Fire and Punishment: Enforcement incentives and strategic fire use in the Brazilian Amazon

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Incomplete monitoring of illegal behavior may cause violators to reoptimize their criminal activities. I study how satellite monitoring of deforestation impacts illegal land-clearing behavior in the Brazilian Amazon. I argue that by detecting primarily mechanical clearings, the introduction of near-real-time satellite monitoring favored a technological substitution towards the use of fire. Using cloud cover as an instrument for satellite-based detection, I find that municipalities under more intensive surveillance experienced a statistically significant substitution from mechanical to fire-based clearing. My findings help explain why Amazon fires have persisted despite the overall decline in deforestation starting from 2005.

Keywords: Forest fires, deforestation, environmental law enforcement

JEL Codes: Q51, Q57, Q58

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1 Introduction

Our sense is that people are betting on this idea: taking advantage of the fact that it is dry and hot, and the forest no longer has the same humidity as it used to. It's a window of opportunity: "Since I can no longer deforest, I'll set it on fire."

- Rodrigo Agostinho, *former IBAMA president, quoted at Girardi (2024)*

Forest fires impose severe negative externalities on the environment and human life (Wen et al., 2023; Heft-Neal et al., 2023; Pullabhotla et al., 2023). While fires start mostly unintentionally in high-income countries, intentional anthropogenic activity is the key driver in the tropics (Balboni et al., 2024). However, evidence on how environmental policies influence anthropogenic fires remains limited. In the tropics, fires are often started for clearing forests, and they can be a substitute for mechanical clearing, which uses equipment such as chainsaws and excavators. In this context, understanding how individuals navigate the trade-off between these deforestation technologies has first-order implications for conservation outcomes and associated externalities.

In this paper, I study how environmental policy affects deforestation behavior, distinguishing between mechanical clearing and fire use in the Brazilian Amazon. I examine the introduction of a near-real-time, satellite-based alert system called DETER, which detects illegal deforestation and triggers on-the-ground enforcement. Crucially, DETER possesses a key technological characteristic: its first generation[1] (2006–2015) detected only mechanical clearings, while its second generation (post-2015) began to identify fire disturbances as well.

I argue that DETER's asymmetry may have created differential incentives for deforestation technology choice. On the one hand, DETER's monitoring existence might deter all deforestation practices, including fire-driven. On the other hand, the system's incomplete

[1]DETER was introduced in 2004, but it only became fully operational in 2006.

monitoring might lead to a strategic response, shifting farmers' land-clearing behavior toward fire. Farmers could therefore respond in two ways: by reducing clearing overall or by strategically substituting away from detectable mechanical clearing toward fire, as it is a less detectable technology. Crucially, this substitution incentive operates even for farmers not directly affected by enforcement, if observing neighbors' fines for mechanical clearing shifts their expectations about the relative risk of each method. These two mechanisms produce opposing predictions for fire use: monitoring's general deterrence would reduce it, whereas strategic substitution would increase it.

To identify the causal effect of enforcement on deforestation-technology substitution, I use cloud cover as an instrument for enforcement, as proposed in Assunção et al. (2023a). The instrument relies on the fact that the DETER satellite monitoring system cannot see through clouds; therefore, municipalities with higher cloud cover receive fewer immediate alerts, face less on-the-ground enforcement, and receive fewer fines. Although the system eventually detects disturbances and triggers an alert once clouds dissipate, in the Brazilian context, immediate response to ongoing deforestation is crucial for issuing fines. Hence, cloud cover prevents satellites from detecting ongoing mechanical deforestation, introducing random variation in enforcement exposure across municipalities. Comparing municipalities with high versus low cloud cover, and thus low versus high enforcement presence, allows me to isolate the enforcement-induced substitution effect. Importantly, I show that clouds and smoke can be distinguished in this context, addressing a key identification concern.

My empirical analysis combines monthly municipal-level data on environmental law enforcement (deforestation fines), cloud cover, and fire ignitions between 2007 and 2023. Across both of DETER's generations, I find that a one-unit increase in deforestation fines in a given municipality-month is associated with 3.3 additional fire ignitions in forest-covered areas the following month ($p < 0.01$). This result indicates that municipalities under stricter enforcement showed a statistically significant shift in land-clearing behavior, consistent with monitoring-induced changes in deforestation behavior. I find statistically significant results of similar magnitude when considering different enforcement exposure windows, beyond the one-month window used in my main estimate. Breaking down these results between DETER's generations - first fire blind and the second fire aware - I find a differential effect between phases. I find that with the introduction of the second DETER generation (post-2015), the substitution effect is reduced (0.714, $p < 0.001$) relative to the first generation (1.927, $p = 0.012$). This result is consistent with my substitution hypothesis, as we would expect a reduction in the technological advantage of fire when it becomes detectable. However, one important caveat is that this result only holds excluding the years under the Bolsonaro administration (post-2019), when environmental law enforcement was severely undermined. Therefore, these results should be interpreted with caution.

