# The Political Logic of Persistent Deforestation:

## Electoral Incentives and Public Goods in the Brazilian Amazon

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**Abstract**

A growing literature links democratic institutions, particularly elections, to increased deforestation but fails to fully explain how politicians manipulate forest access near elections. We propose a theoretical framework connecting electoral incentives, environmental policy, and outcomes, focusing on enforcement efforts. We argue that stringent enforcement often triggers electoral backlash, leading incumbents to reduce and strategically redistribute enforcement to avoid political costs. This results in higher deforestation rates, with enforcement leniency favoring core supporters and stricter penalties targeting opposition areas. This strategic behavior explains both the election-deforestation nexus and the mixed results in existing studies, highlighting the need to account for non-linear policy-making dynamics. Our findings offer a nuanced understanding of how electoral pressures shape environmental outcomes and suggest ways to design more resilient environmental policy.

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# 1 Introduction

Forests cover approximately 31% of the Earth's surface, spanning 4.06 billion hectares, and play pivotal roles in societal, economic, and environmental systems. Despite their essential contributions to climate regulation, biodiversity, and human well-being and livelihoods, deforestation progresses at alarming rates.[1] With 90% of forests under government control, a growing body of work has pointed to political factors and incentives as the reason why governments fail to protect these ecosystems and other public goods like fish stocks and water basins (e.g., Grainger and Parker, 2013; Sanford, 2021; Balboni et al., 2023). This scholarship highlights the detrimental effects democratic institutions — particularly elections — may have on forest degradation globally (e.g., List and Sturm, 2006; Ameet, 2018; Rodrigues-Filho et al., 2015; Pailler, 2018; Ruggiero et al., 2021; Sanford, 2021; Cisneros et al., 2021; Morpurgo et al., 2023; Xu, 2025).[2]

The evidence supporting the election-deforestation nexus is strong in many settings, with more pronounced effects in new democracies (Akhmedov and Zhuravskaya, 2004; Brender and Drazen, 2005), competitive elections (Sanford, 2021; Xu, 2025), and when the levels of governments are aligned (Ruggiero et al., 2021). Still, despite being able to show a negative connection between democratic institutions and forest preservation, this literature has yet to fully explain *why* and *how* politicians manipulate access to forests in exchange for political support.[3]

This paper addresses this gap by directly examining the mechanisms that connect electoral institutions, environmental policy, and environmental outcomes. Specifically, we investigate how electoral incentives influence the way in which national governments approach the implementation of enforcement efforts, a central component of environmental policies.[4]

We theorize enforcement as a lever national politicians can manipulate during elections to influence voter support and environmental outcomes. Thus, even where strong regulations and reasonable capacity exist, policymakers strategically adjust enforcement to balance environmental control with electoral interests.[5] This contributes to deforestation spikes during elections but also influences decisions throughout political cycles. This strategic redistribution

[1] The UN Food and Agriculture Organization (FAO) estimates that 10 million hectares of forest have been cut down each year since 2010, resulting in a net loss of 4.7 million hectares annually over the past decade (FAO and UNEP, 2020)

[2] While much of this literature emphasizes strong correlational evidence, more recent work seeks to establish causal relationships (Cisneros et al., 2021; Xu, 2025).

[3] Appendix A1 provides a more systematic discussion of the relevant literature.

[4] Environmental policies generally adopt one of two primary institutional forms. The first involves incentive-based mechanisms, which use market instruments to internalize the costs of environmental degradation. These approaches often rely on economic incentives, such as taxes, subsidies, or tradable permits, to align individual or corporate behavior with broader environmental goals. The second form consists of command-and-control policies, which set explicit permissions and prohibitions to regulate access to and the use of natural resources. These policies impose direct restrictions, such as limits on pollution or bans on deforestation, often enforced through fines, sanctions, or other legal mechanisms (Keohane and Olmstead, 2016).

[5] As prior work emphasizes, democratic transitions often generate environmental institutions and legislation without necessarily translating into improved environmental outcomes, particularly in Latin America (Hochstetler, 2012). The resulting gap between institutional capacity and environmental performance points to electoral incentives as a key driver of how enforcement is implemented in practice.

of enforcement not only helps explain the central findings of the election-deforestation nexus literature — namely, that electoral institutions often correlates with higher deforestation —, but also sheds light on why these studies occasionally report mixed results, often due to insufficient consideration of strategic policymaking behavior. By exploring these dynamics, this study contributes to a more nuanced understanding of how electoral pressures shape environmental policy and provides insights into designing more robust environmental frameworks that can withstand short-term electoral incentives. The paper makes several contributions.

First, we analyze the calculus of enforcement by national governments. We model incumbents' enforcement choices as a function of ideological commitments and electoral considerations, driven by the anticipated backlash of voters and producers economically affected by enforcement (*cf.*, Stokes, 2016; Aklin and Mildenberger, 2020; Pianta and Rettl, 2023). Importantly, we provide direct empirical evidence of such an electoral backlash, showing that environmental enforcement systematically reduces incumbent vote shares in subsequent elections and can also provoke responses from campaign donors. Crucially, this backlash is not uniform across jurisdictions. Because the distribution of affected voters and producers varies spatially, our analysis uncovers a political geography of enforcement driven by two mechanisms: (1) the electoral importance of particular sub-units for national-level victory and (2) local exposure to economic shocks (such as commodity booms) that alter the opportunity costs of enforcement for voters and producers. We show how these factors shape the spatial allocation of enforcement by parties otherwise ideologically committed to environmental protection. This, in turn, helps explain the lack of robustness in the election–deforestation cycle observed in the literature: due to strategic considerations, enforcement efforts and environmental outcomes can vary substantially across space within a given electoral cycle.

Second, our analysis qualifies a well established literature on the benefits of political competition in established democracies (e.g., Persson and Tabellini, 2002). We explain and show why competition actually serves as a driver of lower levels of enforcement and worse environmental outcomes. An important implication of our analyses is that the political logic governing the *provision* of public goods may differ from the logic governing the *preservation* of public goods. In doing so, we extend a growing literature on the potentially adverse effects of political competition (e.g, Grzymala-Busse, 2007; Baskaran et al., 2015; Gottlieb and Kosec, 2019) by uncovering dynamics that can be especially relevant for environmental public goods (cf., Burgess et al., 2012; Mangonnet et al., 2022).

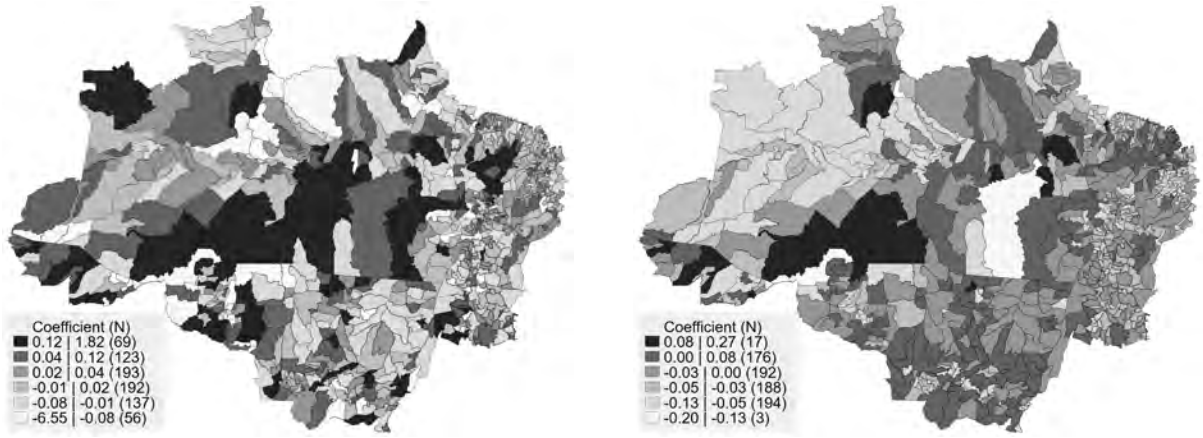
Third, in contrast to the extant literature, we provide a first direct measure of both local enforcement and local *forbearance* (Holland, 2016, 2017) by a national government. We do that by using the actual amount of deforestation observed by the environmental authorities in each jurisdiction and trace that to the contemporaneous level of enforcement (fines and embargoes). By doing so, we have a measure of infractions and the correspondent (lack of) penalties. The difference between these two measures — deforestation occurrences and penalties — capture directly our core theoretical concepts and allow to assess the empirical implications of the argument directly.

We do so in the context of Brazil, home to 60% of the Amazon rainforest, the world's largest tropical forest and the major deforestation hotspot (Figure A1). The Brazilian Amazon has experienced a surge in extractive industries and agricultural expansion since the 1970s, threatening this ecosystem despite widespread public concern inside and outside Brazil. We will show that current deforestation levels in this region cannot be attributed to a lack of command-and-control policies or state capacity — common culprits of high deforestation in the tropics —, since Brazil has an extensive environmental legislation and has made substantial investments in enforcement mechanisms especially in the early 2000s. Still, deforestation remains a weak predictor of environmental enforcement (see Figure 1), highlighting the puzzling reality of a state with the tools to curb deforestation but allocating enforcement based on other factors.

Figure 1: Deforestation and Enforcement in the Brazilian Amazon

(a) Fines

(b) Embargoes




Note: The figures show the correlation between enforcement (count) and deforestation (km²) in the Brazilian Legal Amazon. *N* indicates the number of municipalities in each bracket. Coefficients are based on 2001–2022 data, estimated using OLS regressions with municipality and year fixed effects. Brackets are defined base on a boxplot method that aggregate observations according to their locality and through data quartiles. For the same estimations for the Workers Party's administrations, see Figure A7 in the Appendix.

Beyond its ecological importance, Brazil offers a compelling case for examining environmental governance through a political economy lens. Its relatively recent transition to democracy, coupled with the sustained continuity of democratic institutions, provides a unique context to test key hypotheses in the election-deforestation nexus literature. The centralized oversight of environmental enforcement by the national government, particularly through its primary enforcement agency (IBAMA), creates a clearer framework for analyzing how political incentives shape policy outcomes.[6] This institutional arrangement allows mapping the incentives of critical actors to understand the interplay between national directives and local implementation, offering valuable insights into the dynamics of environmental policymaking. Strategic enforcement is not about capacity. It is about choices driven by politico-economic considerations.

We study the strategic distribution of environmental enforcement in the Brazilian Amazon. We show that, in a context where federal agencies are the primary authorities enforcing en-

[6]For an analytical overview of the evolution of Brazil's environmental and climate institutions, see (Hochstetler, 2021).

vironmental policy,[7] policymakers strategically adjust enforcement to balance environmental control with electoral interests, even in the presence of strong regulations and substantial state capacity since the early 2000s.

Through a variety of methodological strategies, both observational and quasi-experimental, we show that: (1) Enforcement generates political backlash among voters and producers; (2) this in turn shapes the political geography of enforcement across Brazilian municipalities. We provide robust evidence that the PT, ideologically committed to the environment, systematically reduces enforcement efforts in municipalities that are (a) electorally salient and (b) disproportionally benefited by commodity booms. Finally, (3) we show how these strategies translate into worse environmental outcomes.

## 2 Theory: Political Geography and the Calculus of Enforcement

Policies designed to address climate change, from de-carbonization to the protection of forests, and converse environmental resources have one distinctive feature: their short term costs are concentrated whereas their medium term benefits, both locally and globally, are diffused. This much has been widely recognized by an extensive literature in political science and economics (e.g., Stern, 2008; Stokes, 2016). Less recognized is the interaction between these characteristics and the fact that economic and political geography are hardly neutral. While environmental protection laws are usually adopted at the national level, their on-the-ground implementation is subject to discretionary enforcement, which can be tailored spatially to suit political strategies.

The economic activities enabled by deforestation — such as agriculture and cattle ranching — are typically asset-specific and geographically immobile, leading to uneven distributions of economic gains across space (Pendrill et al., 2022). As a result, the political costs and benefits of enforcing environmental protection vary substantially by location. These spatial asymmetries influence the composition of local electorates and producer groups, creating heterogeneous preferences across regions. In turn, this variation shapes the electoral incentives of political actors at higher levels of government, who must strategically weigh how enforcement decisions will resonate with different constituencies. As a result, the spatial and temporal heterogeneity of environmental enforcement emerges as an outcome of strategic political behavior by the national government. Deforestation persists not solely due to weak state capacity or economic pressure, but also because democratic institutions create incentives for selective enforcement in ways that may undermine long-term conservation goals. We formalize the logic behind the calculus of environmental enforcement in a dynamic setting where a political party decides how to spatially allocate enforcement in the presence of economic and political constraints. The model spans two periods, $t = 1, 2$ — such as two subsequent electoral cycles —, capturing how agents balance short-term outcomes against future consequences. Both producers and voters discount future utility using discount factors $\delta_j \in (0, 1]$ and $\delta_i \in (0, 1]$, respectively.

[7] Ample evidence identifies the federal environmental bureaucracy — particularly IBAMA — as the country's most influential enforcement authority (e.g., Sills et al., 2015; Bragança and Dahis, 2022; Assunção et al., 2019; Assunção and Rocha, 2019; Assunção et al., 2023).

## 2.1 The Setting: Parties and Political Geography

Consider a region endowed with a vast natural resource, where the spatial distribution of political support among voters we take as given. Two political parties compete for control of this region, differing in their ideological stances and policy priorities across multiple dimensions, including environmental governance and economic development. Party $E$ (*Extractive*) prioritizes short-term economic gains derived from exploiting natural resources, even at the cost of environmental degradation. Its policy platform appeals to stakeholders benefiting directly or indirectly from resource extraction activities, such as landowners, extractive industries, and workers employed in these sectors. In contrast, Party $P$ (*Protective*) emphasizes the conservation of natural resources and sustainable development, opposing activities that lead to environmental destruction. Party $P$'s platform seeks support from voters concerned about long-term ecological balance, including environmental activists, indigenous communities, and urban populations dependent on ecosystem services. Hence, in this world, $p \in \{E, P\}$.

Each municipality $m \in M$ is characterized, first, by the level of *enforcement intensity* it experiences. Accordingly, $e_{mt} \in [0,1]$ is the level of environmental enforcement implemented by the central government in municipality $m$ at time $t$. Enforcement is assumed to respond to the aggregate level of observed or anticipated deforestation. Let $D_{mt} = \sum_{j \in J_m} d_{jt}$ denote total new deforestation in municipality $m$ at time $t$, where $d_{jt} \in [0,1]$ is the land cleared by producer $j$. Consequently, enforcement is modeled as:

$$e_{mt} = D_{mt} + \varepsilon_{mt}$$

where $\varepsilon_{mt}$ is a municipality-time-specific deviation term capturing discretionary enforcement that is not directly explained by aggregate producer behavior (e.g., due to political, administrative, or technical factors). When $\varepsilon_{mt} = 0$, enforcement perfectly tracks deforestation.

Municipalities are also exposed to *commodity shocks* where $\mathscr{P}_{mt}$ is a municipality-specific commodity price index capturing local exposure to international agricultural markets. $\mathscr{P}_{mt}$ is defined as:

$$\mathscr{P}_{mt} = \sum_{g \in G} w_{mg,2000} \cdot P_{gt}$$

where $P_{gt}$ is the international price (in USD) of commodity $g$ at time $t$, normalized to 1 in the base year 2000. The weights $w_{mg,2000}$ represent the share of crop $g$ in the total planted area of municipality $m$ in 2000. These are fixed to ensure $\mathscr{P}_{mt}$ reflects exogenous variation in exposure, uninfluenced by producer behavior during the study period.[8]

In this setting, both voters and producers anticipate future outcomes when making present-day decisions. Voters evaluate candidates based on the current and expected future state of the environment and economy, while producers factor in future political risks — such as regulation or taxation — when deciding how much land to clear today. The party running the environmental agency, in turn, allocates enforcement effort strategically across municipalities, balancing short-run political trade-offs with long-run environmental goals. To analyze the al-

[8] By construction, $\sum_{g \in G} w_{mg,2000} = 1$ for each $m$.

location problem, we first describe the parties' decision problem and how they approach it (assuming that Party E has an ideological commitment with extraction and will do its best to reduce $e^E_{mt}$ to zero, we focus on describe the strategy most likely implemented by Party *P*); second, we analyze the preferences of the two other actors potentially constraining parties' enforcement decisions: producers, as they are the potential violators of environmental provisions, and voters and their response to actual environmental efforts on the ground; finally, once these elements are in place, we analyze the choice of enforcement levels under different conditions and its implications.

## 2.2 Party P's Problem

In each municipality *m*, Party *P* chooses an environmental enforcement level $e_{mt} \in [0, 1]$ to influence both the equilibrium level of deforestation and the electoral response of local voters. The party faces a dynamic trade-off between reducing deforestation and avoiding electoral backlash in strategically important areas.

We assume that Party *P* maximizes a discounted utility function defined by two components: (*i*) **Policy utility**, derived from reducing environmentally harmful deforestation; and (*ii*) **Electoral utility**, derived from securing votes in electorally relevant and competitive municipalities.

Let $\delta_P \in (0, 1]$ be Party *P*'s discount factor, reflecting its preference for present over future utility (e.g., due to political time horizons or term limits). Importantly, Party *P* updates its strategy over time based on observed electoral responses to past enforcement — capturing a process of political learning.

**Policy Component.** Let $D_{mt}(e_{mt})$ denote the equilibrium level of new deforestation in municipality *m* at time *t*, which is decreasing in enforcement: $D'_{mt}(e_{mt}) < 0$. The discounted policy utility stream is:

$$U^{\text{policy}} = -\sum_{t=1}^{T} \delta_P^{t-1} \sum_{m \in M} \psi \cdot D_{mt}(e_{mt}) \tag{1}$$

Where $\psi$ is a non-zero positive weight that Party P places on reducing deforestation. It captures the party's intrinsic commitment to environmental protection and how the amount of (avoided) deforestation translates into utility.

**Electoral Component.** Voter support in each municipality is shaped by preferences over economic and environmental outcomes, which respond to enforcement. Let $V_{mt}(e_{mt})$ denote the expected vote share for Party *P* in municipality *m*. The utility a party derives from its local electoral performance is given by:

$$U^{\text{electoral}} = \sum_{t=1}^{T} \delta_P^{t-1} \sum_{m \in M} \rho_m \cdot \kappa_{mt} \cdot V_{mt}(e_{mt}) \tag{2}$$

where the electoral utility at time $t$ is weighted by the district's competitiveness $\kappa_{mt}$ and strategic relevance $\rho_m$. [9]

**Dynamic Feedback from past Elections.** Let $\hat{V}_{mt}(e_{mt})$ denote the predicted vote share based on historical data, and let $\varepsilon^v_{mt} = V^{\text{obs}}_{mt} - \hat{V}_{mt}$ denote the observed electoral response of voters, *vis-a-vis* the party's expectations.

Party $P$ responds to this feedback by adjusting future enforcement strategies:

$$e_{m,t+1} = e_{mt} - \iota \cdot \varepsilon^v_{mt} \tag{3}$$

where $\iota > 0$ is a responsiveness — or leaning — parameter capturing how strongly the party adjusts enforcement in response to electoral backlash or support. A negative shock (electoral punishment) causes $P$ to reduce enforcement in $t+1$; a positive surprise may encourage stricter enforcement.

**Total Objective Function.** Putting both components together, Party $P$ chooses a dynamic enforcement path $\{e_{mt}\}_{t=1}^T$ to maximize:

$$U^P = \sum_{t=1}^{T} \delta_P^{t-1} \left[ \omega \cdot \sum_{m \in M} \rho_m \cdot \kappa_{mt} \cdot V_{mt}(e_{mt}) - (1-\omega) \cdot \sum_{m \in M} \psi \cdot D_{mt}(e_{mt}) \right] \tag{4}$$

where $\omega \in [0,1]$ determines the relative weight Party $P$ places on electoral versus environmental objectives.

### 2.3 Relevant actors for the calculus by parties: Producers and Voters

**Producers** Each municipality $m$ contains a set of producers $j \in J_m$, each of whom chooses how much additional land to clear for production at time $t$, denoted $d_{jt} \in [0,1]$. Let $K_{j,t-1}$ denote the cumulative amount of land that producer $j$ has cleared prior to period $t$. Assuming no conversion back to forest and no idle plots, the total productive land ($A$) at time $t$ is:

$$A_{jt} = K_{j,t-1} + d_{jt}$$

For simplicity, we assume output is linearly proportional to land, with revenue determined by the local commodity price index $\mathscr{P}_{mt}$. Producers also incur variable input costs (e.g., labor, fertilizer) at a constant marginal rate $c > 0$ for each unit of productive land. In addition, producers face expected penalties for illegal deforestation: each unit cleared is subject to a fine $f$ with probability $\theta(e_{mt})$, where detection risk increases in local enforcement $e_{mt}$ — as a result of enforcement agents presence, for example.

[9] Electoral relevance is defined as the contribution of a municipality to the overall national performance of the governing party in the most recent election. It captures how much the municipality influenced the party's total vote share or margin of victory at the national level. Municipalities that delivered large vote totals are considered more electorally relevant, as shifts in their political behavior have greater implications for the party's national success.

Critically, producers care not only about current-period profit but also future survival, and discount future utility at a personal discount factor $\delta_j \in (0,1)$. Moreover, producers are risk-aware: they anticipate that deforestation today might raise the probability of future policy targeting (e.g., fines and other penalties). For tractability, we capture this concern as a penalty embedded in $\theta'(e_{mt})$.

The one-period expected profit function is:

$$\pi_{jt} = \mathscr{P}_{mt} \cdot A_{jt} - c \cdot A_{jt} - \theta(e_{mt}) \cdot f \cdot d_{jt} \tag{5}$$

Producers maximize discounted expected income:

$$U_{jt} = \pi_{jt} + \delta_j \cdot \pi_{j,t+1}$$

We assume producers are forward-looking about the implications of their own deforestation: they internalize that increasing $d_{jt}$ today may increase $e_{mt}$ (and thus $\theta$) in the future. Since $e_{mt} = D_{mt} + \varepsilon_{mt}$ and $D_{mt} = \sum_j d_{jt}$, we capture this via the derivative $\partial e_{mt}/\partial d_{jt} = 1$.

Given that, the first-order condition becomes:

$$\frac{\partial U_{jt}}{\partial d_{jt}} = \mathscr{P}_{mt} - c - \left[\theta(e_{mt}) \cdot f + \theta'(e_{mt}) \cdot f \cdot d_{jt}\right] + \delta_j \cdot \frac{\partial \mathbb{E}[\pi_{j,t+1}]}{\partial d_{jt}} = 0 \tag{6}$$

This characterizes the optimal level of deforestation $d^*_{jt}$ under dynamic expectations. The third term now reflects a forward-looking penalty: the more a producer expects their present behavior to trigger future policy changes (e.g., stricter enforcement), the more conservative their land-clearing will be.

To keep notation tractable in equilibrium derivations, we collapse the expectation term into a modified deterrence gradient $\theta^*(e_{mt}, \delta_j)$, yielding a closed-form approximation:

$$d^*_{jt} = \frac{\mathscr{P}_{mt} - c - \theta(e_{mt}) \cdot f - \delta_j \cdot \iota_j}{\theta'(e_{mt}) \cdot f} \tag{7}$$

where $\iota_j$ represents the anticipated marginal cost of future enforcement.

