Title: Protecting Forests: Is It The Policies Or The Actors That Count?

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ABSTRACT

This study assesses the effectiveness of forest conservation policies in reducing carbon emissions from deforestation. To date, the effectiveness of protected areas has been assessed using cross-sectional methods. In this essay, new quasi-experimental models using panel data on annual deforestation are used to reveal new insights into the importance of government oversight of protected areas with findings that counter economists' prior notions of the avoided deforestation of new parks. I extend the analysis to estimate avoided carbon emissions, a key policy metric that varies considerably from deforestation trends.

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# PROTECTING FORESTS: IS IT THE POLICIES OR THE ACTORS THAT COUNT?

Deforestation accounts for 12-20% of global carbon dioxide emissions to the atmosphere—the second largest source after fossil-fuel combustion. Protected Areas (parks) have long served as the primary policy tool to slow deforestation and remain a major component of forest conservation policies. One such model is the Amazon Region Protected Areas (ARPA) Program, a program that doubled park coverage in the Brazilian Amazon from 2002 to 2012 to create the largest system of parks in the world. During this time, Brazil achieved a 70% reduction in annual deforestation rates (Nepstad et al. 2014). Brazil's transformation has been spectacular; in 2005 Brazil was ranked as the 3$^{rd}$ largest emitter of carbon emissions, surpassed only by China and the United States whereas today it stands as the global leader in carbon reduction (FAO/World Bank 2005). However, how much of a role ARPA actually played in achieving these historic reductions is unclear in light of other new policies also addressing deforestation (Nepstad et al. 2014).

Given the scale of investment in parks and the potential role they play in climate policy, surprisingly little is known about how much carbon emissions are avoided by the implementation parks. As industrialized countries are poised to invest in Reduced Emissions from Deforestation and Degradation (REDD) as an integral part of climate policy, there is a timely need for comprehensive evaluations of park effectiveness. Of particular importance is understanding when parks may actually *increase* carbon emissions as a result of policy trends that promote resource extraction, and the concomitant increase in carbon emissions within parks.

Complexities of empirical park evaluation are rooted in the non-random siting of parks, leading to biased estimates from simple comparisons of protected and unprotected areas. Evaluations have also been plagued by a lack of consistent time series data on deforestation and the carbon emissions associated with forest loss. The best existing studies apply matching techniques to target control locations similar to existing parks to correct for non-random site selections. The overwhelming majority of these studies suggest that parks are broadly effective at reducing deforestation. However, few studies consider the decision process underlying site selection. As a result, studies that omit key variables associated with site selection may cause considerable bias in estimates of park effectiveness (Andam et al., 2008). Moreover, traditional use of forest cover as a proxy for ecosystem services, such as carbon sequestration, limit the policy implications of park evaluations (Ferraro et al., Busch et al. 2015).

Cross-sectional studies, which provide most of the available empirical evidence, are vulnerable to “hidden bias” due to omitted variables from matching estimates (Andam et al. 2008). The best empirical studies control for physical characteristics, but ignore the critical role that human inhabitants play in affecting deforestation and park selection. The potential bias from omitting social variables may invalidate central findings in the literature, such as the large deforestation-reducing effect of parks estimated for indigenous groups. Application of panel techniques are needed to control for all time-constant confounding variables, both observed and unobserved, in order to mitigate the problem of “hidden bias” found in existing cross-sectional studies.

Currently, only one study applies panel techniques to compare changes in deforestation rates inside and outside groups of parks. In this study, Blankespoor et al. (2014) claim that Latin American parks created after 2002 have no effect on deforestation rates. Despite the use of panel techniques, however, by restricting their sample to a pairwise comparison of buffer zones around park boundaries, the study ignores the effects of park interiors, and therefore is likely to underestimate the overall effectiveness of park units (Soares-Filho et al. 2010). Furthermore, similar to most literature, this study uses changes in forest cover as a proxy for avoided carbon emission effects.

Only one study estimates emissions-based treatment effects, which uses matching techniques and attributes large-amounts of avoided emissions to Brazilian parks established during 2002-2008 (Ferraro et al., 2015). However, this study uses data on carbon stocks for a single-year, a data limitation that requires unusually strong assumptions to infer the effect of parks on carbon flows.

This essay applies difference-in-difference methods to estimate the avoided carbon emissions from parks in the Amazon basin. The analysis focuses on parks established since 2001 and uses a spatially explicit panel dataset of annual deforestation data from 2000 to 2012, combined with estimates of initial carbon stocks in year 2000, and data on the timing and coverage of parks. This study illuminates the differing objectives of the state, federal, and indigenous agents that designate and administer parks, and empirically tests for consequent heterogeneous effects consistent with varying incentives faced by each agent. This study also highlights the importance of adjusting forest cover estimates for spatial variation in carbon stocks and identifies possible sources of omitted variable bias from the matching estimates is existing literature in the context of park evaluation.

My results challenge conventional claims about park effectiveness, suggesting significant heterogeneity in carbon outcomes driven by contrasting objectives of state and federal governments. Fixed effects estimates show federal parks achieve 18 tons of avoided carbon emissions per $km^2$ per year. However, the full effects of park expansion are offset by adverse selection of parks by state governments that led to 10 tons of addition carbon emissions per $km^2$ per year. Results raise concerns that the ARPA program fails to account for differing incentives facing state and federal governments when balancing tradeoffs between environmental and economic objectives. This study provides a methodological framework for future park studies evaluating social and economic outcomes to better understand the effects of parks on local communities.

This study is structured as follows. The next section discusses related work and how government agents select parks. It foreshadows the regressions to be estimated and motivates the expected signs of various parameters. The subsequent section describes the data and variables used in the analysis, including descriptive statistics. Then the main section develops the econometric evidence regarding determinants of park effectiveness, including sources of heterogeneity and the temporal dynamics of effects. Results are compared to existing cross-sectional estimates. The final section concludes with a discussion of policy implications.

## DEFINING AND MEASURING PARK EFFECTIVENESS

### *Park Location and Management*

To correct for non-random site selections, the best existing studies apply matching techniques to identify control locations similar to designated parks based on observed physical characteristics. However, these studies omit key socio-demographic variables associated with site selection that may cause considerable bias in estimates of park effectiveness (Andam et al., 2008; Pfaff et al., 2014). For example, parks are regularly placed around indigenous populations, who reduce deforestation by preventing access to outside groups. Not surprisingly, studies overwhelmingly find that indigenous parks "cause" avoided deforestation because, when "control" areas lack any indigenous populations, the effect of park designation is confounded with the effect of indigenous groups on deforestation rates.

Few studies consider the decision process underlying site selection. Previous studies focus on two park management categories: either strict parks that allow no human activities, or multi-use parks that allow some economic activities. In the Amazon, studies present mixed results about park management: some claim strict parks are most effective while others claim multi-use parks are most effective (e.g. Soares-Filho et al., 2010; Pfaff et al., 2014). The most sophisticated studies indicate that park location matters most rather than management (Nolte et al., 2013b; Ferraro et al., 2013). The mixed results suggest that location and management considerations, examined in isolation, fail to explain the key factors affecting park effectiveness.

### *Government Actors and Objectives*

This study examines determinants of park effectiveness using a new framework where government actors select park location and management as a joint-decision. Each government actor is considered to have exogenous objectives that strategically select parks to optimize along environmental, cultural, or economic outcomes.

Parks can be grouped in two ways. First, they can be grouped by the level of government responsible for park management, typically state government or federal government. Second, parks differ by strictness of restrictions on human activity, which is generally divided into two categories: strict protection or multiple-use protection. In total, combining government and strictness levels, parks can fall into one of four main groups: state-strict, state-multiple-use, federal-strict, and federal-multiple-use. The strictness of a park designation is only one factor that may influence the avoided deforestation from parks.

Government actors make decisions on park location, strictness of restrictions on human activity, and ultimately plan for park management, law enforcement, and infrastructure development. For parks in the Amazon basin, environmental protection often occurs at the expense of local communities whose livelihoods are based upon resource extraction, timber harvesting, cattle ranching, and agriculture. State and federal governments, the park decision-makers, face different political pressures and economic incentives that influence strategic park selection to favor either environmental objectives or local-economic growth objectives more strongly. Considering alternative possible incentives of government agents can help researchers reveal and differentiate an agent’s objectives when targeting new parks. Furthermore, understanding agent interactions, for example, when one agent's behavior changes the incentives of another agent, will enable more comprehensive evaluations of program effects under alternative objectives, including indirect (unintended) effects on secondary actors.

***Brazil: A Case of Conflicting Government Objectives***

This section characterizes the relevant incentives of federal, state, and indigenous agents, with the specific aim of revealing agents' objectives when selecting new parks. To provide context for real-world incentives faced by actors, this section focuses on park-selecting agents in Brazil during 2000-2010.

Since 2000, the federal government has aligned policies to increasingly target environmental objectives in the Amazon. In 2002, strong international pressure to address agro-industrial deforestation prompted the federal government to initiate the Amazon Region Protected Areas Program (ARPA) as an effort to finance and coordinate a rapid expansion of the park system targeting areas with high development pressure. In 2004, a remote sensing monitoring system, the Detection of Deforestation in Real Time (DETER), increased law enforcement capacity leading to a string of unprecedented high-profile arrests for illegal deforestation. Federal measures to protect Amazon forests were politically popular in the coastal regions of Brazil, which makes up over 80% of the population (Fernside 2002, Nepstad 2014).

In 2008, the federal government strategically positioned Brazil as a climate change leader in order to attract investment and redirect attention from economic growth agendas. During the 2008 climate negotiation at the United Nations, the Brazilian government committed to a 2020 target of reducing deforestation by 80% from baseline rates during 1994-2005. In a sign of support, Norway pledged $1 billion performancebased funds to the Amazon Fund, a Brazilian government fund devoted to achieve deforestation targets. The federal government continues to position Brazil as a strategic recipient of international investments. For example, the 2012 Brazilian Forest Code (NFC) established a geospatial registry of properties, setting the groundwork to assess compliance of individual property owners in future REDD payment programs.

State governments, on the other hand, have stronger incentives to establish parks for economic development. Amazon state governments depend on agricultural expansion, with 90-percent of state revenue collected from value added taxes on municipal exports of beef and agricultural products (Hochstetler and Keck 2007). Further, corruption within state government agencies has been endemic. Some state officials are complicit or collude with illegal deforestation activities (McAllister 2008a, Hochstetleer and Keck 2007).

