Does the Selective Erasure of Protected Areas Raise Deforestation in the Brazilian Amazon?

Derya Keles, Alexander Pfaff, Michael B. Mascia

Abstract: Protected areas (PAs) are the leading policy to lower deforestation. Yet resistance by land users leads PAs to be created in remote sites, lowering impact. Resistance continues after PA creation, with both illegal deforestation and advocacy for PADDD, that is, reducing PA status (downgrading) or PA size (partial or full erasure, downsizing or degazettement). For the Brazilian Amazon, we estimate 2010–15 forest impacts of 2009–12 PA erasures, on average and for distinct states. Before panel-DID regression, to find similar controls we matched using static characteristics and 8–10 years of pretreatment deforestation. PA erasures should raise deforestation if erased PAs faced and blocked pressures. Consistent with this, three conditions for "environmental selection" yielded little short-run impact from PADDD: low pressures, unblocked higher pressures, and pressures blocked less by those PAs selected for erasures. Yet for "development selection," with PA erasures in sites with pressures plus enforcement, PADDD yielded increased deforestation.

JEL Codes: C21, Q01, Q56, Q57

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BRAZIL'S AMAZONIAN REGION CONTAINS half of the world's tropical rainforest and is a biodiversity hot spot (Campos-Silva et al. 2015)—yet Brazil is the globe's seventh largest greenhouse gas (GhG) emitter, due mostly to conversion of Brazilian Amazon rainforest for production (Azevedo-Ramos and Moutinho 2018). Protected areas

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(PAs) have been one leading conservation strategy, in response. Since the 1980s (Veríssimo et al. 2011; Nogueira et al. 2018), Brazil's PA system has expanded, with commitments at the World Parks Congress in Bali, 1992 UN conference on environment and development, and Conventions on Biological Diversity in 2004 and 2010 (Visconti et al. 2019). In the 2016 Paris agreements, Brazil committed to lower GhG emissions to 43% below 2005 levels by 2030, mainly through reductions in deforestation (Gallo and Albrecht 2019). PAs now cover over 30% of Brazil's territory (UNEP-WCMC 2020) and over 50% of its Amazon (Campos-Silva et al. 2015) and on average have reduced deforestation (e.g., Pfaff et al. 2015).

Yet in Brazil, as elsewhere, PAs' impacts are constrained by PAs' locations. Within the Brazilian Amazon, outside high-pressure regions such as the Arc of Deforestation few land uses are profitable, and thus the forest often remains standing without any formal protection at all (Pfaff et al. 2009). Thus, PAs sited outside of high-pressure areas often avoid less deforestation than expected in the short run (Nolte et al. 2013), though they may limit future deforestation by discouraging infrastructure (Herrera 2015). PAs' impacts are also constrained by levels of enforcement, which are uneven across space, with illegal deforestation inside some PAs (Carranza et al. 2014; Jusys 2016, 2018; Kere et al. 2017; Amin et al. 2019).

Adding to such spatial considerations, for the Brazilian Amazon temporal dynamics of policy also matter. Multiple federal conservation policies helped to lower deforestation from 2004 to 2012 by over 70% (Assunção et al. 2015). However, during 2012 to 2020 deforestation rates then rose again (INPE 2019). The initial fall in deforestation followed from increases in PAs' area, the enforcement of PAs, and other policies. In turn, the recent rise in deforestation rates has followed from lowered enforcement of policy and even a "license to deforest," including within PAs (Carvalho et al. 2019; Ferrante and Fearnside 2019).

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at conferences (Ulvön Conference on Environmental Economics, organized by the CERE and by Umeå University; twenty-fifth annual conference of the European Association of Environmental and Resource Economics, organized online by Berlin Technical University), and seminars (Montpellier [CEEM], Clermont-Ferrand [CERDI]) for helpful comments. We also thank four anonymous reviewers for their very useful feedbacks. The research leading to these results received funding from the Bureau d'Economie Théorique et Appliqué (BETA). The BETA contributes to the LabEX ARBRE ANR-11-LABX-0002-01. The research leading to these results also received funding from the French Agence Nationale de la Recherche within the CLAND Program (ANR-16-CONV-0003) as well as the FAST (Facilitate public Action to exit from peSTicides) project (ANR-20-PCPA-0005), as part of the French Priority Research Programme "Growing and Protecting Crops Differently." The French Agence Nationale de la Recherche is not accountable for the content of this research. The authors are solely responsible for any omissions or deficiencies. We also thank Betty Moore and Gordon Moore for their financial support. This is publication 14 of the PADDDtracker Initiative.

This lowering of effective protections even had a formal aspect, with legal challenges of multiple forms: permitting additional productive activities inside some PAs (downgrading), partially erasing some PAs, in order to decrease their sizes (downsizing), and even fully erasing some PAs (degazettement) (Mascia and Pailler 2011). These protection-lowering events—collectively known as "PADDD"—accommodated industrial-scale resource extraction and development and, to a lesser degree, local land pressures as well as specific land claims (Golden Kroner et al. 2019; Naughton-Treves and Holland 2019; Qin et al. 2019).

After very few PADDD events occurred in the Brazilian Amazon during 1970–2000, PADDD's pace rose especially after 2008, when by 2015 44,000 square kilometers of PAs were lost to reductions in sizes, that is, the partial or complete erasures of some PAs (Campos-Silva et al. 2015; Golden Kroner et al. 2019). This acceleration in the lowering of protection reflected a shift in the political economy of conservation in Brazil, including as expressed through the increasing scarcity of funds and human resources allocated for the management of these PAs (Bernard et al. 2014; Ferreira et al. 2014; Campos-Silva et al. 2015).

We evaluate the forest impacts from PA size reductions in the Amazon, in light of their uneven siting. Our contributions are the following. First is a conceptual framework showing that where size reductions occur affects forest impacts, since to have impact requires that PAs faced and blocked pressure. Second, in light of that framework, we focus not on average PADDD impact for an enormous and diverse region but impacts by context. Empirically, we check whether selection across contexts generated or avoided impacts.

To reduce bias in our empirical impact estimates, within each context, we use matching with observed characteristics of forested lands that predict deforestation risk as well as the chance a PA is size-reduced. That includes effectively matching on pre-size-reduction forest impacts of our population of PAs, which vary with pressure. Given that a credible counterfactual is critical, following synthetic-control literature (Arkhangelsky et al. 2021; Ben-Michael et al. 2021) we match units based on pretreatment forest losses. We then employ panel regressions as DID, using two-way fixed effects (TWFE) plus new difference-in-differences (DID) estimators which better test our main identification assumption, that is, parallel trends.

Framing the relevant political economy conceptually, economic development interests propose PADDD where they would gain the most on net from deforesting those PAs. Given their contrasting objectives, conservation interests should bargain harder against PADDD when they gain more from any given PA (Tesfaw et al. 2018; Keles et al. 2020). If such interests bargain, many locations for PADDD are possible.

Empirically, in a limited literature on risks of PADDD events, it has been found that accessibility of a PA to market, the PA's size, and the PA's rate of internal deforestation all increase the likelihood, or the risk, of a PA being reduced in size (Pack et al. 2016; Symes et al. 2016; Tesfaw et al. 2018; Keles et al. 2020). Interestingly, that set of results for PADDD risks—including for size reductions (see Keles et al. [2020] for the entire Brazilian Amazon)—make it hard to predict whether selective PA erasures raise deforestation.

For instance, if the reason that a PA is selected for size reduction is that profitable internal deforestation has already occurred (perhaps one "environmental PADDD-selection rule"), then clearly a size reduction for that PA may have no impact, as no more deforestation is likely to occur. This is a relevant case, given that as just noted prior internal deforestation has increased the risk of size reductions (Tesfaw et al. 2018; Keles et al. 2020). If instead a PA is reduced in a remote location, with low pressures (another possible environmental selection), again it is clear that size reduction for that PA may have no impact on deforestation—but for the opposite reason, that is, there is low deforestation pressure. Yet the result that size reductions are more frequent when near to markets suggests that many size-reduced PAs did face economic pressures, which could well indicate some selection of PADDD locations by local economic-development interests. If some of those PAs blocked pressures, at least somewhat, reducing their sizes could raise deforestation.

The few empirical results for PADDD's impacts on forest address only so many cases—and are mixed. Golden Kroner et al. (2016) report that 150 years of legal changes in the Yosemite National Parks in the United States, with infrastructure to support rural settlement and resource extraction, increased habitat fragmentation. Elsewhere, higher deforestation and greenhouse gas emissions appear to have resulted from PADDD in Peru, as well as in Peninsular Malaysia (Forrest et al. 2015). Yet for Rondônia State, in the Brazilian Amazon, where economic pressure is strong, Tesfaw et al. (2018) found no average short-term forest impact. That is consistent with size reductions being where significant internal deforestation has already occurred. Considering the entire Brazilian Amazon, Pack et al. (2016) employ difference-in-differences to separate PADDD's influence on 2002–11 deforestation from those of fixed other factors. Like Tesfaw et al., Pack et al. found no impact, that is, erased and ongoing PA parts had similar forest losses.

Such policy impacts differ over time and over space for geographic, economic, and also political reasons. For instance, just as infrastructure in remote geographies may not immediately increase output or forest losses (Pfaff et al. 2018), private land-use responses to PADDD similarly may unfold slowly over time. Impacts' magnitudes may themselves vary over time, due to shifts in governance and thus expectations and investments (per recent shifts see, e.g., Carvalho et al. 2019; Escobar 2019; Ferrante and Fearnside 2019). For instance, while as noted Brazilian Amazon deforestation rates fell for some years after 2004 due to policy, rates have been rising since 2012. Reflecting the details of recent PA size reductions within rigorous estimation seems worthwhile to understand impact in temporally and spatially varied contexts. Which agencies dominate bargaining affects PADDD sites, and thus impacts, across and within contexts. Given variable political-economic dynamics across the Amazon, agencies' influences likely vary by state.