Hence the main factors driving deforestation decisions among producers are the potential economic gains, the enforcement policy and their prevailing discount rate. Hence, the aggregate deforestation in any given municipality $m$ is:

$$D_{mt}(e_{mt}) = \sum_{j \in J_m} d^*_{jt}(e_{mt}, \mathscr{P}_{mt}, \delta_j) \tag{8}$$

Across municipalities, the optimal deforestation choice $d^*_{jt}$ is characterized by the first-order condition (Equation 6), and aggregate deforestation is given by Equation 9:

$$D_{mt}(e_{mt}) = \sum_{j \in J_m} d^*_{jt}(e_{mt}, \mathscr{P}_{mt}) \tag{9}$$

This defines the constraints posed by producers on the choice of enforcement levels by party $P$.

**Voters.** A representative voter $i$ in municipality $m$ derives utility from current and future streams of economic benefits from agriculture or forest goods and environmental quality. Economic benefits from agriculture depend on local productive land area $A_{mt}$ in municipality $m$ at time $t$. Diametrically, benefits from forest goods depends on the amount of standing forests $\tilde{A}_{mt}$, *i.e.*, the remaining forest cover. Meanwhile, environmental costs are tied to local deforestation. Voters discount the future at a personal rate $\delta_i \in (0,1)$.

We assume that the voter's concern for environmental degradation is partially endogenous:

$$\alpha_i = \bar{\alpha}_i + \xi_i \cdot \tilde{A}_{mt} \tag{10}$$

where $\bar{\alpha}_i$ is the voter's baseline (normative or ideological) concern for the environment; and $\xi_i \geq 0$ captures their dependence on ecosystem services (e.g., hunting, foraging, or collection of non-timber forest products). Voter $i$'s utility function in each period ($t$ and $t+1$) is then given by:

$$U_{imt} = \eta \cdot A_{mt} - \left(\bar{\alpha}_i + \xi_i \cdot \tilde{A}_{mt}\right) \cdot \gamma \cdot D_{mt} \tag{11}$$

Where $\eta$ is a valuation parameter that captures how much utility the voter gains per unit of productivity land. The term $\gamma \cdot D_{mt}$ is environmental cost of deforestation, where $D_{mt}$ is weighted by damage parameter $\gamma$. The extent to which this cost translates into disutility depends on the voter's concern for the environment ($\alpha$) . So that voter $i$ maximizes her discounted expected utility as in:

$$U^{\text{total}}_{imt} = [\eta \cdot A_{mt} - \alpha_i \cdot \gamma \cdot D_{mt}] + \delta_i \cdot [\eta \cdot A_{m,t+1} - \alpha_i \cdot \gamma \cdot D_{m,t+1}] \tag{12}$$

Voters compare expected utility under the enforcement strategy of Party $P$ versus Party $E$. Let $e^P_{mt}$ and $e^E_{mt}$ denote the expected enforcement levels under the two parties, and let $D^P_{mt}$ and $D^E_{mt}$ denote the associated levels of deforestation. Voter $i$ supports Party $P$ if:

$$U^{\text{total}}_{imt}(e^P_{mt}) > U^{\text{total}}_{imt}(e^E_{mt}) \tag{13}$$

Holding the stock of legacy land constant across parties, the only difference between both parties' policies is the amount of allowed deforestation. Given this assumption, the preference condition reduces to:

$$\alpha_i > \frac{\eta}{\gamma} \quad \text{or equivalently} \quad \bar{\alpha}_i + \xi_i \cdot \tilde{A}_{mt} > \frac{\eta}{\gamma}$$

Thus, a voter prefers Party $P$ if their combined baseline preference and ecological dependence exceed the economic benefit of additional deforestation.[10]

Let $F_m(\cdot)$ denote the CDF of environmental concern $\alpha_i$ in municipality $m$. Then the expected vote share for Party $P$ is:

$$V_{mt}(e_{mt}) = 1 - F_m\left(\frac{\eta}{\gamma}\right) \tag{14}$$

This defines the constraint posed by voters on the choice of enforcement levels by party $P$.

### 2.4 P'S Dynamic Enforcement Strategy in equilibrium:

Party $P$ sets spatially heterogeneous enforcement levels $\{e_{mt}\}$ to maximize discounted utility over time, balancing policy goals and electoral rewards. The party discounts future utility at rate $\delta_P \in (0,1)$. It also updates enforcement in response to observed electoral response, reflecting a process of strategic learning.

The party's dynamic optimization problem is:

$$\max_{\{e_{mt}\}} \sum_{t=1}^{T} \delta_P^{t-1} \left[\omega \cdot \sum_{m\in M} \rho_m \cdot \kappa_{mt} \cdot V_{mt}(e_{mt}) - (1-\omega) \cdot \sum_{m\in M} \psi \cdot D_{mt}(e_{mt})\right]$$

*subject to:*

(i) Producer behavior: $D_{mt}(e_{mt}) = \sum_j d^*_{jt}(e_{mt}, \mathscr{P}_{mt})$

(ii) Voter behavior: $V_{mt}(e_{mt}) = 1 - F_m\left(\frac{\eta}{\gamma}\right)$

**First-Order Condition for Enforcement** At each $t$ and municipality $m$, Party $P$ chooses $e_{mt}$ such that:

$$\omega \cdot \rho_m \cdot \kappa_{mt} \cdot \frac{dV_{mt}(e_{mt})}{de_{mt}} = (1-\omega) \cdot \psi \cdot \left|\frac{dD_{mt}(e_{mt})}{de_{mt}}\right| \tag{15}$$

This condition balances:

- **Marginal electoral benefit of enforcement (LHS):** The political gain from stricter enforcement, weighted by district competitiveness ($\kappa_{mt}$) and relevance ($\rho_m$);

[10] Note that,a s forest cover declines, the marginal importance of $\xi_i$ shrinks, potentially eroding conservation support — particularly among voters who are myopic (low $\delta_i$).

- **Marginal policy benefit from reducing deforestation (RHS):** The environmental utility gained from lower deforestation, which enforcement helps achieve.

This definition of P's calculus suggests that enforcement is heterogeneous across space and responsive to evolving economic and political conditions. This points to a number of implications that guide our empirical analyses.

## 2.5 Empirical Implications

To begin with, the entire set of empirical implications of the analysis on the behavior of parties rests on a premise that is in itself testable — namely the idea that parties adjust their enforcement strategies according to feedback in the form of electoral backlash. Enforcement is inherently dynamic, evolving over time in response to electoral outcomes. If stricter enforcement leads to electoral backlash, Party P may scale back efforts in subsequent periods. Conversely, electoral support may encourage stronger enforcement, reflecting a process of political learning and adaptation. For any case under study, it should be the case that there is a traceable electoral response to enforcement that speaks to the way parties strategize about it.[11]

> *Premise: In regions with high potential for extractive industries, the implementation of environmental protection policies triggers a political backlash from both voters and producers.*

Provided this link exists, our analysis of the calculus of enforcement points to the importance of two drivers of incumbents' choices: the electoral value of municipality and their dependency on extractive economic activities.

### 2.5.1 Political competition

The electoral importance of any particular municipality is jointly defined by their level of electoral competitiveness ($\kappa_{mt}$) and their relevance($\rho_m$). The latter shapes how responsive Party P is to local preferences.In regions where voters and producers depend economically on being able to gain terrain to the forest, Party *P* faces substantial electoral costs.

Consistent with standard models of distributive politics and electoral competition (Persson and Tabellini, 2002; Cox and McCubbins, 1986; Lindbeck and Weibull, 1987; Levitt and Snyder, 1995; Dixit and Londregan, 1996; Stokes, 2005; Cox, 2010) our analysis suggests that Party *P* strategically enhances its enforcement efforts on areas it deems electorally expendable and withholds them in relevant and pivotal districts, even if such areas face strong environmental pressure.

Expendable areas typically fall into two categories: irrelevant strongholds or unwinnable battlegrounds. Irrelevant strongholds are areas where Party *P* enjoys strong preexisting support but which hold little institutional significance in determining overall electoral outcomes. [12] By

[11] Recall that Party P's enforcement strategy evolves through electoral feedback ($\varepsilon^{v}_{mt}$), as observed electoral outcomes inform subsequent adjustments—penalizing the party for overly aggressive enforcement or rewarding it for aligning with constituent preferences.

[12] For example, such regions might be Party *P*-dominated enclaves within otherwise hegemonic Party *E*'s areas. In these contexts, enforcement actions aligned with Party *P*'s programmatic goals might be maintained to showcase consistency to core supporters in other areas, despite the local economic backlash. The identification of irrelevance

contrast, unwinnable battlegrounds are regions of high institutional importance where Party $P$ has little realistic chance of securing victory. [13] Here, Party $P$ may enforce its environmental policies more stringently, as electoral costs are minimal, and such actions serve to strengthen its broader image of commitment to environmental protection at the national and international levels. Enforcement in these areas is not meant to win votes but to signal commitment to voters elsewhere.

In contrast to these two types of areas, expression (15) implies that, for a given level of economic dependency and relevance, the level of electoral competitiveness increases party P's incentives to withhold enforcement.

> *H1: The higher the level of electoral importance of a particular district, the lower the enforcement of environmental protection by Party P.*

#### 2.5.2 Exogenous Shocks and Changing Incentives

The calculus of enforcement is also subject to several potential shocks. On the side of the state, (lack of) adequate technology may increase (limit) the state's monitoring capacity. Technological innovations in extraction/exploitation of land may also raise the opportunity costs of environmental protection for both voters and producers. Finally, enforcement decisions are responsive to fluctuations in commodity prices, which affect producers' incentives to deforest ($\mathscr{P}_{mt}$). Higher international agricultural prices increase the profitability of land conversion (e.g., Abman and Lundberg, 2020; Haddad et al., 2024)), thereby intensifying resistance to enforcement and reducing the political feasibility of strict conservation efforts.

The reason why exogenous forces like commodity shocks matter is that they re-shape the nature of political demand (Crespo Cuaresma et al., 2017). For producers, the enhanced productivity and profitability enabled by technological advances incentivize them to expand operations, converting more natural space into productive land.[14] For citizens, the immediate economic benefits from such activity — such as job creation, increased local revenues, and lower costs of goods — can affect their discount rate, heightening the perceived value of present gains relative to concerns for future welfare (Halland et al., 2015; Hailu and Kipgen, 2017).

The impact of this shift is inherently asymmetric across political parties. Party $E$, whose policy platform aligns with the extractive and expansionist preferences fostered by the new economic context, finds its goals harmonized with the new voter and producer priorities. Party $P$, by contrast, faces a more complex and cross-cutting scenario. While its core ideological commitment to environmental preservation remains steadfast, the party must contend with a growing divide between the elite's ideological principles and the evolving preferences of producers and voters, particularly in areas where economic incentives tied to resource depletion are most pro-

depends on the interaction between socio-economic geography and electoral rules.

[13]Such areas are characterized by overwhelming support for political forces like Party $E$, with margins of victory far exceeding competitive thresholds.

[14]We acknowledge that technological advances can enhance productivity in existing agricultural areas (Stevenson et al., 2013), helping to preserve forests. However, when profitability rises — driven, for instance, by increased demand — the opportunity cost of conserving nearby forests also grows for various economic actors. This may incentivize further deforestation to expand agricultural land (e.g., Abman and Lundberg, 2020).

nounced.This misalignment compels Party $P$ to reassess its intertemporal calculations, balancing its long-term policy commitments against the immediate need to secure electoral support. [15]

If Party $P$ assumes office and fully commits to its core ideological platform — refusing to compromise on its pledge to protect the environment at all costs — a significant share of producers and voters would be required to forgo the potential gains from technological advancements or emerging market opportunities. This strategy could alienate a growing segment of the electorate, particularly those whose preferences now heavily discount future welfare in favor of immediate economic benefits. [16] How much should a party compromise its ideological principles to mitigate electoral losses in the short term?

In analyzing the dilemma, the party, again, must weigh the electoral costs of enforcing protection vs the electoral costs of not doing so. In the absence of backlash there is no trade off between policy and office seeking motivations. If, as many economic voting models would lead us to believe, expected backlash is high, Party $P$'s strategy must minimize two "evils": (*i*) the electoral backlash in its core areas, and (*ii*) the likelihood that the rest of its supporters at the national level perceive a weak commitment to climate protection.

Our analysis suggests that the optimal strategy for party $P$ is to adopt a discriminating enforcement strategy: being marginally more lenient with environmental enforcement in its core areas and potentially competitive swing areas, while imposing stringent enforcement in Party $E$'s strongholds. This approach allows Party $P$ to balance its policy and electoral objectives, minimizing backlash in areas critical to its support base while projecting a strong commitment to environmental protection on a broader scale.

Marginal leniency in Party $P$'s core areas leads to a paradoxical prediction: because of its own opportunity costs, associated with the interplay between local economic structures and exogenous shocks (such as commodity booms), climate enforcement can be weaker in areas where there are more supporters of the protective party at baseline. Lenient implementation is a form of forbearance that generates an implicit transfer to core voters in those districts where it has become strategically necessary (Holland, 2016, 2017).In turn, zealously implementing protection elsewhere allows $P$ to mask the partial concessions by aggregating its overall enforcement record and to retain an image of consistency with its policy goals.

> *H2: Given a strong basis of support for party P, the higher the opportunity costs of enforcement associated with exogenous shocks, the lower the intensity of enforcement by party P*

#### 2.5.3 Corollary: Politically driven persistent deforestation

A corollary of the previous hypotheses, with profound implications for public policy, is that the strategic placement of environmental enforcement is not merely a theoretical exercise but has tangible consequences for ecological outcomes. By selectively reducing enforcement levels

[15] The dilemma is emblematic of a broader tension in political economy, that underscores the trade-off between policy and office-seeking motivations (Przeworski, 1985).

[16] Party $E$, meanwhile, would capitalize on this shift, appealing to voters who prioritize short-term gains, thereby strengthening its electoral prospects.

in specific regions — particularly those with strong political support for Party $P$ or competitive swing areas — Party $P$ effectively reshapes the spatial distribution of environmental degradation. This approach, while politically expedient, undermines the capacity to uniformly contain deforestation and other environmentally harmful activities.

Given the critical role of consistent enforcement in limiting degradation (Bragança and Dahis, 2022; Assunção et al., 2023), targeted leniency introduces vulnerabilities in areas where political considerations outweigh ecological priorities. This uneven application of enforcement disrupts the broader objectives of environmental policy, enabling higher levels of resource depletion and ecological harm in areas where strategic leniency dominates.

> *H3: Areas with stronger support for Party $P$ in previous elections experience higher rates of environmental degradation — reflecting a politically motivated reduction in enforcement intensity.*

### 2.6 From the Theory to the Case

Empirically, we test these theoretical propositions in the context of the Brazilian Legal Amazon region (BLA). This region exemplifies the complex relationship between democracy and climate protection, shaped by the strategic interactions among voters, producers, and political parties. Amazonian voters, like those in other regions rich in natural resources, need to balance immediate economic benefits against future ecological sustainability in their daily lives, including when they vote. Policies designed to curb deforestation impose short-term costs on local economies reliant on agriculture and extractive industries. The salience of these costs may overshadow long-term environmental benefits, especially when the perceived urgency of environmental threats is low.

Moreover, the Amazon is home to powerful producer groups whose livelihoods depend on deforestation-driven activities such as cattle ranching and agriculture. These producers face high "political risks" due to the immobility of their assets, making them highly sensitive to policies like fines, embargoes, and other enforcement measures that restrict their ability to freely exploit the plots under their control. The cost of restrictive policies is even more pronounced in contexts of commodities booms like the one experienced in early 2000s, which put Brazilian extractive industries in a privileged position to exploit abnormal rents facilitated by the country's leadership in agribusiness other primary sectors. In this context, farmer will have extra incentives to exert political influence through lobbying, campaign donations, and efforts to sway local voters.

These characteristics builds a political geography that amplifies the trade-offs for competing parties. In this context, Party $P$ (e.g., the Workers' Party, PT) faces a dual challenge: sustaining its preservationist agenda to appeal to national supporters while mitigating electoral backlash in regions where enforcement imposes significant costs. In contrast, Party $E$ (e.g., Bolsonaro's coalition, Bersch and Lotta, 2023) aligns with extractive interests, leveraging support from areas where voters and producers benefit from relaxed environmental policies.

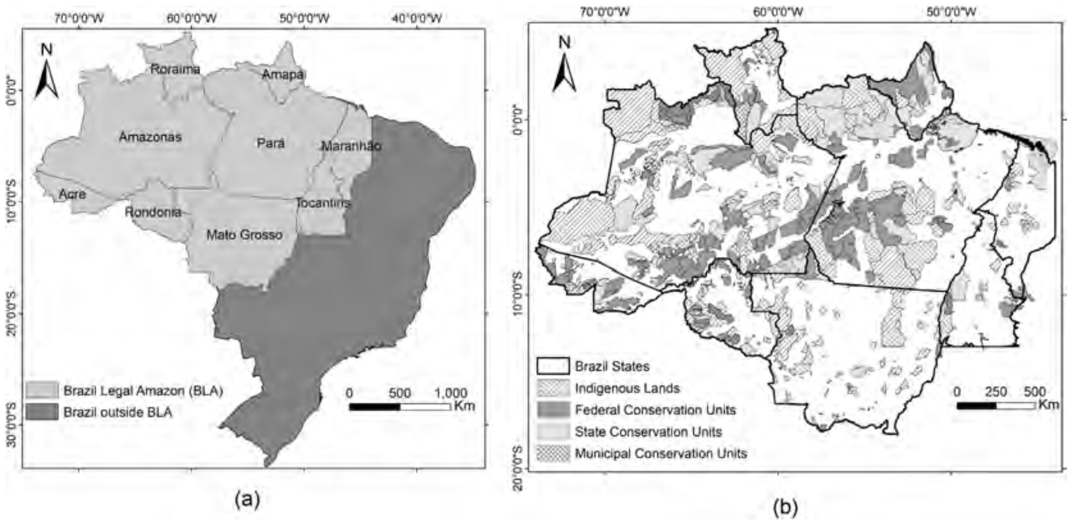
If our main premise holds, the Workers Party (PT) should face an intensified electoral backlash as a result of advancing its environmental agenda — particularly given its leadership in implementing significant environmental policy reforms during the early 2000s. In response to this backlash, the party is likely to rapidly adjust its environmental policies to align with its electoral prospects in specific regions. Consequently, we would expect to observe an uneven distribution of enforcement efforts across the Amazon region, as posited in Hypotheses 1 and 2, leading to significant variations in policy implementation and actual deforestation outcomes, as outlined in Hypothesis 3.

# 3 Background

## 3.1 Deforestation in the Brazilian Amazon

We assess our argument in the context of Brazil, focusing specifically on the administrative region known as the Brazilian Legal Amazon - BLA (Figure 2). Established in 1953, the BLA covers approximately five million km² and includes 772 municipalities across nine states. The area is predominantly (65%) covered by the Amazon biome (tropical rainforest), while a smaller portion is made up of savanna vegetation and transitional forests with grasslands and other forest formations, such as wetlands (Cabral et al., 2018).

Figure 2: Brazil Legal Amazon Region




Location of (a) the Brazilian Legal Amazon in Brazil; (b) Types of Protected Areas by level of government jurisdiction. The term "Amazon Forest" generally refers to the Amazon rainforest or the biome, the largest tropical rainforest in the world, spanning multiple countries in South America. The "Legal Amazon" specifically refers to a legally defined area within Brazil. It was demarcated by the Brazilian government to delineate the boundaries of the Amazon region within the country for administrative and regulatory purposes. The Legal Amazon in Brazil comprises 772 municipalities spanning nine states. This designation has implications for environmental policies, land use regulations, and conservation efforts within this defined area. Source: Cabral et al. (2018)

The BLA, particularly the Amazon biome, is the world's largest deforestation hotspot in absolute terms (Balboni et al., 2023), with degradation processes that began in the 1960s, under the Military Dictatorship, but have intensified in recent decades (see Figure A1). During the military dictatorship (1964-1985), the region experienced a transformation in occupation dynamics.

The government encouraged migration to the area, aiming to boost mineral and agricultural exports and alleviate land reform pressures in other parts of the country (e.g., Bragança and Dahis, 2022; Assunção et al., 2023). Incentives for Amazon occupation included infrastructural developments like roads, hydroelectric dams, mining projects, and the titling of occupied deforested plots (e.g., Pfaff, 1999b). Only in the late 1980s, with Brazil's democratization, conservation policies begin to merge, leading to the creation of agencies like the Ministry of the Environment and an environmental protection agency (IBAMA). In the 1990s, laws to protect forests were introduced, but weak coordination and enforcement allowed deforestation to peak in the early 2000s (Scardua and Bursztyn, 2003; Hochstetler, 2021).

In 2004, the deforested area of the Amazon reached nearly 15% of the original rainforest. By then, Brazil was already the leading nation in tropical forest clearance, both in absolute and relative terms (Hansen et al., 2008). The country still remains the largest contributor to global deforestation, with forest loss still predominantly occurring within the Brazilian Amazon (Freitas et al., 2010; Rezende et al., 2018).[17] Although deforestation in the Amazon stems from complex economic, social, and political factors, agricultural expansion and illegal land grabbing are its primary drivers. Pasture and cropland now occupy 63% and 6% of cleared areas, respectively, making cattle ranching and soybean cultivation major contributors (Boucher et al., 2013; dos Santos et al., 2021). Land grabbing, often targeting public forests for speculative purposes, leads to lasting deforestation, as cleared areas are rarely abandoned Assunção et al., 2023. Infrastructure projects, such as roads and hydropower, further accelerate forest loss by enabling settlement and expansion of economic activities (Pfaff, 1999a; Lapola et al., 2023). Illegal logging and mining also contribute, particularly in poorly regulated regions (Lapola et al., 2023).

Deforestation in the Amazon has far-reaching impacts on biodiversity, human systems, and climate change that felt far beyond the region (Filonchyk et al., 2024). Indeed, since the 1990s, public awareness has been growing, with surveys showing widespread concern among Brazilians, who overwhelmingly believe the government should take stronger action to curb environmental degradation.[18]In response to internal and external pressures, the Brazilian government has expanded its regulatory framework over the past decades to strengthen conservation efforts, but with limited initial impacts.[19] It was only in 2005, with the implementation of a comprehensive set of reforms, that deforestation rates begun to decline significantly. These reforms strengthened regulations, enhanced monitoring, expanded protected areas, and introduced other measures that we detail in the next section.

[17]Other regions, though more deforested in the past, currently contribute less to deforestation than the Amazon (Trigueiro et al., 2020; Rodrigues et al., 2022).

[18]For instance, a 2019 survey found that 88% of Brazilians see Amazon deforestation as a serious concern, and 84% strongly agree that preserving the forest is vital to national identity (https://congressoemfoco.uol.com.br/temas/meio-ambiente/88-dos-brasileiros-acham-desmatamento-da-amazonia-preocupante-aponta-ibope/).

[19]For instance, the 1998 Environmental Crimes Law (Law No. 9,605/1998) made Brazil one of the few countries to have an environmental criminal legislation (de Moura, 2016); however institutional changes such as this one could not revert the upward trends in deforestation rate that continued in the following years (Figure A4).

