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Comparing Protection Types in The Peruvian Amazon: Multiple-Use Protected Areas Did No Worse for Forests

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Protected areas (PAs), which restrict economic activities, are the leading land and marine policy for ecosystem conservation. Most contexts feature different types of protection that vary in their stringency of management. Using spatially detailed panel data for 1986-2018, we estimate PAs' impacts upon forests in the Peruvian Amazon. Which type of protection has greater impacts on the forest is ambiguous, theoretically, given potential for significant differences by type in siting and enforcement. We find that the less strict multiple-use PAs, that allow local livelihoods, do no worse for forests than strict PAs: each PA type holds off small loss spikes seen in unprotected forests; and multiple-use, if anything, do a bit better. This adds to evidence on the coexistence of private activities with conservation objectives.

KEYWORDS

deforestation, Peru, Amazon, protected areas, IUCN, impact evaluation, difference-in-differences

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Comparando tipos de protección en la Amazonía Peruana: las áreas naturales protegidas de uso múltiple no fueron peores para los bosques

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Las áreas naturales protegidas (ANPs), que restringen actividades económicas, son las principales políticas para la conservación de ecosistemas terrestres y marinos. Muchos contextos cuentan con distintos tipos de protección que varían en su rigurosidad. Utilizando datos panel con alta resolución espacial para el periodo 1986-2018, estimamos los impactos de las ANPs en los bosques de la Amazonía Peruana. Qué tipo de protección tiene mayor impacto en el bosque es teóricamente ambiguo, dadas las potenciales diferencias por tipo de ANP en su ubicación y ejecución. Encontramos que las ANPs de usos múltiples (menos estrictas) que permiten el desarrollo local no fueron peores para los bosques que las estrictas: cada tipo de ANP bloquea alzas en la deforestación en bosques no protegidos, e incluso las ANPs de usos múltiples lo hacen un poco mejor. Este estudio contribuye a la evidencia sobre la coexistencia entre actividades privadas y los objetivos de conservación.

KEYWORDS

deforestación, Perú, Amazonas, áreas naturales protegidas, IUCN, evaluación de impacto, diferencias en diferencias

1 | INTRODUCTION

Key roles for tropical forest in both species habitat and carbon storage motivate the consideration of how global actors can support ongoing local provision of all of the local, regional, and global public goods forests provide. The ongoing losses of tropical forests over recent decades, globally (FAO, 2016), heightens the urgency of these concerns. Land-use restrictions are one part of such strategies and protected areas (PAs) that limit the economic activities within their boundaries are the leading ecosystem-conservation policy for forests and marine ecosystems (Gill et al., 2022).

While PAs can generate ecological benefits by reducing rates of forest loss in different contexts, at least on average with widely varying degrees of success (Andam et al., 2008; Joppa and Pfaff, 2011; Pfaff et al., 2015; Herrera et al., 2019; Börner et al., 2020), their restrictions imply local costs which are not appreciated by firms and local forest dwellers whose livelihoods depend on such ecosystems (Agrawal et al., 2008). Locally unappreciated PAs may be more vulnerable to invasions to cut trees, in the context of low monitoring and enforcement, such as when local agency headquarters are far from PAs (Albers, 2010; Urrunaga et al., 2012). Thus, some have proposed that forest governance move toward creating more multiple-use PAs, which impose fewer restrictions than strict PAs, to allow local smallholders to use the forest for economic activities and to play a role in PA management (Agrawal et al., 2008).

Given the importance of PAs on forest frontiers, we investigate empirically for Peru's Amazon whether their multiple-use PAs conserved less or more forest than did the more strict PAs which banned all extractive activities. On the one hand, multiple-use PAs potentially could yield lower conservation, since they permit some economic activity to support livelihoods, which generates forest loss. On the other hand, multiple-use PAs can conserve better since allowing local benefit[1] can forge cooperation that may enhance forest outcomes by allowing a PA to be established then facilitating enforcement and monitoring. With low enforcement, PAs may not conserve so much.

We estimate the impacts on rate of forest loss due to four types of public PAs in the Peruvian Amazon. These four distinct types of protection vary in: i) land-use rights and restrictions; ii) the governance level at which they are managed, national or regional; and iii) their status, transitory or fully established. We generate the first estimates of the impacts upon rates of forest loss due to the public PAs established after 2000 in the Peruvian Amazon, which is the fourth-largest area of tropical forest globally, the country's most important timber region, and an eco-services hotspot.

We extend in two ways Miranda et al. (2016)'s evaluation of the impacts on forest resulting from ten PAs established before 2000. First, we evaluate all PAs in our study area that were created under a new regime, after Peru's Natural Protected Area Act was enacted in 1997. Second, we use space and time variation — in PA existence and the loss of forest — to identify PAs impacts using a long annual panel of forest data (1986-2918) and new difference-in-differences (DID) estimators that offer improved tests of parallel trends — the main identification assumption.

To the best of our knowledge, we are first to: (i) estimate PA impacts on forest losses using DID estimators robust to heterogeneity issues that affect the two-way fixed effects (TWFE) estimators (de Chaisemartin and D'Haultfoeuille, 2020) that have been a workhorse of panel analysis but are now recognized as facing specific challenges — as some of our results support; and (ii) evaluate forest conservation policy using 33-year panel data as well as a continuous forest-loss outcome, to avoid the biases related to using binary outcomes

[1] We do not verify empirically whether locals actually gain more economic benefits from multiple-use PAs, but that has been the case at least for some contexts (Pfaff et al., 2014).

with panel data (Garcia and Heilmayr, 2022). Applying advances in forest data and DID, our methods can guide the future evaluation of PAs.

Overall, we find limited forest gains from protected areas within this context for this time period. Of further interest, we find that when comparing them with stricter protection, multiple-use PAs which allowed some economic activities did not increase rates of forest loss – if anything, these multiple-use PAs may have suffered lower losses (at least on a basis of our preferred estimates, employing the new more robust DID estimators). When PAs do appear to shift outcomes, for any type, it seems to have been by warding off the temporary spikes in clearing of unprotected forest. That suggests some consistency of results for economic activities coexisting with conservation, since that is precisely what was found, on this very same forest frontier, for logging concessions – certified or not – which allow regulated timber extraction by firms (Rico-Straffon et al., 2022).

The rest of this paper is as follows. Section 2 describes the setting, plus relevant prior PA studies. Section 3 describes our data and empirical methods, Section 4 our results, discussed in Section 5.