Considering all of these influences on the deforestation impacts from selective reductions in PAs' sizes, we evaluate impact for enacted 2009–12 PA size reduction (downsizing/degazettement) on 2010–15 forest losses (always post-size-reduction). Like Pack et al. (2016), we study all of the Brazilian Amazon. We extend their results by including more recent PADDD events, as well as more recent deforestation. Critically, we also distinguish multiple contexts for PAs over which impacts of PA erasures should differ.

We find that selection for size reductions of Brazilian Amazon PAs led to three contexts in which little or no forest impact is found from size reductions—at least in the short run. One of these contexts is less common yet still worth noting, as site selection for PADDD within the context is not required for no or low impact. For low-pressure contexts, for example, outside the "arc of deforestation," there is simply little forest loss and thus little PADDD impact. We suspect that environmental interests push PADDD into this context.

Yet the dominant "environmental selection" story is high-forest-loss locations within pressured contexts. For a pressured setting with some enforcement, we find that those PAs selected for 2009–12 reduction had blocked some forest loss before size reduction. Relative to constant-sized PAs with similar partial effectiveness, erasures had no impact. For higher-pressured settings where on average the PAs selected for erasures had not blocked pressure, there were no constant-sized PAs that had performed so poorly. Our third case for no impact from "environmentally selected" erasures is just that those size-reduced PAs blocked no pressures, that is, they had deforestation like fully unprotected areas before and after reductions.

Some size-reduced PAs actually performed as well as constant PAs before their size reductions. They are reduced PAs that faced and blocked pressure prereduction—precisely conditions where erasure should and did increase loss of forest. We suspect that development interests push PADDD toward such contexts.

The rest of the paper is organized as follows. Section 1 offers background concerning the region, then a framework for considering where (partial) erasures of PAs are more likely to increase forest loss. Next, section 2 presents our empirical strategy, while section 3 provides our estimates for forest impacts resulting from PA size reductions—critically including for distinct PA subsets. Then section 4 discusses.

1. BACKGROUND

1.1. Deforestation and Forest Protection in the Brazilian Amazon

Brazilian Amazon deforestation rose during the 1960s, as a military dictatorship opened up the region (Hargrave and Kis-Katos 2013; Souza-Rodrigues 2019). To support settlement and economic activities, roads were built and incentives given, interacting with insecure land tenure to yield land grabbing and illegal logging (Araujo et al. 2009). When the economy stabilized in the 1990s, deforestation increasingly was driven by exports, as the country became a major supplier of beef and soybeans (Arima et al. 2014).

Given international interactions and domestic public concerns (Naughton-Treves et al. 2005; Veríssimo et al. 2011), the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA) was created to enforce environmental laws (Arima et al. 2014). PAs were established (fig. 1) to conserve forest habitats and the required share of forest ("legal reserve') on private land rose from 50% to 80% (Souza-Rodrigues 2019). Yet enforcement was poor (Naughton-Treves et al. 2005; Veríssimo et al. 2011), and deforestation rose until a peak in 2004, when 26,800 square kilometers (km^2) of forested land were cleared (fig. 2).

Given multiple federal policy responses, and the 2008 economic crisis (Arima et al. 2014; Soares-Filho et al, 2014; Assunção et al. 2015), deforestation fell sharply from 2004 to 2012, when it was 4,571 km^2. In 2002, the Amazon PA Program (ARPA) was initiated to extend the PA network and improve PA management. To enforce related laws, the Real-Time System for Detection of Deforestation (DETER), using satellite detection, was implemented by the National Institute for Space Research (INPE) during the first phase of an Action Plan to Prevent and Control Deforestation in the Amazon (PPCDAm-I) (Veríssimo et al. 2011; Arima et al. 2014; Souza-Rodrigues 2019). DETER helped to identify and thus act more quickly on illegal deforestation

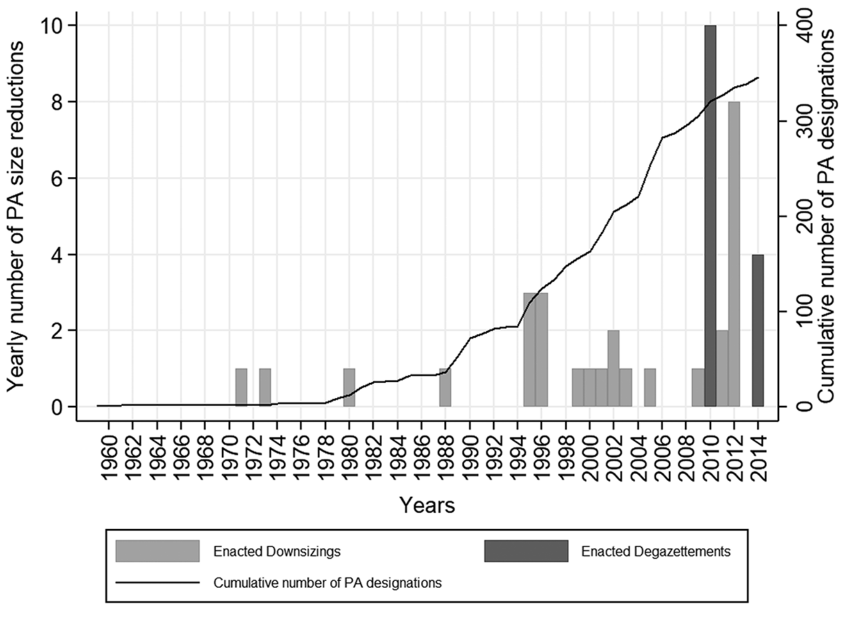

Figure 1. Timing of protected areas (PA) designations (designed pre-2001) and PA size reductions. Source: author (using Conservation International and WWF [2017]; IUCN and UNEP-WCMC [2016], creation dates confirmed in Brazilian data).

Figure 2. Deforestation in the Brazilian Amazon. Source: author (using INPE 2019)

(Assunção et al. 2017). PPCDAm-II (2009–11) then added federal measures such as more frequent inspections, as well as applications of sanctions by IBAMA; a list of "priority" municipalities, which were subject to stricter enforcement (Arima et al. 2014; Assunção et al. 2015; Souza-Rodrigues 2019); new punishment instruments, including embargoes and seizures; and the conditioning of rural credit access upon compliance with environmental regulations (Gibbs et al. 2016).

By 2012, however, the trend of falling deforestation rates had ceased. From 2012 onward, deforestation rates again started to rise, as a result of political change that led to a weakening of environmental laws (Campos-Silva et al. 2015; Fearnside 2016; Rochedo et al. 2018). For example, a 2012 revision of the Forest Code provided amnesties to landowners whose legal forest reserves had been cleared before 2008 (Soares-Filho et al. 2014). In addition, environmental requirements were lowered, further investments in infrastructure (such as highways and dams) were promoted, and the PA network was undermined (Fearnside 2016; Naughton-Treves and Holland 2019). PAs had been reduced in size as early as 1970, yet this phenomenon was accelerated, mostly to accommodate infrastructure projects, settlements, and expansions of agriculture (Mascia and Pailler 2011; Pack et al. 2016; Golden Kroner et al. 2019). Specifically, during recent decades, size reductions were enacted for 40 PAs in the Brazilian Amazon—covering an area of 157,377 km^2—with 25 PA erasures concentrated between 2009 and 2012, covering 42,113 km^2 (fig. 1). The recent election of and actions by President Jair Bolsonaro also have sent clear signals about the prioritization of economic growth over conservation.[1] Thus, the net incentives to clear forests have been increased. Forest fires, which have doubled compared to last year, are in part a consequence of such deforestation (Casarões and Flemes 2019; Escobar 2019).

1.2. Conceptual Framework: Where PAs and PA Size Reductions Have Impacts on Forests

Frontier deforestation for agriculture is often said to follow core patterns observed since von Thünen (Angelsen 2007, 2010; Sims 2014). If a risk-neutral agent makes the choice to clear forest on unprotected parcel i, she earns rents Y_i, equal to the price in the nearest market, p, times yield which is a function of land quality, $f(Q_i)$. From those revenues, we must subtract transport costs for getting output to market, which makes profits (π_i) a function of distance to market. While transport costs might be constant per unit distance, generally transport costs will make agricultural profits a function of distance, $\pi(p, Q_i, d_i)$, which falls with d_i. Forest clearing then falls with d_i and ends at $\bar{d}_i$, where $\pi(d_i)$ equals zero[2] (fig. 3).

If forest clearing is illegal on the parcel—in PAs or on private lands, given regulations—then enforcement with probabilistic apprehension and fines reduces expected profits by an expected fine $F(d_i) = F \times \text{Prob}(d_i)$ ("typical" enforcement regimes support assumptions of imperfect monitoring; Albers 2010; Sims 2014). That is a function of distance, since public agencies are located in market cities; thus, the probability of apprehension is a decreasing function of distance because, just like transport cost to market, the cost of enforcement rises with the urban distance.[3] Net profits when facing enforcement are then $\pi_i(d_i) - F(d_i)$, the difference between two decreasing functions of the distance to the nearest market (and agency) city.

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1. PADDDtracker 2.1 (Conservation International and World Wildlife Fund 2021) shows 127 proposed and enacted PADDD events in total during 2016–21.