### 3.2 Environmental policy and enforcement in Brazil

The Brazilian Constitution define that environmental policies are a shared responsibility across all levels of government (Article 23). To enhance efficiency and reduce overlap, specific regulations define federal, state, and municipal roles within the National Environmental System (SISNAMA). Established in 1981 and reformed in 2011, SISNAMA aimed to improve coordination among the nearly 6,000 federated entities (de Moura, 2016). The SISNAMA establishes that the Ministry of Environment oversees the National Environment Policy (PNMA), coordinating initiatives like environmental education, creation of conservation area, and enforcement — in close cooperation with states and municipalities. However, SISNAMA remains imbalanced, as historical centralization keeps most authority with the federal government — particularly the Ministry of Environment (MMA) and its enforcement arm, IBAMA. Besides, municipal and state agencies, with few exceptions (Brancalion et al., 2016), remain underfunded and understaffed, limiting their role in policy implementation (Araújo et al., 2013).

The implementation of the PNMA faces its greatest challenge at the municipal level Scardua and Bursztyn, 2003. Despite the recent creation of over 4,500 municipal environmental secretariats, local governments have historically neglected this sector (Leme, 2010). At the state level, the absence of specialized environmental agencies in most states has further constrained enforcement, as this responsibility is often carried out by state police whose primary focus is public safety. Consequently, environmental enforcement in Brazil has largely depended on IBAMA and its regional offices.[20] This dominance of federal agencies stems from significant investments in state capacity since the early 2000s, particularly in response to international concern over the Amazon biome (West and Fearnside, 2021). A pivotal development was the launch of the *Action Plan for the Prevention and Control of Deforestation in the Legal Amazon* (PPCDAM) in 2004, which strengthened IBAMA's role in enforcement. A key innovation under PPCDAM was the Real-Time Detection of Deforestation (DETER) system, which uses satellite imagery to identify deforestation hotspots and guide enforcement actions . Designed as an early warning tool, DETER enables near-daily monitoring of clear-cut and degraded areas exceeding 25 ha. The data are transmitted to IBAMA for enforcement, significantly enhancing its capacity to combat illegal deforestation and contributing to a marked decline in deforestation after 2004 (Nepstad et al., 2009; Burgess et al., 2018; Bragança and Dahis, 2022).

Between 2006 and 2008, additional reforms strengthened enforcement capacities through measures such as prioritizing high-deforestation municipalities (the IBAMA's "blacklist"), streamlining environmental crime prosecutions, and enacting financial regulations to restrict credit for violators. These reforms contributed to a 60% decrease in deforestation post-PPCDAM (Sills et al., 2015; Assunção et al., 2019; Assunção and Rocha, 2019; Bragança and Dahis, 2022; Assunção et al., 2015; Assunção et al., 2023). After these reforms, IBAMA, already empowered by environmental legislation since 1998 (Law 9605/98), emerged as the central agency for enforcing these regulations, benefiting from new tools introduced by the PPCDAM to monitor

[20] In 2007, a portion of IBAMA's responsibilities was transferred to the newly established Chico Mendes Institute for Biodiversity Conservation (ICMBio), which was granted authority to enforce legislation pertaining to the National System of Conservation Units.

and impose sanctions.

A typical enforcement action in the Brazilian Amazon is primarily triggered by satellite-based remote sensing. The DETER system, operated by Brazil's National Institute for Space Research (INPE), generates near real-time alerts that identify locations with evidence of recent forest clearing, such as canopy damage or illegal fires (Assunção et al., 2023). Upon receiving these alerts, analysts from IBAMA cross-reference the coordinates with land registry data to prioritize large-scale incidents and plan a targeted operation, with the overall distribution of enforcement resources being managed centrally by the Ministry of the Environment (Schmitt, 2015). The execution phase involves small teams of specialized agents deploying — often via helicopter and with armed escort from federal or state police units — to the remote alert coordinates. Upon confirming the illegal activity on the ground, the team's standard procedure is to issue fines and, most critically, to seize and destroy illegal equipment in situ, a dramatic but necessary tactic that has involved using explosives to disable mining dredges and machinery (Bragança and Dahis, 2022).

The list of sanctioning tools available to environmental authorities include warnings, fines, seizures of illegal products or equipment, and even the destruction of items used in environmental crimes. Among the most significant sanctions are fines and embargoes, which can target both individuals and firms that engage in illegal deforestation or other harmful activities. Embargoes are the most severe sanctions any environmental agency in Brazil can impose, especially in the context of the Brazilian Amazon (Decree 6514/2008). It halts all harmful activities occurring on private properties, preventing further environmental degradation. The consequences of an embargo are far-reaching. Affected landowners face significant land use restrictions, preventing them from using embargoed areas for economic activities such as agriculture or livestock grazing. This not only results in financial losses but also carries potential legal penalties for non-compliance with the embargo. Additionally, there are reputational costs for the violators, as being listed publicly as an environmental offender can lead to public backlash and loss of credibility. However, perhaps the most severe consequence is the restriction on access to credit, as Brazilian law prohibits banks from extending loans to individuals or companies operating in embargoed areas (Resolution 3545/2008 - National Monetary Council). This sanction can hamper financial operations of landed elites and agribusinesses, making embargoes an exceptionally powerful tool in the fight against deforestation.[21]

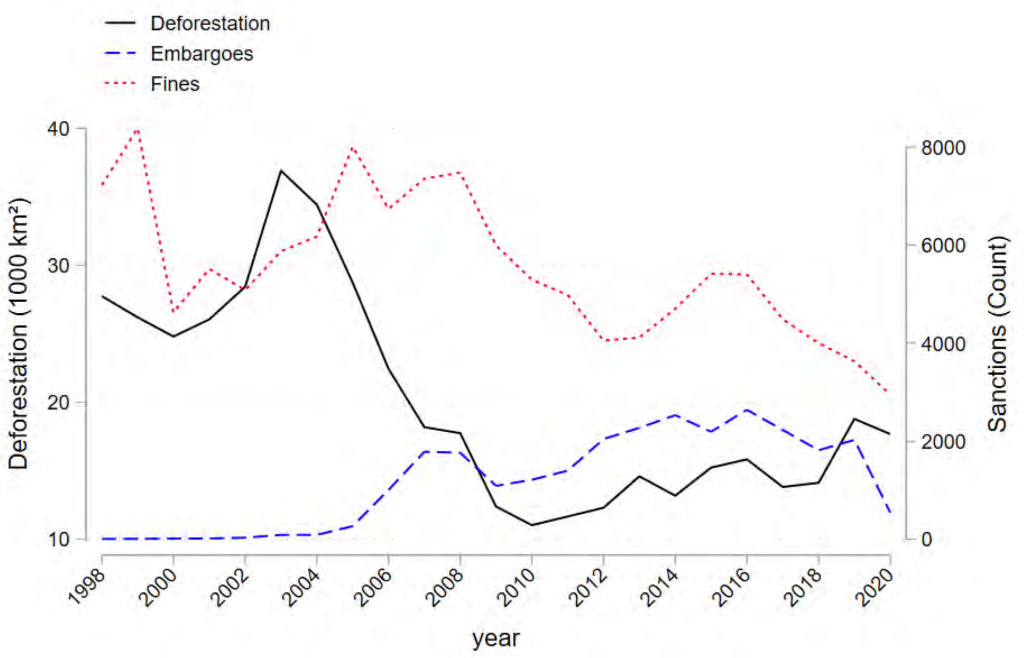
Environmental agents can also issue fines, whether it occurs on private or public land. Unlike embargoes, which can be permanent, fines expires after five years and carry fewer repercussions, as a results less than 1% of them are ever paid (Schmitt, 2015).[22] It is clear, then, that embargoes are potentially more harmful to landed elites than fines, as they not only curtail immediate economic activities but also affect long-term financial capacity. That the reason why we expect embargoes to be more susceptible to political manipulation, as their enforcement could significantly disrupt powerful economic interests on the ground.

[21] Silva et al. (2022) note a significant reduction in the use of embargoes in recent years, alongside a sharp decline in compliance (13%), which they attribute to changes in federal monitoring policies.

[22] Only in certain cases, a fined can prevent offender from accessing subsidized funds and public contracts.

Despite its history of effective action as a professional bureaucracy, IBAMA is not immune to political and administrative factors. Shifts in the federal administration seem to have impacted the efficacy and implementation of environmental policies across Brazil (Rodrigues-Filho et al., 2015; Burgess et al., 2019). For example, IBAMA's staff levels have varied significantly, dropping from around 6,300 employees in 2007 to fewer than 2,000 in 2023 (Araújo, 2022). To address resource limitations, IBAMA collaborates with a network of institutions and receives support from other organizations in field operations, such as the Federal Police, which necessitates the creation of bureaucratic networks and sustained cooperation. These factors suggest that while enforcement is shaped by technical factors, such as the quality of the detection systems, it is also influenced by political dynamics. For that reason, we argue that enforcement levels at any given time result from a combination of technical and political elements. The mismatch between deforestation and sanctions across Brazil corroborates this point (see maps in Figures A5 and 1)Enforcement efforts saw a temporary surge in the early 2000s, coinciding with high deforestation rates in the Amazon, but these efforts have significantly decreased over time, reaching record lows during the Bolsonaro administration (2019-2022) (see Figure 3). Regardless of the steady rise in deforestation since 2010, the proportion of sanctions relative to forest area loss has remained low, particularly the proportion of fines (see Figure A3).

Figure 3: Evolution of Deforestation and Sanctions in the Legal Amazon




Note: The graph shows annual forest cover loss (in thousands of square kilometers) alongside the total number of deforestation-related fines and embargoes issued by the environmental agency for the period 1998-2020.

Some of this reduction in enforcement can be attributed to behavioral changes among offenders, who may have adapted to avoid detection by environmental authorities. For example, the DETER system, originally designed to monitor large-scale clear-cutting and forest degradation over 25 hectares, led to a noticeable increase in small-scale deforestation, likely reflecting an adjustment by offenders to evade detection (Kalamandeen et al., 2018). In response, the government closed public access to the the DETER database and made improvement in the system to detect deforestation on areas as small as one hectare (Diniz et al., 2015). However, even after these technological improvements in monitoring, enforcement levels remained low even during periods of increasing deforestation, suggesting that the decline in sanctions is not merely due to technical limitations or offenders' adjustments, but possibly the result of deliberate choices affecting the enforcement agencies. This period of reduced enforcement, particularly during the Bolsonaro government, has raised concerns that political decisions, rather than just operational challenges, may be driving the weakened response to deforestation (Coelho-Junior et al., 2022). The persistence of low sanction levels despite enhanced monitoring capabilities implies that enforcement priorities may have shifted, reflecting broader political interests or pressures that deprioritized environmental protection during a time when forest conservation was critical.

## 4 Empirical Design

### 4.1 Data

We combine data from several administrative databases covering the Brazil Legal Amazon (BLA) Region. This administrative area, represented in Figure 2, encompasses 772 municipalities (of the 5570 municipalities in Brazil) and spans 9 states. The predominant biome is the Amazon, however, it also covers a small part of the cerrado (or Brazilian savanna) and an even smaller portion of the Pantanal wetlands.[23]

Deforestation and regeneration data are sourced from the MapBiomas Project, Collection 8, which uses Landsat imagery to classify land use and cover changes across Brazilian biomes from 1985 to 2022 (Souza et al., 2020). This comprehensive dataset allows for the identification of land use and land cover (LULC) transitions, such as forest conversion to agriculture, pasture, mining, and other extractive industries commonly cited in deforestation studies. Additionally, we conduct supplementary tests using deforestation data from Global Forest Cover-GFC (Hansen et al., 2013) and the Satellite-Based Deforestation Monitoring Project for the Legal Amazon (PRODES) (De Almeida et al., 2022).[24]

Data on environmental sanctions is publicly available through IBAMA's regular publications, which detail fines, embargoes, and seizures resulting from various environmental infractions.[25] This database contains specifics such as the date of notification, the motivation, the location, and details about the individual or company fined. we examine the association between

[23]We understand that the deforestation dynamics can be different across different biomes (e.g., Ruggiero et al., 2021), for that reason, in some tests we restrict the sample only to municipalities where the predominant biome is the amazon. For that we use the classification methodology developed by da Silva et al. (2022).

[24]The PRODES Project is run by the Brazilian National Institute for Space Research (INPE), which produces the country's official deforestation statistics and operates the DETER system for real-time deforestation monitoring. The data generated by both projects are available on the Terrabrasilis platform (F. G. Assis et al., 2019)

[25]We also include the universe of fines and embargoes issued by the ICMbio, starting in 2008 (this agency was created in 2007).

enforcement actions and deforestation, employing exclusively information on legal actions related to forest and land-based violations. Although the data spans from the early 1990s, we only use information from 2000 onwards due to the significantly lower quality of earlier records.

Election data is sourced from the Superior Electoral Court (TSE), encompassing turnout and voting returns for all elected positions in Brazil, ranging from local council positions to the presidency. It also include information on campaign funds and donations, which are employed in some of the empirical tests. In This project specifically focuses on aggregated results by party in each election and municipality and uses consolidated electoral returns available from 1998 onward.

For sociodemographic and economic variables, we utilize data provided by the Brazilian Institute of Geography and Statistics (IBGE) and available on the SIDRA platform. These databases comprise estimates of the local population starting from 1992 and local GDP from 2002 onwards. The GDP data offers sector-specific breakdowns in absolute values and as proportions of the total product, which is especially useful for our purposes. Note that annual municipal-level poverty data are absent from these databases, hence, we employ the number of families enrolled in the national cash transfer program (*Programa Bolsa Família*) as a proxy for poverty, obtained from the Ministry of Social Development (MDS), however, the program only started in 2004.

Additionally, our study includes local budget data obtained from the National Treasury Office, available through the Brazilian Public Sector Accounting and Tax Information System (SICONFI). This dataset contains information on municipal revenue (from taxes and transfers) and major expenditure classifications ("accounting functions") and encompasses annual reports from nearly 95% of Brazilian municipalities starting from the year 2000.

### 4.2 Methods

To test the hypotheses above, we primarily use two-way fixed effects regression models. Equation 16 exemplifies this approach, analyzing the relationship between sanctions imposed during a given presidential administration and the incumbent party's vote share in subsequent elections.

$$Vote_{me} = \beta + \delta \sum_{y=0}^{3} Sanction_{m(e-y)} + \theta_k X_{me} + \alpha_m + \gamma_e + \varepsilon_{me} \quad (16)$$

Where *Vote* represents the incumbent party's vote share in municipality $m$ during election $e$. The variable *Sanction* captures the total number of sanctions (embargoes or fines) issued in the municipality during the four years ($y$) leading up to the election, including the election year. $X$ is a vector of municipality $k$ characteristics encompassing environmental, demographic and economic variables. In some specifications, we also include climate variables, such as cloud cover, temperature and precipitation, that may influence the government's ability to monitor deforestation.[26] $\alpha$ and $\gamma$ denote election and municipality fixed effects, respectively. The coefficient of interest ($\delta$) is intended to capture the average electoral response to enforcement at the municipality level.

To address potential correlation between observations, the main specifications utilize spatially robust Conley standard errors (Conley, 1999), allowing for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023). In the main specifications, the error terms is assumed to be correlated up to a distance of 100 kilometers, which corresponds to more than twice the average distance between municipalities in the region (which is approximately 45 km) — considering each municipality nearest centroid.

To test the relationship between election result and enforcement, we shift the temporal focus of our regression analysis to what happens after the election. This approach allows us to examine whether, once in office, the victorious party systematically rewards municipalities that supported it in the preceding election by reducing enforcement efforts. The new specification is shown in Equation 17 below:

$$Enforcement_{my} = \beta + \delta Gov_{m(e-1)} + \theta_k X_{my} + \alpha_m + \gamma_y + \varepsilon_{my} \tag{17}$$

Where *Enforcement* is defined as the total number of sanctions (either embargoes or fines) minus the total number of deforestation alerts issued in municipality $m$ in year $y$. Deforestation alerts are newly detected polygons mapped annually by the DETER system, signaling areas where enforcement actions should be taken. Since each alert corresponds to a potential infraction, it is expected to result in a sanction. Thus, values of *Enforcement* greater than zero indicate over-enforcement, while values less than zero suggest some degree of forbearance.[27] *Gov* is a binary variable that equals 1 if municipality $m$ gave the majority of its votes to the winners of the presidential race in the previous election (*e-1*) — i.e., it reflects whether local voters supported the party that subsequently gained authority over the environmental agency. The remaining terms are the same as in Equation 16.

Note that our hypotheses refer only to a type-P party, represented in this case by the Workers' Party (PT), which remained in power from 2003 to 2015.[28]

In alternative specifications, we replace *Gov* with a continuous measure of support for the national government, quantified by the relative winning margin of the national party in the last election (*Margin*). Conceptually this variable ranges from -100 to 100, where negative values indicate that the majority of voters in the municipality supported the opposition candidate.

Our theoretical framework also emphasizes that economic incentives — especially those stem-

[26]The control variables include maximum annual temperature ($^{o}$C), total annual precipitation (mm), current-year deforestation measured using MapBiomas (logged), local GDP in 2010 BRL (logged), the number of families enrolled in the conditional cash transfer program (IHS-transformed), an indicator for whether the municipality was blacklisted by the environmental agency, and the percentage of the municipality designated as a protected area.

[27]Summary statistics for this variable are provided in Section A4 of the Appendix.

[28]Temer's administration (2016–2018) is excluded from the analysis. Member of the MDB Party, Temer was elected as vice president under Rousseff (PT) and took office following a controversial impeachment process, preventing a direct connection to electoral results.

ming from opportunities costs involved in conservation — can influence environmental enforcement by adding pressure over the Party P. We measure these incentives using a composite price index that captures annual international price variation for key deforestation-linked commodities, particularly soybeans and corn, which dominate export-oriented agricultural production in the Amazon region.

Since global commodity prices are plausibly exogenous to local political dynamics, this index allows us to examine the causal impact of commodity shocks on enforcement outcomes. Specifically, we estimate the Equation:

$$\begin{gathered} Enforcement_{my} = \beta_0 + \beta_1 Exposure_y + \beta_2 Gov_{me} + \\ \delta(Exposure_y \times Gov_{m(e-1)}) + \theta_k X_{my} + \alpha_m + \gamma_y + \varepsilon_{my} \end{gathered} \tag{18}$$

Here, the variable $Gov$ and $Enforcement$ are defined as in the previous equations. $Exposure_{my}$ is a measure of the local economy's exposure to international commodity prices fluctuations (cf. Harding et al., 2021). It represents the weighted index of export cash crops, such as soybeans and corn, adjusted by the economic relevance of these crops in each municipality. More formally, The index is defined as:

$$\text{Exposure}_{mt} = \sum_{c \in \mathscr{C}} w_{cm,2000} \cdot P_{ct} \tag{19}$$

where: $\text{Exposure}_{mt}$ is the exposure index for municipality $m$ in year $t$. $c \in \mathscr{C}$ denotes a crop in the set of relevant commodities (e.g., soy, corn, cotton, which accounted for more than 79% of all crops fields in the region in 2013). $P_{ct}$ is the international price of crop $c$ in year $t$, normalized in reference to the baseline year 2000. $w_{cm}$ is the weight of crop $c$ in the municipality's baseline crop composition, computed as:

$$\text{w}_{mc} = \frac{area_{mc,2000}}{\sum_{c \in \mathscr{C}} area_{cm,2000}} \tag{20}$$

That is, $w_m^c$ represents the share of crop $c$ in the total cropland area of municipality $m$ during the baseline period.

Thus, the exposure index captures the extent to which each municipality is exposed to exogenous international commodity price fluctuations, weighted by historical crop production patterns. The coefficient of interest is $\delta$, the interaction term between commodity prices and political alignment, it captures the differential effects of variations in commodities prices for electorally aligned municipalities.

We conclude the empirical analysis by assessing the practical consequences of enforcement for environmental outcomes. Specifically, we ask whether prior experience with below-expected levels of enforcement — i.e., forbearance — leads to increased deforestation in subsequent years. To do so, we estimate Equation 21, it examines whether municipalities that experienced systematically low levels of enforcement exhibit higher rates of deforestation ($Defor_{my}$) in the following year:

$$Defor_{my} = \beta + \delta forbearance_{m(y-1)} + \theta_k X_{my} + \alpha_m + \gamma_y + \varepsilon_{my} \tag{21}$$

The independent variable, $forbearance$, is a binary indicator equal to 1 if, in year $y-1$, the municipality received fewer sanctions than deforestation alerts — *i.e.*, $Enforcement < 0$ — and 0 otherwise. This variable classifies municipalities into an "under-enforcement" group, capturing whether local actors observed signals of forbearance from enforcement authorities in the recent past. This specification allows us to test whether institutional leniency — operationalized through the gap between monitoring and sanctioning — emboldens deforestation behavior over time. As in the previous models, $\alpha$ and $\gamma$ are municipality and year fixed-effects, respectively; $X$ is a vector of time-varying municipality specific controls, and $\varepsilon$ is the error term

**Examining Causality:** Where possible, we investigate the potential causal relationship between political support and enforcement by leveraging empirical strategies commonly used in political economy, including instrumental variables and regression discontinuity (RD) designs centered on close elections. For each strategy, we articulate the underlying rationale, identify the contexts in which causal identification is plausible, and discuss the limitations inherent to the approach.

## 5 Premise: The Electoral Backlash of Environmental Enforcement

We begin our empirical analysis by examining how local voters respond to enforcement actions. Table 1 presents the estimated effects of various measures of enforcement on the vote share of the incumbent party in national elections. In each estimation, we regress the overall level of enforcement total number of fines or embargoes issued during a president's terms on the his/her performance locallly in the next elections. We focuses specifically on national election due to the national government central role in environmental enforcement in Brazil (as discussed in Section 3.2). The key takeaway is that, irrespective of the enforcement metric used, the electoral response is consistently negative, indicating that enforcement actions tend to provoke a backlash from voters.[29] As shown in Panel B, of Table 1, the estimates are robust to the introduction of various controls selected to account for other municipalities characteristics that may affect incumbent performance - such as GDP and participation in major social programs.[30]

[29]We also estimated these models using voter turnout as the dependent variable. As shown in Table A2, we find less consistent effects on voter participation. However, this result may stem from Brazil's mandatory voting system, which typically ensures consistently high turnout rates.

[30]These estimates remain robust when incorporating interactive fixed effects (see Table A12).