Regarding park designation, state agents may often respond to federal programs, which is an example of agent interactions with wide-reaching implications for program evaluation. Public opinion has been marked with antagonism against federal intervention limiting land use for environmental conservation at the expense of local populations. Prior to 2005, state government involvement in establishing parks may thus target economic development rather than carbon reduction, and may serve the purpose of establishing state jurisdiction of parklands to avoid seizure of land for federal parks. Furthermore, in anticipation of 2006 Forest Concessions Laws, state governments have used ARPA funds to build infrastructure and develop "sustainable" management plans as a basis for attracting investment, generating employment, and generating income from timber harvesting and Brazil nut collection (Impa, Bandiera et al., 2010).

On the other hand, in 2008, the Critical Counties program suspended access to agricultural credit for all farmers in 36 counties placed on a deforestation “blacklist” and further developed a list of specific properties “embargoed” from any type of government loan. Thus, following 2008, state incentives to create parks may have shifted towards environmental outcomes to remove municipalities from blacklists and to access revenue from the Amazon Fund.

Descriptive statistics of parks selected by federal and state governments demonstrate systematic differences in strictness of protection and baseline deforestation pressures. Table 1 shows total area of park designations by federal and state governments, aggregated by strictness of protection and 3-year presidential terms. Trends show a considerable increase in federal park designations in both strict and sustainable use areas during 2003-2006, followed by a large drop in federal park designations during 2007-2010 after low deforestation rates eased international pressure. State park designations dramatically increased favoring multi-use parks to strict parks by 3-to-1 during 2003-2006, followed by a drop in state designations after threats of federal park designations subsided during 2007-2010.

Table 2 shows the 2001 baseline deforestation rate in areas later targeted for protected status during 2002-2009. The proportion of parks across different designations is divided into three levels of human pressure using baseline deforestation rates: no pressure (< 0.05%), moderate pressure (0.05-0.1%), and high pressure (>0.1%). During 2002-2009, states located 84 percent of strict parks in areas with no human pressure, whereas only 42 percent of federal strict parks were placed in areas with no human pressure. Similarly, 71 percent of state multi-use parks were located in areas with no human pressure, compared to 43 percent of state multi-use parks.

As this brief review illustrates, prior matching studies that fail to differentiate the incentives for park formation likely yield very incomplete information for policy-making purposes. Federal governments apparently seek strict protection in areas of high deforestation pressure in response to international pressure to curtail high rates of deforestation. Conversely, state governments apparently seek multiple-use protection in areas of low deforestation pressure to promote economic development while preempting federal seizure of land for conservation purposes. The purpose of this study is to use available data to investigate the effects of this differentiation in incentives on the effectiveness of parks for carbon reduction. Results indeed demonstrate a dramatic difference that can be attributed to differing incentives of federal and state governments.

***Measuring Park Effectiveness: Carbon Emissions Versus Deforestation***

By using carbon data observed immediately prior to the period of deforestation data, treatment effect estimates for avoided carbon emissions should be unbiased. In fact, this is the first study to estimate emissions-based treatment effects using directly observed carbon stocks in the pre-treatment period. The two existing studies that directly estimate emissions-based treatment effects both use carbon data estimated during the post-treatment period after the implementation of conservation policies (Ferraro et al., 2015; Busch et al., 2015). These studies must interpolate unobserved, pre-treatment carbon densities by imposing assumptions that average carbon density remains constant over time, so that carbon measures of survived forests can be used to predict those of cleared forests. In the Amazon, this assumption is likely to fail because carbon-dense hardwoods, such as mahogany, are selectively targeted by loggers due to their high-value on international markets.

Emissions-based treatment effects estimated in this study provide new insights about the heterogeneous ecosystem-service benefits across park types. Unlike Ferraro et al. 2015, which estimates the cumulative effect for parks in Brazil, the analysis here tests separately for heterogeneity in avoided emissions across different park types. Heterogeneous effects across different park types may exist even when deforestation rate effects are similar. For example, some types of parks may be intentionally sited on land with unobserved unifying ecological characteristics that affect carbon densities as well as the siting decision. Or, due to differences in management, some types of parks may prevent deforestation in areas of the park with the highest-carbon density (primary forests), while other park types only have effects in areas of the park with the lowest-carbon density (secondary forests). Hence, strict parks may, at the same time, generate the least avoided deforestation and also generate the most avoided carbon-emissions, assuming strict parks have the highest carbon densities. Thus, impacts estimated in terms of avoided deforestation may be inadequate to compare policies designed to generate avoided-emissions. As a further example, if multi-use parks permit selective logging of high-value tree species with high carbon densities, there is potential for multi-use parks to accelerate carbon emissions. In such cases, studies that estimate average park effects will average across park effects with opposing signs.

## EMPIRICAL SETTING AND DATA COLLECTION

### *Study Area*

The study area is the humid tropics biome in the Amazon region of South American, where more than 40 percent of the world's deforestation emissions are located (Harris et al., 2012). Rainforests cover 5,500,000 $km^2$ spread across nine countries in the Amazon region. Brazil contains the lions-share of forests, with 63% of the rainforest area, followed by Peru with 17%, Columbia with 12%, Bolivia with 5%, and minor amounts in Venezuela, Ecuador, Guyana, Suriname, and French Guyana.

Figure 1 illustrates the study area including country boundaries (yellow lines), protected area coverage (light green areas), annual forest loss data from 2000-2012 (rainbow areas denoting year-of-forest-loss), and year 2000 forest cover density (greyscale ranging from 100% forest in black, to 0% forest in white). Figure 1 includes four panels that present data at varying spatial scales. Panel (a) shows the entire study area, with all 9 countries and shows that parks cover 36% of the Amazon. Despite the attention given to forest loss, more than 80% of the Amazon rainforest remains. During 2000-2012 deforestation affected only about 2% of the Amazon rainforests. Panel (b) zooms-in on an area with high-levels of deforestation since 2000, providing some visual evidence that deforestation in Brazil is higher than nearby areas within Peru and Bolivia. Panel (c) further zooms-in on the same region and illustrates that pre-2000 deforestation (white) around the inter-oceanic highway represents a frontier for progressive deforestation since 2000 (shown in colors). Panel (d) zooms-in on an adjacent area showing fish-bone patterns of deforestation on the Brazil-side during 2000-2005, and small hot-spots of deforestation in Bolivia after 2006.

### *Protected Areas Data*

Protected area boundaries come from the World Database on Protected Areas (WDPA) created by the United Nations Environment Program and the International Union for the Conservation of Nature (IUCN). For each protected area (PA), the database includes information on the year of establishment, IUCN management category, the government agency with decision-making authority, and government agency with management responsibility. The WDPA sets a consistent standard for park information across all countries and represents a complete and accurate dataset when cross-validated with country-level government databases in the study area (UNEP-WCMC, 2007).

### *Forest Loss Data*

The panel data techniques applied in this essay require longitudinal data comprising repeated observations on units of analysis over time. Until recently, consistent panel data on deforestation rates over did not exist. Although some studies have attempted to compare various forest cover maps across time to generate epochal forest loss products, such "panel" data contain considerable measurement error because static forest cover maps vary in quality across time (e.g. Sims 2010). Recently, consistent datasets of annual deforestation have been created by using satellite images recorded by the same sensor at regular intervals over time.

To characterize deforestation rates over time, this study uses the Hansen et al. (2012) dataset produced at a 30-meter spatial resolution with annual time-steps based on Landsat satellite imagery. It spans years 2000-2012.

Despite the seemingly coarse resolution of park-level data, econometric theory provides unambiguous guidance to aggregate data up to the level of variation in policies

(Angrist and Pinsche, 2007). Unlike analyses that select subsamples of 30-m pixels, which reduces efficiency to relieve computational problems, this analysis captures the full-variation in the 8 billion pixels that comprise the 12-year 30-m panel dataset without diminishing the statistical power to identify effects in a difference-in-difference model. In fact, after weighting observations by land area, PA-level analyses produce unbiased estimates identical to a panel model of each individual pixel (Angrist and Pinsche, 2007). As an additional benefit, coarser spatial resolution data mitigates spatial correlation and diminishes measurement error effects of possible spatial misalignments between datasets.

***Carbon Biomass Data***

Annual carbon emissions from each park are derived by combining annual forest loss products with existing data on forest carbon stocks prior to park designation. As an input, spatially explicit carbon density data provided by Saatchi et al. (2011) are used to estimate forest carbon stocks in 2000 at 1-km spatial resolution. These data contain estimates for above-ground biomass, below-ground biomass and carbon density.

Carbon loss variables are calculated in three steps.[18] First, to resolve differences in the spatial-resolution, data on annual forest loss are aggregated from 30-m to 1-km resolution by calculating the 30-m forested pixels and forest loss pixels as a percentage of each 1-km grid. Second, for each 1-km cell, forest carbon stocks in 2000 and annual forest carbon loss were calculated by multiplying carbon density with the percent forest cover and percent annual forest loss, respectively. Third, the 1-km grids over the study

[18] I thank Xiaopeng Song, who performed the calculations to generate annual carbon loss variables.

area were aggregated to derive PA-level estimates of forest carbon loss for each year between 2000 and 2012.

***Land Characteristics Data***

Ecoregions are classified by the World Wide Fund for Nature (Olson et al., 2001). Agricultural suitability is derived from the Global Agro-Ecological Zones dataset provided by the International Institute for Applied Systems Analysis. For each 1-km$^2$ grid cell covering forest lands, this index ranks agricultural potential on a scale of 1 (very high potential) to 7 (very marginal potential) with an additional category of 8 for land not suitable for agriculture (Fischer et al., 2002).

Physical landscape characteristics include slope, elevation, and accessibility. Slope is measured in degrees from horizontal for 1-km$^2$ grid cells (Fischer et al., 2002). Elevation is measured in meters and is derived at a 90-m spatial resolution by the Shuttle Radar Topography Mission and published online by the Consortium for Spatial Information (Jarvis et al., 2008). Accessibility measures travel time to major cities along transportation networks (e.g. roads, navigable rivers) and off-transport networks (walking speed given environmental factors). These measures were created at a100-m scale by the World Bank and published online by the European Union Joint Research Centre (Uchida and Nelson, 2009). Climate variables for monthly mean precipitation in millimeters and monthly mean temperature in degrees Celsius are provided for 1-km$^2$ grid cells by WorldClim Global Climate Data (Hijmans et al., 2005).