2. Deforestation could go beyond $\bar{d}_i$ given speculative deforestation to capture future expected profits, including in land sales (Angelsen 2007; Miranda et al. 2019). Yet even if our predicted clearing level could be off (e.g., is not truly zero beyond $\bar{d}_i$), speculative clearing can occur anywhere, and thus we believe that our comments on gradients across space remain relevant. That remains true for expectations of infrastructure development, if those are not strongly positively correlated to distance. Other deviations from literal interpretations of our model exist, including if frontier inhabitants are clearing for subsistence. Whether that scenario upsets the gradients we discuss again depends on a strong positive correlation with market distance. Certainly we do not wish to rule either of these out, even while laying out this big-picture framework we believe is relevant.

3. This idea likely applies to the distance into a PA from its edge (Albers 2010)—which yields predictions about pristine core areas, and effects of PA size, plus implications for optimal enforcement. Here we are not focused on the within-PA pattern.

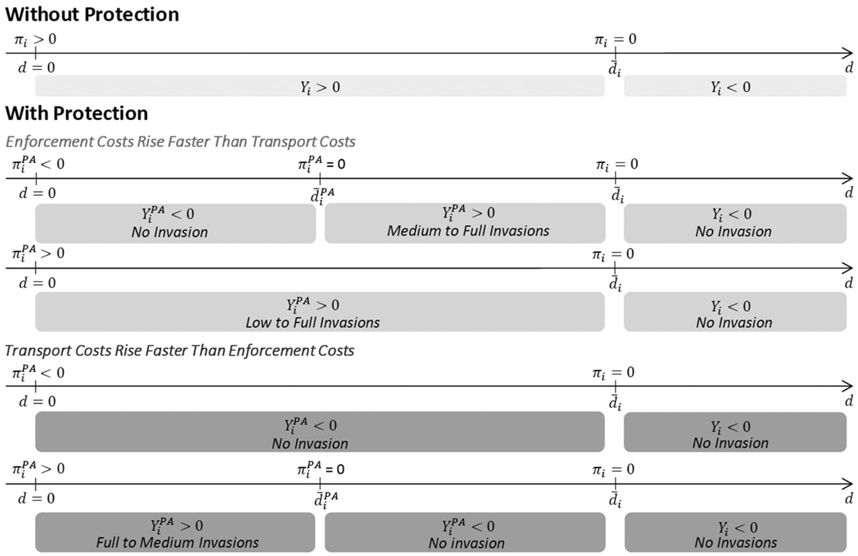

Figure 3. Landscape locations and protected areas (erasure) impacts

This applies to the Brazilian Amazon, where the imposition of costs on those acting illegally often takes the form of fines, or seizures (Assunção et al. 2017), while transport costs do indeed hinder enforcement; for example, patrol costs are lower near hubs (Börner et al. 2015). Consistent with that idea, illegal deforestation is higher when farther from urban centers (Sims [2014]; Keles et al. [2020] for Brazilian Amazon), although enforcement using satellite detection could now focus where observed losses are high (Chen et al. 2021).

We focus on illegal clearing in PAs and, thus, the fine F that applies for PAs and the probability of clearing $\text{Prob}(d_i)$ that applies within PAs (which for any given distance is probably higher than on private lands). We assume F is fixed across PAs, while $\text{Prob}(d_i)$ varies across PAs because they vary in urban distance, and define $\bar{d}_i^{\text{PA}}$ as a distance at which the profits with enforcement $\pi^{\text{PA}}{}_i = \pi(p, Q_i, d_i) - F \times \text{Prob}(d_i) = 0$. Development agents bargain to reduce PAs' sizes to raise profit from forest clearing (Tesfaw et al. 2018; Keles et al. 2020), since if part of any PA is erased then the fines disappear for clearing that forest area.

Across the scenarios we consider in figure 3, we see that where PADDD occurs affects its impact. As stated earlier, the erasure of a PA raises deforestation only where that PA faced and blocked pressure. In each scenario, as noted just above, profits and expected fines fall as the distance to the city increases. However, which of these two functions falls faster with urban distance will vary across those scenarios. The other thing that varies across scenarios is whether PA invasions are profitable very close to the city, which we believe could go either way. On the one hand, enforcement clearly is easiest close to the city. On the other hand, clearly more people face the highest possible profits if they can extract near a market.

In figure 3, in the first and second With Protection rows, expected fines fall faster with distance than profits, implying that profit with enforcement will be rising as we move away from the city (although since the lowest chance of being caught is zero, the maximum for this is just regular profit, which is zero at $\bar{d}_i$). In the first row, that trend in the profits starts out with enforcement being effective near a city. Profit with enforcement is negative when the distance is zero. It could stay negative until $\bar{d}_i$, yet as shown here may become positive for a range. PAs block clearing out to $\bar{d}_i^{PA}$; thus size reductions hurt closer to the city.

In contrast, in the second row, that same trend starts with the enforcement not being effective near the city, that is, profit is positive in PAs. If so, rising profit with enforcement only further raises clearing incentives, such that the PA never blocks clearing. In that case, we do not expect PA size reductions to increase losses.

In figure 3's third and fourth With Protection rows, now profits fall faster with distance than expected fines, implying that profit with enforcement will be falling as we move away from the city (unlike for above). In the third row, that trend in profit with enforcement starts with enforcement being effective near a city. Profit with enforcement is negative if distance is zero. If so, falling profit means the PA blocks clearing out to where profit is zero (so PAs cannot have impact). Here, we expect PA size reductions to raise loss. In the fourth row, that same trend starts with ineffective enforcement (profits > 0 in PAs) near to the city. Then faster-falling profits costs can yield an intermediate range with impacts, where PA reductions hurt.

2. EMPIRICAL APPROACH

2.1. Data

2.1.1. Units of Observation

We randomly drew 1,027,881 pixels[4] from across the entire Brazilian Legal Amazon, checking that the initial distribution of pixels in PAs and unprotected lands matched land use (≃10% of land protected as of 2000). To address spatial autocorrelation, we enforced a 1 km minimum distance between draws (Blackman 2013; Avelino et al. 2016; Velly and Dutilly 2016). We also dropped some observations, due to the possibility of local PA "leakage," which affects land use nearby. Specifically, we exclude

4. Using pixels may not be best if the process leading to land-use change occurs at a larger scale and if it has any spillovers in space, while grids may help to overcome these issues, as they aggregate pixels within a defined polygon (Avelino et al. 2016). Naturally, any arbitrarily chosen polygon size may also miss the true process scale, with inefficiencies (Blackman 2013; Avelino et al. 2016). Yet pixels can allow more precise definitions of treated and controls groups (Le Velly and Dutilly 2016).

from the controls a 20 km buffer zone around each PA (Joppa and Pfaff 2011; Blackman 2013; Nolte et al. 2013), and we also have run robustness checks in which, instead, we drop buffers around PAs of only 10 km.

2.1.2. Variables

We use forest loss at a 30 × 30 m resolution from Global Forest Change (Hansen et al. 2013). These data indicate tree-cover density (10%–75%) in 2000, for trees over 5 meters in height, and whether a pixel was cleared each year from 2001 to 2015 (the distribution of forest loss can be seen in fig. 4, juxtaposed with PAs and size reductions). We use the label "forest" if tree-cover density is at least 30%.[5] Global Forest Change data do not indicate a difference between natural and secondary planted forests (Tropek et al. 2014; Sexton et al. 2016) and do not allow computation of net annual forest-cover losses. Our deforestation outcome is a binary variable indicating whether forest cover has been lost: in 2001–8, pre-size-reduction, or in 2010–15, per impacts of size reductions (considering points forested in 2010). Forest cover is seen as lost when the forest indicator falls to zero during the period in question.

To check robustness, we also use Tropical Moist Forest (TMF) data from the European Commission's Joint Research Centre (Vancutsem et al. 2021). Measured at the same resolution as Global Forest Change, TMF data also depict a land-transition map, with degradation and regrowth, trying not to include tree plantations. We start with undisturbed forests, defined as a "closed evergreen or semievergreen forest without any disturbance . . . with old secondary forests or forests that have been degraded in years before the start of the Landsat archive" (Vancutsem et al. 2021, 1). Our binary outcome variable equals one if any such pixel was deforested or degraded by the end of the period. Deforestation refers to "a change in land cover (from forest to nonforested land)" while degradation refers to "a temporary disturbance in a forest remaining forested such as selective logging, fires and unusual weather events (hurricanes, droughts, blowdown)" (JRC 2022).

We use PAs from the World Database on Protected Areas (WDPA) (IUCN and UNEP-WCMC 2016), a spatially explicit database of PAs' boundaries. We only use PAs that could be recorded as reduced in size, the "units of conservation" in the National System of Protected Areas (Sistema Nacional de Unidades Conservação [SNUC]) for Brazil. Thus, we dropped both Indigenous Lands and Quilombola Territories. Conservation units are classified by their IUCN categories defining the activities permitted inside.[6] If a location appears in multiple PAs' boundaries, we assigned it to the strictest classification among them.

5. Per the definition of tropical forest in the United Nations Framework Convention on Climate Change ("area of at least 0.5 ha with 10 to 30% tree cover density" [Chazdon et al. 2016]) as well as the CBD (Convention on Biological Diversity 2019).

6. Categories I to III are considered strictly managed, with human uses from strictly prohibited to recreational purposes. Categories IV to VI are sustainable use, where people are a central element or where sustainable use of resources is allowed.

