2019	-0.415** (0.167)
			e=10	-0.068 (0.290)	*t*=2020	-0.209 (0.202)
			e=011	-0.384 (0.408)	*t*=2021	-0.391 (0.251)

Notes: The Table reports aggregated treatment effect parameters under the conditional parallel trends assumptions and with clustering at the province level. The estimates in Panel (A) is for unconditional trends and (B) for conditional trends. The column "TWFE" reports the coefficient on a post-treatment dummy variable from a two-way fixed-effects regression. The column "Group-Specific Effects" summarizes average treatment effects by the timing of the stakeholder engagement: here, *g* indexes the year that a province is first treated. The column "Event Study" reports average treatment by the length of the exposure to the stakeholder engagement; here *e* is the length of exposure to the treatment. The column "Calendar Time Effects" reports average treatment effects by year; here, *t* is "year".

Figure A.1: UN-REDD group-time average treatment effects, deforestation

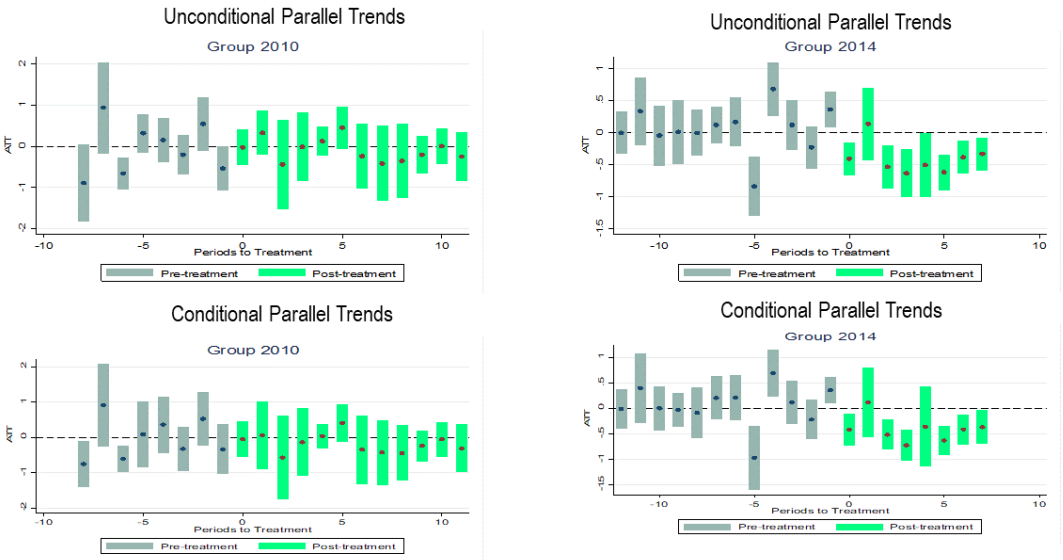

Figure A.2: UN-REDD group-time average treatment effects, emissions

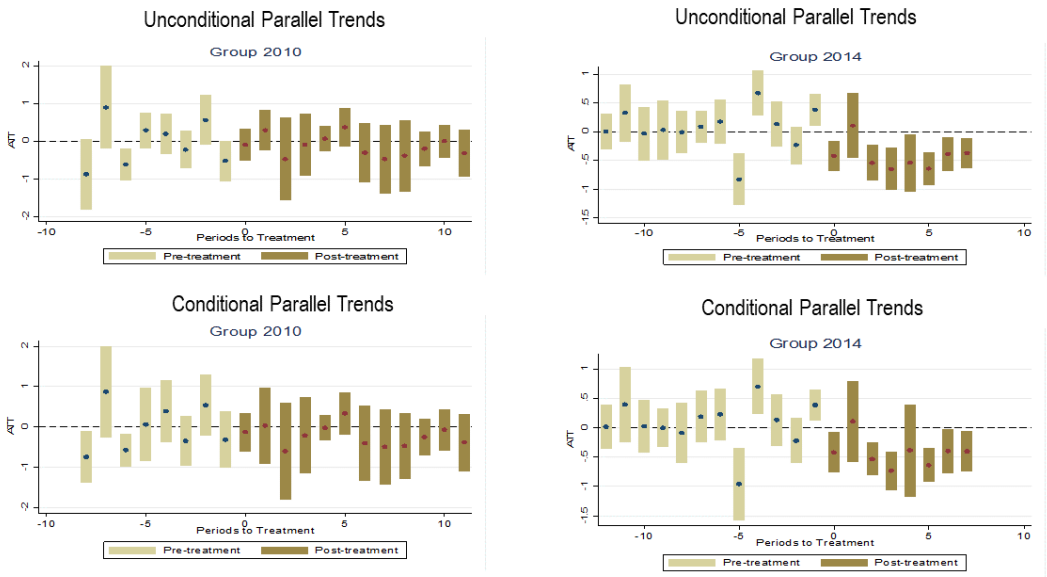

Figure A.3: UN-REDD event study, deforestation

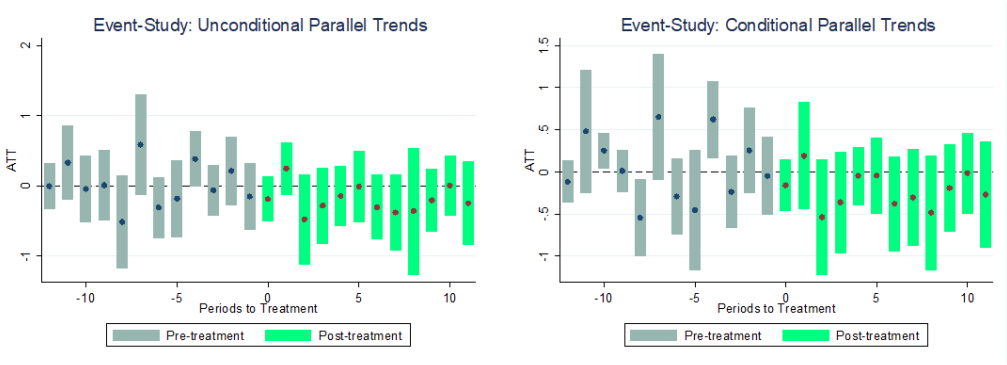

Figure A.4: UN-REDD event study, emissions