### *Strictness of Protection Variables*

The variable for "strictness" of protection in this study is defined using the six IUCN management categories adopted for national protected areas. These standardized classifications identify management types based on the restrictions on human activity, loosely ranked from most strict (category I) to least strict (category VI). In cases where park sites are nationally recognized as protected but have not been assigned an IUCN category, data are not. Some indigenous areas that are considered international parks that are listed as "Non-Applicable" under management categories, as their primary purpose is not intended for conservation or sustainable development.

This study follows conventions in the literature (e.g., Nelson and Chomitz, 2011) that define four classes of park strictness: strict protection (IUCN categories I-IV), multi-use protection (IUCN categories V-VI), and not-reported (no IUCN category).[19] The fourth class of indigenous protection cannot be defined using IUCN categories; instead indigenous parks are defined from governance variables detailed in the following section.

### *Government Ownership Variables*

The government agent variable classifies park ownership across four government types: federal, state, indigenous, and non-government entities. These agent-types are derived from WDPA information on governance that describes the decision-making structure of the PA, or the government agent(s) responsible for selecting, declaring, and administering park lands. First, federal ownership applies to governance identifying "federal or national agencies" in charge of parks. Second, state ownership applies where

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[19] Strict parks include state and national biological stations, biological reserves, and national and state natural areas. Multi-use parks include state and national forests, extractive reserves, and sustainable development reserves.

“sub-national” agencies are in charge. Third, indigenous ownership includes lands identified as “declared and run by indigenous people.” Fourth, non-government ownership includes small areas of lands declared and run by individual landowners, non-profit organizations, for profit organizations, or with unreported ownership.

Additional rules are applied to classify federal and state ownership for the 3.5% of parks where the governance type is ambiguous.[20] In cases where the governance type is reported as “government delegated management” or “collaborative or joint management” parks are assigned to either federal or state governance depending upon which level of government that officially declared the PA. For example, federal ownership would be applied when a federal agency designates a PA, even in cases where management tasks are later delegated to local state agencies. This is because the designating government selects the park siting and strictness of protection, the two permanent characteristics affecting selection bias, and also sets the basis for cooperation or antagonism with human inhabitants. Recent research suggests that management activities have little impact, if any, on deforestation outcomes—a finding that validates the importance of initial selection decisions (Nolte et al., 2013a).

Unlike IUCN categories used to define strictness of protection, the WDPA variable for governance clearly defines indigenous parks. Hence, for this analysis, indigenous parks are always defined from the WDPA governance variable. Thus, the sample of indigenous parks is identically labeled as ‘Indigenous’ in both the government ownership variable and the strictness of protection variable. In contrast, parks owned by

[20] Ambiguous governance categories make up 3.5% of individual parks but represent only 0.35% of total land area in parks.

state and federal governments can take on strictness of protection values of either multi-use parks or strictly protected parks.

Indigenous parks represent a special category of protected area found predominately in Latin America. Furthermore, within the Amazon, Brazil is the only country to designate new indigenous parks during the past 20 years. Although formally established by Brazil's federal government, indigenous parks are governed through different regulator frameworks than other parks and grant considerable autonomy and land-rights to indigenous inhabitants. Indigenous lands are subject to restrictions on development and resource use that are devised through a joint planning process involving federal, state, and local governments and indigenous communities.

## EMPIRICAL METHODS

### *Selection of the Sample*

In order to study the impact of declaring a piece of land a PA, one needs to have the deforestation data of that land both before it was declared a park and after it was declared a PA. Such data is available for parks that were created between 2001 and 2009 in four countries in the Amazon: Brazil, Peru, Bolivia and Columbia. Of the park land in this data, 83% is located in Brazil, 14% is located in Peru with the remaining 3% located in Bolivia and Columbia.

However, it is not enough to look at deforestation rates before and after land becomes a PA. There are other factors, such as changes in climate, accessibility, and economic demand that also affect deforestation rates over time and occur regardless of whether the land is protected or not. In order to control for changes in deforestation rates that are independent of the land becoming protected, the deforestation rates of lands that were already parks at the start of the time period of this study can be compared with the deforestation rates of lands that transitioned into parks during the course of the study's time period. Accordingly, the lands in the comparison group in this study are lands designated as parks before the time period of this study began, i.e., before 2001. These are compared to the lands transitioning to parks between 2001 and 2009.

One might also suggest doing a comparison as well with lands that were never designated protected areas throughout this study's time period to see what changes in deforestation rates they experienced. However, problems of consistency exist across those lands that make them unsuitable for this study. Those lands may not have been selected for parks because they were never good candidates for park designation. For example, some lands are large, sprawling, urban areas. Other the lands might be good candidates, but for various reasons, such as a variety of political factors, they have not been chosen (yet) for park designation. This may apply to remote jungle areas. Without detailed knowledge about the selection process and the data to replicate it, identifying which among the undesignated lands are potentially good park candidates for comparison purposes has the risk of being too speculative for this study.

In summary, the panel data models used in this essay are estimated with two groups of lands: one group consists of lands that are transitioning to parks between 2001 and 2009 and the other group consists of lands already transitioned to parks before 2001. The causal effect of parks is estimated for those lands that were undesignated as of 2001, and transitioned to parks at some point during the period of 2001 and 2009. To control for other factors affecting deforestation over the 2001-2009 time period, the impact of park designation on transitioning lands is examined using lands that became parks before 2001, which remain protected throughout the study time period, for comparison purposes.[21] Figure 2 presents a map showing the spatial configurations of pre-2001 and post-2001 parks.

Collectively, the parks in this sample cover a large fraction of Amazon rainforest in each country, including 45% of rainforest in Brazil, 22% of rainforest in Peru, 19% of rainforest in Bolivia, and 10% of rainforest in Colombia. More broadly, the sample of parks established during 1985-2009 covered 34% of the Amazon rainforest in 2009, while parks established before 1985 covered only 3% of rainforest, and unprotected lands covered the remaining 64% of rainforest.

***Unit of Analysis***

Ideally, the unit of analysis should correspond to the decision making process. Following this principal, the unit of analysis in this study is the individual park, which constitutes the spatial scale at which a piece of land becomes protected at a point in time.

This is, in fact, the first study to apply a park-level unit of analysis. By comparison, previous studies typically use pixels, aggregated cells, or administrative divisions as the unit of analysis. This limitation stems from a reliance on cross-sectional analysis, as well-defined "unprotected areas" analogous to parks simply do not exist (Blackman, 2013). In this study, panel data are used to circumvent this problem by exploiting variation in the timing of park designation.

[21] Specifically, the comparison group includes parks established during 1985-2000, which includes 85% of all Amazon park lands created prior to the study time period. The remaining 15% of parks established before 1985 are excluded from the sample, as the selection process for older parks is likely to differ from the selection process of more recent parks considered in this study. Among the Amazon parks created between 1985 and 2000, 79% of park land is located in Brazil, 8% is located in Columbia, 6% is located in Peru, 4% is located in Bolivia, and the remaining 3% is located in Guyana and Venezuela.

There were 610 parks designated between 1985 and 2009 in the Amazon tropical forest biome that contained at least 1 $km^2$ of tropical forest. All datasets were first aggregated to 5,738,163 1-$km^2$ grid cells that collectively covered the Amazon humid tropics biome. Next, the 1,963,594 1-$km^2$ grid cells contained within the park sample were aggregated to the PA-level. The final sample includes 7,320 PA-year spatial-temporal units of observation for the 12 year panel of 610 parks.[22]

The unit of observation for this study is a park-year, and the dependent variable is either annual deforestation rate (percent forest loss per year), or carbon loss per year, depending on the model. To construct the variables from binary forest loss data at a 30m or 250m resolution, data are aggregated to a 1$km^2$ unit of location with a continuous measure of deforestation in each year from 2000 to 2012. For the sample of parks established between 1985 and 2009, indicator variables for each type of park designation are equal to one if a protection status is present in a given location and year and zero otherwise. Due to uncertainty in the date of forest loss within a given year, I exclude the dependent variable in the year of designation.

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[22] Since the empirical objective is to estimate average "treatment" effect of park designation on carbon emissions (and forest loss) in absolute terms, estimates place more weight on larger parks to allow inference of area-based treatment effects in terms of percentage based metrics.

### *Empirical Model*

In the case of a several types of park designations, the quasi-experiment entails estimating the following two-way fixed effects model:

$$Y_{\{it\}} = \theta_{\{i\}} + \varphi\tau_{\{t\}} + \gamma_{\{j\}} AT_{\{ijt\}} + \varepsilon_{\{ijt\}} \tag{3.1}$$

where $Y_{\{it\}}$ is either the deforestation rate or carbon loss at park *i* in year *t*; $\theta_{\{i\}}$ are park-specific indicator variables that capture mean differences in deforestation across parks due to differences in factors that remain constant over time, such as landscape characteristics or stable human settlements; $\tau_{\{t\}}$ are year-specific indicator variables capturing broad trends that affect deforestation over time; and $AT_{\{ijt\}}$ is an indicator variable equal to 1 for years after a park of type *j* is designated and equal to 0 otherwise where type *j* indicates either government ownership or strictness of protection, and $\varepsilon_{ijt}$ is an error term that represents unmeasured factors.

The coefficient $\gamma_{\{j\}}$ isolates a separate effect of designation for each park type (i.e. average treatment effect); while coefficient $\varphi$ separates counterfactual deforestation trends.The model therefore estimates the relative effectiveness designation status across park types. Because all parks are designated by year 2009, effects are identified for parks established after 2001 that experience a change in protection status during the time interval of available deforestation data.  Additional models include state-by-year effects that absorb state-specific shocks, as well as park-specific linear and quadratic time trends that allow park deforestation rates to trend nonlinearly.  Alternate specifications include spatial leads and lags, which test for temporal trends in effects.

## EMPIRICAL ANALYSIS

### *Baseline Difference-in-Difference Estimates*

Initial estimates of equation (3.1) are contained in table 1. Each column resents a regression of the rate of deforestation on park and time indicator variables, state-by-year effects (columns 2, 3, 5 and 6), linear and quadratic park time trends (columns 3 and 6), and indicator variables for the four types of park designation, which are equal to one if a protection status is present in a given park and year and zero otherwise. The first three columns contain simple estimates for the effect of park designation on deforestation rates. The coefficient of -0.039 in column 1 indicates that after removing mean park deforestation levels and common year effects, the deforestation rate fell by approximately 0.04 percentage points more in parks with a designated protection status than in candidate areas without any park designation. However, this effect is estimated imprecisely.