Table 1: The Effect of Enforcement on the Incumbent's Vote Share

| Dependent Variable | Incumbent's Vote Share (%) | | | | | |
|---|---|---|---|---|---|---|
| Enforcement Metric | (1) Fines Normalized§ | (2) Fines Standardized | (3) Embargoes Normalized | (4) Embargoes Standardized | (5) Embargoed area (%) Standardized† | (6) Embargoed area (%) Normalized† |
| **Panel A**: Estimations without covariates | | | | | | |
| Sanction | -1.32*** | -1.45*** | -1.49*** | -0.77** | -0.43 | -0.82*** |
| | (0.47) | (0.45) | (0.57) | (0.36) | (0.28) | (0.22) |
| Observations | 3,856 | 3,856 | 3,856 | 3,856 | 3,856 | 3,856 |
| R-squared | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.34 |
| **Panel B**: Estimations with covariates | | | | | | |
| Sanction | -1.20*** | -1.64*** | -2.15*** | -1.27*** | -0.88*** | -0.94*** |
| | (0.46) | (0.53) | (0.56) | (0.45) | (0.30) | (0.21) |
| Observations | 3,853 | 3,853 | 3,853 | 3,853 | 3,853 | 3,853 |
| R-squared | 0.41 | 0.41 | 0.42 | 0.41 | 0.41 | 0.42 |
| DP Mean | 57.13 | 57.13 | 57.13 | 57.13 | 57.13 | 57.13 |

Note: The table presents the estimated effects of enforcement on the presidential incumbent party's vote share. § *Sanctions* are normalized using the inverse hyperbolic sine (IHS) transformation.† Embargoed area (%) is measured as a proportion of total private property area in the municipality. All regressions include municipality and electoral cycle fixed effects. Regressions in Panel 2 includes the following controls: average maximum temperature (°C), average annual precipitation (mm), total deforestation, km2 (log); local GDP (Logged); number of families enrolled in the national cash transfer program CCT (IHS); a dummy variable indicating whether a municipality have been "blacklisted" by the environmental agency; and extension of Protected Areas (% of municipality area). The analysis covers 1998–2020 (excluding 2018 to avoid impeachment-related noise) and aggregates data by national electoral cycles. Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

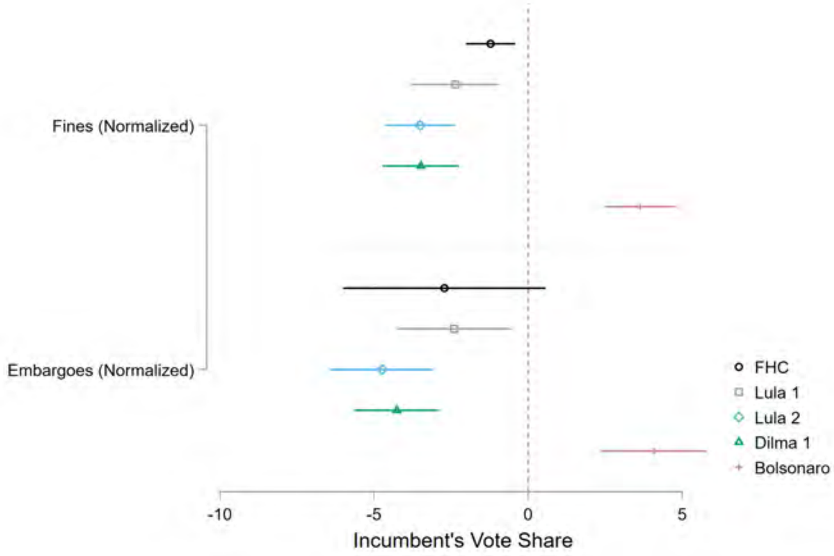
To determine whether the observed backlash is a mechanical reaction or a rational, calculated response to enforcement, we analyze voter reactions across different administrations. The reasoning behind this approach is straightforward: Fernando Henrique Cardoso's (FHC) administration initiated key reforms that enhanced the federal government's capacity to impose sanctions on environmental offenders. Later, Workers' Party (PT) administrations significantly expanded these efforts through additional institutional reforms and substantial investments in state capacity, achieving an unprecedented level of enforcement capability.

If voters are rational and respond to enforcement levels, they should attribute these actions to the appropriate political actors (cf. Marsh and Tilley, 2010). This would imply that PT administrations — and, to a lesser extent, FHC's second term—would face the strongest backlash from environmental enforcement. At the same time, the Bolsonaro administration, which actively dismantled enforcement mechanisms, should not experience voter punishment for any residual enforcement actions carried out during its tenure — since any enforcement measure during his term can be seem as an act of defiance realized by a non-conforming bureaucracy.[31]

Figure 4 illustrates the varying electoral responses to enforcement measures under different

[31] Bolsonaro cultivated a strong reputation as an opponent of environmental policies and authorities long before assuming the presidency. While serving as a congressman, he was fined by IBAMA for illegal fishing in a marine conservation area — a penalty he later retaliated against during his presidency by imposing administrative sanctions on the environmental agents involved. Once in office, Bolsonaro frequently expressed his opposition to environmental regulation, particularly regarding the conservation in the Amazon, through both public statements and policy actions (Section A2 of the appendix presents a few instances when Bolsonaro made clear his opposition to IBAMA and other environmental agencies). More significantly, his administration actively worked to dismantle the environmental governance framework established by his predecessors. This included introducing executive orders that weakened regulatory protections and pursuing punitive measures against individual bureaucrats (Bersch and Lotta, 2023). These initiatives reflected Bolsonaro's strategy of eroding institutional capacity in this area and signaling his prioritization of any other agenda over environmental preservation.

Figure 4: The Effect of Enforcement on the Incumbent's Vote Share, by Administration




Note: The graph displays the marginal effect of sanctions (fines and embargoes) on the incumbent party's vote share in the presidential election held at the end of their term. Sanctions are aggregated over the four-year presidential term and normalized using the inverse hyperbolic sine (IHS) transformation. Each estimation corresponds to a standard cross-sectional linear regression. Vote share is measured in percentage points (0–100). Spatially robust Conley standard errors allows for spatial correlation within a 100 km radius of the municipality centroid. For additional measures of enforcement effects by administration, refer to Figure A8.

administrations. The most pronounced backlash is witnessed during Lula's second term, with the PT's candidate losing nearly 0.05 percentage points in vote share for every 1% increase in embargoes in the following election. This period coincides with the apex of federal reforms initiated under PPCDAM, which significantly expanded the scope and frequency of sanctions, especially embargoes.

In contrast, the second term of FHC shows smaller effects for both fines and embargoes, with the latter being statistically insignificant — a result consistent with the limited use of embargoes during his administration. The starkest contrast, however, emerges with the Bolsonaro administration. Rather than experiencing backlash, Bolsonaro's administration saw electoral gains linked to enforcement actions. For every 1% increase in fines and embargoes, Bolsonaro gained approximately 0.03 and 0.04 percentage points in vote share, respectively, during his reelection campaign. This unique dynamic likely stems from Bolsonaro's well-publicized opposition to environmental enforcement and his consistent efforts to dismantle environmental policies and institutions established by previous administrations. His ability to frame residual enforcement actions as relics of an outdated environmental framework—one he claimed to be actively dismantling—may have resonated with this electorate, transforming what traditionally provoked backlash into a perceived advantage.

It is noteworthy that embargoes consistently exhibit larger coefficients across nearly all specifications. This aligns with the fact that embargoes impose significantly higher costs on affected individuals compared to other types of sanctions, as discussed in Section 3.2. Unlike fines, which may often go unpaid or expire after a relatively short period, embargoes remain in effect indefinitely, restricting land use and access to credit until compliance is achieved. This enduring impact likely amplifies the political backlash associated with their enforcement, making them a particularly salient issue for both landowners.

One puzzling aspect of this process is how a policy that directly impacts a relatively small landed elite — landowners — can resonate throughout the broader electorate to the extent that it influences electoral outcomes. One plausible explanation is straightforward clientelism or patronage, wherein landowners leverage their political influence to compel voters to oppose leaders associated with stricter enforcement. While we do not dismiss this possibility, we argue that such coercive strategies are unlikely to fully account for the systematic results observed here — especially considering that some of these practices are considered criminal under Brazilian law and could impose significant costs on perpetrators.

Instead, we posit that landed elites utilize a much safer and more effective channel to translate their interests into electoral outcomes: their economic power, particularly through campaign donations (Weschle, 2022). By directing substantial financial resources to candidates who share their stance on environmental enforcement, these elites can amplify their influence over electoral campaigns and shape public opinion indirectly. This strategy not only avoids the legal risks associated with direct coercion but also aligns with the literature that underscore the role of campaign financing and election outcome in Brazil (e.g., Samuels, 2001, Avis et al., 2022).

We examine this mechanism by first assessing changes in campaign contributions and their relationship with enforcement using municipality data aggregate by national electoral cycle. Table 2 shows that environmental enforcement is associated with significant increases in fund-

Table 2: Campaign Contributions and Environmental Enforcement

| Dependent Variable | Campaign Contributions (Normalized) | | | | | |
|---|---|---|---|---|---|---|
| Variables | (1) Fines Normalized | (2) Fines Standardized | (3) Embargoes Normalized | (4) Embargoes Standardized | (5) Embargoed area † Standardized | (6) Embargoed area† Normalized |
| **Panel A**: Contributions to Right-Wing Parties | | | | | | |
| Sanction | 0.15** | 0.20 | 0.44*** | 0.31*** | 0.28*** | 0.15*** |
| | (0.06) | (0.14) | (0.08) | (0.08) | (0.09) | (0.03) |
| Observations | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 |
| R-squared | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 |
| DP Mean | 2.281 | 2.281 | 2.281 | 2.281 | 2.281 | 2.281 |
| **Panel B**: Contributions to Left-Wing Parties | | | | | | |
| Sanction | 0.01 | 0.17 | 0.22*** | 0.34*** | 0.17** | 0.05** |
| | (0.04) | (0.11) | (0.05) | (0.08) | (0.08) | (0.02) |
| Observations | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 |
| R-squared | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 |
| DP Mean | 0.742 | 0.742 | 0.742 | 0.742 | 0.742 | 0.742 |

Note: The table shows the change in total amount of campaign contributions (normalized) as a function of enforcement level in each municipality in the Legal Amazon region. *Sanctions* represents the total number of fines or embargoes issued during each 4-year presidential term. The total amount of contributions in R$ has been adjusted to 2022 values before normalization using the General Price Index – Internal Availability (IGP-DI/FGV). Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. All estimations include municipality and electoral cycle fixed-effects. Table A3, in the appendix, replicates the same estimations but with covariates. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

ing for right-wing candidates, who, in our context, are generally linked to more lenient environmental policies (Panel A). In contrast, sanctions tend to have either no effects or be considerably weaker for funding flowing to leftist parties.[32]

An important caveat must be considered when analyzing the results from Table 2. The microdata on campaign donations contain many entries with missing or very low values, suggesting a susceptibility to measurement error. For that reason, we build an individual-level panel data that matches the database of registered donors (individuals and firms) spanning 6 national elections and 24 years with the list of offenders published by the environmental authorities. We then evaluate whether receiving a sanctions increases the likelihood of these individuals or firms donating to right-wing parties in the next elections — regardless of the value.[33]

Table 3 presents the results of these estimations, offering suggestive evidence that the likelihood of becoming a donor increases after sanctions imposed by environmental authorities. This tendency is particularly pronounced in the financial support for Right-Wing parties and for sanctions administered in elections years — a timing consistent classic works in retrospective voting theory (see Healy and Malhotra, 2013 for review).[34] Estimates for Leftist parties are less stable and often statistically insignificant, which is probably a consequence of the small number of left-wing donors in the the sample.[35]

[32]Including municipality-specific time trends yields similar results (see Table A13).

[33]We run variations of the following generic logistic model:

$$P(Donate_{ie}) = F(\beta_0 + \theta_1 Sanction_{ie} + \theta_2 Sanction_{i(e-t)} + \gamma_e)$$

where *Donate* is binary variable that indicating whether individual $i$ made a campaign contribution in election $e$. *Sanction* indicates whether this individual/firm received a fined or embargo in the year of election $e$ or in the year leading to the election ($e$-$t$). $\gamma_e$ and $\psi_i$ represent election and individual/firm fixed effects, respectively.

[34]We restrict the time frame of our analysis to only two periods to avoid conflating the estimations with local elections, which occurs in middle of presidential terms.

[35]It is important to note that donation is a rare event. Among the 112,425 offenders with valid identification, only 8,472 made a registered campaign contribution in the period between 1998-2024. Most of the donors in this subsample donates to right-wing parties (N=6,658) and only a fraction to centrist (N=886) and Leftist parties (N=1,489).

Table 3: Probability of Becoming a Donor after Sanctioned

| | Probability of Becoming a Campaign Donor | | | |
|---|---|---|---|---|
| Variables | (1) Fines | (2) Fines | (3) Embargoes | (4) Embargoes |
| Model | Pooled | Cond. TWFE | Pooled | Cond. TWFE |
| ***Panel A**: Contributions to Right-Wing Candidates* | | | | |
| Sanctions | 0.21*** | 0.30*** | 0.41*** | 0.26** |
| | (0.04) | (0.05) | (0.09) | (0.12) |
| Sanctions (t-1) | 0.11*** | 0.23*** | 0.12 | 0.01 |
| | (0.04) | (0.05) | (0.13) | (0.14) |
| Observations | 643,972 | 18,863 | 643,972 | 18,863 |
| Odds Ratio | 1.23 | 1.35 | 1.51 | 1.3 |
| Odds Ratio Lagged | 1.12 | 1.26 | 1.12 | 1.01 |
| Number of id | | 3,155 | | 3,155 |
| ***Panel B**: Contributions to Left-Wing Candidates* | | | | |
| Sanctions | -0.02 | -0.08 | 0.28** | 0.50 |
| | (0.14) | (0.09) | (0.14) | (0.41) |
| Sanctions (t-1) | 0.16*** | 0.34** | 0.13 | 0.27 |
| | (0.05) | (0.16) | (0.31) | (0.50) |
| Observations | 643,972 | 2,217 | 643,972 | 2,217 |
| Odds Ratio | .98 | .93 | 1.32 | 1.64 |
| Odds Ratio (t-1) | 1.17 | 1.41 | 1.14 | 1.31 |
| Number of id | | 372 | | 372 |

Note: The table presents the results of logistic regressions using individual-level data on campaign donations from the 1998–2022 period. The dependent variable takes a value of 1 if an individual or firm made a campaign contribution in election $e$, regardless of the amount. The dataset includes all registered donations made to a political party in a year with a national election, covering contributions to all elected positions on the ballot. Firms and individuals who donates to both right and left-wing parties are not included in the estimations. For the pooled estimations (column 1 and 3), standard errors are clustered at the municipal level. In estimations with conditional two-way fixed effects (column 2 and 4), standard errors are computed using the observed information matrix. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

## 6 Strategic placement of enforcement I: Political Competition

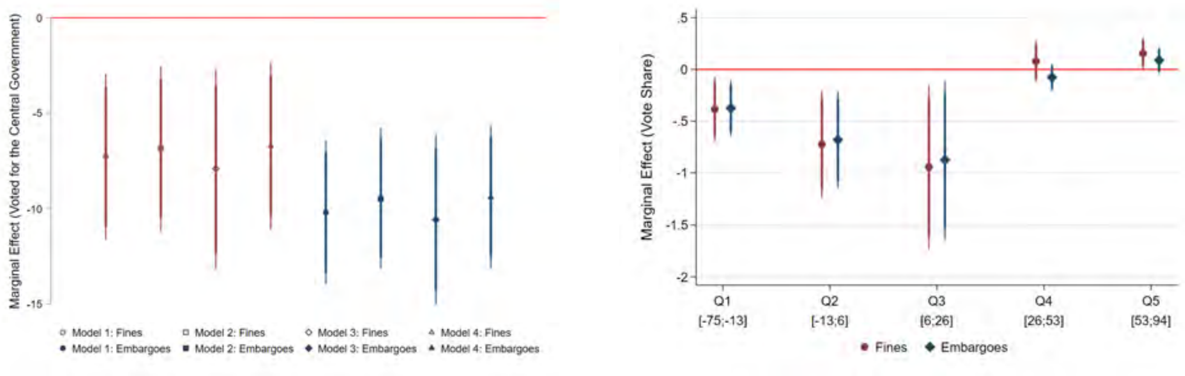
The evidence presented thus far strongly supports the existence of a backlash from environmental sanctions.[36] This premise is particularly relevant for parties traditionally associated with more conservation efforts (a type P party in our framework). Given this, we now evaluate how Party $P$ navigates two opposing pressures: the legal and programmatic imperative to implement effective environmental policies, and the need to moderate enforcement to mitigate the costs of locally concentrated .

Before we examine directly H1 on the moderating effect of the district's electoral importance, let us examine a simple relationship wherein support for for Party $P$ is rewarded with lower

[36] To determine whether the effects of environmental enforcement on incumbent electoral performance can be interpreted causally, we conduct an instrumental variable regression analysis. Our results offer partial evidence supporting a causal interpretation especially for effects of embargoes. For further details, see Section A6 of the Appendix.

Figure 5: Support for the National Party and Enforcement Placement

(a) "Extensive" Margin (b) "Intensive" Margin




Note: The figures show the marginal effect of voting for the party running the national government on enforcement level, across four specifications of Equation 17. Enforcement is measured as the difference between the number of sanctions (fines or embargoes) minus the number of deforestation alerts. (a) In Graph 5a support is a binary variable equal to 1 if the national party was the most voted locally. Model 1 is the baseline without controls. Models 2–4 progressively add alternative control configurations, including deforestation (log), average cloud cover (NASA), enforcement priority status, local demographics, land use, and economic factors. The analysis covers the Workers' Party administrations (2004-2015) with Deter data available. Table A4 presents the detailed results of this regressions showing all coefficients considered. (b) In Graph 5b, the measure of support for the central government is replaced by a continuous variable representing the national party's winning margin (*Margin*) in each municipality, with $Margin \in [-100, 100]$, where values below 0 indicates that the opposition won locally. The sample is divided into quintiles of *Margin* so that each coefficient represents individual regressions on subsamples defined by each quintile. The brackets in the x-axis indicate the bandwidth of each quintile. The estimations include the same set of controls used in model 2 of graph 5a. Table A5 presents the detailed results of this regressions showing all coefficients considered. In both set of estimations, spatially robust Conley standard errors (Conley, 1999) account for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. All specifications includes municipality and year fixed-effects.

enforcement. We examine this relationship in a stepwise approach using variations of Equation 17 and data from the Workers' Party administrations only (2003-2015), as the PT is the prototype of a Type P party in our framework.[37]

First, we evaluated the effect of electoral support for the national party on the *extensive margin* using a categorical variable equal to one if the party controlling the environmental agency won locally in the last presidential election ($\delta$ in Equation 17). Figure 5a presents the marginal effects of this variable equal, along with 90% and 95% confidence intervals, across four model specifications with varying control configurations. Model 1 serves as the baseline without controls, while the other models incorporate factors such as local GDP, deforestation levels, average cloud cover, and dependence on the primary sector (e.g., pasture and cropland land areas).[38] The results indicate that municipalities where the PT won the last election tend to face fewer embargoes and fines. It is worth noting that these results are substantial, given that the average level of enforcement during the period is –0.17 when defined as the difference between fines and alerts, and –5.86 when defined as the difference between embargoes and

[37]More precisely, our analyses cover the period from 2004, when the DETER system was launched, to 2015, when the PT was ousted from government.

[38]For the specific effects of each variable included in the models, see Tables A4 and A5. The results presented in Figure 5 are also robust to the inclusion of municipality-specific time trends (see Table A13).

alerts (see Table A1).

Next, to understand how enforcement responds to various *levels* of support for the national party, we replace the binary variable by a continuous measure of support to the central government — which is equal to the margin of victory the national party in the last election with *Margin* ∈ [-100, 100]. We then split the sample in five equal parts of Margin and run separated regressions for each quintiles. This exercise enables us to map how enforcement levels vary across different degrees of government support, offering insight into how this relationship operates at the intensive margin. Figure 5b presents the results of these revised estimations, displaying the marginal effects of *Margin* along with the corresponding 95% confidence intervals. The estimations controls for objective factors that could influence the government's ability or motivation to impose sanctions, namely deforestation and whether a municipality have been blacklisted by the environmental agency.[39] These findings reinforce the previous results, indicating that support for the central government tends to reduce the number of embargoes and fines. Interestingly, and consistent with our theory, they also suggest that this effect is less pronounced in areas considered opposition or government strongholds. The strongest effects are observed where the victory margin approaches zero — i.e., in competitive jurisdictions — implying that, beyond political support, the level of competitiveness is also a key predictor of enforcement.

H1 posits that in municipalities that are both relevant and competitive, $P$ will cut back its enforcement zeal for strategic reasons. While the previous analysis provides some support for this hypothesis — as suggested by the quintile analysis in Figure 5b — admittedly, it is not the most rigorous test of this relationship. Notably, the prior analysis focused on the government's electoral strength, measured using final runoff results from presidential elections, where voters choose between the top two candidates rather than expressing their true preferences across multiple options. As a result, it does not fully capture district competitiveness, as it overlooks the broader field of candidates typically present in the first round. First-round results, therefore, offer a more precise measure of political competition, as they account for a wider range of candidates, including those with genuine chances of advancing to the runoff.

Moreover, our argument suggests that the government adopts different strategies based on a district's electoral relevance, with higher enforcement in less politically significant areas. In practical terms, we define relevance as a municipality's proportional contribution to the national party's overall performance in the previous elections. To capture both dimensions — competitiveness and relevance — we construct a competitiveness score using first-round returns and include this variable, along with its quadratic term, in regressions following the structure of Equation 17, using the same set of controls employed in the previous analysis.[40]

[39]We also run estimations that incorporate climate factors (cloud cover, temperature, and precipitation). Despite their collinearity with deforestation, the results remain largely similar and are not reported.

[40]Our Electoral Competition Score is defined as follows:

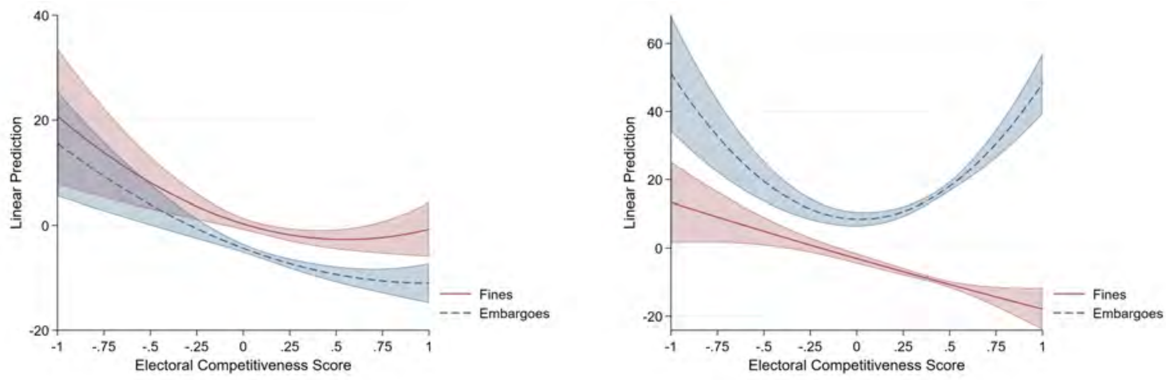
$$CompetitionScore_{me} = \left[ \frac{H_{me} - \min(H)}{\max(H) - \min(H)} \right] \times Op_{me} \tag{22}$$

where $H$ is the Herfindahl-Hirschman Index (HHI) of municipality $m$ in election $e$. $min(H)$ $max(H)$ are the minimum and maximum values of $H$ across all municipalities and elections in the dataset. These terms are used to normalize

We incorporate electoral relevance into our estimations in two ways, as discussed below.