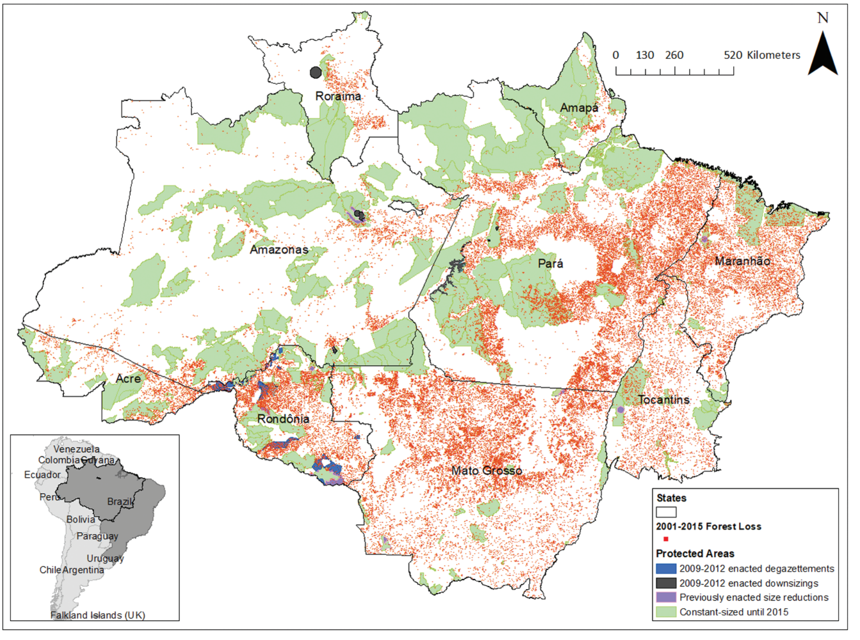

Figure 4. Protected areas (PAs), PA size reductions, and deforestation in the Brazilian Amazon. Source: author (using Hansen et al. 2013; IUCN and UNEP-WCMC 2016; Conservation International and WWF 2017).

To study PADDD—specifically PA size reductions (downsizing and degazettement—we utilize the PADDDtracker.org Data Release Version 1.1 (Conservation International and World Wildlife Fund 2017), which provides spatially explicit data describing all the reductions in PAs' boundaries from 1970 to 2015. We study impacts of size reductions for pixels protected in 2008 (147,041 pixels), distinguishing which PAs were reduced in size during 2009–12, instead of remaining constantly protected through 2015, that is, the constant-sized PAs (see fig. 4). We find 3,369 of the former pixels and 143,672 of the latter.

Conservation's opportunity cost is affected by lands' biophysical and socioeconomic characteristics that affect agricultural suitability. We use slope and elevation from the Shuttle Radar Topography Mission (SRTM) (Jarvis et al. 2008), 1995–2015 rainfall levels from version 2.0 of Climate Hazard Group InfraRed Precipitation with Station Data (CHIRPS) and WorldClim (Funk et al. 2015) and an indicator for whether soil from Global Agro-Ecological Zones (FAO and IIASA 2020) is suitable for high-input rain-fed farming.

Rents also depend on market access. We use roads as a proxy: in 1996, from the Center for International Earth Science Information Network (CIESIN 2015) and, in 2006, from the Brazilian Departamento Nacional de Infraestrutura de Transportes

(DNIT 2017). We also use the network of navigable rivers as well as "major cities," both from the Environmental Systems Research Institute (IBGE 2017; ESRI 2019).[7] As supplementary indicators of overall economic pressure, we use 2001–12 agricultural fires from the Socioeconomic Data and Application Center (SEDAC) (van der Werf et al. 2017) as well as 2000–13 nighttime lights from the National Centers for Environmental Information (Baugh et al. 2010).

2.2. Methods

2.2.1. States as Contexts

We presume that the three states in which PAs were reduced in size represent different contexts. Working within a state holds fixed many variables—some hard to observe—while the states differed in average deforestation pressures. As in section 3.2, Roraima has low pressure and size reductions in 2009; Pará has more pressure, with reductions in 2012; and Rondônia has higher pressure, with 2010 reductions.

2.2.2. Two-Way Fixed Effects

For each context, we run two-way fixed-effects panels (TWFE) differences-in-differences, of the form:

$$Y_{it} = \beta_0 + \beta_1 \mathrm{PADDD}_i + \alpha_i + \lambda_t + \theta X_{it} + \varepsilon_{it}, \quad (1)$$

where Y_{it} represents whether a pixel i is deforested at year t, while PADDD_i equals 1 when a PA has been reduced in size and 0 otherwise, noting that our untreated units are PAs that remained constant in size. We also include pixel fixed effects α_i and year fixed effects λ_t that account, respectively, for fixed unobservable differences between treated and untreated units and common shocks that could influence our outcome. The term X_{it} is a vector of time-varying control variables, while ε_{it} is the error term of the model.

2.2.3. New DID Estimators

TWFE identifies treatments' effects if the assumption of "parallel trends" holds, that is, the evolutions of treated and untreated units' mean outcomes would be the same without treatment (below we present our effort to use matching to raise the chance this holds for subsets). Recent literature shows that another key assumption is a homogeneous effect of the treatment for all units and over time (de Chaisemartin and D'Haultfœuille 2020). As previewed above, that assumption is unlikely to hold across our contexts.

7. We use driving factors regularly found as significant in literatures on tropical deforestation (distance, slopes, soil quality). These covariates are significant here in a ordinary least squares regression where deforestation is the dependent variable.

Standard TWFE estimators can helpfully be viewed as weighted sums of individual treatment effects for each unit-year cell (de Chaisemartin and D'Haultfœuille 2020), revealing that TWFE estimators can be biased if treatment effects are heterogeneous. Some underlying effects can then receive negative weight (de Chaisemartin and D'Haultfoeuille 2020; Callaway and Sant'Anna 2021; Sun and Abraham 2021). Our main results thereby make use of de Chaisemartin and D'Haultfoeuille's (2022, 2020) DID estimator (DID_L), which is robust to heterogeneous treatment effects. Our standard errors are estimated using a bootstrap with 100 replications. We also present parallel-trends tests from FEct (in R, Liu et al. 2022).[8]

2.2.4. Prepanel Matching (Effectively Identifying Subcontexts)

TWFE's main identification assumption is parallel trends, that is, that the deforestation trends in the size-reduced and constant-sized PAs would have been the same had there not been any PA size reductions. Site selection for size reduction due to bargaining can make this unlikely or at least challenging to assert. Selection could be across state, of course, if environment or development interests prefer some contexts. Within any state, significant selection implies that settings for the size-reduced PAs differ, meaningfully, from other settings in that state. This, in turn, suggests that at least some constant PAs are not good controls.

Fortunately, while our matching is not always successful (as is documented below regarding selection), efforts to match treated and untreated PAs within each state often find subgroups of the constant-sized PAs for which prereduction trends are parallel to prereduction loss in size-reduced PAs (for average treatment effects on the treated [ATTs] and vice versa for average treatment effects on the untreated [ATUs]). We use propensity-score matching, defining "similarity" as treatment probabilities from probit models for the size reductions (Caliendo and Kopeinig 2008; Ferraro and Hanauer 2014; Velly and Dutilly 2016). To raise observations for postmatching inferences, we could match a treated observation to multiple untreated observations—raising dissimilarity and bias. We employ the nearest neighboring pixels, without replacement, using a caliper of 0.5 standard deviations of the estimated propensity scores.[9] Thus, we exploit pretreatment years. Beyond visually inspecting pretreatment dynamics, we use de Chaisemartin and D'Haultfoeuille and the FEct R package (Liu et al. 2022)

8. It is worth noting that the de Chaisemartin and D'Haultfoeuille's DID_L estimator also (and perhaps uniquely to date) applies also to "unstaggered" designs, in which the treatment not only "switches on," i.e., starts, but also then can "switch off" again. Further, de Chaisemartin and D'Haultfoeuille (2022) showed that when such TWFE regressions include multiple treatments, the TWFE estimators for each of those treatments can be biased by the effects of all the other treatments.

9. Given a small sample in Roraima, we use 3-1 matching (again with replacement and caliper of 0.5 standard deviations).

for pretreatment placebo tests. We estimate TWFE and DID_L for the groups that pass parallel-trends tests, with an indication of (negative) weights on each treatment effect (de Chaisemartin and D'Haultfœuille 2020).

Concerning the similarity achieved, we examine standardized mean differences, tests of distributions, and remaining standardized biases. Gains from matching depend upon these differences being reduced (Ferraro and Hanauer 2014; Velly and Dutilly 2016). Hidden biases may remain if confounding variables are unobserved. Given this possibility, our standard errors use the variance approximation developed by Abadie and Imbens (2006). We also follow Rosenbaum (2002) to check how sensitive are propensity-score-matching results to potential biases. This "bounding" test reveals what value of such unobserved confounders would, itself, raise the odds of protection and deforestation by a factor of τ. If the average treatment effects are still significant for a large τ increase, it indicates some insensitivity to such biases.

3. RESULTS

3.1. Overall Descriptive Statistics

Among all locations protected in 2000, ~ 98% of pixels were within PAs that remained constant in size, until at least 2015, while ~ 2% were in those PAs selected to be reduced in size between 2009 and 2012. The three states we examine represent 95% of all PA size reductions and 39% of constant-sized PAs. Most reductions (65%) are in Rondônia, while 17.8% and 12.5% are, respectively, in Pará and Roraima. Inside constant-sized PAs, on average, during 2001–8 only 0.9% of tree cover was lost (0.2% lost in Roraima, 0.6% in Rondônia, 1.7% in Pará). Except in Roraima, tree-cover losses during 2001–8 were far higher, on average, in the PAs selected to be reduced: 22.1% in Rondônia and 2.2% in Pará.