The second column adds 180 state-by-year effects to the model, decreasing the point estimate considerably to -0.027 percentage points and reducing the standard error slightly after controlling for yearly shocks in each of the 15 states. The third column adds 610 park-specific linear time trends and 610 quadratic time trends to the model, decreasing the point estimate slightly for the effect of park designation.

### *Heterogeneity across Government Actors*

The last three columns of table 1 estimate separate effects of park designation across each of four levels government: federal, state, indigenous, and non-government entities. The point estimate for a federal park designation is strongly negative at -0.07 percentage points with park and year effects, and is only minimally affected by the inclusion of state-by-year fixed effects. Adding linear and quadratic park time trends to the model increases the magnitude of the federal park point estimate considerably to -0.12 percentage points, and remains significant despite the inclusion of more than 2,000 covariates. Thus, federal parks appear to generate avoided deforestation, a result that is robust to model specification.

Unlike federal park designations, point estimates of indigenous and state parks are sensitive to the addition of covariates. Not surprisingly, indigenous parks appear initially to contribute to lower deforestation rates, a result that echoes findings in previous cross-sectional studies. However, the point estimate for indigenous parks approaches zero and becomes insignificant after adding state-by-year effects, and remains insignificant after the inclusion of park time trends. It appears that indigenous parks were established in areas where deforestation rates were already decreasing and are thus not significantly additive.

Upon closer inspection, sensitivity of estimates for indigenous areas to state-specific shocks is not surprising, as deforestation drivers vary widely across space. Since 2001, most indigenous areas were located in three remote states of the northern Amazon: Amazonas, Para, and Roraima. In contrast, during 1985-2000, a large number of indigenous areas were also located in two highly populated states inside the arc of deforestation: Mato Grosso and Rodonia. Since indigenous parks are designated in different regions over different time periods, the omission of state-by-year indicator variables (column 4) confounds the effect of designating indigenous parks with any regional variation in deforestation trends. The indigenous coefficient diminishes in magnitude and significance (column 5) after controlling for state-by-year effects.

State parks, on the other hand, have a quite surprising evolution of point estimates. While state park point estimates are negative and insignificant with few controls, the point estimate reverses signs to become positive and significant once park time trends are included. It appears that state parks prop up elevated deforestation rates in areas where deforestation rates were already starting to decrease. These results support the hypothesis that state agents create parks to advance economic objectives that, on average, accelerate deforestation rates. The addition of linear and quadratic time trends control for park-specific factors affecting deforestation trends and reflect state actor's selection of park sites with declining deforestation pressure. Estimates suggest that the state policy intervention of establishing a park slowed this decline in deforestation pressure, creating a positive impact on deforestation rates. State actors may increase deforestation directly, through issuance of legal logging concessions, or indirectly by building infrastructure or supporting local livelihoods that may attract illegal deforestation or land speculation by poor migrant groups.

The remaining group of non-government owned parks, which are designated by non-profit organizations, private land owners, or undefined ownership yield point estimates that are insignificant across all models. The reasons for the overall low impact of non-government owned parks may vary across constituent groups. In Brazil, large private landowners often declare forested areas as parks in order to avoid paying property taxes; however, landowners may set aside only the marginal forest lands that were never worth clearing. Meanwhile, non-profit and for profit groups may have limited resources to enforce park regulations. In addition, a large portion of the undefined category is in Peruvian parks designated as "buffer zones" or rings of land that surround existing parks

These buffers may serve to limit access to interior parks rather than restricting deforestation within the buffers themselves.

Tests of joint significance confirm the existence of treatment effects and the relevance of covariates. Specifically, using the model presented in column 6, an F-test of the hypothesis that all four government treatment coefficients are jointly equal to zero is rejected at a 5-percent level, with a p-value of 0.04. In addition, an F-test of the hypothesis that state-by-year coefficients and park time trends are jointly zero is strongly rejected at the 1-percent level. Further F-tests of joint significance separately applied to state-by-year coefficients, linear park time trends, and both linear and quadratic park time trends are all rejected at the 1-percent level. Hence I employ linear and quadratic park trends and state-by-year covariates in all remaining specifications.

***Controlling for Strictness of Protection***

The results in table 1 suggest that parks declared by federal governments are the only one of the four types of government parks to reduce deforestation. It is possible, however, that the difference is explained not by the role of the federal government itself, but other facets of the park designation that are correlated with federal parks. Measures of the "strictness" of protection, which are commonly used to test for heterogeneous effects of park designation, deserve particular attention.

To examine this issue, I begin with the specification from column 6 of table 1 (containing quadratic time trends and state-by-year effects) as column 1 of table 2. Table 2 column 2 presents estimates from a similar model using explanatory variables measuring strictness of protection, and column 3 presents model estimates including strictness of protection variables and government ownership variables. The second column of table 2 shows that of three common groupings of strictness—strict, multi-use, and indigenous—none have an effect on deforestation that is different from zero at relevant levels of statistical significance. The third column of table 2 shows that point estimates remain insignificant with the inclusion of controls for type of government.[23] Consistent with ambiguity in the existing literature, these results provide little evidence that strictness of protection is a key determinant of avoided emissions from parks (e.g. Ferraro et al., 2013).

Furthermore, point estimates of effects across government type are robust to models that control for the strictness of park designation. For federal parks, while adding controls for strictness to the model reduces the point estimate somewhat, from -0.12 percentage points (column 1) down to -0.09 points (column 3), the effect remains large and statistically significant. For state parks, including controls for strictness increases the point estimate considerably, from 0.046 percentage points to 0.074 points, with a slight increase in significance. Thus, the type of government ownership appears to be much more important than the strictness status of protection.

### *Comparing Panel and Cross Sectional Estimates*

The fixed effects estimates in table 2 differ from cross-sectional matching estimators in existing literature. In particular, studies based on matching estimators consistently find indigenous parks to reduce deforestation, whereas fixed effects results show little evidence of effects from the establishment of indigenous parks (e.g. Nelson and Chomitz 2011). One possible reason could be differences in methodology: if

[23] Indigenous parks are defined in the same way for both the government-ownership variable and the strictness-of-protection variable. Hence, to avoid mulicolinearity, only one "indigenous" indicator is included in specifications that include treatment variables for both government ownership and strictness of protection.

matching omits important determinates of deforestation on indigenous lands then matching estimators will be biased, while any bias from time-invariant unmeasured determinants is purged from fixed effects estimators. It is also possible, however, that disagreement with conventional wisdom stems from the use of different data on deforestation, rather than differences in methods.

To examine the role of methodology, I repeat the specifications in table 2 using cross-sectional estimators on the data—namely effects by government type, categories of strictness, and simultaneous estimation of government and strictness measures. As presented in table 3, each model is estimated with a naïve specification, a specification that adds controls, and with a sample restricted to a matched control group. First, naïve models (columns 1, 4, and 7) include year effects and park indicator variables equal to one if a protection status is present in a given park and year, and equal to zero for always-unprotected areas. It is worth noting that parks appear in the data only for years following formal park designation. Using always-unprotected areas as an alternative control group, as in previous matching studies, allows the most direct comparison of the cross-sectional approaches used in other studies to the panel approach introduced in this study.

Next, in columns 2, 5, and 7, I add state-by-year effects and detailed geographic variables related to deforestation, including: initial tree cover density, elevation, slope, accessibility (travel time to major cities), an agricultural suitability index (ranging [0-10]), average monthly precipitation, and average annual temperature. To employ a simple matching model, Columns 3, 6, and 9 use propensity score matching at the 1-km$^2$ pixel level using variables for state and travel time to major cities.

Estimates of effects by government ownership are presented in columns 1-3 of table 3, and estimates of effects by strictness of protection are presented in columns 4-6 of table 3. The first and fourth columns of table 3 show that naïve model estimates are significant and negative for all government types and all strictness categories, with estimates in the range of -0.18 and -0.31 percentage points. These estimates, that compare parks to unprotected lands, however, contain bias due to the non-random selection of park locations. The second and fifth columns of table 3 show that the addition of state-by-year effects and geographic covariates has minimal effects on federal, state, strict, and multi-use designations. In contrast, point estimates for indigenous designations jump considerably from -0.31 to -0.55 percentage points in both models, suggesting indigenous park cross-sectional estimates are sensitive to model specification.

Figure 3 graphically displays naïve (column 1) and matching (column 3) point estimates alongside fixed-effects estimates (table 4, column 1) for federal, state, and indigenous parks. For federal parks, matching model estimates are almost identical to fixed-effects estimates, suggesting that matching methods eliminate bias present in naïve cross-sectional specifications. For state parks, matching model estimates are insignificantly negative, suggesting that matching reduces some cross-sectional bias but does not lead to the significant positive estimate of the fixed-effect model. For indigenous parks, matching estimates maintain a strong negative point estimate of -0.29, almost identical to the naïve estimate with minimal bias corrections towards the insignificant near-zero estimates of the fixed effects model.

Figure 4 displays comparable estimates of naïve (column 4), matching (column 6), and fixed-effects estimates (table 4, column 2) for strict, multi-use, and indigenous parks.  Matching model estimates for strict and multi-use parks fall between larger naïve estimates and small fixed-effects estimates: strict matched estimates correct for approximately half of the naïve bias, and multi-use matched estimates correct for most of the naïve bias.  Again, matching model estimates for indigenous parks seem to be equally biased as naïve models.  Apparently, there are important unmeasured determinants of deforestation in indigenous areas, which are effectively purged by the fixed effects models used for the primary analysis.

In general, the bias of matching estimators varies greatly across park type, suggesting that fixed-effects estimators are better suited for comparing the relative effectiveness of park types.

### *Inferring Avoided Carbon Emissions*

Returning to the preferred difference-in-difference panel technique presented in equation (3.1), the estimates above measure the effectiveness of parks in terms of reduced rates of deforestation and generate an area-based forest loss measure that is standard in existing literature. For these estimates to serve as valid metrics for program evaluation, however, imposes the faulty assumption that every hectare of forest in the Amazon provides equal benefits in terms of programs goals.  Due to the vague term "forest," most often defined as land with 30 percent tree cover or greater, an area-based metric of "deforestation" treats a 100-percent tree covered hectare the same as a 30-percent tree covered hectare.  Furthermore, area-based metrics do not distinguish across forest quality: a hectare of 150-year old-growth forest is equal to a hectare of 5-year-old trees in a regenerated forest, despite vast differences in biomass, carbon storage, and other ecosystem services.