2 | BACKGROUND

2.1 | Peruvian Amazon Forests & PAs

Peru's tropical forests are the second-largest in Latin America and the fourth-largest worldwide (Rainforest Alliance, 2014), with over 70 million hectares in 2011 (Ministerio del Ambiente, 2015). They host ecosystems which provide valuable goods and services such as water supply, timber (cedar, mahogany), non-timber forest products, and biodiversity. These forests also host over one thousand indigenous communities and fifty ethnic groups (Ministerio del Ambiente and Ministerio de Agricultura, 2011). Forest losses in Peru have been driven by productive activities that include logging and mining (legal and illegal), cattle ranching, oil extraction, and agriculture – all facilitated by investments in infrastructure (Laurance et al., 2001; DeFries et al., 2010).

The Peruvian Amazon is an important and sensible setting for evaluating PAs' impacts, given national and regional PAs with varied management, size, location, and accessibility (Figure 1). Protection initially was always managed at the national level, but a Natural Protected Area Act (Law No. 26834 of 1997) introduced a new regime that decentralized the management of some protected areas by also recognizing regional and private PAs (MINAM, 2016; República del Perú, 1997). The National Service of Natural Protected Areas (SERNANP) is the institution in charge of regulating and managing protected areas in Peru, including coordinating regional and local governments and private actors who are also in charge of managing certain types of PAs (SERNANP, 2022b).

The Peruvian Amazon has four main types of public PAs. Indirect Use PAs are the strictest form, allowing research, tourism, and recreation but no forms of resource extraction or transformation (República del Perú, 1997). These strict PAs are managed at the national level and this category includes National Parks, National Sanctuaries, and Historical Sanctuaries (SERNANP, 2022d).

Peru's Amazon has three types of multiple-use PAs that are less strict, i.e., allow some extraction. Direct Use PAs are also managed at the national level and also have subcategories (Table 1) that all allow resource management and extraction by local communities in specific areas defined by management plans (República del Perú, 1997). The specific activities allowed and the degree of local communities' involvement in PA management vary by the subcategory of Direct Use PA. For example, Community Reserves are co-managed by local communities and allow traditional and sustainable resource use, while the Hunting

Reserves subcategory allows regulated sport hunting (SERNANP, 2022d). Another type of multiple-use PAs is called Regional. These are managed at sub-national levels, i.e., by regional governments and municipalities (República del Perú, 1997).

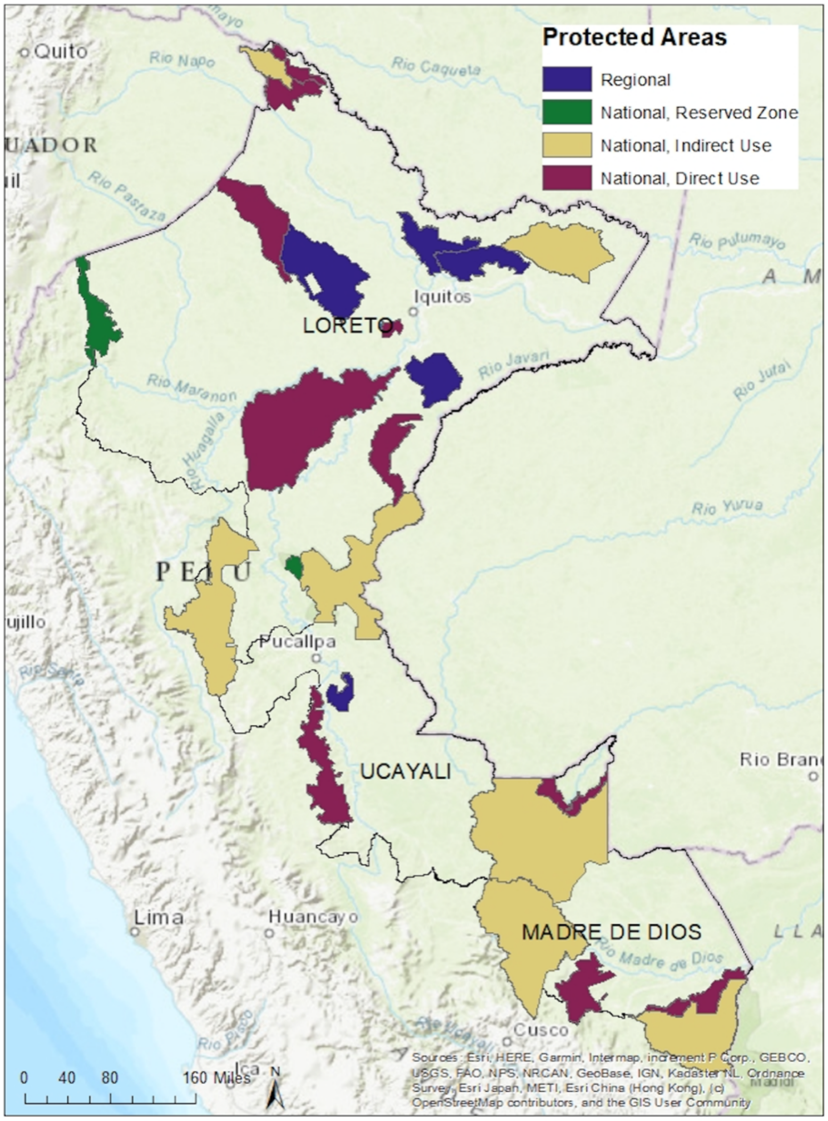


FIGURE 1 **Peruvian Amazon Post-1997 Protected Areas (PAs) of Different Types**
Notes: This map shows the protected areas established in our study area (Loreto, Madre de Dios, and Ucayali) in 1997 or later. *Source:* We produced this map using data from SERNANP (2022a).

Reserved Zones are the last type of multiple-use PAs. They are managed nationally but they have a transitory status. They are in the process of becoming PAs, which can take decades since Reserved Zones require further technical studies and negotiations with local communities, industries, and governments before being fully established (Solano, 2010). A Reserved Zone can become an Indirect Use PA and/or a Direct Use PA. For example, Reserved Zone Güeppí in Loreto was established in 1997, then its area was divided into three established PAs in 2012: one National Park (Indirect Use), as well as two Community Reserves (Direct Use) (WWF, 2013). This is an example of local communities supporting

TABLE 1 Types of Protection in the Peruvian Amazon

Category	Type	Level	Extraction?	Status	PA Subcategories
Indirect Use	strict	national	no	established	National Parks National Sanctuaries Historical Sanctuaries
Direct Use	multiple-use	national	yes, limited	established	Wildlife Refuges National Reserves Community Reserves Protected Forests Hunting Reserves Scenic Reserves
Regional	multiple-use	subnational	yes, limited	established	–
Reserved	multiple-use	national	yes, limited	in transition	–

Source: Authors based on SERNANP (2022d).