Forest-loss rates in the PAs selected for size reduction were above those in unprotected forest (table 1B in the supplementary materials; supplementary materials are available online). As to how deforestation rates differ so much for these PA subsets: constant PAs are, on average, farther from roads than unprotected forest (table 1B in the supplementary materials), while the opposite is true of size-reduced PAs (p-values at 1%). Thus, size-reduced PAs faced more pressures than constant PAs, and sometimes unprotected forests, given selection (Pack et al. 2016; Tesfaw et al. 2018; Keles et al. 2020).

3.2. Distinguishing Settings: Distinct Time Paths, with Spatiotemporal Matching

3.2.1. Low Pressure Nonimpacts of Reductions: Not Requiring Selection within Context

Figure 5*A*, for Roraima, supports our conjecture that low pressure limits impacts of PAs and, in turn, also limits the potential for a rise in forest loss due to PA size reductions. With low pressure, PAs that remained constant and to-be-reduced PAs suffered few 2001–8 losses. Selection for PA reductions thereby had little scope for impacts: pressures are low; thus reductions could do little short-run damage.

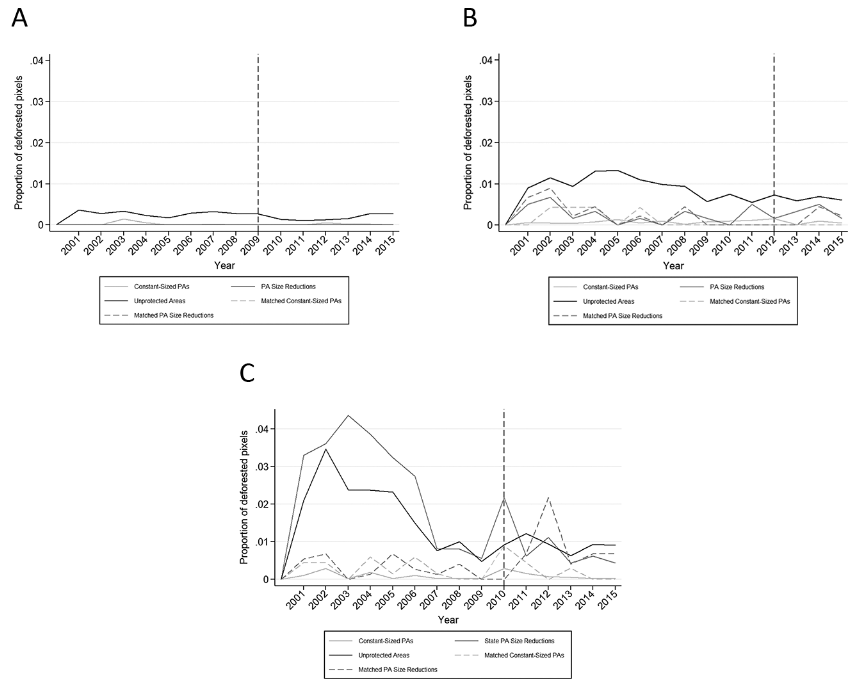

Figure 5. Deforestation trends. *A*, Roraima: low pressure limits impacts of protected areas (PAs) and size reductions. *B*, Pará: medium pressure and some enforcement, impacts depend on selection. *C*, Rondônia: higher pressure, considerable selection for state PA size reductions.

Confirming visual inspection (it is hard to see dotted lines for matched subsets as multiple lines overlap), placebo testing within the FEct R package (Liu et al. 2022) in figure 6*A* supports parallel trends. The *F* and equivalences test show that size-reduced PAs had the same deforestation trend as the best matched constant-sized PAs (supplementary materials table 2A for covariate balance before and after matching).

3.2.2. Medium Pressure: Nonimpact of PA Reductions Depends on the Selection for Reductions
Figure 5*B*, for Pará, shows that selection for size reductions affects their impacts. As seen in the rate of deforestation for unprotected forest (solid black line), pressure is higher than in Roraima. That provides potential for PA impacts and on average constant-sized PAs (solid light gray line) blocked most 2001–12 forest losses. Selection for size reductions is clear because the size-reduced PAs (solid medium gray line) did worse. Yet matching constant-sized PAs to the size-reduced PAs could allow for parallel trends and a defensible estimate of ATT. In figure 5*B* we see that matched constant-sized PAs (dotted light gray line) are more similar to the size-reduced PAs (solid medium gray line). Figure 6*B* confirms that postmatching, these PA subsets

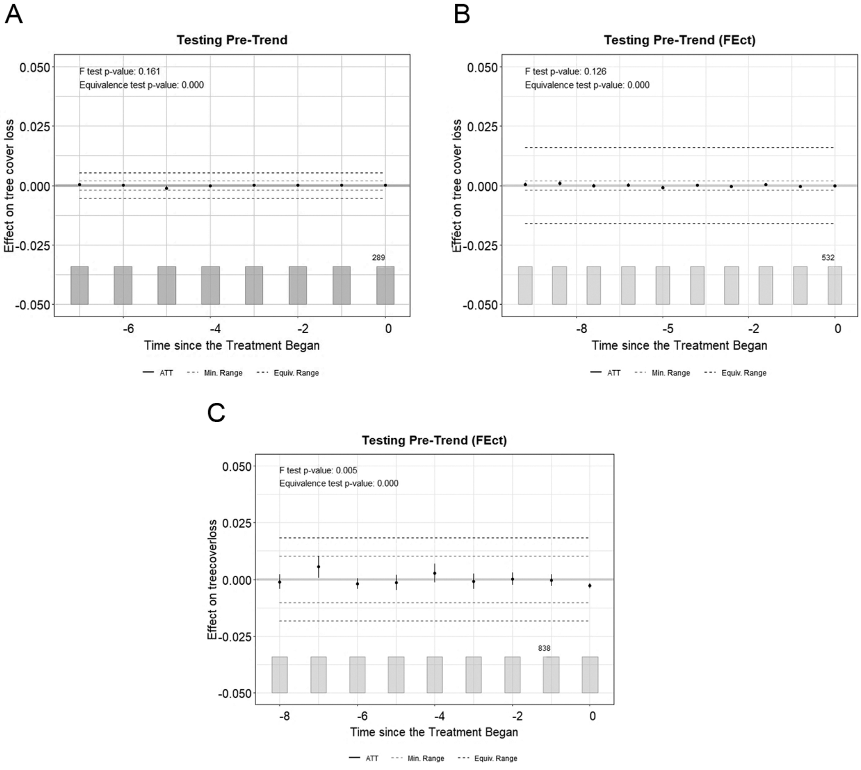

Figure 6. Parallel trends test (FEct). *A*, Roraima average treatment effect on the untreated (ATU). *F*: tests if average (observed – predicted) outcome before treatment equals 0. Equivalence: tests the same versus a prespecified difference (Liu et al. 2022). *B*, Pará average treatment effect on the treated (ATT). *F*: tests if average (observed – predicted) outcome before treatment equals 0. Equivalence: tests the same versus a prespecified difference (Liu et al. 2022). C, Rondônia ATU. *F*: tests if average (observed – predicted) outcome before treatment equals 0. Equivalence: tests the same versus a prespecified difference (Liu et al. 2022).

trend similarly enough to estimate ATT (table 2B in supplementary materials for covariate balances). However, where we most expect to find impacts of size reductions would be within the ATU, as these constant-sized PAs performed well. If any size-reduced PAs performed similarly, the matched subset of sized-reduced PAs would have faced and blocked pressure, the recipe for impact. Yet figure 5*B* reveals that the matched size-reduced (dotted gray line) did not perform like the constant PAs (light gray line).

3.2.3. High Pressure: Again Nonimpact for Reductions Depends on the Selection for Reductions
Figure 5C, for Rondônia, again shows that selection for size reductions affects the impacts of reductions. As clear from the deforestation for unprotected forest (solid black

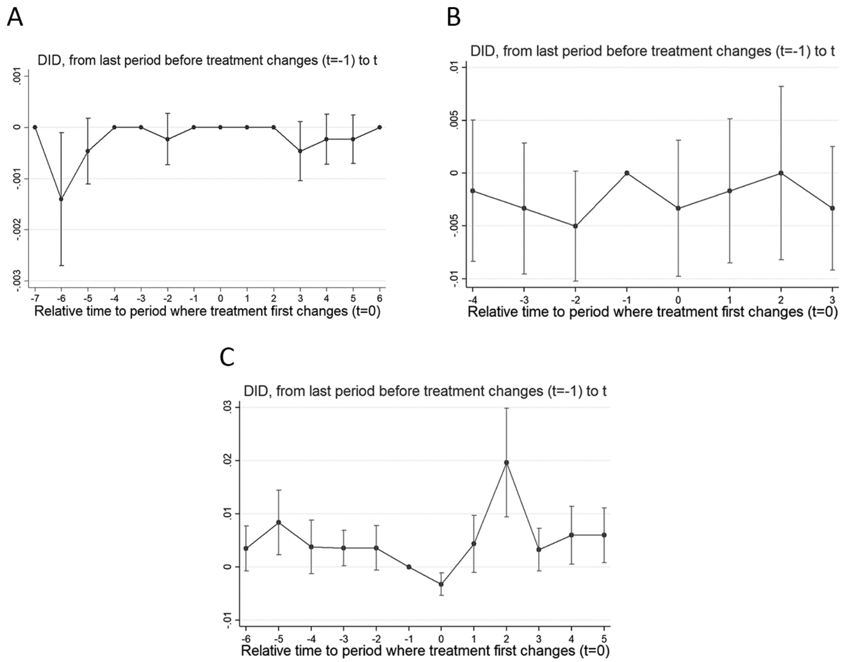

Figure 7. Trends tests and estimates. *A*, Roraima average treatment effect on the untreated (ATU) (de Chaisemartin and D'Haultfœuille 2020). Average effect: −.000 (SE: .000); *p*-value of the joint test that all the placebos are equal to 0: 0.38. *B*, Pará average treatment effect on the treated (ATT) (de Chaisemartin and D'Haultfœuille 2020). Average effect: −0.002 (SE: 0.003); *p*-value of the joint test that all the placebos are equal to 0: 0.16. *C*, Rondônia ATU (de Chaisemartin and D'Haultfœuille 2020). Average effect: .007 (SE: 0.006***); *p*-value of the joint test that all the placebos are equal to 0: 0.00.