To address limitations of deforestation rates, I use an alternative metric of carbon loss per square kilometer. Carbon loss is equal to the share of forest loss multiplied by the carbon density of the original forest. The carbon density map is created at the 1 $km^2$ unit by combining maps of percentage tree cover with above-ground carbon density maps (Hansen et al., 2012; Sacchi 2001). To examine the effect of parks on carbon loss, I begin with the specification of deforestation rates from column 3 of table 4 (containing simultaneous estimates of government and strictness treatment effects) and introduce in table 4 comparable estimates using carbon loss as the dependent variable.

The second column of table 5 shows the effect of park designations on annual levels of carbon loss, measured in units of megagrams (Mg) of carbon per square kilometer per year (Mg C/$km^2$/year), where 1 Mg is equal to 1 metric ton (1.1 US tons). The federal park coefficient of -18.46 in column 2 indicates that after removing mean park carbon loss levels, common state-by-year effects, and park-level carbon loss time trends, carbon loss slowed by approximately 18.5 Mg/$km^2$ per year more in parks with a federal park designation compared with non-designated candidate parks. The state park point estimate is significantly positive, and suggests that carbon emissions grew by 10.7 Mg/$km^2$ per year in state parks compared with non-designated candidate parks.

Comparing columns 1 and 2 of table 4, carbon loss point estimates for federal and state parks match the signs of deforestation rate estimates, but the relative magnitude of federal effects grew considerably more compared to state effects when estimated using carbon loss as the dependent variable. Simply dividing carbon loss coefficients by deforestation rate coefficients suggests that forests in federal parks prevented deforestation in carbon-dense forests containing approximately 200 Mg of carbon per hectare—or a carbon density 38 percent greater than forests affected by state parks, which contain approximately 145 Mg per hectare. All remaining coefficients are insignificant in the carbon loss model. An F-test of the hypothesis that the six designation coefficients are jointly zero is rejected at a 1-percent significance level with a p-value of 0.00002.

Without additional context, it is unclear whether federal parks are sited in areas with high carbon density, or whether federal parks effectively protect those areas with the highest carbon storage. The relative carbon density of state and federal parks at the time of site selection, but prior to park designation, can help identify the relative impact of selection bias on carbon-based treatment effects. In 2000, prior to park designation, the average carbon density of federal parks was 167 Mg of carbon per hectare, surprisingly similar to that of state parks with 161 Mg of carbon per hectare. Since federal and state parks had similar carbon densities prior to site selection, it appears that federal parks effectively protect the high-carbon forests, while state parks permit deforestation primarily in low-carbon forests.

Relative to forest loss treatment effects, carbon estimates suggest that park networks are more effective, in aggregate, because avoided forest loss occurs in high-carbon areas and increased forest loss occurs in low-carbon areas. Table 4 shows that federal parks prevented deforestation in high-quality forests, a mean carbon density more than 30 Mg higher than average, perhaps by restricting access to primary forests in the park interior. In contrast, state parks facilitated deforestation in low-quality forests with a mean carbon density of about 15 Mg lower than average, perhaps due to forest clearing activities in secondary forests. These results are consistent with a recent study that finds deforestation of unprotected areas in Rodonia occurred in in forests with lower than average carbon density (Song et al., 2014).

Estimates of avoided carbon emissions have direct policy implications.[24] For example, in the context of REDD+, one could use estimates in column 2 of table 4 to estimate the avoided carbon emissions from all federal parks in the Amazon designated between years 2001 and 2009. During these 8 years, 38 federal parks were established over 310,733 km$^2$ of the Amazon forest. Using the estimate of 18.5 Mg/km$^2$ implies avoided carbon emissions of approximately 5.7 million metric tons per year, which at a carbon price of $20 per metric ton has an annual value of $115 million from post-2000 federal parks. A comparable estimate shows that the adverse selection of state park designations actually detracted from the net value of carbon sequestration by $53 million per year from post-2000 state parks. This calculation assumes state parks generate 2.7 million metric tons of carbon emissions per year, using estimates of 10.5 Mg/km$^2$ additional carbon emissions sourced from each of the 250,146 km$^2$ contained in the 52 state parks established after 2001.

In sum, results suggest that parks designated between 2001 and 2009 collectively reduced annual carbon emissions approximately 3 million metric tons per year through 2012. By comparison, these estimates are lower than the avoided carbon emissions reported in another recent study. Ferraro et al. (2015) estimate that Brazil's post-2000 protected areas reduced carbon emissions by 749 million metric tons between 2000 and 2008. Using results in this study, the cumulative effects over a 9-year period would

[24] It should be noted that the estimated forest carbon loss only represents "committed carbon emissions" rather than the total carbon emissions from deforestation. A full accounting of carbon emissions associated with deforestation must include estimates of other fundamental carbon pools, such as soil carbon, dead organic matter, and carbon emissions from the succeeding land uses after deforestation (e.g. ranching), etc.

imply a reduction in carbon emissions of 27 million metric tons—less than 4 percent of total reductions estimated by Ferraro et al. (2015). Although this study uses a different source of carbon data than Ferraro et al. (2015), disagreement in carbon-based treatment effects is most likely due to differences in methodology. Compared to cross-sectional methods, superior panel estimators show a loss of significance for indigenous parks and a reversal in sign for state park effects. If one simply applied the carbon-effects estimated for federal parks to all 1,166,106 $km^2$ of total park area established between 2001 and 2009, and multiplied by 9-years, the estimates in this study would increase to 194 million metric tons per year—a magnitude that is reasonably similar to estimates of Ferraro et al. (2015).

***Inferring Causality via the Timing of Park Designation***

Panel data techniques inherently identify effects based on changes in treatment status over time. In the case of multiple experiments, where parks are designated at different points in time, panel analyses can also provide insights on whether park effectiveness has evolved over time.

The difference-in-difference estimates in equation (3.1) provide no sense of the dynamics of park designation and forest loss: how quickly deforestation declines after a park is designated and whether this effect accelerates, stabilizes, or reverts to a mean. If deforestation declines lead to the designation of parks, rather than vice versa, the previous estimates would obscure this reverse causality. On the other hand, if a temporary surge in deforestation leads to the designation of parks, then previous estimates would obscure this reversion to the mean. To explore these dynamics, table 5 provides estimates of a subset of the models in table 4, augmented with leads and lags of park designation. Specifically, I add indicator variables for years 1, 2, and 3 before designation, years 0-3 after designation, and year 4 forward.[25] Of these eight indicator variables, the first seven are equal to one only for a single year, while the final variable is equal to one in each year starting with the fourth year of designation.

The first column of table 5 presents the base specification augmented with the leads and lags. The coefficients on the two and three year designation lags are close to zero, showing little evidence of an anticipatory response within parks about to receive federal protection status[26]. In the year prior to adoption, however, deforestation decreases substantially by -0.2 percent and remains at this level during the year of designation. Since this initial decline occurs within one year of designation, the negative coefficient on the one year designation lag may simply reflect measurement error in the forest loss dataset. This follows because I am unable to identify the date of forest loss within a time interval shorter than a year, so forest loss occurring in the time period surrounding designation cannot be accurately assigned to a pre-designation or post-designation regime. After the year of designation, however, annual deforestation rates drop an additional -0.3 percentage points in the subsequent two years, after which annual effects stabilize to average -0.5 percentage points in year 4 forward.

[25] Additional models were estimated with additional leads and lags, including eleven indicator variables for 1, 2, 3, and 4 years before designation, years 0-5 after designation, and year 6 forward. Alternative estimates are similar in sign, significance, and magnitude to the estimates presented in the model with eight indicator variables representing leads and lags and so are not included here.

[26] The three-year lead has a substantially smaller standard error than the two-year lead, although both are statistically insignificant, and than other leads and lags. In alterative specifications, leads further from the year of designation consistently have relatively small standard errors. This may be due to limited variation in forest loss in the period before effects. In addition, earlier periods are less likely to have any variation caused by anticipation effects or measurement error in forest loss date assignment, and thus much less change in variation.

Subsequent columns repeat these estimates using a sample of parks established after 2001, and using carbon loss as the dependent variable for the sample of all parks established since 1985 and a sample restricted to parks established after 2001. The pattern of coefficients is comparable for each case, providing robust evidence that designation of federal parks has led to a reduction in forest loss rather than vice versa. Figure 5 depicts this pattern, with 95-percent confidence bars, for carbon loss estimates in table 5 column 4, the preferred specification using all parks established since 1985. Anticipation effects are not indicated for 3 and 2 year leads. An initial effect of 30 Mg C/km$^2$/year begins with a 1-year lead and in the year of protection, followed by a second drop through the 2 year lag, followed by stabilization at levels between 70 and 80 Mg C/km$^2$/year where estimates become statistically significant at the 5-percent level.

Estimates of dynamic effects offer compelling evidence that park establishment has a near-immediate causal effect on avoided carbon emissions. The results on the timing of effects make two distinct contributions to the literature. First, the discrete onset of effects around the timing of designation strengthens causal claims that the park designation does, in fact, drive the results presented in this essay. Second, the quick onset of effects provides important policy insights that are missing from previous literature. In particular, it appears that "paper parks" work. Legal statues appear to become effective immediately at the time of designation, perhaps by eliminating access to titles for would-be land grabbers. Meanwhile, parks seem to be effective 2 years after designation—well before new infrastructure, staffing, and enforcement protocols take effect. These are planning steps that typically require 5 years or more to implement.

## CONCLUSIONS

This essay makes three central contributions to existing literature. First, the fixed effects model finds that government-ownership is a key determinant of effectiveness. The surprising finding is that federal and state governments have dramatically different effects that are of opposite qualitative directions. Specifically, federal parks are immediately effective in reducing deforestation, while state parks cause a considerable increase in deforestation over time. Contrary to conventional wisdom, panel results suggest that the establishment of indigenous parks causes no change in deforestation.

Second, this essay demonstrates the limitations of cross-sectional matching estimators that dominate the deforestation literature. For example, cross-sectional matching estimators applied to the same data find that indigenous parks are very effective at reducing deforestation, which illustrates the inherent bias of studies that rely on cross-sectional matching. The findings in this essay suggest that indigenous people monitor forests regardless of legal park status, which will bias matching estimators that fail to control for the presence of indigenous populations.

Third, results highlight the importance of spatial variation in forest carbon storage. These results show that studies that measure only avoided deforestation are misleading as a reflection of avoided carbon emissions. This is particularly true given evidence that deforestation effects target either high-carbon or low-carbon forest areas across different governance regimes.