PA establishment and contributing to forest protection. Local ethnic groups worked for 15 years to achieve this legal definition and to block illegal logging (WWF, 2013, 2010).

Since 1961, Peru's government has created 254 national, regional, and private PAs covering 29.6 million hectares of land and marine territory (SERNANP, 2022c). By August of 2022, 18% of its land was covered by PAs (SERNANP, 2022c). Forests outside PAs include logging concessions with limited timber extraction, non-timber concessions (e.g. Brazil nut, rubber, petroleum), and native communities.

2.2 | PA Impacts

Studies in many other locations find that PAs reduce rates of forest loss, on average, although the impact varies considerably with PA type, location, and enforcement (Andam et al., 2008; Joppa and Pfaff, 2011; Pfaff et al., 2015; Herrera et al., 2019; Börner et al., 2020). They often highlight that local residents oppose PA restrictions. Given a baseline landscape, in which profits and forest clearing are higher when near to markets, private resistance to establishment of a new PA tends to rise with the level of profit that would be surrendered. Thus, new PAs tend to be pushed off to isolated frontiers where people are sparse and where there is a lower probability of deforestation (Joppa and Pfaff, 2009) – which, in turn, limits the conservation potential of the PAs.

This background is useful for considering why different types of protection could vary in impacts — a priori, it may be impossible to rank these PA types by their conservation effectiveness. Multiple-use PAs potentially could generate lower conservation than strict PAs since they permit some economic activity to try to support livelihoods which can generate forest loss. However, that very support could change local political attitudes about allowing any PAs at all, including for regions within which there are enough people and pressures to allow PAs to have impacts.

Further, those livelihood gains could motivate local actors to help to enforce such PAs.

For example, Agrawal et al. (2008) find that local stakeholders allowed to benefit from local forests acted in order to lower forest invasion. Thus, which type of PA helps forests more is ambiguous. Enforcement is critical. If a PA allows economic gain by simply not enforcing any restrictions, e.g., due to distant public agencies with weak monitoring, that PA is not going to yield benefits from forest conservation. PAs that provide rights to a limited group of private actors, allowing them to gain economically, could, in principle, generate incentives for such actors to block others and thereby protect forest.

Finally, Reserved Zones are a special case, since they are not yet established PAs. They could be just like other multiple-use PAs. They could instead be like unprotected forest – with no impact relative to truly unprotected forest or, worse, locations where deforestation rates rise, to extract before restrictions are enforced. Thus, it is difficult to be sure even of the direction of impact for these areas.

3 | DATA & METHODS

3.1 | Data

3.1.1 | Protected Areas

We evaluate the 21 National Indirect-Use or Direct-Use PAs, Regional PAs, and Reserved Zones established during 1997-2018 within the Peruvian Amazon regions of Madre de Dios, Ucayali, and Loreto (Table A.1). We build on Miranda et al. (2016) who evaluated pre-2000 public PAs in these regions, as well as Pasco and Huánuco regions, albeit using solely cross-sectional analyses. We cannot examine many of those pre-2000 PAs, i.e., those established before our forest data started (1986). We also exclude private PAs that are much smaller, in private lands, managed by private actors who voluntarily seek conservation, and established towards the end of the study period. We acquired publicly available data on the PAs' boundaries and characteristics from SERNANP.

3.1.2 | Forest Outcomes and Sample

Our main analysis uses public data from MapBiomas Amazon Project (2021), specifically annual forest loss at a 30-meter resolution for the Peruvian Amazon forests (Madre de Dios, Loreto, and Ucayali) during the period 1986-2018. To check robustness we use an alternative outcome of annual tree-cover loss at a 30m resolution from the *Global Forest Change* data (Hansen et al., 2013) that are widely used in such literature. Both forest data sources are publicly available.

We compile annual panel data for large aggregate pixels (9000x9000m) covering all forest areas inside and outside the 21 PAs and Reserved Zones in our study area. Our aggregate-pixel unit of analysis implies continuous rates of forest loss. This avoids bias in previous literature evaluating conservation policies using panel data with more spatially precise pixels (30x30m) and a binary deforestation outcome (0 if the pixel has never been deforested, 1 the year the pixel is deforested after which without forest regrowth the outcome has missing values (Garcia and Heilmayr, 2022)).

As some aggregated pixels are partially treated, we define any pixel as treated if over 95% of its area intersects with a PA or with a Reserved Zone created in 1997 or later.[2] We then drop pixels that partially intersect a PA or a Reserved Zone, i.e., with an intersection between 0% and 95%. We restrict our control group to "fully untreated forests", i.e., pixels

[2]We drop the pixels that fall within PAs or Reserved Zones created before 1997, the year when the Natural Protected Areas Act was enacted.

that do not intersect any PA, Reserved Zone, logging concession or native community — using data from WWF Peru in 2014 and 2015. The final balanced panel of aggregated pixels for analyses includes 105,006 pixel-year observations for 1986-2018, of which 39,327 (37%) were ever treated in a PA or Reserved Zone.

3.2 | Empirical Strategy

3.2.1 | New DID Estimators (lead results)

The traditional TWFE specification — as discussed just below for robustness and comparison — identifies treatment effects when the assumption of "parallel trends" holds. That is true here too. Recent literature shows another important TWFE assumption is homogeneous treatment effects across all of the spatially distinct groups — which are aggregated pixels for us — and over time (de Chaisemartin and D'Haultfoeuille, 2020). Those assumptions are unlikely to hold.

The new DID papers point out that one can see TWFE estimators as weighted sums of treatment effects for each group-year cell (de Chaisemartin and D'Haultfoeuille, 2020) which yield biases if treatment effects are heterogeneous – as some underlying effects from some group-year cells could receive negative weights (Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021). Also, de Chaisemartin and D'Haultfoeuille (2022a) found that when a TWFE regression includes multiple treatments, the TWFE estimators for each treatment can be biased by the effects of another treatment. In our setting, 'contamination' could be quite relevant when estimating the effects of protected areas that were Reserved Zones before becoming PAs.

Our main results use de Chaisemartin and D'Haultfoeuille (2021, 2022a)'s DID estimators (DID_L), since they are robust to heterogeneous treatment effects and to contamination across treatments. We compare those results with TWFE for robustness including to understand effects of weights.