line), pressures are higher than above. Impressively, constant-sized PAs still show little loss (solid light gray line). In great contrast, state-managed size-reduced PAs (solid medium gray line) seem effectively unenforced: forest loss is equal, or above, unprotected. That parallel movement of unprotected and sized-reduced PAs continues after 2010 PA size reductions, while even the best-matched constant PAs (dotted light gray line) performed far better than reduced PAs, undermining ATT (yet post-2007 trends are more parallel) (see table 2C in supplementary material for covariate balances). Nonetheless, we feel that the solid medium gray line tracking the solid black line supports the "unblocked pressure" case for no impact. Again, with well-functioning constant PAs, ATU could find some PADDD impacts: "imperfect environmental selection" (or "development selection"), in which size-reduced PAs did well before being reduced, makes PAs candidates for impacts. Figure 5*B* shows that the matched subset of reduced PAs (dotted gray line) is far closer to constant PAs (solid light gray line). Figure 6C confirms parallel trends.

3.3. Panel Regressions Using Matched Subsets for Forest Impacts of Selective PA Erasures

3.3.1. Low Pressure Nonimpacts of Reductions: Not Requiring Selection within Context

Figure 7*A* shows the results of the DID_L estimator for both pretreatment and posttreatment periods, that is, another test of parallel trends (to go with fig. 6*A* from FEct) plus estimates of PADDD impacts. With at least five pre-PADDD periods of no significant differences, de Chaisemartin and D'Haultfoeuille (2020) would have us consider only five periods posttreatment, all of which show no significant effect.

Table 1 shows TWFE panel regressions for Roraima (from fig. 6*A*). The regression for 2000–2015, in its only column, reveals no significant impact from PA size reductions in comparing matched subsets. For this case, it is hardly surprising that any of the sets of legitimate comparisons find no PADDD impact.

3.3.2. Medium Pressure: Nonimpact of PA Reductions Depends on the Selection for Reductions

Figure 7*B* conveys that with some pressure, resulting in some loss of forest within the PAs selected for size reductions, it was not as easy to very closely match the treated PA with a subset of the constant PAs. However, matching on both fixed characteristics and pretreatment deforestation levels (see fig. 5*B*) manages to find similar enough PAs that

Table 1. Roraima ATU (TWFE)

	2000–2015
PA size reductions	–.000
	(.001)
Year	–.000
	(.000)
Agricultural fires	–.000
	(.000)
Average temperatures	.000
	(.000)
Average rainfalls	.000
	(.000)
Constant	.038
	(.044)
R^2	.09
N	51,205

Note. Due to the low number of observations, it is not possible to estimate the coefficient during 2007–15. ATU = average treatment effect on the untreated; TWFE = two-way fixed effects; PA = protected area.

parallel trends hold again. Relative to those strongly matched constant PAs, looking out three periods there does not appear to be a significant impact from size reduction.

Table 2 shows TWFE panel regressions for Pará (from fig. 6*B*). The regression for 2000–2015, in its initial column, reveals no significant impact from PA size reductions, comparing the matched subsets (recalling that for this case, with some pressure, ATU might have had impacts yet that the match was poor).

3.3.3. High Pressure: Again Nonimpact for Reductions Depends on the Selection for Reductions

Figure 7C shows the DID_L results for pre- (to go with fig. 6C from FEct) and posttreatment periods. With at least five pre-PADDD periods of no significant differences, de Chaisemartin and D'Haultfoeuille (2020) would have us consider only five periods posttreatment—which, in this case, show forest impacts. Given that here the PAs selected for size reduction were those that performed like the constant PAs that in turn performed quite well, finding a rise in deforestation due to PADDD is exactly what is predicted.

Table 3 shows TWFE panel regressions for Rondônia ATU, the matching for which parallel trends held (see fig. 5C), that is, size-reduced PAs that performed well prereduction, as did the constant-sized PAs. The TWFE regression for 2007–15 outcomes in studying state PA size reductions, in its second column, shows an average

Table 2. Pará ATT (TWFE)

	2000–2015	2007–15
PA size reductions	.002	–.001
	(.003)	(.004)
Year	–.000	.000
	(.000)	(.001)
Agricultural fires	.000	.000
	(.000)	(.000)
Average temperatures	.001	–.003
	(.002)	(.003)
Average night lights	–.000	–.000
	(.002)	(.002)
Average rainfalls	.000	.000
	(.000)	(.000)
Constant	.970	–..944
	(.664)	(1.977)
R^2	.09	.25
N	7,898	2,872

Note. ATT = average treatment effect on the treated; TWFE = two-way fixed effects; PA = protected area.

Table 3. Rondônia, State Events, ATU (TWFE)

	2000–2015	2007–15
PA size reductions	.005	.008
	(.001)***	(.002)***
Year	.000	.000
	(.000)	(.000)**
Agricultural fires	.000	–.000
	(.009)	(.000)**
Average temperatures	–.000	–.003
	(.000)	(.01)**
Average night lights	–.003	–.012
	(.002)	(.004)***
Average rainfalls	–.000	–.000
	(.000)	(.000)
Constant	–.057	–1.386
	(.1441)	(.593)**
R^2	.09	.25
N	42,962	15,628

Note. ATU = average treatment effect on the untreated; TWFE = two-way fixed effects; PA = protected area.

annual loss of 0.008%. That is also true, if smaller in magnitude, when using all events in Rondônia for 2000–2015. This result is robust to a 10 km buffer (section 3C in the supplementary materials).

4. DISCUSSION

Global commitments by the Brazilian government on biodiversity and the reduction of GhG emissions already were somewhat difficult to reach (Campos-Silva et al. 2015; Gallo and Albrecht 2019; Visconti et al. 2019) despite past PA investments that, on average, had reduced deforestation (Amin et al. 2019). Achieving them seems far less likely given recent policy, including implicit and explicit permissions for economic activity to impinge on PAs. That includes PADDD (downgrading, downsizing, degazettement of PAs) (Naughton-Treves and Holland 2019; Qin et al. 2019). Few have studied PADDD, in particular controlling for where PAs were selected to be reduced in size—which affects those reductions' impacts.

In evaluating impacts of 2009–12 PA size reductions in the Brazilian Amazon upon post-erasure 2010–15 forest loss, we go beyond Pack et al. (2016) and Tesfaw et al. (2018). We extend understanding of erasures' impacts by looking further over time and considering heterogeneity in impacts across space. We consider contexts that diverge from "canonical" contexts for PADDD to lead to short-run forest loss. Conceptually we lay out which size reductions should increase forest loss by more or by less, noting that only for those PAs that had previously lowered deforestation should we expect impacts from erasures.

Empirically, we evaluate impacts of PA size reductions upon rates of tree-cover loss, for specific contexts. We documented that the relevant selection dynamics led to the 2009–12 PA size reductions within the Brazilian Amazon occurring within three contexts implying (little or) no impact from PA size reductions, at least in the short run. First, for low pressure outside of the "arc of deforestation," there is little loss of tree cover and, thus, no impacts. This requires no selection within this context—only selections into it.

Second, for medium pressure, if the PAs selected for size reductions are those that blocked pressure considerably less than PAs allowed to remain constant in size, there is much less room for impacts on the forest from erasing PAs. "Environmental selection" of the worst-performing PAs limits the damage. In this case, that is the situation for which we can best find good matches and we again find no impact.

Third, for high pressure, selection of the PAs which effectively fail to block that pressure can effectively guarantee that erasure of those PAs cannot do much damage. To first order, the worst that could happen should be that the PAs continue to be unenforced, with deforestation rates like the unprotected forests. We see this case, again implying no impact. However, for this case, "development selection" of some PAs for reductions which had been performing well before reduction could well lead to impacts of erasures. That is precisely the situation for which we could find some good matches, to show that forest was lost.

While we extend prior studies (Pack et al. 2016; Tesfaw et al. 2018), our results are relatively short term. Over time, size reductions and more generally PADDD can unleash distinct socioeconomic dynamics. Our results also do not consider spatial spillovers from PA erasures that can extend beyond PAs' borders (Herrera et al. 2019). Prodevelopment signals could foster land-clearing behaviors, even within PAs, and could be investigated by looking at how PADDD events affect land prices (Miranda et al. 2019).

Depending on their causes (rural settlement, extraction, or infrastructure like roads), PADDD may have longer-run, spatially broader impacts on economic activities (Tesfaw et al. 2018). Further research will be needed to examine such reversal of proforest signaling achieved by protection (Herrera 2015). Even in low-pressure areas, PAs could act as a barrier to future development pressure, which PADDD would threaten. Evaluating that impact would require different approaches from those employed here.

We note that, since 2015, further PA size reductions have been proposed and enacted, consistent with a relaxation of environmental policies in the Amazon since 2012 (Rochedo et al. 2018; Carvalho et al. 2019; Ferrante and Fearnside 2019). Thus, calls to extend the PA network and to effectively manage the PAs to limit environmental degradation now seem less likely to be answered (Golden Kroner et al. 2019). If the scale of PA size reductions keeps rising, limiting those to contexts with low damage could get harder.