To date, the effectiveness of protected areas has been assessed using cross-section matching estimators. In this essay, new evidence is derived using quasi-experimental models on two panel datasets of deforestation. The results reveal dramatic new insights into the importance of government oversight of protected areas and the jurisdiction from which government oversight is provided—findings that counter economists' prior notions of the avoided deforestation from park designation. I extend the analysis to estimate avoided carbon emissions. I show that this key metric, which is of much more policy importance than deforestation, varies considerably from deforestation trends. For the both science and policy communities, I underscore uncertainty in policy evaluation based on imperfect satellite-derived deforestation data products compared to data products that measure carbon.

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**FIGURES**

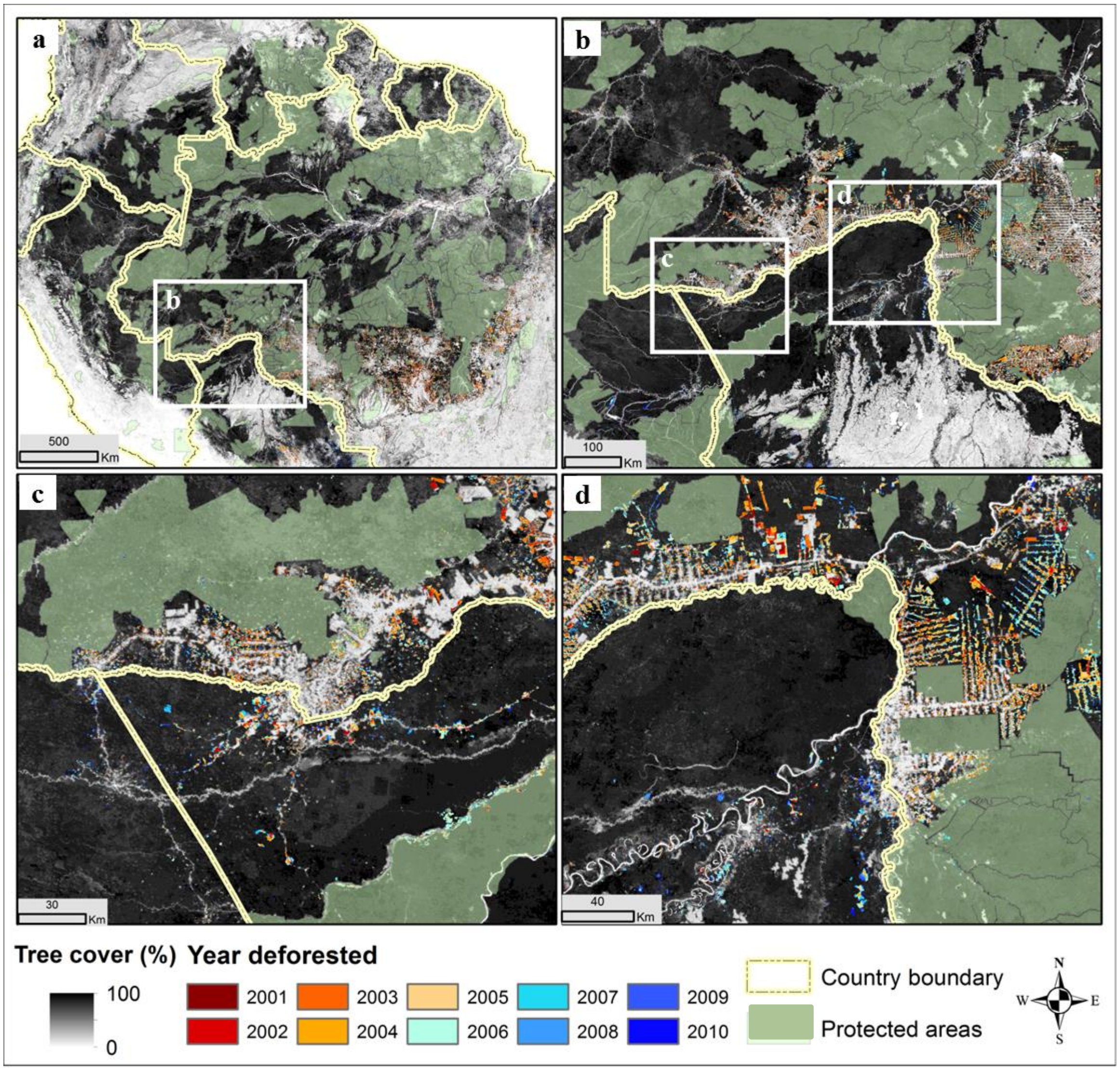


Figure 1 Forest, deforestation and protected areas in the Amazon basin, where over 50% of forests have been designated as protected areas. The four map layers are overlaid in the order from top to bottom of country boundaries, protected areas, deforestation year, and tree cover percentage in the year 2000. Panel (a) is a full-view of protected areas in the entire study area. Panel (b) is a close-up in the Brazil/Bolivia/Peru tri-national border region where forests on the Brazil side are either cleared or protected. Panel (c) zooms-in over the city of Cobija, the capital of the Bolivian Pando Department. The inter-oceanic highway begins in this region. Panel (d) zoom-in over the city of Guayaramerin, where more deforestation is observed on the Bolivia side after 2006.

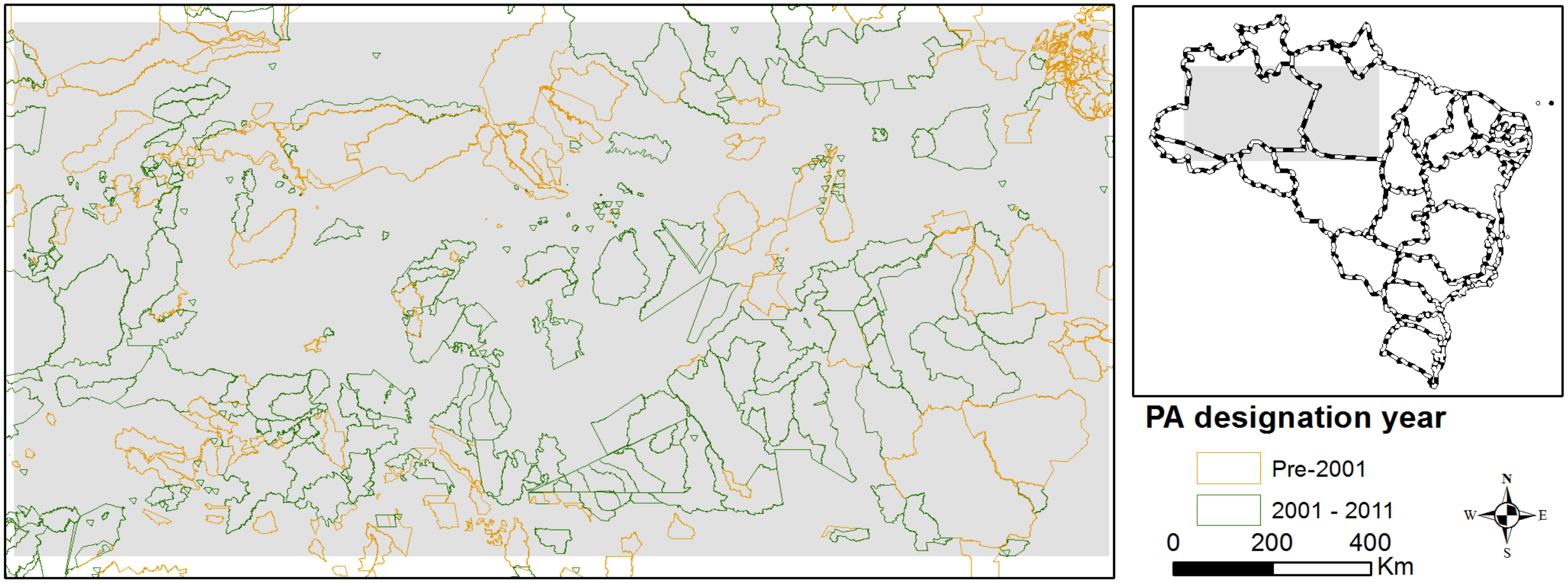


Figure 2 A sub-sample that includes approximately 50% of the Amazon study area, centered over the two largest Brazilian states of Amazonas and Pará. Parks designated as pre-2001 (the comparison group) are shown as orange polygons, while parks designated post-2001 (the treatment group) are shown as green polygons.