Figure 6: Sanctions and Political Competition

(a) Regular OLS (b) Weighted Regression




Note: The figures show the predicted level of enforcement at various levels of political competition, based on regressions with a specification similar to Equation 17, where the main regressors are Political Competition and its quadratic term. Political competition is defined as in Equation 22. Enforcement is defined as the difference between the number of sanctions and the number of deforestation alerts issued for each municipality. Graph 6a presents regressions that control for electoral relevance — i.e., the municipality's relative contribution to the national party's victory. In Graph 6b, electoral relevance is used as an analytical weight. The data covers the 2004–2015 period (PT administration with available DETER data). All regressions include municipality and year fixed effects, as well as the following controls: deforestation in km² (log), the proportion of the municipality designated as a protected area (%), and whether the municipality was included in the priority list for enforcement. Standard errors are clustered at the municipality and intermediate-region-year levels.

Figure 6 illustrates the relationship between sanctions and political competition using two alternative specifications that account for *electoral relevance*. Operationally, relevance is defined as the contribution of a municipality to the overall national performance of the governing party in the most recent election. It captures how much the municipality influenced the national party's total vote share or margin of victory at the national level. Municipalities that delivered large vote totals are considered more electorally relevant, as shifts in their political behavior have greater implications for the party's national success.. Graph 6a incorporates electoral relevance as an additional control, while Graph 6b presents estimates from a weighted regression, where each observation is weighted according to its electoral relevance to the national party's performance in the last election. Both approaches support Hypothesis 1, particularly in the case of embargoes.

In Graph 6a, the expected quadratic relationship is present but less pronounced, suggesting that while opposition strongholds face heavy enforcement, enforcement in government strongholds increases only when the government holds a very strong majority. However, when observations are weighted by their relative electoral relevance — appropriately accounting for heterogeneity in political significance (Solon et al., 2015) — the relationship implied by Hypothesis 1 becomes more evident, with embargoes reaching their lowest levels in highly com-

the *HHI* to a 0–1 scale for comparability across places and time. *Op* is an indicator equal to -1 if a party other than the PT won locally. Conceptually, this indicator ranges from -1 to +1, where -1 indicates an opposition stronghold, 1 represents a government core area, and 0 marks the point of highest competitiveness.

petitive areas (Graph 6b).

Interestingly, this pattern does not hold for the less severe type of enforcement—fines—which decline monotonically from opposition strongholds to government strongholds, regardless of the level of competition. This suggests a dynamic driven solely by a logic of political reward.

Overall, this analysis strengthens the argument that strategic considerations influence the distribution of enforcement in the Amazon region, particularly for the more consequential type of sanction, i.e., embargoes. A critical question that remains is whether this relationship can interpreted causally.

***Investigating causality:*** We complement the analysis of political competition by conducting a regression discontinuity design (RDD) using close elections.[41] Our argument is about the local distribution of national results and how it affects the calculus of national incumbents. Appendix A7 discusses the important of winning locally even for parties focusing in national elections. As in the previous analysis, the sample is restricted to the PT administration years, covering the four national elections held between 2002 and 2014. Given that environmental policy during this period was primarily focused on the Amazon biome, the analysis is further limited to municipalities where the biome is the predominant one (initial $N$=556).

Table 4 presents the results of the RD analysis, using a symmetric window of $h$ percentage points around the cutoff. Observations below the cutoff are assigned to the control group, while those above are assigned to the treatment group.[42] Before estimating the local average effect of voting for the government, we partial out our measure of environmental enforcement to account for factual factors that could justify enforcement (e.g., the amount of deforestation observed in municipality $m$), as well as technical limitations and existing policies that could influence monitoring.[43] Thus, the outcome variable in our main RD estimation represents the average level of enforcement after controlling for these factors, along with municipality and time fixed effects. The estimates suggest that municipalities that become supporters of the national party receive, on average, 4.5 fewer fines and 6.5 fewer embargoes than expected, given

[41]This approach examines municipalities with similar support levels for the national party, differing only in whether they are electorally aligned by a narrow margin. we adopt the local randomization RD framework (see Cattaneo et al., 2024a for a review). Unlike the continuity approach, which relies on extrapolating smooth regression functions across a cutoff, the local randomization approach explicitly assumes that near the cutoff, treatment assignment approximates a randomized experiment. In our case, this means treating alignment or opposition as randomly assigned near the cutoff, enabling valid comparisons between units within a small window around the threshold.

[42]The window for establishing the "as-if random assignment" was determined by an automatic data-driven selection process that checks the balance between treatment and control groups across covariates that relevant for the running variable and the outcome observed during the election year (i.e., when "treatment" is assigned). The treatment effect is then assessed using data from the subsequent administration, covering the four years following the election that determined treatment assignment. For more information on the window selection process and variables used, see Figure A11.

[43]We estimate the following model:

$$Enforcement(Sanction - Alerts)_{my} = \theta_k X_{my} + \alpha_m + \gamma_y + \varepsilon_{my} \tag{23}$$

Where *Enforcement* is the number of sanctions (fines or embargoes) minus the total number of alerts. $X$ is a vector that includes deforestated area (km2), total area designated as protected areas ( measured as a proportion of the municipality Area), Average Cloud Cover and a binary variable that indicates whether the municipality is in the IBAMA priority list. $\alpha$ and $\gamma$ are municipality and year fixed effects, respectively. and $\varepsilon$ is the error term. Standard errors are clustered at the municipality and intermediate region-year levels.

the number of alerts issued in their jurisdiction. However, only the estimate for embargoes is statistically significant at conventional levels.

Table 4: The Effect of Being a National Party supporter on Enforcement Placement

| Variable | LATE | Fisherian P-value | N controls | N treatment | N |
|---|---|---|---|---|---|
| Residuals: Fines | -4.5 | 0.258 | 293 | 258 | 551 |
| Residuals: Embargoes | -6.5*** | 0.004 | 293 | 258 | 551 |

Table displays the results of RD regressions with the following specifications: The dependent variable is residuals of regressions implemented according to Equation 23, and the running variable is the margin of victory for the national party in the previous election. The "as-if random assignment" window includes observations with margin values within 4.25 points above and below the cutoff. Fisherian p-values are calculated using 1,000 simulations. The kernel used is uniform, and the polynomial order is zero. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These results remain consistent across multiple robustness tests, including estimations that use the standardized number of fines and embargoes instead of residuals (Table A8), a manipulation test assessing the density of observations around the cutoff (Figure A12), placebo tests using pre-treatment covariates and alternative outcome variables (A9), estimations with artificial cutoff values (Table A10), and analyses using alternative, smaller bandwidths (Table A11).

## 7 Strategic Placement of Incentives II: Commodity Booms and Economic Incentives

Thus far, our empirical analysis has emphasized the role of electoral dynamics in shaping environmental enforcement. However, our theoretical framework also highlights a second key driver: the role of economic incentives, particularly those triggered by commodity booms, as reflected in H2. In this section, we examine how exposure to commodity price booms interacts with political alignment to affect enforcement. If Party $P$ prioritizes electoral survival over programmatic enforcement, we expect a stronger reduction in sanctions during commodity booms in municipalities that supported the national government. In other words, we anticipate $\delta < 0$ in Equation 18.

As shown in Table 5, enforcement is significantly lower in aligned municipalities during years of high commodity prices. Across all specifications, the interaction term is negative and statistically significant, indicating that commodity booms are associated with a sharper decline in enforcement in municipalities that supported the national government. Notably, the direct effect of commodity exposure ($\beta_1$) is statistically insignificant, indicating that commodity booms do not uniformly reduce enforcement. Rather, it is the interaction with political alignment that drives the effect, reinforcing our argument about the strategic nature of enforcement under electoral constraints.

Table 5: Effect of Commodity Shocks on Enforcement: Interaction with Political Alignment

| VARIABLES | (1) Embargoes | (2) Embargoes | (3) Fines | (4) Fines |
|---|---|---|---|---|
| Exposure | 2.26 | 1.25 | 2.43 | 1.42 |
| | (1.96) | (1.39) | (2.25) | (1.73) |
| National party won locally | -0.24 | -1.12 | 1.43 | 0.32 |
| | (2.96) | (2.21) | (3.52) | (2.98) |
| Interaction | -3.70*** | -2.03*** | -3.28*** | -1.77** |
| | (1.07) | (0.78) | (1.12) | (0.89) |
| Observations | 6,838 | 6,838 | 6,838 | 6,838 |
| R-squared | 0.42 | 0.51 | 0.28 | 0.36 |
| Controls | NO | YES | NO | YES |
| DP Mean | -5.86 | -5.86 | -.17 | -.17 |
| Embargoes Mean | 1.904 | 1.904 | | |
| Fines Mean | | | 7.590 | 7.590 |

Note: The table reports the results of regressions estimating the effect of commodity price shocks and political alignment on environmental enforcement. Enforcement is defined as the difference between deforestation and sanctions (embargoes and fines). The key variable of interest is the interaction between the commodity price index and an indicator for whether the national party won the most recent presidential election in the municipality. All standard errors are spatially robust Conley standard errors (Conley, 1999), which account for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. All specifications include municipality and year fixed-effects. Columns (2) and (4) include socioeconomic and geographic controls. *** p<0.01, ** p<0.05, * p<0.1.

In terms of magnitude, the results are substantively meaningful. In municipalities aligned with the national government, a one-unit increase in the commodity price exposure index is associated with roughly 2–4 fewer sanctions than expected given deforestation alerts — for reference, the index varies between 0.7 and 6.8. This pattern holds for both fines and embargoes, but is particularly strong for embargoes — the more consequential form of sanction (see Section 3.2).[44]

These results reinforce our argument that political and economic geography interact to shape enforcement behavior. While commodity booms alone do not systematically reduce enforcement across the board (the main effect of the CPI is mostly insignificant), they do exacerbate political pressures in electorally sensitive areas. Facing backlash from voters and producers who stand to benefit from higher prices, Party $P$ appears to selectively reduce enforcement in its strongholds.

This suggests that the environmental consequences of commodity booms are not merely the result of private actor behavior but also reflect political decisions to relax enforcement in response to changing economic conditions. It also underscores the need to understand enforcement as a function of both political alignment and local exposure to global markets.

[44] To address concerns about potential bias from contemporaneous effects, we re-estimate the regressions reported in Table 5 using lagged exposure to price variation. The results remain consistent.

## 8 Corollary: The consequences for deforestation

Thus far, we have presented evidence that enforcement is not solely driven by objective monitoring data or environmental necessity, but also responds to political and economic incentives. We showed that enforcement is systematically lower in municipalities where electoral risks are higher and in times of commodity booms. While these findings do not fully discard the role of factual and technical determinants of enforcement — which remain an important part of the environmental policy functioning, as documented by prior literature — they suggest that strategic considerations distort, at least partially, where and when enforcement is applied.

In this section, we explore the downstream consequences of such distortion. Specifically, we ask whether past under-enforcement — which could be called a type of forbearance — affects future patterns of deforestation. Even if strategic forbearance is applied only to a subset of municipalities, its practical implications may be far-reaching if it alters local expectations, emboldens illegal actors, or signals impunity.

Table 6 presents the results bearing on H3. Across four specifications, we estimate the effect of experiencing under-enforcement in the previous year on current-year deforestation. Columns (1) and (2) use a binary indicator for whether the number of embargoes was less than the number of satellite alerts in previous years, while columns (3) and (4) use an analogous measure based on fines.

Table 6: Effect of Past Forbearance on Current-Year Deforestation

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Deforestation (Log) | | | |
| VARIABLES | Embargoes | Embargoes | Fines | Fines |
| Forbearance$_{(t-1)}$ | 0.16*** | 0.15*** | 0.18*** | 0.18*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Observations | 10,789 | 10,781 | 10,789 | 10,781 |
| R-squared | 0.90 | 0.90 | 0.90 | 0.90 |
| Controls | No | Yes | No | Yes |
| Mean Deforestation | 2,970 hectares | | | |

Note: The table reports the results of regressions estimating the effect of past institutional forbearance on current-year deforestation. The main independent variable is a binary indicator equal to 1 if, in the previous year, the municipality received fewer sanctions than deforestation alerts — i.e., experienced under-enforcement—and 0 otherwise. Columns (1) and (2) use embargo-based forbearance; columns (3) and (4) use fine-based forbearance. All standard errors are spatially robust Conley standard errors (Conley, 1999), which account for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. All models include municipality and year fixed effects; columns (2) and (4) include the full set of socioeconomic and geographic controls. *** p<0.01, ** p<0.05, * p<0.1.

Consistent with H3, the results show a consistent and statistically significant relationship between past forbearance and subsequent deforestation. Municipalities that received fewer sanctions than alerts in the previous year — whether measured by embargoes or fines — experience significantly higher deforestation in the following year. The magnitude of the effect is both statistically and substantively meaningful. A municipality in the forbearance group sees, on average, an increase of 15–18 percent in deforestation.

These findings suggest that institutional leniency has practical consequences. When municipalities experience under-enforcement, it appears to relax deterrent effects and incentivize further illegal land clearing. While such distortions may emerge for strategic or short-term electoral reasons, they can generate persistent environmental harm by undermining the credibility and deterrence value of the enforcement regime. Taken together, our findings underscore that even partial and targeted forbearance — applied in response to political or economic incentives — can have broad effects. Once enforcement loses its consistency and perceived impartiality, local actors may adjust expectations and behaviors in ways that amplify forest loss over time.

## 9 Discussion

Consistent enforcement is crucial to limiting deforestation and other forms of ecological harm. Our findings suggest that enforcement is not uniformly applied but strategically adjusted based on electoral considerations — especially when sanctions have serious economic repercussions, as in the case of embargoes. By selectively reducing enforcement in politically significant areas — whether strongholds of support or competitive districts — Party $P$ effectively alters the spatial distribution of environmental degradation. This uneven application of enforcement not only weakens the deterrent effect of environmental regulations but also enables higher levels of resource depletion in areas where political considerations outweigh ecological priorities.

Our results also open new questions on the political economy of environmental policies. The first on is more immediate and speaks to the institutional conditions that weaken command-and-control policies, i.e., enforcement. Our analysis points to a potential role of malapportionment as an institutional moderator: insofar as areas with higher potential of political backlash are overrepresented, environmental protection under democracy suffers. No national party will abandon highly salient areas on the altar of initiatives that are certain to generate significant costs in the short run and uncertain benefits in the future.

This raises a second, broader question: how should the welfare effects of pro-environment parties' policy choices be evaluated? The counterfactual is hard to define *ex ante*: if the full implementation of forest protection paves the way for a victory of Party E-types, does environmental protection ultimately improve relative to outcomes under strategic enforcement? Is the partial sacrifice documented in our findings democracy's second best then? The record of Bolsonaro's administration speaks to the pertinence of these questions (e.g. Araújo, 2020; Hochstetler, 2021; Dutra da Silva and Fearnside, 2022).

Finally, our analysis points to the importance of institutional safeguards that insulate environmental enforcement from electoral pressures and political interference. This raises a classic problem of institutional design: to what extent should democratic discretion be constrained in the provision of environmental public goods? Environmental enforcement may face credibility problems analogous to those identified in the political economy of inflation, where delegation to independent agencies has been used to mitigate short-term political incentives (see Fernández-Albertos, 2015, for review). Identifying institutional arrangements that preserve democratic accountability while protecting enforcement capacity is therefore central to effective environmental governance and the prevention of long-term ecological degradation.

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## Conflict of Interest

The authors have no conflict of interest to declare.

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Online Appendix

The Political Logic of Persistent Deforestation:
Electoral Incentives and Public Goods in the Brazilian Amazon

## A1 Related literature: Deforestation, Policy and Electoral cycles

Nearly every country with forests has adopted some environmental regulations or policies designed to protect these areas (FAO and UNEP, 2020).[1] However, the stark contrast between the widespread adoption of environmental regulations and the persistent high rates of deforestation raises questions about the effectiveness of such policies. Common explanations for the failure to protect forests, particularly in the developing world, often emphasize two factor: poorly designed command-and-control policies, which are insufficient to curtail the influence of economic incentives and transformations, and the lack of state capacity to enforce environmental protections (for a review, see Balboni et al., 2023).

The literature on economic incentives highlights the role of demographic and economic transformations, such as urbanization, agricultural expansion, and the development of infrastructure, such as hydroelectric plants and roads ( e.g., Allen and Barnes, 1985; Hosonuma et al., 2012; Ritchie and Roser, 2021; Geist and Lambin, 2002; Leblois et al., 2017; Gibbs et al., 2010). Yet, there have been few attempts to develop comprehensive theories that consistently elucidate why, in the interplay between immediate economic incentives and policy, the latter frequently yields and succumbs, even when the economic harms of pursuing this route in the long run are evident (Leite-Filho et al., 2021; Delgado et al., 2022).

Meanwhile, the state capacity literature suggests that governments often fail to enforce environmental regulations due to capacity constraints (e.g., Schwartz, 2003; Mol, 2016; Meckling and Nahm, 2018). These studies typically assume that with adequate capacity, states would achieve their environmental objectives, even in the face of strong economic pressures from powerful interest groups, such as landed elites.[2] Undoubtedly, some level of capacity is essential for implementing any policy objective; however, capacity alone does not guarantee effective implementation, even when there is a clear policy mandate. Political calculations can influence whether existing resources are mobilized to enforce policies, particularly when competing interests come into play. (e.g., Beramendi and Rogers, 2021; Fergusson et al., 2022). Thus, deforestation may not always result from a problem of capacity but be the product of specific institutional dynamics affecting state agents' incentives and decisions (e.g. Burgess et al., 2012; Harding et al., 2024).

The recognition that economic incentives and capacity alone cannot fully explain the persistent failure of environmental policies, particularly in forest protection, has led to a renewed focus on the *political drivers of deforestation*, with new studies highlighting the role of elections as a

[1] Throughout this article, the terms "environmental policy" and "environmental regulation" are used interchangeably to refer to the set of command-and-control policies that regulate access and use of natural resources.

[2] This argument implies the existence of a professional bureaucracy operating with reasonable levels of autonomy that would be capable of avoiding capture and implementing policy goals (e.g., Evans, 1995; Skocpol, 2014).

significant factor in environmental degradation.[3] These studies argue that electoral pressures incentivize politicians to allow resource extraction, granting access to forests in exchange for votes (e.g., Klopp, 2012; Ameet, 2018), or to prioritize policies that benefit key constituencies such as those in agriculture, logging, or mining — sectors known to contribute significantly to deforestation (e.g., Gibbs et al., 2010; Burgess et al., 2012; Leblois et al., 2017). Central to this scholarship is the testing of an *electoral cycle of deforestation*, akin to the political business cycle (Nordhaus, 1975), where politicians engage in opportunistic behavior before elections to gain voter support, often allowing voters to extract more natural resources, including through illegal means (Ruggiero et al., 2021).

This scholarship suggests that elections can significantly influence deforestation dynamics. However, this effect is contingent upon various contextual factors. Specifically, deforestation rates tend to increase during elections when electoral competition is high — particularly in recent democracies (Sanford, 2021; Cisneros et al., 2021; Morpurgo et al., 2023; Xu, 2025) — when incumbents involved in corruption are seeking reelection (Pailler, 2018), when alternative sources of rent extraction are limited (Burgess et al., 2012), or when there is alignment between central and local governments in multilevel systems, particularly in regions experiencing high deforestation pressures (Ruggiero et al., 2021). While the evidence does not yet establish a robust and consistent political cycle of deforestation, these studies indicate that, under certain conditions, electoral processes can undermine conservation efforts.

Despite significant progress in documenting the relationship between elections and deforestation, the literature has only begun to probe the mechanisms that drive this connection and to clarify the logic behind its mixed empirical findings. Harding et al. (2021), for instance, Rodrigues-Filho et al. (2015) demonstrate that deforestation rates in the Brazilian Amazon peak during presidential elections but depart from conventional explanations centered on possible clientelistic or corruption practices (Klopp, 2012; Ameet, 2018; Burgess et al., 2012). Instead, they suggest that electoral periods trigger significant administrative shifts, leading to managerial instability and "episodic inefficiency." This instability, in turn, temporarily undermines institutional capacity, weakening enforcement and enabling illegal deforestation. Though compelling, their analysis does not directly measure administrative changes — the very mechanism purported to weaken state capacity after presidential elections. In this regard, Xu (2025) makes a significant contribution by demonstrating that, under electoral competition, local governments engage in a strategy termed "bureaucratic packing," whereby they fill bureaucratic offices with personnel aligned with their agenda to obstruct bureaucratic actions that might threaten the economic interests linked to resource extraction. Note that both studies do not questions the content of existing regulation, but the central role political factors affecting enforcement.

In sum, while early explanations for deforestation emphasized structural economic pressures and limited state capacity, a growing body of research highlights the centrality of political

[3] The link between elections and deforestation is not a new topic in environmental literature though. Earlier works on the drivers of tropical deforestation offered anecdotal evidence suggesting that political factors, such as patronage, could explain the limited success of environmental policies in various contexts (e.g., Bates, 1979, *apud* Sanford, 2021)

dynamics — particularly electoral incentives — in shaping environmental outcomes. Recent work has begun to unpack how elections influence enforcement, not only through overt clientelism or corruption, but also through subtler mechanisms such as bureaucratic turnover, managerial disruption, and strategic politicization of the state apparatus. However, important gaps remain in our understanding of when and how these political dynamics override formal environmental mandates. Our research addresses this gap by investigating the institutional and electoral conditions under which political actors choose to enforce — or to undermine — environmental regulation, paying close attention to the ways political incentives interact with administrative structures and enforcement capacity on the ground.

## A2 Bolsonaro's Public Statements on Environmental Policy

Upon being elected, Bolsonaro stated that he would put an end to the "radical way" in which environmental agencies like the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) and the Chico Mendes Institute for Biodiversity Conservation (ICMBio) "go around issuing fines." He claimed that he himself had been fined by IBAMA in 2012 for around R$10,000. "I am living proof of the negligence, bias, and poor service provided by some IBAMA and ICMBio agents. That will come to an end," he said. The president-elect also stated he would dismantle what he called the country's "flawed environmental and Indigenous policy." [4]

In 2019, Bolsonaro defended changes to the enforcement process, claiming that 40% of the fines issued in rural areas "served only to feed a radical enforcement agenda that aimed to please specific interest groups — groups that neither protected the environment nor supported those who produce." Also in 2019, IBAMA field agents reported that loggers had begun making open threats against environmental workers, claiming they "felt empowered by Bolsonaro's rhetoric."[5]

In 2022, during his reelection campaign, Bolsonaro once again openly criticized IBAMA's actions under his own administration and publicly defended illegal deforesters during a televised interview. [6]

In 2024, speaking to supporters, Bolsonaro once again took pride in having dismantled environmental enforcement capacity, stating: *"We repealed more than 5,000 regulatory rules. I didn't authorize a single hiring process for IBAMA or ICMBio. The fewer of those people out there, the better for everyone."*[7]

[4]Source:Source: https://www.congressoemfoco.com.br/noticia/26623/bolsonaro-critica-ibama-e-icmbio-e-diz-que-acabara-com-politica-tacanha-e-mesquinha

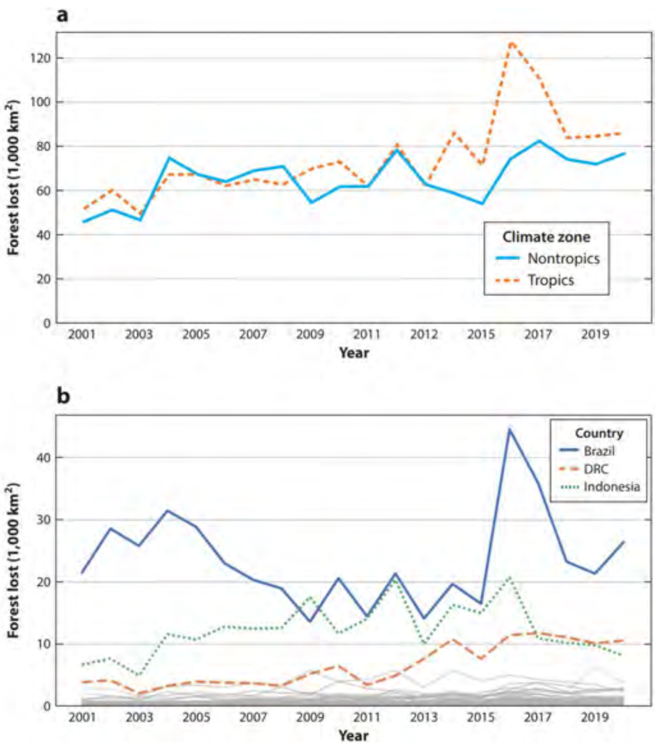
[5]Source: https://veja.abril.com.br/politica/madeireiros-usam-discurso-do-governo-bolsonaro-para-intimidar-ibama.