Understanding risks and impacts of PA size reductions informs PA siting, enforcement, management, and advocacy—including efforts to guide size reductions to lower damages. These points hold globally, noting that PADDD and other regulatory rollbacks are arising broadly of late, in part with some connections to economic pressures from many shutdowns due to the pandemic (Conservation International 2020). Should our conceptual framework and empirical results be a guide, from the development side PA size reductions are likely to be proposed near forest pressure (Symes et al. 2016; Tesfaw et al. 2018; Golden Kroner et al. 2019; Qin et al. 2019; Keles et al. 2020). For conservation, enforcement in such sites has big gains.

REFERENCES

Abadie, Alberto, and Guido W. Imbens. 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica* 74 (1): 235–67.

Albers, H. J. 2010. Spatial modeling of extraction and enforcement in developing country protected areas. Special issue, Spatial Natural Resource and Environmental Economics. *Resource and Energy Economics* 32 (2): 165–79.

Amin, A., J. Choumert-Nkolo, J. L. Combes, P. Combes Motel, E. N. Kéré, J. G. Ongono-Olinga, and S. Schwartz. 2019. Neighborhood effects in the Brazilian Amazônia: Protected areas and deforestation. *Journal of Environmental Economics and Management* 93:272–88.

Angelsen, Arild. 2007. Forest cover change in space and time: Combining the Von Thunen and forest transition theories. Policy Research Working paper, World Bank, Washington, DC.

———. 2010. Policies for reduced deforestation and their impact on agricultural production. *Proceedings of the National Academy of Sciences* 107 (46): 19639–44.

Araujo, Claudio, Catherine Araujo Bonjean, Jean-Louis Combes, Pascale Combes Motel, and Eustaquio J. Reis. 2009. Property rights and deforestation in the Brazilian Amazon. *Ecological Economics* 68 (8): 2461–68.

Arima, Eugenio Y., Paulo Barreto, Elis Araújo, and Britaldo Soares-Filho. 2014. Public policies can reduce tropical deforestation: Lessons and challenges from Brazil. *Land Use Policy* 41:465–73.

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager. 2021. Synthetic difference-in-differences. *American Economic Review* 111 (12): 4088–4118.

Assunção, Juliano, Clarissa Gandour, and Romero Rocha. 2017. DETERring deforestation in the Amazon: Environmental monitoring and law enforcement. Climate Policy Initiative/PUC-Rio Working paper.

Assunção, Juliano, Clarissa Gandour, and Rudi Rocha. 2015. Deforestation slowdown in the Brazilian Amazon: Prices or policies? *Environment and Development Economics* 20 (6): 697–722.

Avelino, Andre Fernandes Tomon, Kathy Baylis, and Jordi Honey-Rosés. 2016. Goldilocks and the Raster grid: Selecting scale when evaluating conservation programs. *PLOS One* 11 (12): e0167945.

Azevedo-Ramos, Claudia, and Paulo Moutinho. 2018. No man's land in the Brazilian Amazon: Could undesignated public forests slow Amazon deforestation? *Land Use Policy* 73:125–27.

Baugh, Kimberly, Christopher Elvidge, Ghosh Tilottama, and Daniel Ziskin. 2010. Development of a 2009 stable lights product using DMSP-OLS data. *Proceedings of the Asia-Pacific Advanced Network* 30.

Ben-Michael, Eli, Avi Feller, and Jesse Rothstein. 2021. The augmented synthetic control method. *Journal of the American Statistical Association* 116 (536): 1789–1803.

Bernard, E., L. A. O. Penna, and E. Araújo. 2014. Downgrading, downsizing, degazettement, and reclassification of protected areas in Brazil. *Conservation Biology* 28 (4): 939–50.

Blackman, Allen. 2013. Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics* 34:1–16.

Börner, Jan, Krisztina Kis-Katos, Jorge Hargrave, and Konstantin König. 2015. Post-crackdown effectiveness of field-based forest law enforcement in the Brazilian Amazon. *PLOS One* 10 (4): e0121544.

Caliendo, Marco, and Sabine Kopeinig. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22 (1): 31–72.

Callaway, Brantly, and Pedro H. C. Sant'Anna. 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics* 225 (2): 200–230.

Campos-Silva, João Vitor, Sinomar Ferreira da Fonseca Junior, and Carlos Augusto da Silva Peres. 2015. Policy reversals do not bode well for conservation in Brazilian Amazonia. *Natureza y Conservação* 13 (2): 193–95.

Carranza, Tharsila, Andrew Balmford, Valerie Kapos, and Andrea Manica. 2014. Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: The Brazilian Cerrado. *Conservation Letters* 7 (3): 216–23.

Carvalho, William D., Karen Mustin, Renato R. Hilário, Ivan M. Vasconcelos, Vivianne Eilers, and Philip M. Fearnside. 2019. Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed. *Perspectives in Ecology and Conservation* 17 (3): 122–30.

Casarões, Guilherme, and Daniel Flemes. 2019. *Brazil first, climate last: Bolsonaro's foreign policy*. GIGA Focus Lateinamerika 5. Hamburg: GIGA German Institute of Global and Area Studies, Leibniz-Institut für Globale und Regionale Studien, Institut für Lateinamerika-Studien.

Chazdon, Robin L., Pedro H. S. Brancalion, Lars Laestadius, Aoife Bennett-Curry, Kathleen Buckingham, Chetan Kumar, Julian Moll-Rocek, Ima Célia Guimarães Vieira, and Sarah Jane Wilson. 2016. When is a forest a forest? Forest concepts and definitions in the era of forest and landscape restoration. *Ambio* 45 (5): 538–50.

Chen, Bohan, Kaiyan Peng, Christian Parkinson, Andrea L. Bertozzi, Tara Lyn Slough, and Johannes Urpelainen. 2021. Modeling illegal logging in Brazil. *Research in the Mathematical Sciences* 8 (2): 29.

CIESIN (Center for International Earth Science Information Network). 2015. *Gridded population of the world, version 4 (GPWv4): Administrative unit center points with population estimates*. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC), Columbia University.

Conservation International. 2020. Moore Center for Science mid-year highlights. Moore Center for Science, Arlington, VA.

Conservation International and WWF (World Wildlife Fund). 2017. PADDDtracker.org Data release version 1.1 (January 2017). Conservation International, Arlington, VA; World Wildlife Fund, Washington, DC.

———. 2021. PADDDtracker.org Data release version 2.1. Conservation International, Arlington, VA; World Wildlife Fund, Washington, DC.

Convention on Biological Diversity. 2019. Definitions. https://www.cbd.int/forest/definitions.shtml.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* 110 (9): 2964–96.

———. 2022. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. Working paper, National Bureau of Economic Research, Cambridge, MA.

DNIT (Departamento Nacional de Infraestrutura de Transportes). 2017. Sistema Nacional de Viação. http://www.dnit.gov.br/sistema-nacional-de-viacao/sistema-nacional-de-viacao.

Escobar, Herton. 2019. Brazilian president attacks deforestation data. *Science* 365 (6452): 419.

ESRI (Environmental Systems Research Institute). 2019. World cities. ESRI, Redlands, CA.

FAO (Food and Agriculture Organization) and IIASA (Institute for Landscape Architecture in South Africa). 2020. GAEZ Global Agro-Econological Zones. https://gaez.fao.org/pages/theme-details-theme-4.

Fearnside, Philip M. 2016. Brazilian politics threaten environmental policies. *Science* 353 (6301): 746–48.

Ferrante, Lucas, and Philip M. Fearnside. 2019. Brazil's new president and "ruralists" threaten Amazonia's environment, traditional peoples and the global climate. *Environmental Conservation* 46 (4): 261–63.

Ferraro, Paul J., and Merlin M. Hanauer. 2014. Advances in measuring the environmental and social impacts of environmental programs. *Annual Review of Environment and Resources* 39 (1): 495–517.

Ferreira, J., L. E. O. C. Aragão, J. Barlow, P. Barreto, E. Berenguer, M. Bustamante, T. A. Gardner, et al. 2014. Brazil's environmental leadership at risk. *Science* 346 (6210): 706–7.

Forrest, Jessica L., Michael B. Mascia, Sharon Pailler, Siti Zuraidah Abidin, Mara Deza Araujo, Roopa Krithivasan, and Juan Carlos Riveros. 2015. Tropical deforestation and carbon emissions from protected area downgrading, downsizing, and degazettement (PADDD). *Conservation Letters* 8 (3): 153–61.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, et al. 2015. The climate hazards infrared precipitation with stations: A new environmental record for monitoring extremes. *Scientific Data* 2.

Gallo, P., and E. Albrecht. 2019. Brazil and the Paris Agreement: REDD+ as an instrument of Brazil's Nationally Determined Contribution compliance. *International Environmental Agreements: Politics, Law and Economics* 19 (1): 123–44.

Gibbs, Holly K., Jacob Munger, Jessica L'Roe, Paulo Barreto, Ritaumaria Pereira, Matthew Christie, Ticiana Amaral, and Nathalie F. Walker. 2016. Did ranchers and slaughterhouses respond to zero-deforestation agreements in the Brazilian Amazon? *Conservation Letters* 9 (1): 32–42.

Golden Kroner, Rachel E., Roopa Krithivasan, and Michael B. Mascia. 2016. Effects of protected area downsizing on habitat fragmentation in Yosemite National Park (USA), 1864–2014. *Ecology and Society* 21 (3).