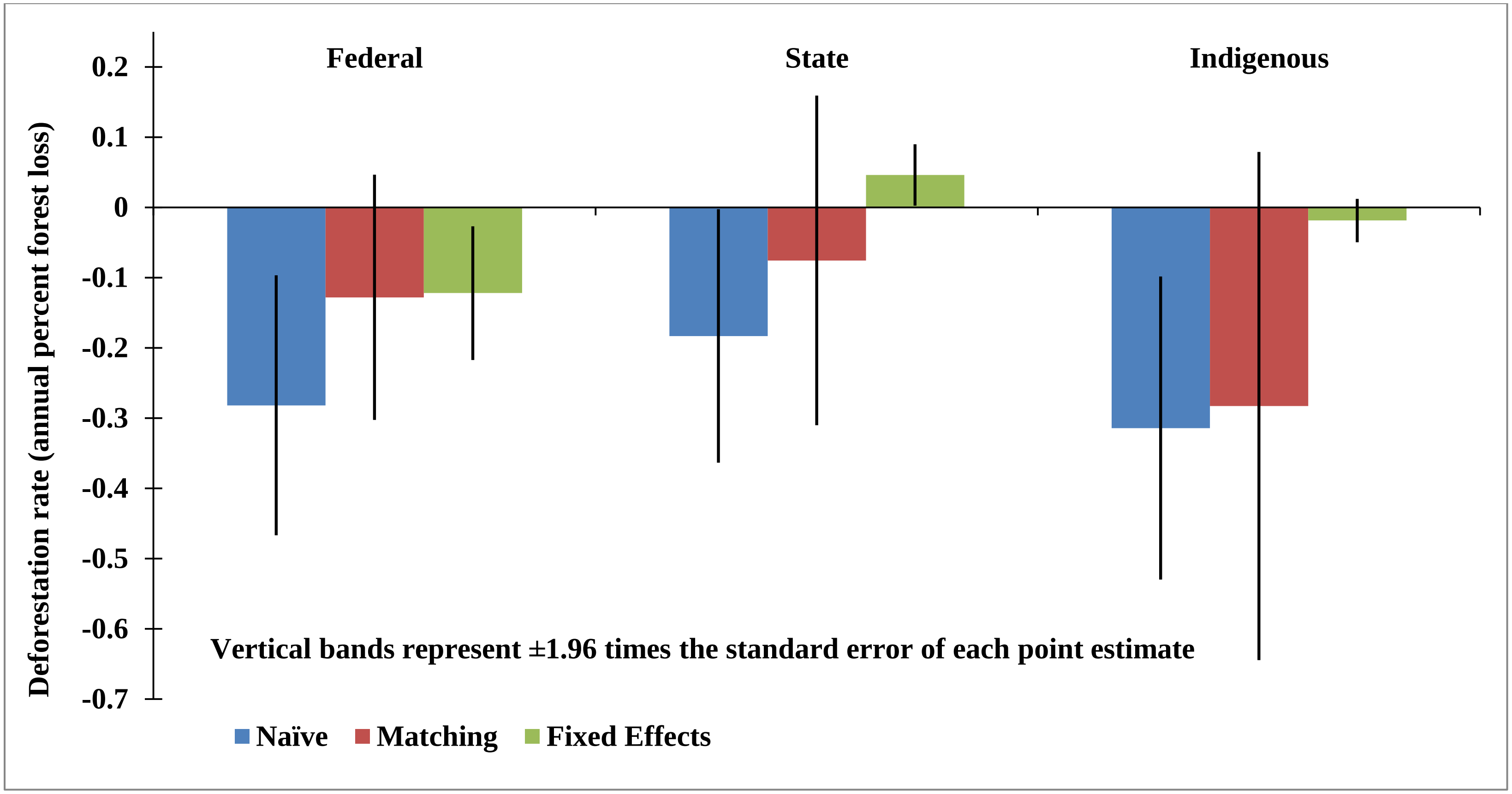


Figure 3 Effects of government park designations on percentage forest loss estimated from naïve, matching, and fixed-effects models.

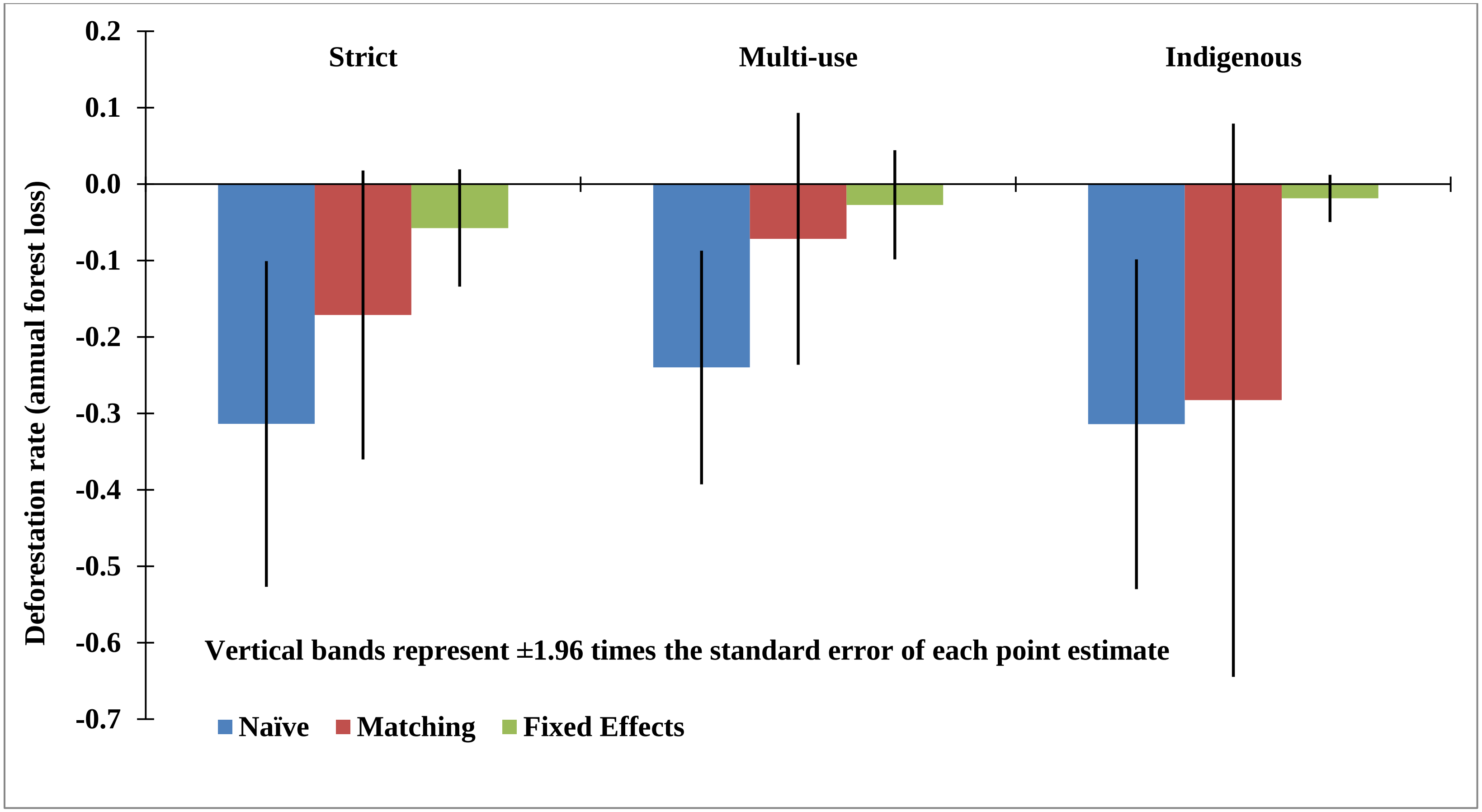


Figure 4 Effects of park strictness designations on percentage forest loss estimated from naïve, matching, and fixed-effects models.

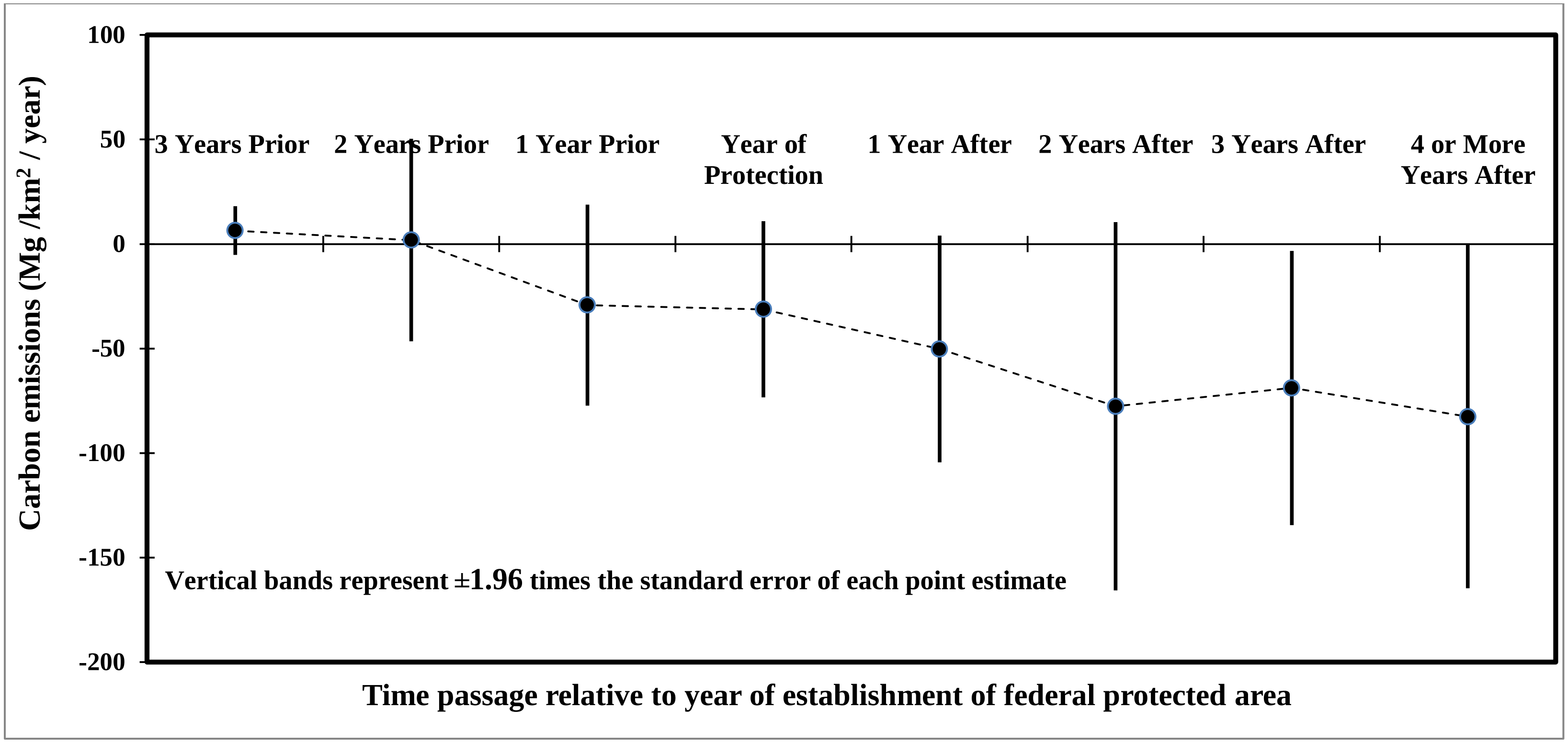


Figure 5 Estimated effects of federal park designation on carbon loss for years before, during, and after park designation. (See table 5, model 4).

**TABLES**

Table 1 The Estimated Effect of Park Designations on Annual Deforestation Rates in the Amazon, 2000-2012

| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Park designation: | | | | | | | | | | | | |
| Any type | -0.039 | *** | -0.027 | ** | -0.025 | * | | | | | | |
| | (0.014) | | (0.011) | | (0.013) | | | | | | | |
| Federal | | | | | | | -0.071 | *** | -0.066 | *** | -0.122 | ** |
| | | | | | | | (0.021) | | (0.022) | | (0.049) | |
| State | | | | | | | -0.059 | | -0.035 | | 0.046 | ** |
| | | | | | | | (0.038) | | (0.035) | | (0.022) | |
| Indigenous | | | | | | | -0.041 | ** | -0.022 | | -0.019 | |
| | | | | | | | (0.017) | | (0.019) | | (0.016) | |
| Non-government | | | | | | | 0.044 | | 0.025 | | 0.000 | |
| | | | | | | | (0.031) | | (0.017) | | (0.028) | |
| Park and year dummies | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| State x year dummies | No | | Yes | | Yes | | No | | Yes | | Yes | |
| Park x time trends and park x time$^2$ trends | No | | No | | Yes | | No | | No | | Yes | |
| $R^2$ | 0.015 | | 0.070 | | 0.378 | | 0.02 | | 0.072 | | 0.377 | |

Source: The dependent variable is constructed from Hansen et al. 2012, and is defined as average percent forest loss per year in each of 610 parks in each of 12 years (7,320 observations). Ordinary least squares estimates are weighted by park area. The sample includes parks established since 1985. Standard errors in parentheses are clustered by park to allow for arbitrary correlation of residuals within each park. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *).