As all National PAs but two Direct-Use PAs were Reserved Zones before becoming official PAs, we follow a strategy in de Chaisemartin and D'Haultfoeuille (2022a) to isolate the effects of those Reserved Zones. We restricted observations to those pixel-year cells where the PA treatment was not yet active, and then employed their DID_L strategy to estimate the effects of the Reserved Zones.

3.2.2 | Two-Way Fixed Effects (robustness check)

Our two-way fixed effects (TWFE) specification, employed to evaluate the forest impact of each type of protections by using our 'super pixel' panel to compare forests inside and outside PAs, is:

$$L_{it} = \beta_0 + \beta_1 PA_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where L_{it} is the share of forest in super-pixel i deforested during year t; and $PA_{it} = 1$ if the PA for pixel i was active in year t, and zero otherwise. We run this for each PA type in the study area. We cluster our standard errors with the PA ID if a pixel is in a PA, in order to account for spatial autocorrelation within the PA, but using the pixel ID instead when the pixel falls outside PAs.[3]

[3] Here we assume that spatial autocorrelation is limited in untreated forests since we do not have a more aggregate geographical unit in such forests that is analogous to PA polygons.

3.2.3 | Pre-Estimation Matching (checking past outcomes for 'similarity')

Multiple evaluations of PA impacts have matched treated with untreated pixels based on various observed characteristics of forested lands. This started with fixed geographic characteristics (e.g., Andam et al. (2008); Joppa and Pfaff (2011)) that are relevant for deforestation rates such as distances to cities, distances to roads, the quality of the soil, the slope of the land, rainfall levels, and more.

However, many unobserved characteristics affect deforestation rates. Thus, while matching on observed characteristics improves similarity of parcels – at the least in terms of those observed characteristics – it does not guarantee forest trends will be parallel between any treated parcel of forest and some potential controls. Further, the synthetic-control literature (e.g. Arkhangelsky et al. (2021); Ben-Michael et al. (2021)) has pushed forward on using pre-treatment outcomes as the basis for matching units, in that case to find good comparisons for single spatial units receiving treatments of interest, in order to better evaluate treatment impacts. Putting all that together, we believe that using pre-treatment outcomes for matching the treated pixels with untreated pixels, before constructing the panel analyses, could help to generate data sets featuring parallel trends.

MapBiomas data offer forest observations at least 11 years before PAs are established as well as up to 18 years after PAs become active, which helps to find a better control group and to test the critical identifying assumption of parallel trends. We match aggregated pixels that eventually are in a PA with those that were never inside a PA using Propensity Score Matching with replacement and three neighbors based on forest-loss rates before the PA was established. We do so for each type of protection, including Reserved Zones. We use such matched samples to construct an aggregated pixel-by-year panel for each PA type. Section 4 shows that matching on pre-treatment forest losses (Figures 2b, 3b, 4b, 5b) resulted in large improvements in terms of parallel trends, relative to no matching (Figures 2a 3a, 4a, 5a).

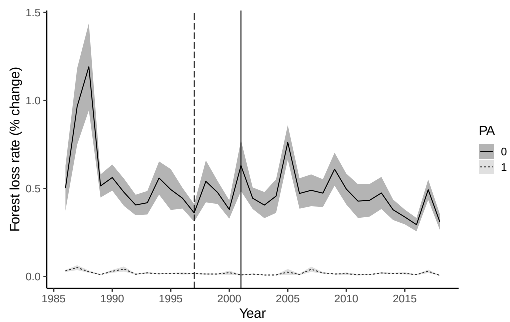
As matching on pre-treatment outcomes does not guarantee past forest loss trends will be parallel across the treated versus the control units, we test formally the plausibility of the parallel trends identifying assumption. We do so with a joint significance test for the $\mathrm{DID}_{\mathrm{L}}$ placebo estimators (which also are robust to both heterogeneous treatment effects and dynamic treatment effects), using the null that all placebo estimators are zero, i.e., of no differences in pre-treatment trends.

4 | RESULTS

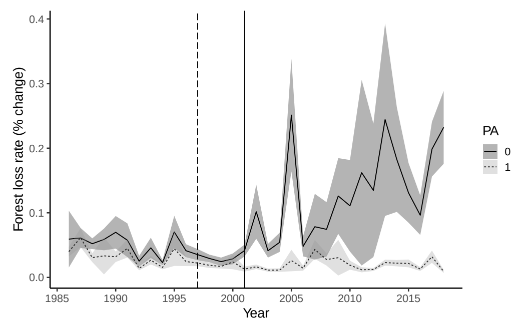
We present the estimated forest loss impacts of each type of protected area and/or reserved zone. We lead with new DID results, given all of the arguments above concerning its superiority under realistic conditions. We also, though, consider TWFE results, which generally are quite similar – then we mention several variations and robustness checks which are included in the Appendices.

4.1 | Indirect-Use (Strict) PAs

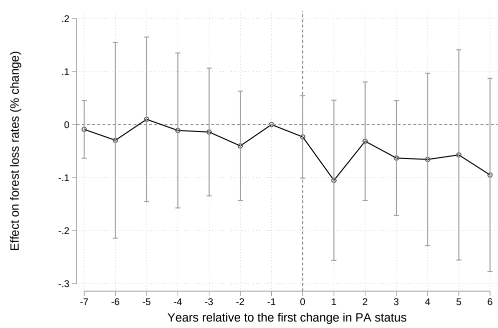
We employ $\mathrm{DID}_{\mathrm{L}}$ to estimate the effects of Indirect-Use PAs on forest loss. We utilize a sample of pixels after matching on pre-2001 forest-loss levels (the first Indirect-Use PA was established in 2001 (Table A.1)). We start by checking the plausibility of parallel trends, i.e., identification. We find evidence supporting that assumption when we include up to six placebo estimators, and note that all six placebo estimators (to the left of t=0, Figure 2c) are close to zero and are not statistically significant. A test of these six placebos' joint significance fails to reject the null (p-value=0.94). Thus, we show up to six dynamic effects, i.e. the effects of Indirect-Use PAs 6 years after having started. This blends all the PA cohorts, i.e., PAs established in different years.