[6]Source: https://oeco.org.br/noticias/bolsonaro-critica-ibama-e-defende-desmatadores-em-sabatina-na-tv

[7]For a broader list of Bolsonaro's environmental rollbacks while in office, see: https://www.cartacapital.com.br/blogs/brasil-debate/as-26-principais-violacoes-ao-meio-ambiente-feitas-por-jair-bolsonaro/

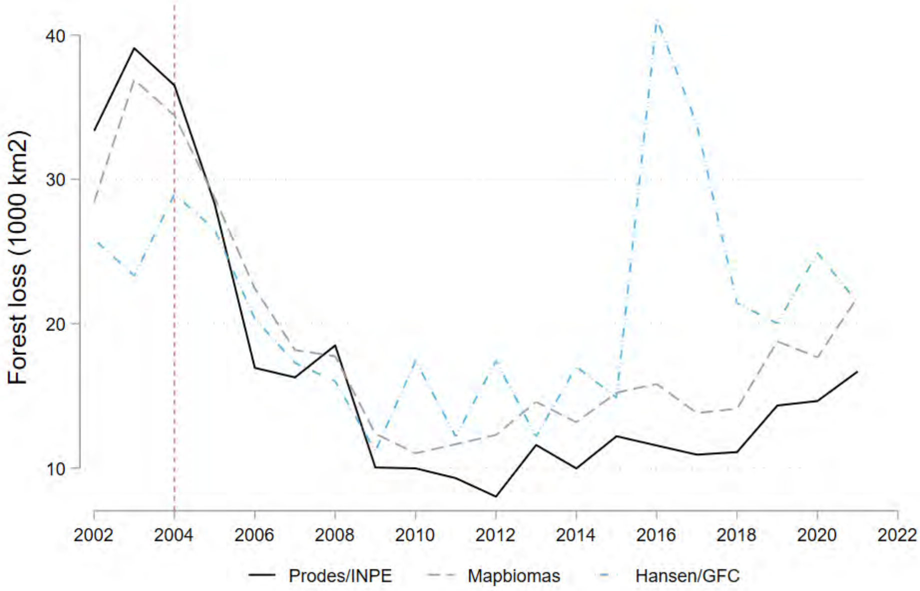
## A3 Descriptive Statistics

Figure A1: Brazil's contribution to Global Deforestation



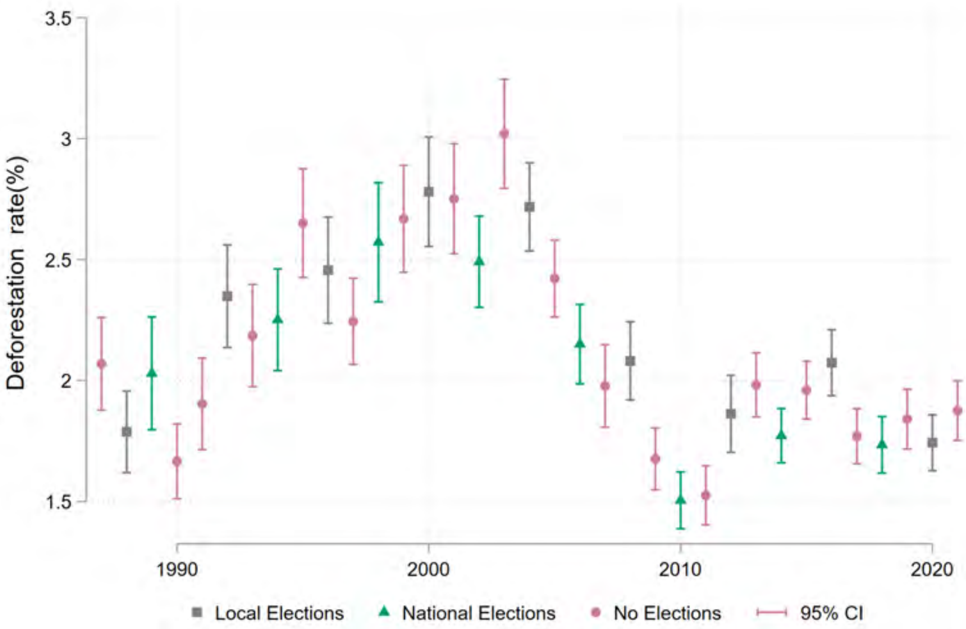

Note: Figure shows forest loss by climate zone (panel a) and by country within the tropics (panel b) estimated using data from Hansen et al. (2013). Source: Balboni et al. (2023).

Figure A2: Deforestation in the Legal Amazon




Note: The graph shows the annual forest cover loss, measured in thousands of square kilometers (1000 km²) for the period 2002-2021. For the GFC computations, we utilize a threshold of 50% and a minimum forest area equivalent to 6 pixels (approximately 0.5 hectares), following the recommendation of the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) guidelines for forest cover analysis. The reference line indicates the launch of first Action Plan for Deforestation Prevention and Control in the Legal Amazon (PPCDAm), a series of reforms in the environmental policy enacted starting in 2004. Data sources: MapBiomas, Collection 8 (Souza et al., 2020); Global Forest Change (GFC), Version 1.10 (Hansen et al., 2013); and PRODES/TERRABRASILIS/INPE.

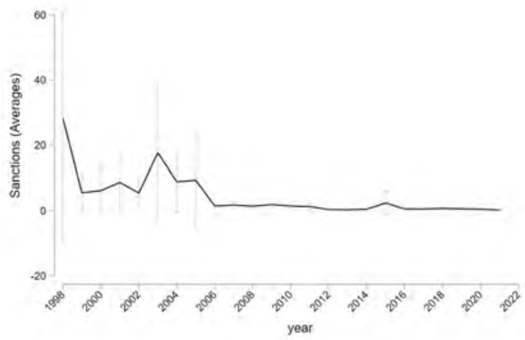
Figure A4: Evolution of deforestation rate and elections in post-democratization Brazil



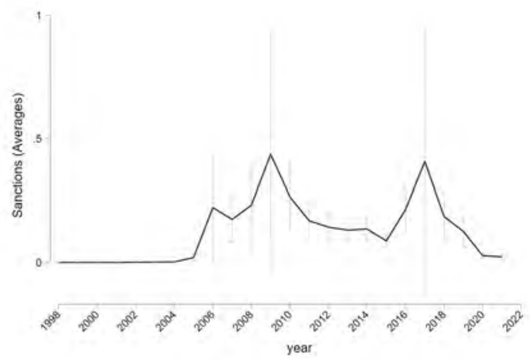

Note: Figure shows the average deforestation rates observed in election and non-election years between 1987 and 2020 in the municipalities inside the Brazilian Legal Amazon region. Deforestation rates is defined as the percentage of standing forest lost in a given year. Data source: Mapbiomas, Collection 8.

Figure A3: Evolution of enforcement as proportion of deforested area in the Legal Amazon

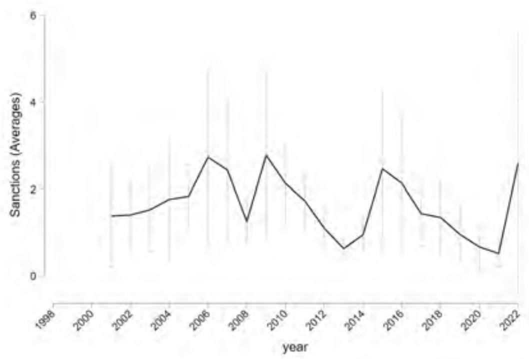
(a) Fines per km2 of loss forest (Mapbiomas)



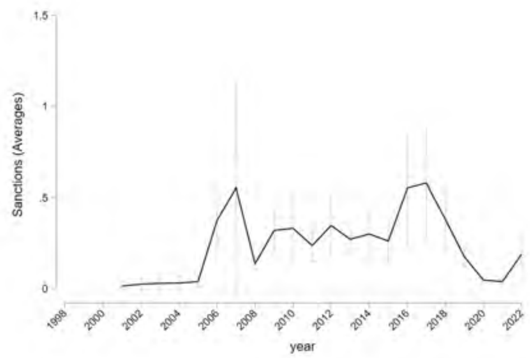

(b) Embargoes per km2 of loss forest (Mapbiomas)




(c) Fines per km2 of forest loss (Prodes)



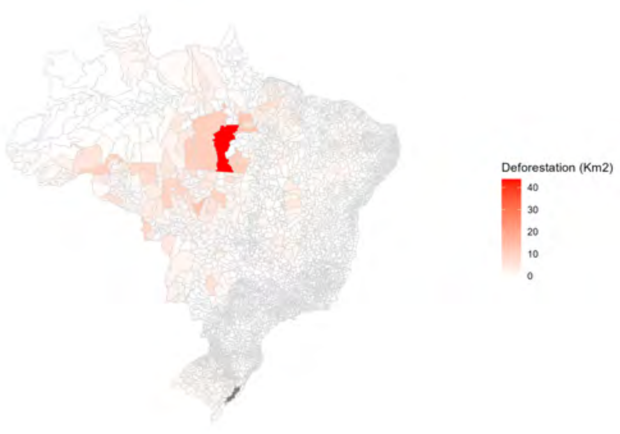

(d) Embargoes per km2 of forest loss (Prodes)




Note: The graph shows the evolution of average enforcement in the Legal Amazon region. Enforcement is defined as the number of sanctions (fines or embargoes) per total deforested areas, in squared kilometers calculated using Mapbiomas or Prodes data. (a) and (c) show the number of forest-related fines. (b) and (d) plots the evolution of embargoes.

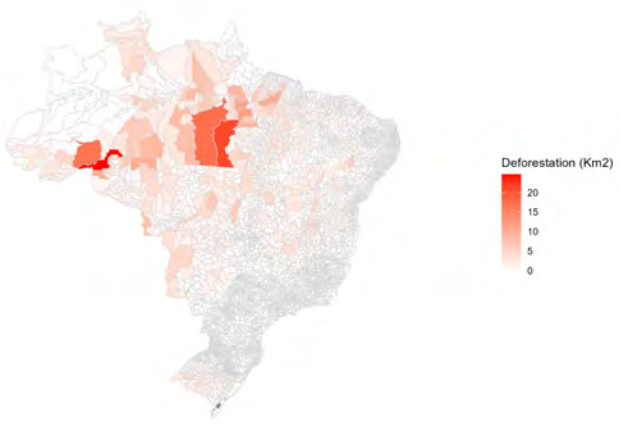
Figure A5: Spatial distribution of deforestation and enforcement in Brazil (2002 and 2016)

(a) Deforestation in 2002

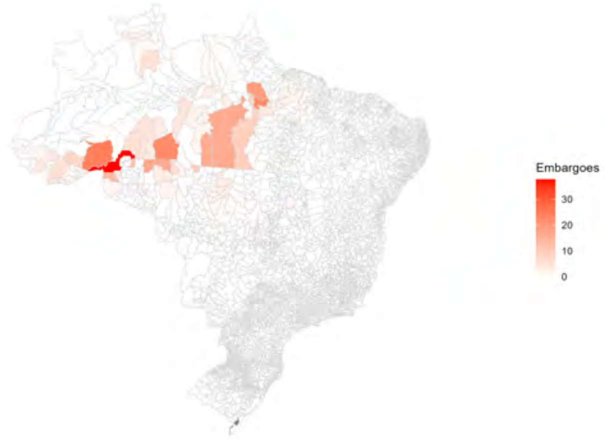



(b) Fines in 2002


(c) Deforestation in 2016



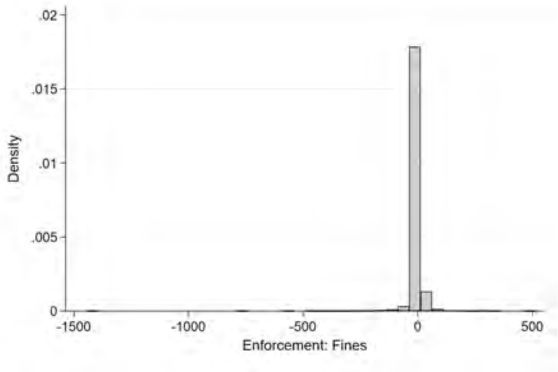

(d) Embargoes in 2016



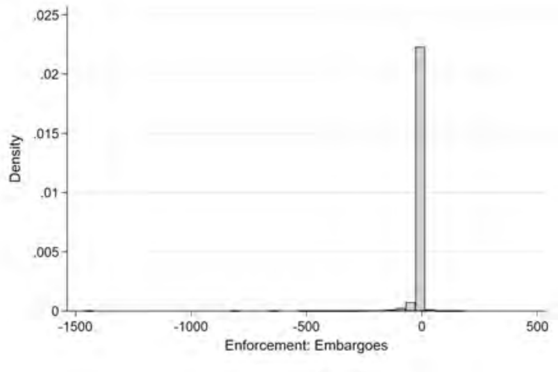

Note: The maps show the standardized distribution of deforestation and sanctions (fines or embargoes) across Brazilian municipalities in the years 2002 and 2016. They illustrate that, although correlated, there is no perfect match between deforestation and enforcement. Data sources: Deforestation data from MapBiomas (Collection 8) and sanctions data from IBAMA.

Figure A6: Distribution of enforcement level relative to alerts (2004-2015)

(a) Fines




(b) Embargoes




Note: The figure shows histograms with the distribution of dependent variable used in Equation 17 and in the RDD estimation using data from the PT administrations (2004-2015).

## A4 Definition of Enforcement

Table A1: Summary Statistics for the Dependent Variable used in Equation 17 (2004-2015)

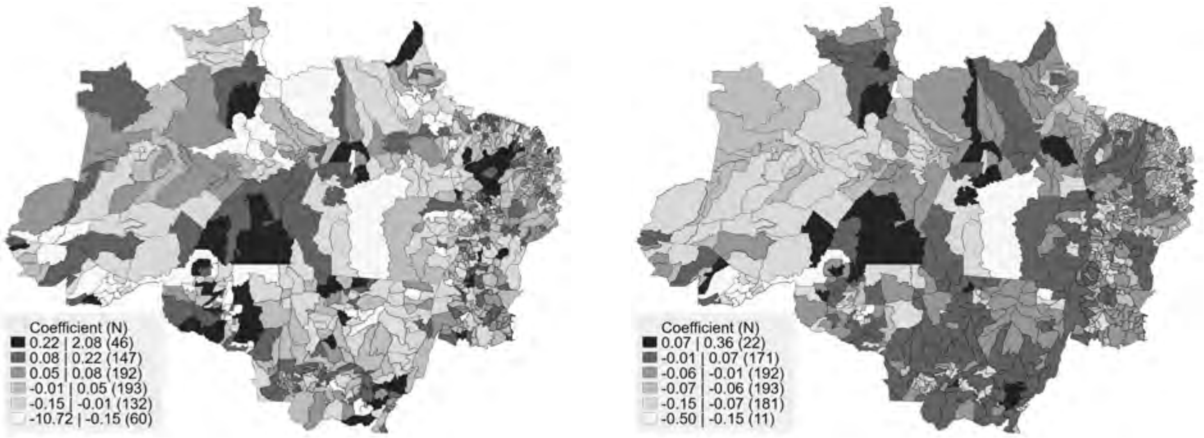
| Definition | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Enforcement (Fines - Alerts) | 9,253 | - 0.17 | 32.41 | - 1,442 | 514 |
| Enforcement (Embargoes - Alerts) | 9,253 | - 5.86 | 31.59 | - 1,462 | 182 |

Note: The table presents the basic summary statistics for the dependent variable used in Equation 17 and in the RDD estimation using data from the PT administrations (2004-2015).

# A5 Other figures and tables

Figure A7: Deforestation and Enforcement in the Brazilian Amazon (PT Administrations)

(a) Fines (b) Embargoes



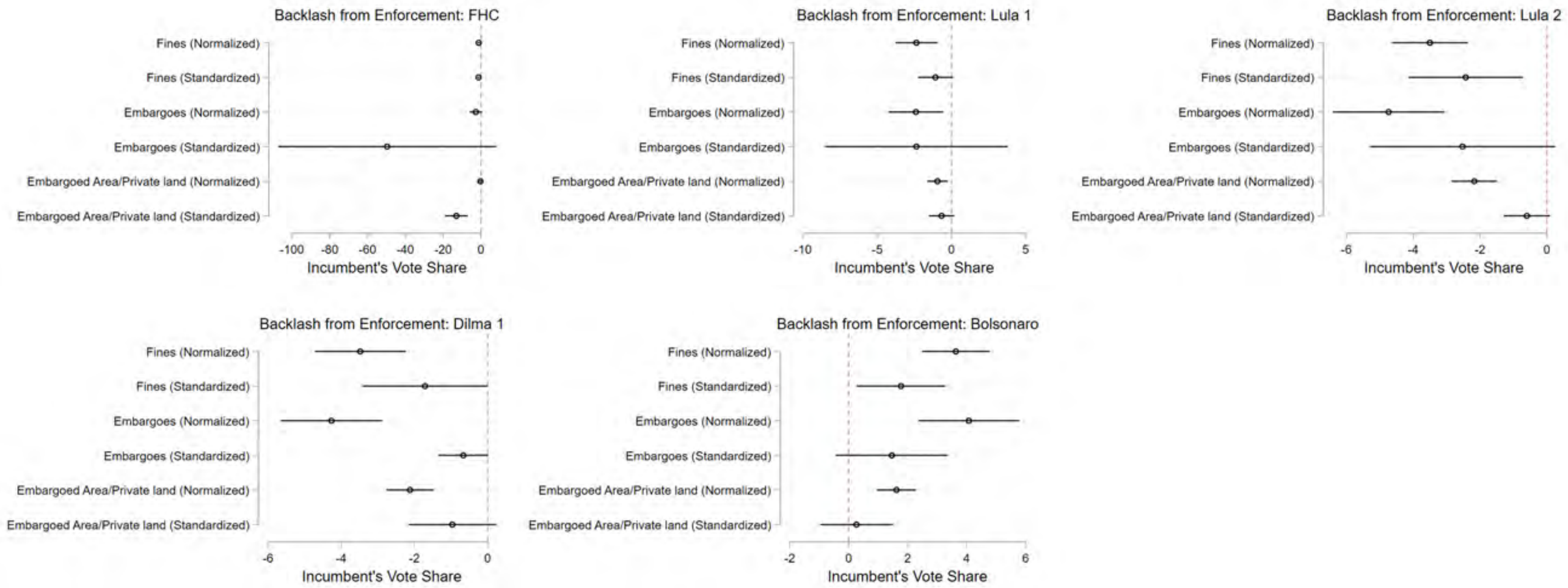

Note: The figures show the correlation between enforcement (count) and deforestation (km²) in the Brazilian Legal Amazon during the Workers Party's administrations (2003-2014), omitting the last years of Dilma's term. *N* indicates the number of municipalities in each bracket. Coefficients are based on 2001–2022 data, estimated using OLS regressions with municipality and year fixed effects. Brackets are defined base on a boxplot method that aggregate observations according to their locality and through data quartiles.

Table A2: Effects of enforcement on turnout

| Dependent Variable | Incumbent's Vote Share (%) | | | | | |
|---|---|---|---|---|---|---|
| Enforcement Metric | (1) Fines Normalized§ | (2) Fines Standardized | (3) Embargoes Normalized | (4) Embargoes Standardized | (5) Embargoed area (%) Standardized† | (6) Embargoed area (%) Normalized† |
| **Panel A**: Estimations without covariates | | | | | | |
| Sanction | -0.24*** | 0.01 | -0.20* | -0.09 | 0.03 | -0.06 |
| | (0.09) | (0.06) | (0.11) | (0.06) | (0.08) | (0.04) |
| Observations | 4,628 | 4,628 | 4,628 | 4,628 | 4,628 | 4,628 |
| R-squared | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 |
| **Panel B**: Estimations with covariates | | | | | | |
| Sanction | -0.20** | 0.08 | -0.18* | 0.01 | 0.10 | -0.04 |
| | (0.09) | (0.07) | (0.11) | (0.06) | (0.08) | (0.04) |
| Observations | 4,625 | 4,625 | 4,625 | 4,625 | 4,625 | 4,625 |
| R-squared | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 | 0.69 |
| DP Mean | 71.07 | 71.07 | 71.07 | 71.07 | 71.07 | 71.07 |

Note: The table presents the estimated effects of enforcement on the presidential elections turnout. §*Sanctions* are normalized using the inverse hyperbolic sine (IHS) transformation.† Embargoed area (%) is measured as a proportion of total private property area in the municipality. All regressions include municipality and electoral cycle fixed effects. Regressions in Panel 2 includes the following controls: average maximum temperature (°C), average annual precipitation (mm), total deforestation, km2 (log); local GDP (Logged); number of families enrolled in the national cash transfer program CCT (IHS); a dummy variable indicating whether a municipality have been "blacklisted" by the environmental agency; and extension of Protected Areas (% of municipality area). The analysis covers 1998–2020 (excluding 2018 to avoid impeachment-related noise) and aggregates data by national electoral cycles. Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A8: The Effect of Enforcement on the Incumbent's Vote Share by Administration




Note: The graph displays the marginal effect of sanctions (fines and embargoes) on the incumbent party's vote share in the election held at the end of their term. Sanctions are aggregated over the four-year presidential term and, in the indicated cases, normalized using an inverse hyperbolic sine (IHS) transformation. Each estimation corresponds to a cross-sectional regression. Vote share is measured in percentage points (0–100). Standard errors are clustered at the intermediate region level.