Table 2 The Estimated Effect of Park Designations on Annual Deforestation Rates in the Amazon, 2000-2012: Testing the Effect of Government Ownership versus Protection Strictness.

| | (1) | | (2) | (3) | |
|---|---|---|---|---|---|
| Park designation: | | | | | |
| Federal | -0.122 | ** | | -0.093 | * |
| | (0.049) | | | (0.052) | |
| State | 0.046 | ** | | 0.074 | ** |
| | (0.022) | | | (0.033) | |
| Non-government | 0.000 | | | | |
| | (0.028) | | | | |
| Indigenous | -0.019 | | -0.019 | -0.019 | |
| | (0.016) | | (0.016) | (0.016) | |
| Strict | | | -0.057 | -0.033 | |
| | | | (0.039) | (0.033) | |
| Multi-use | | | -0.027 | -0.025 | |
| | | | (0.036) | (0.030) | |
| Not reported | | | 0.009 | 0.009 | |
| | | | (0.033) | (0.033) | |
| $R^2$ | 0.377 | | 0.609 | 0.636 | |

Source: For the dependent variable, see Hansen et al. 2012
Dependent variable: percent forest loss per year; n=7,320. Sample includes parks established between 1985 and 2009. Ordinary least squares estimates include weights for park area. Standard errors in parentheses are clustered by park to allow for arbitrary correlation of residuals within each park. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include park main effects, state-by-year effects, and park specific linear and quadratic time trends. Omitted treatment group in model 3 is non-government park designations.

Table 3 The Estimated Effect of Park Designations on Annual Deforestation Rates in the Amazon: Cross-section Estimators

| Park designation: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Federal | -0.282 ** | -0.332 * | -0.128 | | | | -0.235 * | -0.218 | -0.046 |
| | (0.094) | (0.154) | (0.089) | | | | (0.124) | (0.139) | (0.052) |
| State | -0.183 * | -0.239 ** | -0.075 | | | | -0.140 | -0.104 | 0.009 |
| | (0.092) | (0.108) | (0.120) | | | | (0.116) | (0.127) | (0.093) |
| Non-government | -0.301 ** | 0.003 | -0.036 | | | | -0.271 * | 0.086 | 0.013 |
| | (0.122) | (0.068) | (0.046) | | | | (0.139) | (0.102) | (0.028) |
| Indigenous | -0.314 ** | -0.551 ** | -0.289 | -0.314 ** | -0.548 ** | -0.283 | -0.314 ** | -0.557 ** | -0.287 |
| | (0.110) | (0.223) | (0.188) | (0.110) | (0.225) | (0.185) | (0.110) | (0.230) | (0.189) |
| Strict | | | | -0.314 ** | -0.285 ** | -0.171 | -0.093 | -0.136 | -0.150 ** |
| | | | | (0.109) | (0.117) | (0.096) | (0.059) | (0.090) | (0.060) |
| Multi-use | | | | -0.240 ** | -0.267 * | -0.072 | -0.028 | -0.144 | -0.058 |
| | | | | (0.078) | (0.131) | (0.084) | (0.074) | (0.144) | (0.046) |
| Not reported | | | | -0.264 * | 0.002 | -0.001 | | | |
| | | | | (0.126) | (0.045) | (0.044) | | | |
| Geographic covariates: | | | | | | | | | |
| Tree cover in 2000 | | -0.657 | -0.096 | | -0.534 | -0.067 | | -0.611 | -0.047 |
| (percent) | | (0.381) | (0.105) | | (0.431) | (0.080) | | (0.411) | (0.093) |
| Elevation | | -0.057 | -0.005 | | -0.042 | -0.008 | | -0.056 | -0.007 |
| (meters) | | (0.039) | (0.031) | | (0.041) | (0.034) | | (0.039) | (0.033) |
| Slope | | 0.040 ** | 0.018 | | 0.047 ** | 0.027 | | 0.042 ** | 0.025 |
| (degrees) | | (0.017) | (0.015) | | (0.018) | (0.017) | | (0.017) | (0.016) |
| Travel time to city | | 0.088 ** | 0.026 * | | 0.121 ** | 0.026 * | | 0.088 ** | 0.029 ** |
| (days) | | (0.043) | (0.014) | | (0.058) | (0.014) | | (0.043) | (0.014) |
| Crop suitability | | -0.041 | -0.044 * | | -0.033 | -0.042 * | | -0.038 | -0.040 * |
| (index) | | (0.049) | (0.022) | | (0.050) | (0.019) | | (0.050) | (0.021) |
| Precipitation | | 0.030 ** | 0.000 | | 0.400 * | 0.000 | | 0.300 ** | 0.000 |
| (cm/month) | | (0.014) | (0.005) | | (0.167) | (0.064) | | (0.140) | (0.054) |
| Mean temperature | | -0.008 | 0.000 | | -0.050 | -0.010 | | -0.080 | -0.010 |
| (C) | | (0.007) | (0.006) | | (0.077) | (0.062) | | (0.073) | (0.061) |
| region x year | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| matched sample | No | No | Yes | No | No | Yes | No | No | Yes |
| $R^2$ | 0.078 | 0.814 | 0.335 | 0.077 | 0.81 | 0.34 | 0.078 | 0.815 | 0.342 |

Dependent variable: percent forest loss per year. Unit of observation is km2-year. All samples include parks established since 1985. Models 1-2, 4-5, and 7-8 also include unprotected areas (N=84,625,901); models 3, 6, and 9 include only matched unprotected areas (N=25,223,513). Standard errors in parentheses are clustered by park. All models include year effects. Significance: *1%, **5%, ***10%

Table 4 The Estimated Effect of Park Designations in the Amazon: Comparisons Of Percent Deforestation and Carbon Loss Estimates Across Data Sets

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Park designation: | | | | | | | | |
| Federal | -0.093 | * | -18.460 | ** | -0.050 | | -10.738 | ** |
| | (0.052) | | (9.251) | | (0.033) | | (5.254) | |
| State | 0.074 | ** | 10.690 | ** | 0.043 | | 7.465 | * |
| | (0.033) | | (5.385) | | (0.027) | | (4.464) | |
| Non-government | | | | | | | | |
| Indigenous | -0.019 | | -3.286 | | -0.002 | | -1.722 | |
| | (0.016) | | (2.519) | | (0.018) | | (2.337) | |
| Strict | -0.033 | | -3.585 | | -0.008 | | -0.560 | |
| | (0.033) | | (5.681) | | (0.017) | | (2.802) | |
| Multi-use | -0.025 | | -4.105 | | -0.007 | | -1.321 | |
| | (0.030) | | (5.078) | | (0.022) | | (3.705) | |
| Not reported | 0.009 | | 1.098 | | -0.043 | ** | -5.657 | ** |
| | (0.033) | | (4.431) | | (0.018) | | (2.439) | |
| $R^2$ | 0.636 | | 0.377 | | 0.609 | | 0.636 | |

Source(s) - Hansen et al. forest loss 2000-2012 (models 1 and 2).
Dependent variable(s): percent forest loss per year (models 1 and 3), or metric tons of carbon loss per $km^2$ per year (models 2 and 4); n=7320. Samples include all parks established since 1985. Ordinary least squares estimates include weights for park area. Standard errors in parentheses are clustered by park to allow for arbitrary correlation of residuals within each park. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include park main effects, state-by-year effects, and park specific linear and quadratic time trends. Omitted treatment group in is non-government park designations.

Table 5 The Estimates Effects of Federal Park Designation on Annual Deforestation Rates and Annual Carbon Loss in the Amazon, for Parks Designated After 2002 and 1985

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Federal park leads and lags: | | | | |
| Status change$_{t+3}$ | 0.034 | 0.035 | 5.87 | 6.45 |
| | (0.036) | (0.032) | (06.82) | (5.92) |
| Status change$_{t+2}$ | -0.047 | -0.012 | - 2.46 | 1.90 |
| | (0.153) | (0.149) | (24.78) | (24.72) |
| Status change$_{t+1}$ | -0.202 | -0.177 | -34.48 | -29.18 |
| | (0.174) | (0.158) | (27.64) | (24.53) |
| Status change$_{t0}$ | -0.220 | -0.191 | -37.78 | -31.22 |
| | (0.161) | (0.145) | (24.50) | (21.50) |
| Status change$_{t-1}$ | -0.314 | -0.303 * | -55.33 * | -50.20 * |
| | (0.201) | (0.183) | (31.04) | (27.66) |
| Status change$_{t-2}$ | -0.500 | -0.474 | -84.60 * | -77.60 * |
| | (0.327) | (0.294) | (50.76) | (44.92) |
| Status change$_{t-3}$ | -0.447 * | -0.413 * | -78.02 ** | -68.88 ** |
| | (0.243) | (0.215) | (39.07) | (33.49) |
| Federal park status$_{t-4\ forward}$ | -0.535 * | -0.498 * | -92.67 * | -82.60 ** |
| | (0.302) | (0.270) | (47.77) | (41.87) |
| $H_0$: designation$_{(t0-t4)}$ = 0 | 0.000 | 0.000 | 0.000 | 0.000 |
| $R^2$ | 0.371 | 0.369 | 0.390 | 0.367 |
| No. Observations | 3,684 | 7,320 | 3,684 | 7,332 |
| No. PAs | 307 | 610 | 307 | 611 |

Source: For the dependent variable, see Hansen et al. 2012.
Dependent variable(s): percent forest loss per year (models 1 and 2), or metric tons of carbon loss per $km^2$ per year (models 3 and 4). Samples include parks established since 2002 (models 1 and 3), or parks established since 1985 (models 2 and 4). Ordinary least squares estimates include weights for park area. Standard errors in parentheses are clustered by park to allow for arbitrary correlation of residuals within each park. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include leads and lags for strict and multi-use designations, park main effects, state-by-year effects, and park specific linear and quadratic time trends.