(a) Unmatched Data



(b) Matching on Pre-Treatment Forest Loss Levels



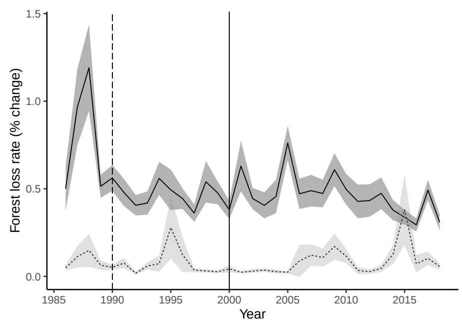
(c) Indirect-Use PAs' Forest Loss Impacts (DID_L)

FIGURE 2 **Forest Loss Inside vs. Outside Indirect-Use PAs & Resulting Impact Estimates.** *Notes:* Panels A and B show mean annual forest loss trends and 95 percent confidence intervals for different samples of forested pixels in our study area during 1986-2018 by protection status (PA=1 if ever inside an Indirect-Use PA, and 0 for never treated pixels). The dashed vertical line indicates 1997, the first year a Reserved Zone was declared that eventually became an Indirect-Use PA. The solid vertical line indicates 2001, the first year that an Indirect-Use PA was established in our sample. We calculated forest loss rates from Collection 5 of MapBiomas Amazon Project (2021). Panel C plots the DID_L point estimates across event time (i.e., years relative to the first change in PA status) for Indirect-Use PAs using the matched sample of pixels in Panel B. Standard errors are clustered by pixel ID or PA ID for treated and untreated pixels respectively.

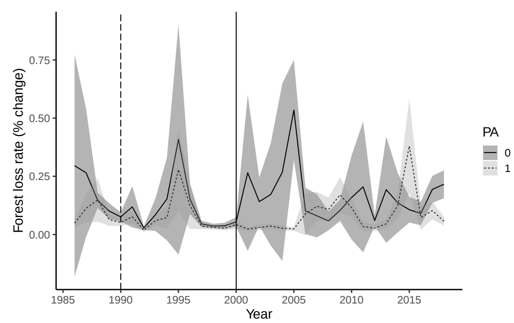
We find the instantaneous effect of Indirect-Use PAs on forest loss (i.e. at $t = 0$) and all dynamic effects (to the right of $t = 0$, Figure 2c) are slightly negative. That suggests an average reduction in forest loss of at most 0.1% per year, i.e., any effect we find is small in magnitude. We also estimate an average effect using DID_L, for Indirect-Use PAs' influences on forest losses. The DID_L average effect is a weighted sum of the instantaneous and the 6 dynamic DID_L effects. We find that the estimated average effect of changing a pixel from untreated (not a PA) to treated in an Indirect-Use PA form, for seven years, is -0.061% (Table 2). That is equivalent to 3/100 of a standard deviation of the annual forest loss rates during 1986-2018 in our sample (mean=0.32, SD=1.80). This estimated effect is not statistically significant at the 5% level (SE=0.056).

4.2 | Direct-Use (Multiple-Use) PAs

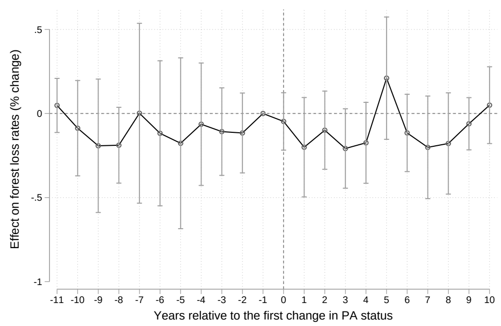
We also employ DID_L to estimate the effects on forests of Direct-Use PAs here using a sample of pixels matched on pre-2000 loss levels since the first Direct-Use PA was granted in 2000 (see Table A.1). We find that all of these placebo estimators are close to zero and are not statistically significant (to the left of $t = 0$, Figure 3c). A joint test of significance fails to reject the null with up to 10 placebo estimators (p-value = 0.477); thus, we estimate 10 dynamic effects.



(a) Unmatched Data



(b) Matching on Pre-Treatment Forest Loss Levels



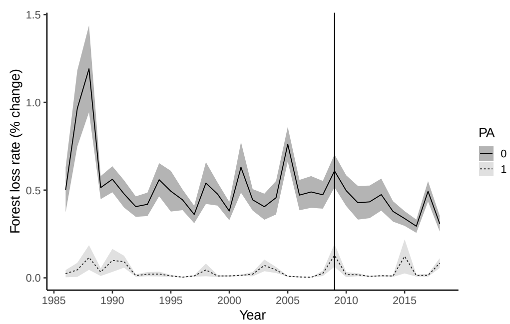
(c) Direct-Use PAs' Forest Loss Impacts (DID_L)

FIGURE 3 **Forest Loss Inside vs. Outside Direct-Use PAs & Resulting Impact Estimates.** *Notes:* Panels A and B show mean annual forest loss trends and 95 percent confidence intervals for different samples of forested pixels in our study area during 1986-2018 by protection status (PA=1 if ever inside a Direct-Use PA, and 0 for never treated pixels). The dashed vertical line indicates 1990, the first year a Reserved Zone was declared that eventually became a Direct-Use PA. The solid vertical line indicates 2000, the first year that a Direct-Use PA was established in our sample. We calculated forest loss rates from Collection 5 of MapBiomas Amazon Project (2021). Panel C plots the DID_L point estimates across event time (i.e., years relative to the first change in PA status) for Direct-Use PAs using the matched sample of pixels in Panel B. Standard errors are clustered by pixel ID or PA ID for treated and untreated pixels respectively.

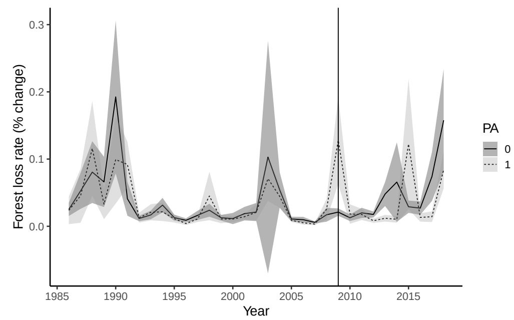
For the estimated forest impacts of Direct-Use PAs, we observe that the instantaneous effect on forest loss is close to zero. All of the dynamic effects (to the right of t=0, Figure 3c) are slightly negative (less than -0.5%) except for the fifth and tenth dynamic effects. The average effect of Direct-Use PAs is a reduction in forest loss of 0.10%, which is not statistically significant (SE= 0.089). We note that the magnitude of the effect is larger than that of Indirect-Use PAs, though, suggesting that Multiple-Use PAs do at least as much to protect forests as Strict PAs.