Golden Kroner, Rachel E., Siyu Qin, Carly N. Cook, Roopa Krithivasan, Shalynn M. Pack, Oscar D. Bonilla, Kerry Anne Cort-Kansinally, et al. 2019. The uncertain future of protected lands and waters. *Science* 364 (6443): 881–86.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. High-resolution global maps of 21st-century forest cover change. *Science* 342 (6160): 850–53.

Hargrave, Jorge, and Krisztina Kis-Katos. 2013. Economic causes of deforestation in the Brazilian Amazon: A panel data analysis for the 2000s. *Environmental and Resource Economics* 54 (4): 471–94.

Herrera Garcia, L. D. 2015. Protected areas' deforestation spillovers and two critical underlying mechanisms: An empirical exploration for the Brazilian Amazon. Doctoral diss., Duke University.

Herrera, Diego, Alexander Pfaff, and Juan Robalino. 2019. Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 116 (30): 14916–25.

IBGE (Brazilian Institute of Geography and Statistics). 2017. All products. IBGE: Geosciences. https://www.ibge.gov.br/en/geosciences/full-list-geosciences.html (accessed 2017).

INPE. 2019. PRODES: Coordenação-Geral de Observação da Terra. http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes.

IUCN (International Union for Conservation of Nature) and UNEP-WCMC (UN Environment Programme, World Conservation Monitoring Centre). 2016. The world database on protected areas (WDPA). UNEP-WCMC, Cambridge.

Jarvis, A., H. I. Reuter, A. Nelson, and E. Guevara. 2008. Hole-filled SRTM for the globe Version 4. CGIAR-CSI SRTM 90m Database. http://srtm.csi.cgiar.org.

Joppa, Lucas N., and Alexander Pfaff. 2011. Global protected area impacts. *Proceedings of the Royal Society B: Biological Sciences* 278 (1712): 1633–38.

JRC (Joint Research Centre). 2022. Tracking long-term (1990–2022) deforestation and degradation in tropical moist forests. https://forobs.jrc.ec.europa.eu/TMF/.

Jusys, Tomas. 2016. Quantifying avoided deforestation in Pará: Protected areas, buffer zones and edge effects. *Journal for Nature Conservation* 33:10–17.

———. 2018. Changing patterns in deforestation avoidance by different protection types in the Brazilian Amazon. *PLOS One* 13 (4): e0195900.

Keles, Derya, Philippe Delacote, Alexander Pfaff, Siyu Qin, and Michael B. Mascia. 2020. What drives the erasure of protected areas? Evidence from across the Brazilian Amazon. *Ecological Economics* 176:106733.

Kere, Eric Nazindigouba, Johanna Choumert, Pascale Combes Motel, Jean Louis Combes, Olivier Santoni, and Sonia Schwartz. 2017. Addressing contextual and location biases in the assessment of protected areas effectiveness on deforestation in the Brazilian Amazônia. *Ecological Economics* 136:148–58.

Liu, Licheng, Ye Wang, and Yiqing Xu. 2022. A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *American Journal of Political Science*.

Mascia, Michael B., and Sharon Pailler. 2011. Protected area downgrading, downsizing, and degazettement (PADDD) and its conservation implications. *Conservation Letters* 4 (1): 9–20.

Miranda, Javier, Jan Börner, Matthias Kalkuhl, and Britaldo Soares-Filho. 2019. Land speculation and conservation policy leakage in Brazil. *Environmental Research Letters* 14 (4): 045006.

Naughton-Treves, Lisa, and Margaret Buck Holland. 2019. Losing ground in protected areas? *Science* 364 (6443): 832–33.

Naughton-Treves, Lisa, Margaret Buck Holland, and Katrina Brandon. 2005. The role of protected areas in conserving biodiversity and sustaining local livelihoods. *Annual Review of Environment and Resources* 30 (1): 219–52.

Nogueira, Euler Melo, Aurora Miho Yanai, Sumaia Saldanha de Vasconcelos, Paulo Maurício Lima de Alencastro Graça, and Philip Martin Fearnside. 2018. Brazil's Amazonian protected areas as a bulwark against regional climate change. *Regional Environmental Change* 18 (2): 573–79.

Nolte, Christoph, Arun Agrawal, Kirsten M. Silvius, and Britaldo S. Soares-Filho. 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 201214786.

Pack, Shalynn M., Mariana Napolitano Ferreira, Roopa Krithivasan, Jennifer Murrow, Enrico Bernard, and Michael B. Mascia. 2016. Protected area downgrading, downsizing, and degazettement (PADDD) in the Amazon. *Biological Conservation* 197:32–39.

Pfaff, Alexander, Juan Robalino, Diego Herrera, and Catalina Sandoval. 2015. Protected areas' impacts on Brazilian Amazon deforestation: Examining conservation-development interactions to inform planning. *PLOS One* 10 (7): e0129460.

Pfaff, A., J. Robalino, E. J. Reis, R. Walker, S. Perz, W. Laurance, et al. 2018. Roads and SDGs, tradeoffs and synergies: Learning from Brazil's Amazon in distinguishing frontiers. *Economics* 12 (1).

Pfaff, Alexander, Juan Robalino, G. Arturo Sanchez-Azofeifa, Kwaw S. Andam, and Paul J Ferraro. 2009. Park location affects forest protection: Land characteristics cause differences in park impacts across Costa Rica. *B. E. Journal of Economic Analysis and Policy* 9 (2): 1–26.

Qin, Siyu, Rachel E. Golden Kroner, Carly Cook, Anteneh T. Tesfaw, Rowan Braybrook, Carlos Manuel Rodriguez, Claire Poelking, and Michael B. Mascia. 2019. Protected area downgrading, downsizing, and degazettement as a threat to iconic protected areas. *Conservation Biology* 33 (6): 1275–85.

Rochedo, Pedro R. R., Britaldo Soares-Filho, Roberto Schaeffer, Eduardo Viola, Alexandre Szklo, André F. P. Lucena, Alexandre Koberle, Juliana Leroy Davis, Raoni Rajão, and Regis Rathmann. 2018. The threat of political bargaining to climate mitigation in Brazil. *Nature Climate Change* 8 (8): 695–98.

Rosenbaum, Paul R. 2002. Overt bias in observational studies. In *Observational studies*, ed. Paul R. Rosenbaum, 71–104. Springer Series in Statistics. New York: Springer New York.

Sexton, Joseph O., Praveen Noojipady, Xiao-Peng Song, Min Feng, Dan-Xia Song, Do-Hyung Kim, Anupam Anand, et al. 2016. Conservation policy and the measurement of forests. *Nature Climate Change* 6 (2): 192–96.

Sims, Katharine R. E. 2014. Do protected areas reduce forest fragmentation? A microlandscapes approach. *Environmental and Resource Economics* 58 (2): 303–33.

Soares-Filho, Britaldo, Raoni Rajão, Marcia Macedo, Arnaldo Carneiro, William Costa, Michael Coe, Hermann Rodrigues, and Ane Alencar. 2014. Cracking Brazil's forest code. *Science* 344 (6182): 363–64.

Souza-Rodrigues, Eduardo. 2019. Deforestation in the Amazon: A unified framework for estimation and policy analysis. *Review of Economic Studies* 86 (6): 2713–44.

Sun, Liyang, and Sarah Abraham. 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Themed issue, Treatment Effect. *Journal of Econometrics* 225 (2): 175–99.

Symes, William S., Madhu Rao, Michael B. Mascia, and L. Roman Carrasco. 2016. Why do we lose protected areas? Factors influencing protected area downgrading, downsizing and degazettement in the tropics and subtropics. *Global Change Biology* 22 (2): 656–65.

Tesfaw, Anteneh T., Alexander Pfaff, Rachel E. Golden Kroner, Siyu Qin, Rodrigo Medeiros, and Michael B. Mascia. 2018. Land-use and land-cover change shape the sustainability and impacts of protected areas. *Proceedings of the National Academy of Sciences* 115 (9): 2084–89.

Tropek, Robert, Ondřej Sedláček, Jan Beck, Petr Keil, Zuzana Musilová, Irena Šímová, and David Storch. 2014. Comment on "High-resolution global maps of 21st-century forest cover change." *Science* 344 (6187): 981.

UNEP-WCMC (UN Environment Programme, World Conservation Monitoring Centre). 2020. Protected area profile for Brazil from the World Database of Protected Areas.

Vancutsem, C., F. Achard, J. F. Pekel, G. Vieilledent, S. Carboni, D. Simonetti, J. Gallego, L. E. O. C. Aragão, and R. Nasi. 2021. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Science Advances* 7 (10): eabe1603.

van der Werf, Guido R., James T. Randerson, Louis Giglio, Thijs T. van Leeuwen, Yang Chen, Brendan M. Rogers, Mingquan Mu, et al. 2017. Global fire emissions estimates during 1997–2016. *Earth System Science Data* 9 (2): 697–720.

Velly, Gwenolé Le, and Céline Dutilly. 2016. Evaluating payments for environmental services: Methodological challenges. *PLOS One* 11 (2): e0149374.

Veríssimo, Adalberto, Alicia Rolla, Mariana Vedoveto, and Silvia de Melo Futada. 2011. *Protected areas in the Brazilian Amazon: Challenges and opportunities*. Belém/São Paulo: IMAZON/ISA.

Visconti, Piero, Stuart H. M. Butchart, Thomas M. Brooks, Penny F. Langhammer, Daniel Marnewick, Sheila Vergara, Alberto Yanosky, and James E. M. Watson. 2019. Protected area targets post-2020. *Science* 364 (6437): 239–41.