Table A3: Campaign Contributions and Environmental Enforcement - With Controls

| Dependent Variable | Campaign Contributions (Normalized) | | | | | |
|---|---|---|---|---|---|---|
| Variables | (1)<br>Fines<br>Normalized | (2)<br>Fines<br>Standardized | (3)<br>Embargoes<br>Normalized | (4)<br>Embargoes<br>Standardized | (5)<br>Embargoed area †<br>Standardized | (6)<br>Embargoed area†<br>Normalized |
| **Panel A**: Contributions to Right-Wing Parties | | | | | | |
| Sanction | 0.15** | 0.20 | 0.44*** | 0.31*** | 0.28*** | 0.15*** |
| | (0.06) | (0.14) | (0.08) | (0.08) | (0.09) | (0.03) |
| Observations | 5,404 | 5,404 | 5,404 | 5,404 | 5,404 | 5,404 |
| R-squared | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 | 0.49 |
| DP Mean | 2.281 | 2.281 | 2.281 | 2.281 | 2.281 | 2.281 |
| **Panel B**: Contributions to Left-Wing Parties | | | | | | |
| Sanction | 0.01 | 0.17 | 0.22*** | 0.34*** | 0.17** | 0.05** |
| | (0.04) | (0.11) | (0.05) | (0.08) | (0.08) | (0.02) |
| Observations | 5,404 | 5,404 | 5,404 | 5,404 | 5,404 | 5,404 |
| R-squared | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 |
| DP Mean | 0.742 | 0.742 | 0.742 | 0.742 | 0.742 | 0.742 |

Note: The table shows the change in total amount of campaign contributions (normalized) as a function of enforcement level in each municipality in the Legal Amazon region. *Sanctions* represents the total number of fines or embargoes issued during each 4-year presidential term. The total amount of contributions in R$ has been adjusted to 2022 values before normalization using the General Price Index – Internal Availability (IGP-DI/FGV). All estimations include municipality and electoral cycle fixed-effects. They also include the following controls: : average maximum temperature (°C), average annual precipitation (mm), total deforestation, km2 (log); local GDP (Logged); number of families enrolled in the national cash transfer program CCT (IHS); a dummy variable indicating whether a municipality have been ”blacklisted” by the environmental agency; and extension of Protected Areas (% of municipality area). Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. All $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

## Table A4: Support for the National Party and Enforcement Placement

| Variables | Enforcement (Fines-Alerts) | | | | Enforcement (Embargoes-Alerts) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| National party won locally | -7.28*** | -6.85*** | -7.93*** | -6.72*** | -10.19*** | -9.47*** | -10.57*** | -9.40*** |
| | (2.21) | (2.21) | (2.67) | (2.23) | (1.92) | (1.88) | (2.27) | (1.91) |
| Deforestation , Prodes/Inpe (log)(t-1) | | 1.18 | 1.52 | 1.23 | | 0.48 | 0.82 | 0.52 |
| | | (1.45) | (1.72) | (1.47) | | (1.34) | (1.58) | (1.35) |
| Priority list (t-1) | | 50.60*** | 52.03*** | 50.72*** | | 56.84*** | 57.96*** | 56.91*** |
| | | (9.50) | (9.44) | (9.53) | | (8.83) | (8.76) | (8.86) |
| Protected Areas (% of Municipality Area)(t-1) | | 0.41* | 0.48 | 0.43* | | 0.41* | 0.49* | 0.43* |
| | | (0.24) | (0.29) | (0.24) | | (0.23) | (0.29) | (0.24) |
| Average Cloud Cover, calendar year (NASA)(t-1) | | -30.83** | -26.36 | -34.86** | | -25.07** | -20.43 | -28.51** |
| | | (14.20) | (16.96) | (14.28) | | (11.82) | (14.21) | (11.79) |
| Maximum temperature in the year (C)(t-1) | | 0.18 | -0.06 | 0.15 | | 0.37 | 0.14 | 0.34 |
| | | (0.66) | (0.77) | (0.66) | | (0.55) | (0.65) | (0.55) |
| Precipitation (mm)(t-1) | | -0.01*** | -0.01*** | -0.01*** | | -0.01*** | -0.01*** | -0.01*** |
| | | (0.00) | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) |
| Local GDP (log) | | | 6.19** | | | | 2.86 | |
| | | | (2.50) | | | | (2.15) | |
| Pasture(log) | | | -1.97 | | | | -3.45 | |
| | | | (3.40) | | | | (3.23) | |
| Cropland - Perennial and Temporary Crops(log) | | | 0.89* | | | | 0.86* | |
| | | | (0.53) | | | | (0.48) | |
| Local GDP - Added Value Agribusiness (% of total) | | | | -0.05 | | | | -0.08 |
| | | | | (0.11) | | | | (0.10) |
| Local GDP - Added Value Industry (% of total) | | | | 0.02 | | | | -0.02 |
| | | | | (0.08) | | | | (0.07) |
| Local GDP - Added Value service (% of total) | | | | 0.19 | | | | 0.09 |
| | | | | (0.14) | | | | (0.12) |
| Constant | 0.00 | 0.00 | -0.00 | 0.00 | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.37) | (0.37) | (0.42) | (0.37) | (0.35) | (0.33) | (0.38) | (0.33) |
| Observations | 9,253 | 8,440 | 7,140 | 8,434 | 9,253 | 8,440 | 7,140 | 8,434 |
| R-squared | 0.28 | 0.32 | 0.33 | 0.32 | 0.42 | 0.47 | 0.48 | 0.47 |
| Controls | NO | YES | YES | YES | NO | YES | YES | YES |

Note: The table shows the estimated level of enforcement as function of various factors including support for the central government, across four specifications of Equation 17. Enforcement is defined as the number of sanctions minus the number of deforestation alerts. All specifications includes municipality and year fixed-effects. Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. The sample cover the period between 2004-2015 (PT administration with available alert data). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Support for the National Party and Enforcement Placement - Per quintile

| | Enforcement (Fines-Alerts) | | | | | Enforcement (Embargoes-Alerts) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Margin | -0.39** | -0.72*** | -0.94** | 0.08 | 0.16** | -0.37*** | -0.68*** | -0.88** | -0.07 | 0.09 |
| | (0.16) | (0.27) | (0.41) | (0.10) | (0.08) | (0.14) | (0.24) | (0.39) | (0.07) | (0.06) |
| lagged_logdef_prodes | 0.61 | 0.81 | 3.66 | 0.07 | -0.66 | -0.24 | 0.44 | 3.13 | -0.28 | -0.58 |
| | (0.78) | (0.96) | (2.60) | (0.34) | (0.44) | (0.71) | (0.87) | (2.47) | (0.24) | (0.39) |
| lagged_blacklisted | 15.32** | 39.73*** | 70.87*** | 6.07 | 0.58 | 23.62*** | 44.46*** | 75.31*** | 19.12 | 3.78 |
| | (7.18) | (8.36) | (20.01) | (10.69) | (21.39) | (6.01) | (7.56) | (19.43) | (13.92) | (20.79) |
| lagged_pa | 0.52 | 0.84 | 1.57 | 0.14 | -0.83** | 0.57 | 0.82 | 1.63 | -0.04 | -0.68* |
| | (0.80) | (1.11) | (1.07) | (0.23) | (0.38) | (0.71) | (1.03) | (1.10) | (0.10) | (0.37) |
| lagged_clouds_nasa_annual | 28.52 | 69.97* | -23.78 | -5.13 | 3.94 | 23.17 | 60.83* | -7.87 | -0.29 | 2.71 |
| | (37.15) | (39.79) | (35.99) | (16.88) | (14.23) | (34.26) | (34.96) | (33.68) | (11.01) | (8.18) |
| lagged_temperature_max | 0.89 | 1.13 | 0.14 | 0.18 | 0.05 | -0.12 | 1.32 | -0.80 | 0.56 | -0.10 |
| | (1.19) | (1.51) | (2.29) | (0.82) | (0.36) | (1.07) | (1.14) | (2.06) | (0.62) | (0.23) |
| lagged_prec_annual | -0.01* | -0.01*** | -0.01 | -0.01** | -0.00 | -0.01** | -0.01** | -0.01** | -0.00*** | -0.00 |
| | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) |
| Constant | 0.00 | 0.00 | 0.00 | -0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.00 | -0.00 |
| | (0.48) | (0.55) | (0.62) | (0.26) | (0.18) | (0.44) | (0.48) | (0.61) | (0.20) | (0.14) |
| Observations | 1,678 | 1,683 | 1,712 | 1,770 | 1,595 | 1,678 | 1,683 | 1,712 | 1,770 | 1,595 |
| R-squared | 0.34 | 0.59 | 0.51 | 0.56 | 0.53 | 0.54 | 0.67 | 0.55 | 0.76 | 0.54 |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Note: The table reports estimates of enforcement levels as a function of political support for the central government, based on Equation 17. Support is measured continuously using the government s Margin of victory in the last election — i.e., the relative vote share difference between the national ruling party and the main opposition in the most recent election. This variable ranges from –100 to 100, with negative values indicating that a majority of voters in the municipality supported the opposition. Enforcement is defined as the number of sanctions issued minus the number of deforestation alerts. All specifications include municipality and year fixed effects. Each column presents an estimation based on a subsample of the data defined by quintiles of the *Margin* variable. Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of each municipality's centroid. The sample covers the period from 2004 to 2015, corresponding to the PT administration years for which alert data are available. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

## A6 Backlash: IV Regressions

The results reported in Section 5 reveal a robust association between sanctions and electoral outcomes — with environmental enforcement leading to high electoral costs to parties associated with more stringent policies. While such consistent pattern is unlikely to arise from mere coincidence, our ability to make definitive causal claims is still limited. To address concerns about endogeneity, we employ an instrumental variable (IV) approach, leveraging a key innovation introduced by the PPCDAM reforms: the DETER system. This near-real-time deforestation monitoring tool, based on satellite imagery, has been credited as a central piece of Brazil's post-PPCDAM efforts to curb deforestation (Bragança and Dahis, 2022). However, in its early years, the system's performance was significantly affected by cloud cover, which hindered detection and, consequently, the ability of authorities to impose sanctions on environmental offenders.[8]

This technical specificity supports our IV strategy, wherein cloud cover serves as an instrument for enforcement (*c.f.*, Assunção et al., 2023; Merkus, 2024). The key (exclusion) assumption is that any effect of cloud cover on voters' behavior operates indirectly through its influence on enforcement levels. We focus on the period spanning PT's administrations for three primary reasons. First, this period aligns with the most substantial reductions in deforestation in the region, which the literature attributes to institutional and policy innovations introduced under the PPCDAM (e.g., Sills et al., 2015; Assunção et al., 2015; Bragança and Dahis, 2022). Second, focusing on this period allows the use of cloud cover data from the DETER database, which is available only for the years 2004–2017 (subsequent years remain accessible exclusively to public officials, INPE researchers, and enforcement agents). Third, enforcement during this period is strongly associated with electoral backlash, as demonstrated in the preceding analysis. This context gives us three subsequent elections (2006, 2010 and 2014) to test a causal relationship between sanctions and electoral backlash.

We attempt to align our empirical strategy with previous studies that adopt similar IV approach (Assunção et al., 2023; Merkus, 2024). To this end, we adjust enforcement and cloud cover data to "Prodes years" (August of year $y$ to July of $y+1$), use the total number of sanctions issued in each year without any functional form transformation, and restrict our analysis to municipalities in the Amazon Biome (N=556). Nonetheless, we face the additional challenge of an outcome observed only every four years, which reduces statistical power and dilutes part of the variation in cloud cover. Yet, the estimations reported in this section are able to capture two dynamics that suggest a causal effects of sanctions, especially embargoes. The first-stage regressions confirm that average cloud cover in previous years significantly reduces enforcement (Table A6, columns 2 and 5) suggesting that technical factors play a considerable role in shaping enforcement activities in the Brazilian Legal Amazon (BLA). More pertinent to our

[8]DETER underwent significant improvements in 2015 and further advancements in 2019, expanding its coverage to include the Cerrado (the Brazilian Savanna) biome as well. These enhancements rendered the system less reliant on cloud conditions and significantly more precise, enabling it to detect deforestation in smaller plots. Initially, DETER could only detect clearing above 25 hectares, but with the improvements, it became capable of alerting deforestation in areas smaller than 6.5 hectares and later even as small as one hectare (`http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/deter/deter`).

focus are the second-stage regression results, which suggest that enforcement has a negative impact on electoral outcomes, especially in the case of embargoes.

Table A6: IV Regressions: The Effect of Enforcement on the Incumbent's Vote Share

| VARIABLES | (1)<br>1st Stage | (2)<br>2nd Stage | (3)<br>1st Stage | (4)<br>2nd Stage |
|---|---|---|---|---|
| *Panel A: Regressions without covariates* | | | | |
| Average Cloud Cover (Deter) | -6.44* | | -5.64** | |
| | (3.91) | | (2.54) | |
| Fines, Prodes Year | | -1.10 | | |
| | | (0.81) | | |
| Embargoes, Prodes Year | | | | -1.25* |
| | | | | (0.72) |
| Observations | 1,663 | 1,663 | 1,663 | 1,663 |
| F-stat | 2.68 | | 4.86 | |
| *Panel B: Regressions with covariates* | | | | |
| Average Cloud Cover (Deter) | -5.64 | | -6.96** | |
| | (4.60) | | (3.13) | |
| Fines, Prodes Year | | -1.62 | | |
| | | (1.45) | | |
| Embargoes, Prodes Year | | | | -1.31* |
| | | | | (0.70) |
| Observations | 1,551 | 1,551 | 1,551 | 1,551 |
| F-stat | 1.47 | | 4.86 | |

Note: The table presents the estimated effects of enforcement on the presidential incumbent party's vote share using data from the national elections of 2006, 2010 and 2014. The number of *Sanctions* have been standardized. All regressions include municipality and election fixed effects. Spatially robust Conley standard errors (Conley, 1999) are reported in parentheses, accounting for arbitrary serial correlation (Hsiang, 2010; Colella et al., 2023) and two-dimensional spatial correlation within a 100 km radius of the municipality centroid. Regressions in panel B include the following controls: Maximum temperature in the year (C), Precipitation (mm), area of the municipalioty not covered by remote sensing (%), Deforestation, current year, Mapbiomas (log), Number of families in the CCT program (log), Local GDP (log) $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

Note, however, that weak instrument concerns arise in several specifications. The first-stage F-statistics fall consistently below conventional thresholds, indicating potential issues with instrument strength. We attribute this weak identification, in part, to a dynamic outlined in our theoretical model: political learning (see Equation 3). As a protectionist party gains experience in office and recognizes that environmental enforcement may trigger electoral backlash, it begins to strategically adjust its behavior to minimize such costs. By concentrating enforcement efforts in core areas, the initially strong relationship between sanctions and electoral outcomes weakens over time. This learning process becomes more apparent when the data are disaggregated by election year. To examine this, we estimate cross-sectional regressions separately for each national election, controlling for the incumbent's vote share in the prior election to provide a consistent baseline. Table A7 reports the results of these estimations.

Table A7: IV Regressions: Individual Elections

| Variables | Lula 1 (2006) | | Lula 2 (2010) | | Dilma 1 (2014) | |
|---|---|---|---|---|---|---|
| | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage |
| ***Panel A: Fines*** | | | | | | |
| Average Cloud Cover (Deter) | -27.43*** | | -16.43*** | | -15.09** | |
| | (7.27) | | (6.32) | | (6.12) | |
| Fines, Prodes Year | | -1.84*** | | -0.67 | | -2.57 |
| | | (0.46) | | (1.01) | | (2.70) |
| Observations | 554 | 554 | 554 | 554 | 555 | 555 |
| R-squared | 0.05 | -3.28 | 0.02 | 0.03 | 0.01 | -31.02 |
| F-stat | | 15.62 | | .65 | | .93 |
| ***Panel B: Embargoes*** | | | | | | |
| Average Cloud Cover (Deter) | -6.61*** | | -5.97*** | | -8.09*** | |
| | (1.86) | | (2.18) | | (3.01) | |
| Embargoes, Prodes Year | | -7.36*** | | -1.50 | | -3.21 |
| | | (2.12) | | (1.82) | | (2.18) |
| Observations | 554 | 554 | 554 | 554 | 555 | 555 |
| R-squared | 0.03 | -5.64 | 0.02 | 0.42 | 0.01 | -14.10 |
| F-stat | | 13.91 | | 1.11 | | 2.32 |

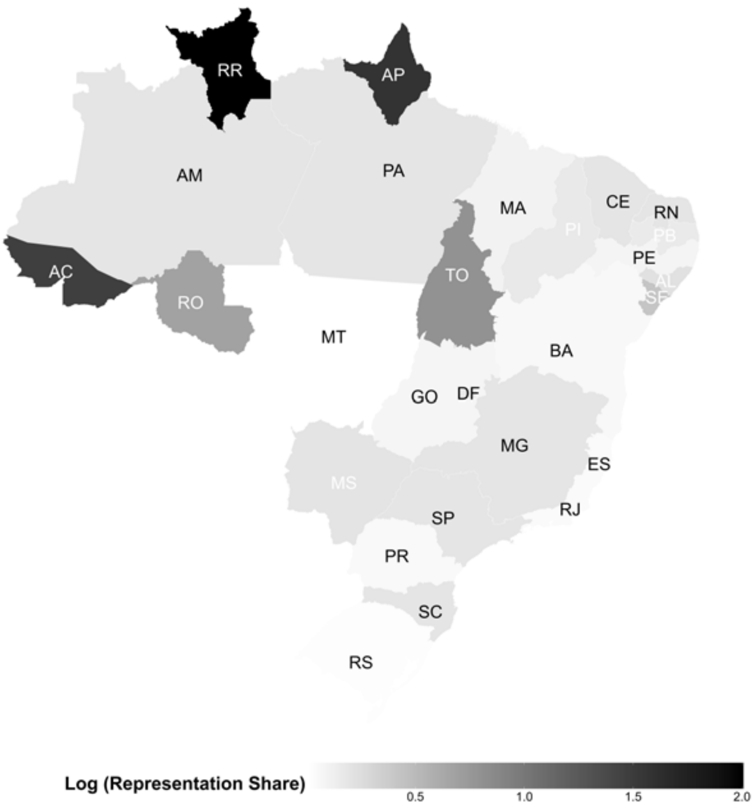
The table presents cross-sectional instrumental variable (IV) regressions estimating the effect of environmental enforcement on the presidential incumbent party's vote share in the 2006, 2010, and 2014 national elections. Cloud cover (from DETER) is used as an instrument for enforcement, measured as the total number of sanctions (fines and embargoes) issued during each Prodes year. All regressions include controls for the incumbent's vote share in the previous election. Spatially robust Conley standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The disaggregated results shows a strong first-stage relationships between cloud cover and both fines and embargoes across all elections, particularly in 2006. Notably, the second-stage estimates for 2006 show large and statistically significant negative effects of sanctions—especially embargoes—on incumbent vote share. These effects weaken or disappear in later years, consistent with our theoretical expectation that political learning reduces exposure to backlash over time. This temporal pattern reinforces the notion that early enforcement efforts had sharper political costs, which incumbents subsequently sought to manage or mitigate.

## A7 The Importance of Winning National Elections Locally

This section investigates whether presidential voting patterns for the Workers' Party (PT) translate into increased support for the party in subsequent elections for other elected offices. The analysis speaks directly to our broader claim: that local electoral outcomes matter — even for parties primarily oriented toward national contests like PT. One key reason for this local concern is the high degree of malapportionment that characterizes the Brazilian political system. As illustrated in Figure A9, smaller states tend to be significantly overrepresented in the legislature, amplifying their influence in national policymaking — particularly in decisions that require congressional approval.

Figure A9: Representation Share by State (logged value)




Note: The map display the representation share of each Brazilian state in the Federal Deputy Chamber for the 2010 election, where higher values indicate more disproportional (over) representation. Source: (Beramendi et al., 2025).

We evaluate this relationship between offices and elections more formally by estimating the model defined in Equation A1 below:

$$Performance_{it} = \alpha + \beta \cdot VotePT_{i,t-1} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{A1}$$

where Performance$_{it}$ is the PT vote share (0–100) for a specific office (governor, senator, federal deputy, state deputy, mayor, or councillor) in municipality $i$ and election year $t$. $VotePT_{i,t-1}$ is either:

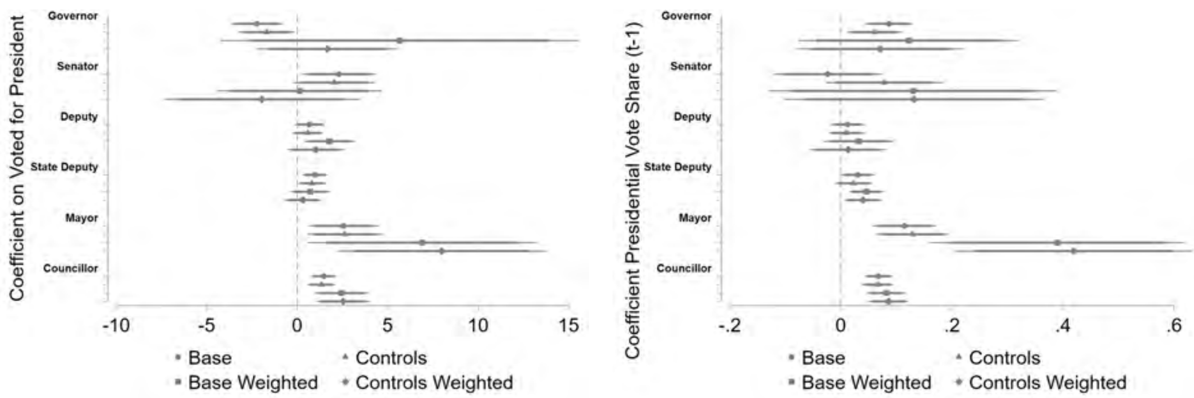
- A binary indicator for PT victory in the previous presidential election (Panel A), or
- The continuous PT vote share (0–100) in the previous presidential election (Panel B)

$X_{it}$ is a vector of socioeconomic and land-use controls: log GDP, log population, inverse hyperbolic sine of deforestation, inverse hyperbolic sine of farming, log cattle density, and (inverse hyperbolic sine) of Bolsa Família coverage. $\mu_i$ and $\lambda_t$ represent municipality and year fixed effects. Standard errors are clustered at the municipality level to account for autocorrelation in the panel.

Figure A10: The Importance of winning National Elections Locally for other Elections

(a) The Effect of Winning Locally

(b) The Effect of Vote Share




Note: These panels estimate the persistence of presidential voting patterns for the Workers' Party (PT) in subsequent subnational elections across Amazonian municipalities (2002-2015). Panel A uses a binary measure of PT presidential victory; Panel B uses continuous PT vote share (0-100). Each point represents coefficients from two-way fixed effects regressions with four specifications per office (baseline, controlled, and weighted variants). Controls include socioeconomic and land-use factors. The analysis reveals significant downstream effects of presidential performance on PT success in gubernatorial, legislative, and local races, with an average baseline PT presidential vote share of 59% providing context for effect magnitudes.

Figure A10 reports the results for these regressions regressions using data from elections that took place during the PT years 2002-2014. During this period, the average PT presidential vote share was 59%.

Panel A shows the effect of a binary indicator for whether the PT won the presidential election in the municipality on PT's performance in subsequent races. Panel B examines the continuous relationship between the PT's previous presidential vote share (0-100) and subsequent down-ballot performance.