4.3 | Regional PAs

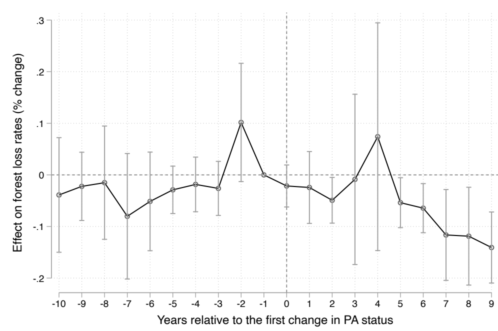
We again employ DID_{L} to estimate the effects of Regional PAs, here matched on pre-2009 losses as the first Regional PA was granted in 2009 (see Table A.1). We find that almost all the placebo estimators are close to zero and not statistically significant (to the left of t=0, Figure 4c) except placebo 2 which is small and positive. A test of these placebos' joint significance rejects the null hypothesis (p-value 0.002), yet a weaker version using first-difference placebos does not reject the null for up to 9 placebos (p-value=0.141, Figure B.1).[4] Thus, we have included 9 dynamic effects.



(a) Unmatched Data



(b) Matching on Pre-Treatment Forest Loss Levels



(c) Regional PAs' Forest Loss Impacts (DID_{L})

FIGURE 4 **Forest Loss Inside vs. Outside Regional PAs & Resulting Impact Estimates.** *Notes:* Panels A and B show mean annual forest loss trends and 95 percent confidence intervals for different samples of forested pixels in our study area during 1986-2018 by protection status (PA=1 if ever inside a Regional PA, and 0 for never treated pixels). The solid vertical line indicates 2009, the first year that a Regional PA was established in our sample. We calculated forest loss rates from Collection 5 of MapBiomas Amazon Project (2021). Panel C plots the DID_{L} point estimates across event time (i.e., years relative to the first change in PA status) for Regional PAs using the matched sample of pixels in Panel B. Standard errors are clustered by pixel ID or PA ID for treated and untreated pixels respectively.

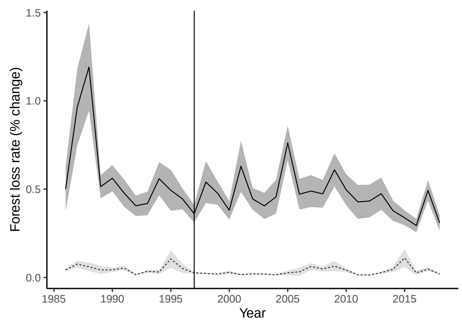
For the impacts on rates of forest loss due to these Regional PAs, the instantaneous effect upon forest loss is close to zero, while all of the dynamic effects (to the right of t=0, Figure 4c) are negative, except for dynamic effect 4. We see effects 2 and 5-9 are negative and statistically significant at the 5% level, however the magnitudes are small, suggesting a reduction of less than 0.2% per year. The estimated average effect of these Regional PAs is a reduction in forest loss of 0.039%, although that is not statistically significant (SE=0.025). This

[4] You can see more details of these placebos estimators in de Chaisemartin and D'Haultfoeuille (2021).

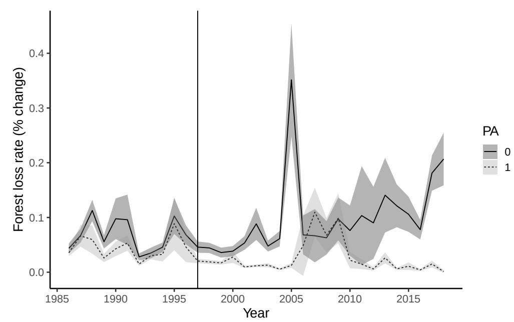
result certainly suggests, though, that allowing economic activities in Regional multiple-use PAs did not harm the forest.

4.4 | Reserved Zones

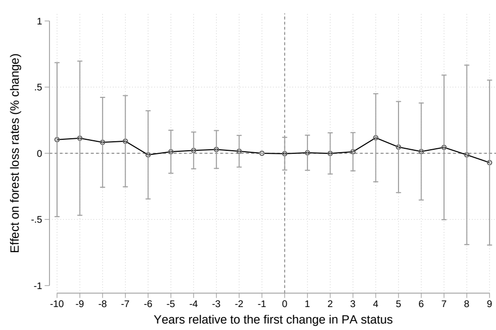
We employ $\mathrm{DID_L}$ to estimate the effects of Reserved Zones. We matched them using pre-1997 loss rates, as the first Reserved Zones in our study area were established in 1997 (see Table A.1). As most Reserved Zones eventually became Direct-Use and/or Indirect-Use PAs, we eliminate the pixel-year observations where either of these PAs were already active to isolate the effect of Reserved Zones (as generically recommended by de Chaisemartin and D'Haultfoeuille (2022a)).



(a) Unmatched Data



(b) Matching on Pre-Treatment Forest Loss Levels



(c) Regional PAs' Forest Loss Impacts ($\mathrm{DID_L}$)

FIGURE 5 **Forest Loss Inside vs. Outside Reserved Zones & Resulting Impact Estimates.** *Notes:* Panels A and B show mean annual forest loss trends and 95 percent confidence intervals for different samples of forested pixels in our study area during 1986-2018 by protection status (PA=1 if ever inside a Reserved Zone, and 0 for never treated pixels). The solid vertical line indicates 2009, the first year that a Reserved Zone was established in our sample. We calculated forest loss rates from Collection 5 of MapBiomas Amazon Project (2021). Panel C plots the $\mathrm{DID_L}$ point estimates across event time (i.e., years relative to the first change in PA status) for Reserved Zones using the matched sample of pixels in Panel B. Standard errors are clustered by pixel ID or PA ID for treated and untreated pixels respectively.

We find that all of the placebo estimators are very close to zero. Also, the joint significance test of 9 placebos does not reject the null (p-value=0.994). We also find that the instantaneous and all dynamic effects on forest loss of Reserved Zones are near zero, especially close to the treatment (Figure 5c). We see that the estimated average effect of Reserved Zones is a small but insignificant rise in forest loss of 0.016% per year (SE=0.107). These are not yet protected areas, and they allow multiple economic activities, which makes them the least restrictive multiple-use PAs in our sample. However, we do not find evidence of them harming the forest in this period.

TABLE 2 DID_L and TWFE Estimators of Forest Loss Impacts of Different PA Types

Estimator	Average Effect	S.E.	N	P-value Joint Placebo Test
Panel A. Indirect-Use PAs				
DID_L	-0.061	0.056	39,748	0.940
TWFE	-0.082	0.018	49,038	–
Panel B. Direct-Use PAs				
DID_L	-0.100	0.089	35,397	0.477
TWFE	-0.003	0.054	20,922	–
Panel C. Regional PAs				
DID_L	-0.039	0.025	14,652	0.141
TWFE	-0.018	0.012	20,625	–
Panel D. Reserved Zones				
DID_L	0.016	0.107	53,682	0.994
TWFE	-0.019	0.013	47,626	–

Notes: We present the results of both de Chaisemartin and D'Haultfoeuille (2021) average DID_L estimator and the two-way fixed effects (TWFE) estimator of the forest loss impacts of each PA type created in 1997 or later in the Peruvian Amazon (Loreto, Madre de Dios, and Ucayali). We estimated a separate model for each PA type and each estimator. Recall that these estimators are different methods for making use of different subsets of the panel data set (i.e. DID_L selects particular transitions for comparisons to compute each instantaneous and dynamic effect underlying these average effects). Thus, the sample size differs. We present a trimmed average DID_L estimator using the same number of long-difference placebos and dynamic effects as in Figures (Figures 2c, 3c, 4c, 5c). The last column shows the p-value of a joint significance test of the long-difference placebo estimators for each treatment except for Regional PAs– we present the one for the test using first-difference estimators since the former test rejected the null (p-value=0.002). We ran the TWFE regression in equation 1 for each treatment and found that one of the ATTs in the TWFE estimators receive negative weights, except for the one for Indirect-Use PAs, where less than 1% of the ATTs receive a negative weight. We clustered standard errors at the pixel level for untreated pixels and at the PA level for treated pixels. We calculate forest loss from Collection 5 of MapBiomas Amazon Project (2021).

4.5 | Robustness Checks

We estimated TWFE regressions for each PA type and the main conclusion does not change: multiple-use PAs do not increase forest loss rates on average (Table 2 and Figure 6). Though we generally did not find negative weights in the TWFE estimators,[5] these estimated effects differed in magnitude from the average DID_L estimators. Our preferred specification is DID_L because the TWFE estimator does not estimate the average treatment effect on the treated even under parallel trends if we have variation in the treatment year (de Chaisemartin and D'Haultfoeuille, 2022b).

In addition, we ran a robustness check changing the outcome to Hansen et al. (2013)'s

[5]We found zero negative weights for all PA types except for Indirect Use PAs, which had less than 1% of group-year effects receiving negative weights.

tree- cover loss rates and we found similar results (Figure B.2). With these data, however, the effects of all PA types on tree-cover loss using both DID_L and TWFE are negative and statistically significant at the 5% level — except for the Regional PAs' average DID_L effect, which is not significant.

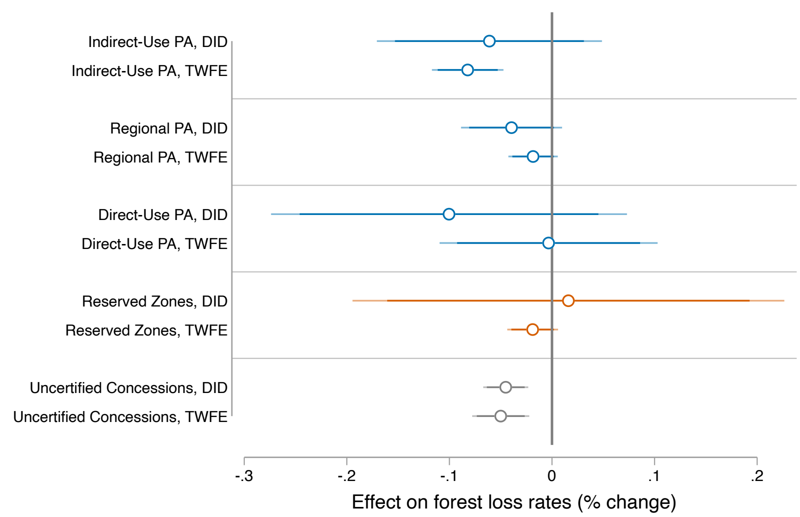


FIGURE 6 **Summary of Effects with MapBiomas Outcome and DID_L Estimator**
Notes: This figure shows de Chaisemartin and D'Haultfoeuille (2021)'s DID_L estimator of the average total effect of each forest intervention on forest loss rates. We compare these estimates of the impacts of the four types of protected areas (PAs) analyzed in this paper to the impacts of logging concessions estimated in Rico-Straffon et al. (2022) using the same data and methods for the same study area and study period. The spatial unit is 9x9 km for PAs and reserved zones, 3x3 km for uncertified concessions. We also present the TWFE estimator of the forest loss impacts of each intervention. For all estimators and policies, we cluster standard errors at the forest policy level for pixels within the boundaries of a protected area or a concession, and at the pixel level for untreated pixels. For each estimator, the graph shows the point estimate in a circle, as well as the 90% and 95% confidence intervals, in dark and lighter color respectively.
Source: We calculated forest loss rates using Collection 5 of MapBiomas Amazon Project (2021).

5 | DISCUSSION

We estimated the impacts upon annual forest-loss rates due to each of multiple types of protected areas for an important forest region, the Peruvian Amazon, and for a time period that is appropriate for shedding light upon ongoing conservation policy choices, 1986-2008. For both methodological and novelty reasons, we focus on PAs established after the 1997 Natural Protected Areas Act (a new regime), for which we have at least 11 years of pre-protection data on forests. Alongside new DID estimators for panel data sets, the data allow better tests of the key identifying assumption within panel estimation — parallel trends — and thus more defensible estimates of forest impacts.

We found limited impacts. While public tenure did not open the doors to free-for-all extraction, i.e., 'unclaimed space' in PAs did not hurt forests, still these PAs' forest benefits are small. That tended to be uniformly true, across types of PAs we evaluated — meaning the strict Indirect-Use PAs and three types of multiple-use PAs (Direct-Use PAs, Regional PAs, and Reserved Zones).

We note that, at least for our leading DID estimates, it appears that allowing officially for some limited smallholder activity within the Direct-Use PAs did not do worse for forests than did the strict Indirect-Use PAs. If anything, in estimates using the longest data sets and the most bias-reducing approaches, Direct-Use PAs appear to have performed just a bit better. While for this setting we must summarize that different PA types had similar conservation impacts, these results imply at the least that a PA type aimed at improving livelihoods (i.e., multiple-use) did not harm forests. That is consistent with Rico-Straffon et al. (2022)'s estimates of impacts from logging concessions in Peru (estimated impacts using the same underlying data and $\mathrm{DID_L}$ are juxtaposed in Figure 6).