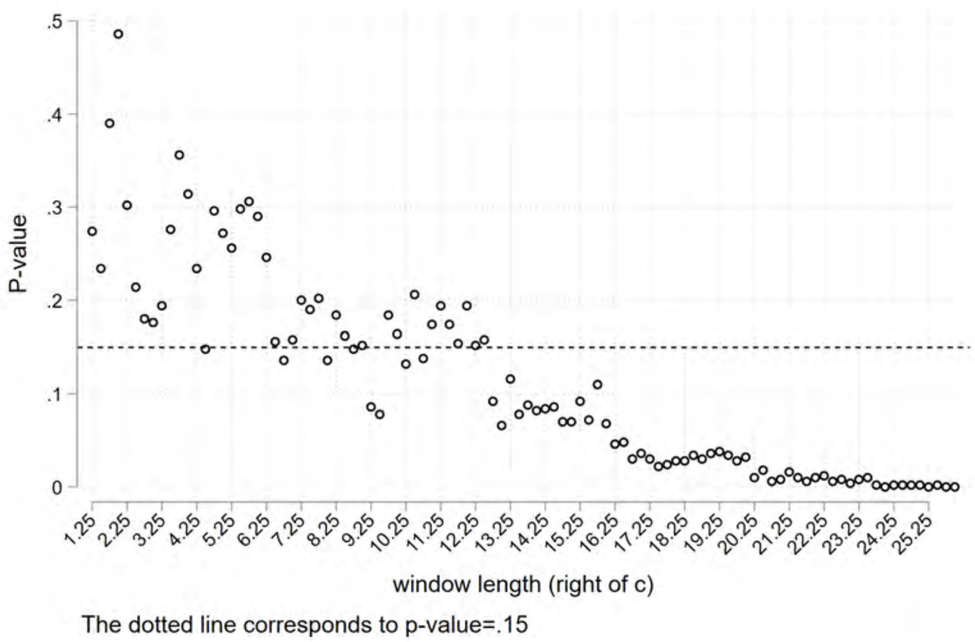
For each office, we estimate four specifications: (1) baseline model without controls; (2) model with socioeconomic and land-use controls (log GDP, log population, deforestation intensity, agricultural activity, cattle density, and Bolsa Família coverage); (3) baseline weighted by municipal political relevance; and (4) controlled model weighted by political relevance.

The results demonstrate substantial coattail effects, with presidential electoral performance significantly predicting PT success in subsequent gubernatorial, legislative, and local elections.

The results are especially strong for state and local elections, highlighting the importance of national political momentum for subnational electoral outcomes.

## A8 Regression Discontinuity Design: Supporting tests

Figure A11: Minimum P-Value from Covariate Test



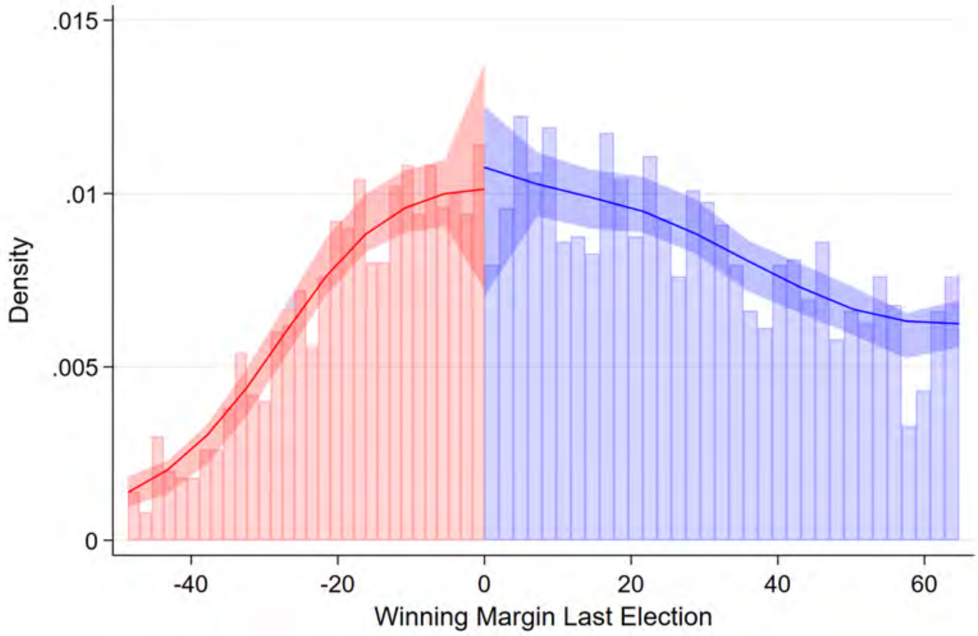

Note: The graph displays the results of balance tests conducted over 100 symmetric windows around the cutoff, starting with an initial window of $Margin \in [-1.25, 1.25]$, which is expanded in increments of 0.25 points. The lowest Fisherian p-value for each tested window is reported. The test uses data from the previous election year only — i.e., "pre-treatment" data. The selected covariates include forest cover (% of municipality area), pasture and cropland area (km²), population density, number of cattle, local per capita GDP, agriculture's contribution to local GDP, proportion of the municipality designated as a protected area, total annual precipitation (mm), and average temperature (°C). The selected window, using a statistical significance threshold of 0.150, is $Margin \in [-4.25, 4.25]$.

Table A8: The Effect of Being a National Party supporter on Enforcement Placement

| Variable | LATE | Fisherian P-value | N controls | N treatment | N |
|---|---|---|---|---|---|
| Embargoes (Standardized) | -0.27*** | 0.008 | 332 | 295 | 627 |
| Fines (Standardized) | -0.11 | 0.464 | 332 | 295 | 627 |

Note: The table displays the results of RD regressions with the following specifications: The dependent variable is the number of fines and embargoes (standardized), and the running variable is the margin of victory for the national party in the previous election. The "as-if random assignment" window includes observations with margin values within 4.25 points above and below the cutoff. Fisherian p-values are calculated using 1,000 simulations. The kernel used is uniform, and the polynomial order is zero. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A12: Density Test




Note: The graph presents the results of the density discontinuity ("Heaping") test, implemented using local polynomial density estimators proposed by Matias D. Cattaneo and Ma (2020), with 95% confidence intervals from Cattaneo et al. (2024b). Although there appears to be an initial imbalance—more observations on the opposition side—this difference is not statistically significant at conventional levels, suggesting that bunching is not a pervasive issue in the data.

Table A9: RDD: Balance and Placebo tests

| Variable | LATE | Fisherian P-value | N controls | N treatment | N Total |
|---|---|---|---|---|---|
| ***Panel A: Predetermined Covariates*** | | | | | |
| Forest Cover (%) | -0.17 | 0.982 | 101 | 88 | 189 |
| Pasture (ha) | -5355.84 | 0.778 | 101 | 88 | 189 |
| Cropland - Perennial and Temporary Crops (ha) | 6444.66 | 0.574 | 101 | 88 | 189 |
| Population Density | -12.54 | 0.782 | 100 | 88 | 188 |
| Cattle (count) | -13989.23 | 0.612 | 100 | 88 | 188 |
| GDP per capita | -0.44 | 0.764 | 100 | 88 | 188 |
| Local GDP - Added Value Agribusiness (% of total) | -0.69 | 0.719 | 100 | 88 | 188 |
| Protected Areas (% of Municipality Area) | -0.70 | 0.896 | 101 | 88 | 189 |
| Precipitation (mm) | -73.70 | 0.254 | 101 | 88 | 189 |
| Average Maximum Temperature (C) | -0.02 | 0.846 | 101 | 88 | 189 |
| Priority list | -0.04 | 0.220 | 101 | 88 | 189 |
| Deforestation (km²), Prodes/Inpe | -0.33 | 0.948 | 101 | 88 | 189 |
| ***Panel B: Placebo Outcomes*** | | | | | |
| Average Cloud Cover (Deter) | 0.00 | 0.978 | 65 | 51 | 116 |
| Average Cloud Cover, calendar year (Deter) | -0.03 | 0.128 | 258 | 221 | 479 |
| Rocky Outcrop (ha) | -644.49 | 0.626 | 187 | 136 | 323 |
| Precipitation (mm) | $-79.48^{**}$ | 0.028 | 332 | 295 | 627 |
| Maximum temperature in the year (C) | 0.11 | 0.278 | 332 | 295 | 627 |
| Average Maximum Temperature (C) | -0.01 | 0.856 | 332 | 295 | 627 |

Note: The table reports a series of placebo tests. In Panel A, the main estimation is replicated using predetermined covariates, following an approach similar to a balance test. In Panel B, the same estimator is applied to outcomes that, for scientific reasons, could not have been affected by the treatment. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

Table A10: RDD: Placebo Cutoffs

| Variable | LATE | Fisherian P-value | N controls | N treatment | N | artificial cutoffs |
|---|---|---|---|---|---|---|
| ***Panel A: Positive artificial cutoffs*** | | | | | | |
| Residuals: Embargoes | 2.31 | 0.350 | 258 | 328 | 586 | 4.25 |
| Residuals: Embargoes | 3.18 | 0.244 | 277 | 337 | 614 | 5.25 |
| Residuals: Embargoes | 4.33 | 0.160 | 336 | 312 | 648 | 6.25 |
| Residuals: Embargoes | 2.30 | 0.448 | 331 | 300 | 631 | 7.25 |
| Residuals: Embargoes | 2.01 | 0.570 | 317 | 308 | 625 | 8.25 |
| Residuals: Fines | -2.44 | 0.630 | 258 | 328 | 586 | 4.25 |
| Residuals: Fines | -1.23 | 0.736 | 277 | 337 | 614 | 5.25 |
| Residuals: Fines | 2.59 | 0.470 | 336 | 312 | 648 | 6.25 |
| Residuals: Fines | 1.67 | 0.602 | 331 | 300 | 631 | 7.25 |
| Residuals: Fines | 1.97 | 0.592 | 317 | 308 | 625 | 8.25 |
| **Panel B:Negative artificial cutoffs** | | | | | | |
| Residuals: Embargoes | 5.53 | 0.136 | 315 | 293 | 608 | -4.25 |
| Residuals: Embargoes | 1.49 | 0.696 | 305 | 308 | 613 | -5.25 |
| Residuals: Embargoes | 3.07 | 0.232 | 319 | 274 | 593 | -6.25 |
| Residuals: Embargoes | -0.16 | 0.942 | 318 | 304 | 622 | -7.25 |
| Residuals: Embargoes | -2.21 | 0.344 | 328 | 309 | 637 | -8.25 |
| Residuals: Fines | 6.22 | 0.168 | 315 | 293 | 608 | -4.25 |
| Residuals: Fines | 0.93 | 0.864 | 305 | 308 | 613 | -5.25 |
| Residuals: Fines | 4.24 | 0.178 | 319 | 274 | 593 | -6.25 |
| Residuals: Fines | -0.75 | 0.818 | 318 | 304 | 622 | -7.25 |
| Residuals: Fines | -1.44 | 0.656 | 328 | 309 | 637 | -8.25 |

Note: The table reports placebo cutoff tests — i.e., tests that artificially shift the cutoff to alternative points along the running variable (*Margin*) scale, using bandwidths similar to those in the main estimations. If the observed treatment effect is truly driven by meaningful changes around the actual cutoff, estimates at these artificial thresholds should yield statistically insignificant results. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: RDD: Sensitivity to Bandwidth Choice

| Variable | LATE | Fisherian P-value | N controls | N treatment | N | Bandwidth | |
|---|---|---|---|---|---|---|---|
| Residuals: Embargoes | -6.47*** | 0.008 | 293 | 258 | 551 | -4.25 | 4.25 |
| Residuals: Embargoes | -6.79** | 0.016 | 284 | 245 | 529 | -4.00 | 4.00 |
| Residuals: Embargoes | -6.83** | 0.012 | 267 | 230 | 497 | -3.75 | 3.75 |
| Residuals: Embargoes | -5.72** | 0.044 | 250 | 212 | 462 | -3.50 | 3.50 |
| Residuals: Embargoes | -5.68* | 0.060 | 235 | 195 | 430 | -3.25 | 3.25 |
| Residuals: Embargoes | -5.81* | 0.070 | 221 | 179 | 400 | -3.00 | 3.00 |
| Residuals: Embargoes | -0.07 | 0.990 | 203 | 158 | 361 | -2.75 | 2.75 |
| Residuals: Embargoes | 0.16 | 0.924 | 193 | 139 | 332 | -2.50 | 2.50 |
| Residuals: Embargoes | -0.91 | 0.742 | 182 | 117 | 299 | -2.25 | 2.25 |
| Residuals: Embargoes | -1.62 | 0.522 | 165 | 107 | 272 | -2.00 | 2.00 |
| Residuals: Fines | -4.49 | 0.186 | 293 | 258 | 551 | -4.25 | 4.25 |
| Residuals: Fines | -4.41 | 0.270 | 284 | 245 | 529 | -4.00 | 4.00 |
| Residuals: Fines | -4.32 | 0.304 | 267 | 230 | 497 | -3.75 | 3.75 |
| Residuals: Fines | -6.77** | 0.038 | 250 | 212 | 462 | -3.50 | 3.50 |
| Residuals: Fines | -6.67* | 0.058 | 235 | 195 | 430 | -3.25 | 3.25 |
| Residuals: Fines | -6.93* | 0.076 | 221 | 179 | 400 | -3.00 | 3.00 |
| Residuals: Fines | 0.25 | 0.886 | 203 | 158 | 361 | -2.75 | 2.75 |
| Residuals: Fines | 0.56 | 0.812 | 193 | 139 | 332 | -2.50 | 2.50 |
| Residuals: Fines | -1.06 | 0.726 | 182 | 117 | 299 | -2.25 | 2.25 |
| Residuals: Fines | -1.49 | 0.596 | 165 | 107 | 272 | -2.00 | 2.00 |

The tests reported in this table assess the sensitivity of the main results to narrower bandwidth choices. Specifically, we re-estimate the treatment effects using smaller windows around the cutoff. In nearly all cases, the point estimates shift in the expected direction—indicating a reduction in enforcement—as the bandwidth narrows. For embargoes, the estimates remain statistically significant at conventional levels down to a bandwidth of 3.00, with only the smallest windows (2.75 and below) yielding insignificant results. Fines exhibit less stability across bandwidths; while some statistically significant effects emerge at intermediate windows, these results are not consistent and should be interpreted with caution. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## A9 Estimations with Interactive Fixed Effect

For the estimations based on two-way fixed effects models, we also conduct robustness tests that include unit-specific linear time trends — as specified in the model below:

$$Y_{mt} = \beta_0 + \beta_1 X + \lambda_k Z_{mt} + \alpha_m + \gamma_t + \alpha_m t + \varepsilon_{mt} \tag{A2}$$

Where $Y_{mt}$ is the outcome of interest in period $t$ for municipality $m$. $X_{mt}$ is the regressor of interest — as in the analog of Equation 16, $X$ represents the number of sanctions issued during a presidential term. $Z_m$ is a vector of municipality-specific characteristics. $\alpha_m$ and $\gamma_t$ represent municipality and time fixed effects, respectively, ; and $\alpha_m t$ captures time-varying effects of $\alpha$ specific to each municipality.

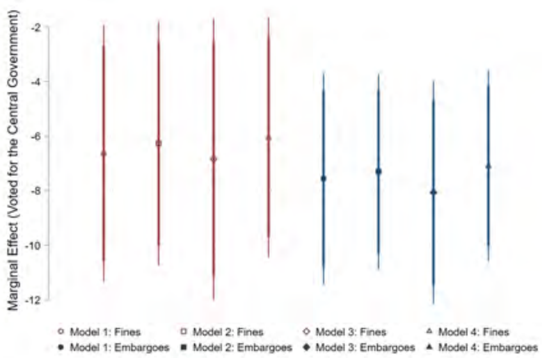
Table A12: The Effect of Enforcement on the Incumbent's Vote Share

| Dependent Variable | Incumbent's Vote Share (%) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Enforcement Metric | Fines Normalized§ | Fines Standardized | Embargoes Normalized | Embargoes Standardized | Embargoed area (%) Standardized† | Embargoed area (%) Normalized† |
| **Panel A**: Estimations without covariates | | | | | | |
| Sanction | -1.70* | -1.22 | -4.94*** | -2.29*** | -1.45*** | -1.93*** |
| | (0.91) | (0.77) | (0.80) | (0.82) | (0.41) | (0.32) |
| Observations | 3,855 | 3,855 | 3,855 | 3,855 | 3,855 | 3,855 |
| R-squared | 0.56 | 0.56 | 0.59 | 0.56 | 0.56 | 0.59 |
| **Panel B**: Estimations with covariates | | | | | | |
| Sanction | -1.44** | -1.37** | -5.03*** | -1.95** | -1.31*** | -1.80*** |
| | (0.72) | (0.63) | (0.76) | (0.83) | (0.39) | (0.28) |
| Observations | 3,852 | 3,852 | 3,852 | 3,852 | 3,852 | 3,852 |
| R-squared | 0.63 | 0.63 | 0.65 | 0.63 | 0.63 | 0.65 |

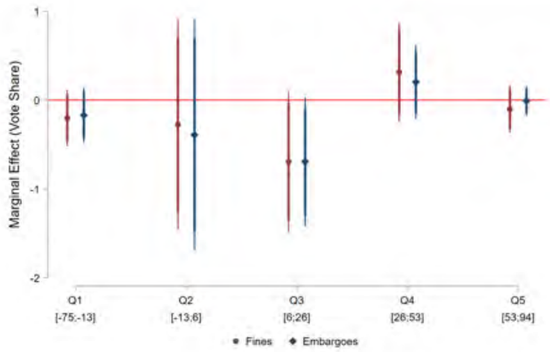
Note: The table presents the estimated effects of enforcement on the presidential incumbent party's vote share. § *Sanctions* are normalized using the inverse hyperbolic sine (IHS) transformation.† Embargoed area (%) is measured as a proportion of total private property area in the municipality. All regressions include municipality and electoral cycle fixed effects and municipality-specific linear time trends. Regressions in Panel 2 includes the following controls: average maximum temperature (°C), average annual precipitation (mm), total deforestation, km2 (log); local GDP (Logged); number of families enrolled in the national cash transfer program CCT (IHS); a dummy variable indicating whether a municipality have been "blacklisted" by the environmental agency; and extension of Protected Areas (% of municipality area). The analysis covers 1998–2020 (excluding 2018 to avoid impeachment-related noise) and aggregates data by national electoral cycles. SStandard errors are clustered at the municipality and intermediate-region-year levels.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A13: Support for the National Party and Enforcement Placement

(a) Extensive Margin




(b) Intensive Margin




Note: The figures show the marginal effect of voting for the party running the national government on enforcement level, across four specifications of Equation 17. Enforcement is measured as the difference between the number of sanctions (fines or embargoes) minus the number of deforestation alerts. (a) In Graph A13a support is a binary variable equal to 1 if the national party was the most voted locally. Model 1 is the baseline without controls. Models 2–4 progressively add alternative control configurations, including deforestation (log), average cloud cover (NASA), enforcement priority status, local demographics, land use, and economic factors. The analysis covers the Workers' Party administrations (2004-2015) with Deter data available. (b) In Graph A13b, the measure of support for the central government is replaced by a continuous variable representing the national party's winning margin (*Margin*) in each municipality (and its quadratic term), with *Margin* $\in$ [-100, 100], where values below 0 indicates that the opposition won locally. The sample is divided into quintiles of *Margin* so that each coefficient represents individual regressions on subsamples defined by each quintile. The brackets in the x-axis indicate the bandwidth of each quintile. The estimations include the same set of controls used in model 2 of graph 5a. Standard errors are clustered at the municipality and intermediate-region-year levels. All specifications includes municipality and year fixed-effects, and municipality-specific linear time trends.

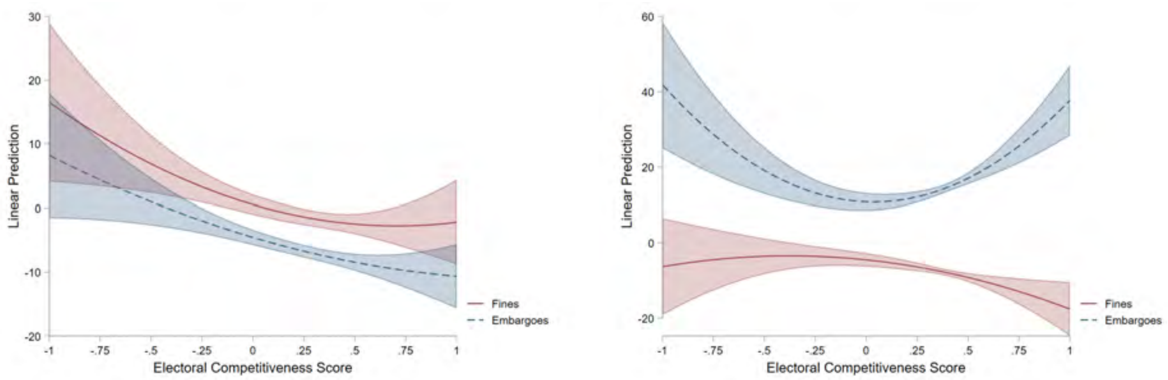
Table A13: Campaign Contributions and Environmental Enforcement

| Dependent Variable | Campaign Contributions (Normalized) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Enforcement Metric | Fines Normalized | Fines Standardized | Embargoes Normalized | Embargoes Standardized | Embargoed area † Standardized | Embargoed area† Normalized |
| **Panel A**: Contributions to Right-Wing Parties | | | | | | |
| Sanction | 0.13* | 0.43* | 0.34*** | 0.21*** | 0.22** | 0.10*** |
| | (0.07) | (0.23) | (0.08) | (0.06) | (0.09) | (0.03) |
| Observations | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 |
| R-squared | 0.56 | 0.56 | 0.57 | 0.56 | 0.56 | 0.56 |
| **Panel B**: Contributions to Left-Wing Parties | | | | | | |
| Sanction | -0.00 | 0.23 | 0.22*** | 0.34*** | 0.18* | 0.04* |
| | (0.06) | (0.15) | (0.06) | (0.11) | (0.10) | (0.02) |
| Observations | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 | 5,403 |
| R-squared | 0.40 | 0.40 | 0.41 | 0.41 | 0.40 | 0.40 |

Note: The table shows the change in total amount of campaign contributions (normalized) as a function of enforcement level in each municipality in the Legal Amazon region. *Sanctions* represents the total number of fines or embargoes issued during each 4-year presidential term. The total amount of contributions in R$ has been adjusted to 2022 values before normalization using the General Price Index – Internal Availability (IGP-DI/FGV). Standard errors are clustered at the municipality and intermediate-region-year levels. All estimations include municipality and electoral cycle fixed-effects, and municipality-specific linear time trends. Table A3, in the appendix, replicates the same estimations but with covariates. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

Figure A14: Sanctions and Political Competition

(a) Regular OLS (b) Weighted Regression




Note: The figures show the predicted level of enforcement at various levels of political competition, based on regressions with a specification similar to Equation 17, where the main regressors are Political Competition and its quadratic term. Political competition is defined as in Equation 22. Enforcement is defined as the difference between the number of sanctions and the number of deforestation alerts issued for each municipality. Graph A14a presents regressions that control for electoral relevance — i.e., the municipality's relative contribution to the national party's victory. In Graph A14b, electoral relevance is used as an analytical weight. The data covers the 2004–2015 period (PT administration with available DETER data). All regressions include municipality and year fixed effects, as well as municipality-specific linear time trends. The estimations also include the following controls: deforestation in km² (log), the proportion of the municipality designated as a protected area (%), and whether the municipality was included in the priority list for enforcement. Standard errors are clustered at the municipality and intermediate-region-year levels.