These PAs impacts, and gradient by PA type, were quite robust to varying estimators and data. Concerning these estimators, for our results TWFE findings often were quite similar to $\mathrm{DID_L}$'s. Concerning data sets, while we tested not only far longer MapBiomas data but also widely used Hansen data, we believe newly available degradation data could add to analyses of PA impacts. Further, while we averaged results across the Peruvian Amazon, future analyses could explore policy relevant variations – for any PA type — e.g., for high versus low deforestation pressures.

Acknowledgements

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A | PROTECTED AREAS IN OUR STUDY AREA AND STUDY PERIOD

TABLE A.1 Protected Areas in our Study Area and Study Period by Type

Name	Category	Year Reserved	Year PA	Region(s)
Tambopata	Direct	1990	2000	MDD
Cordillera Azul	Indirect	2000	2001	Loreto & Ucayali
El Sira	Direct	–	2001	Ucayali
Amarakaeri	Direct	2000	2002	MDD
Allpahuayo Mishana	Direct	1999	2004	Loreto
Alto Purús	Indirect	2000	2004	MDD & Ucayali
Purús	Direct	2000	2004	Ucayali
Comunal Tamshiyacu Tahuayo	Regional	–	2009	Loreto
Matsés	Direct	–	2009	Loreto
Ampiyacu Apayacu	Regional	–	2010	Loreto
Imiria	Regional	–	2010	Ucayali
Pucacuro	Direct	2005	2010	Loreto
Alto Nanay- Pintuyacu Chambira	Regional	–	2011	Loreto
Airo Pai	Direct	1997	2012	Loreto
Güeppí-Sekime	Indirect	1997	2012	Loreto
Huimeki	Direct	1997	2012	Loreto
Maijuna Kichwa	Regional	–	2015	Loreto
Sierra del Divisor	Indirect	2006	2015	Loreto & Ucayali
Yaguas	Indirect	2011	2018	Loreto
Santiago Comaina	Reserved	1999	–	Loreto
Sierra del Divisor	Reserved	2006	–	Loreto

Note: MDD stands for Madre de Dios.
Source: We created this table using information from SERNANP (2022d).

B | OTHER TABLES AND FIGURES

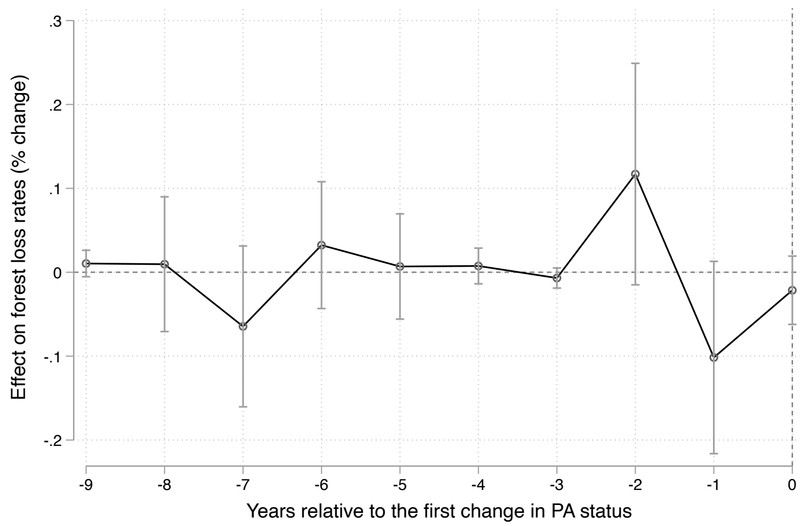

FIGURE B.1 **First-Difference Placebos of Regional Protected Area's Effects (**$\mathrm{DID_L}$**)**
Notes: This figure shows the first difference placebos of the effects of Regional Protected Areas (PAs) on forest loss rates. See more details in de Chaisemartin and D'Haultfoeuille (2021). The p-value of the joint significance test of such placebos is 0.14.

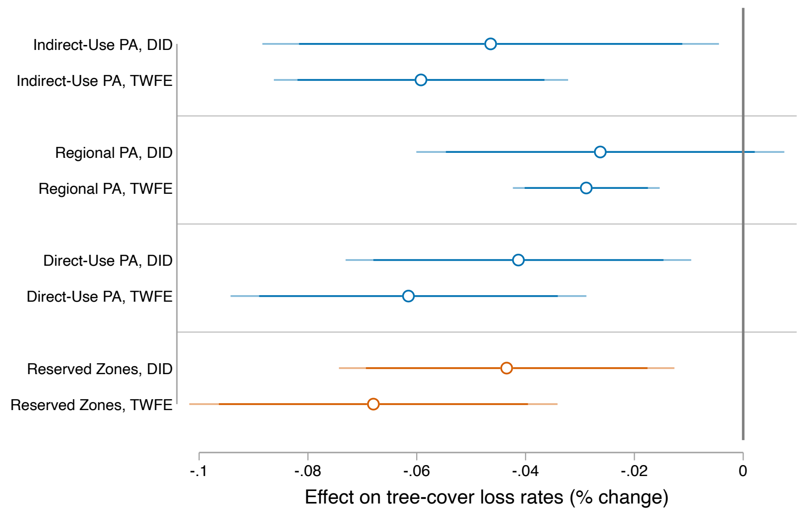

FIGURE B.2 **Summary of Effects with Hansen et al. (2013) Tree-Cover Loss**
Notes: This figure shows de Chaisemartin and D'Haultfoeuille (2021)'s DID_L estimator of the average total effect of each of the four types of Protected Areas on tree-cover loss rates. We compare these estimates of the impacts of the four types of protected areas (PAs) analyzed in this paper to the impacts of logging concessions estimated in Rico-Straffon et al. (2022) using the same data and methods for the same study area and study period. The spatial unit is 9x9 km for PAs and reserved zones, 3x3 km for uncertified concessions. We also present the TWFE estimator of the tree-cover loss impacts of each intervention. For all estimators and policies, we cluster standard errors at the forest policy level for pixels within the boundaries of a protected area or a concession, and at the pixel level for untreated pixels. For each estimator, the graph shows the point estimate in a circle, as well as the 90% and 95% confidence intervals, in dark and lighter color respectively.
Source: We calculated forest loss rates using Hansen et al. (2013)'s *Global Forest Change* data.