My paper's novel contribution is discussing the differential effects of conservation policy across deforestation technologies. This distinction matters because fire can have unique and severe consequences for forest regeneration: unlike mechanical clearing, burned areas risk being locked into a permanent grassland state, preventing forest recovery (Drüke et al., 2023). This is particularly consequential given the risk that the Amazon may be approaching a tipping point (Nobre et al., 1991), with fire identified as a key compounding disturbance that could trigger an irreversible transition to savanna (Flores et al., 2024). Fire also poses substantial health externalities. Koplitz et al. (2016) estimates that haze from a singular fire season, Indonesia's 2015 forest fires, resulted in 100,300 excess deaths. Taken together, the health and environmental externalities of fire use make understanding what drives individuals to use fire a question with direct policy relevance.

My work speaks to the literature on behavioral responses to environmental regulation. Gibson (2019), for example, shows how, in response to the Clean Air Act, firms substitute from air emissions to pollution in other media, i.e., waterways. While most of the literature focuses on the substitution induced by air pollution regulation (Fowlie, 2009; Danae

Hernandez-Cortes, 2025; Costa et al., 2025; Zivin et al., 2026), to the best of my knowledge, my work is the first to propose substitution across deforestation technologies due to incomplete monitoring. Understanding agents' responses to regulatory incentives is central to designing environmental regulation, since an efficient policy should account for adaptive responses. However, in many contexts, it is difficult to observe the environmental outcomes of interest needed to assess a potential substitution effect. Remotely sensed data, paired with detailed enforcement information, allows me to observe the effect of regulatory presence on substitution across a new, relevant environmental channel.

This paper also contributes to the literature on monitoring and deterrence of illegal deforestation in the Brazilian Amazon. While previous work has documented how satellite monitoring and environmental regulation reduced deforestation in the mid-2000s (Assunção et al., 2023a,b), new evidence suggests these policies were only partially effective, as agents adapted their behavior to evade detection. For instance, Baragwanath and Shinde (2025) documents how deforestation shifted toward smaller patches to evade satellite detection, and Cammelli et al. (2026) shows that these policies did not deter forest degradation. My work speaks to these findings by identifying substitution across deforestation technologies, suggesting that the apparent success of conservation policies adopted in the 2000s may be overstated if observed reductions stem from displacement into less detectable activities rather than true deterrence. Accurately distinguishing between the two is crucial as misattributing substitution as deterrence risks overstating enforcement effectiveness and misdirecting policy.

Finally, this paper contributes to the literature on the drivers and control of forest fires in the developing world. While Balboni et al. (2021) and Balboni et al. (2023) focus on fire use in Indonesia, no prior study has examined how environmental enforcement shapes fire use in the Brazilian Amazon, a region of global conservation importance. Although Araujo et al. (2024) is among the few economics papers addressing this context, it focuses on how media attention influences government action in response to a single fire episode in August 2019 and does not address the broader, longer-term effects of enforcement. In parallel, my research complements the natural science literature, which predominantly investigates the roles of climate phenomena and weather events in determining fire incidence (Aragão and Shimabukuro, 2010; Libonati et al., 2021; Valente and Laurini, 2023; Flores et al., 2024). By identifying enforcement incentives as an additional driver of fire use, my work introduces a policy-relevant mechanism largely unexplored by the economics and natural sciences literatures.

The remainder of this paper is organized as follows. Section 2 describes how environmental law enforcement operates in the Brazilian Amazon. Section 3 presents a theoretical model of the trade-off between land clearing technologies. Section 4 describes the data sources, details the patterns of forest fires, and examines their relationship with land use and land clearance. Section 5 presents the main empirical strategy, and Section 6 presents my main results and multiple robustness checks. Section 7 concludes.

2 Background

2.1 Deforestation and fires in the Brazilian Amazon

Between 2000 and 2023, the Brazilian Amazon lost an average of 15,819 square kilometers to fire annually — nearly matching, and in several years exceeding, the area officially recorded as deforested by PRODES[2] in the same period (MapBiomas, 2024). In 2004, Brazil established PPCDAm, the acronym for Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, which encompassed multiple policies and has been recognized as fundamental to the sharp reduction in deforestation starting in the mid-2000s (West and Fearnside, 2021). Figure 1 illustrates these distinct trends. While deforestation fell dramat-

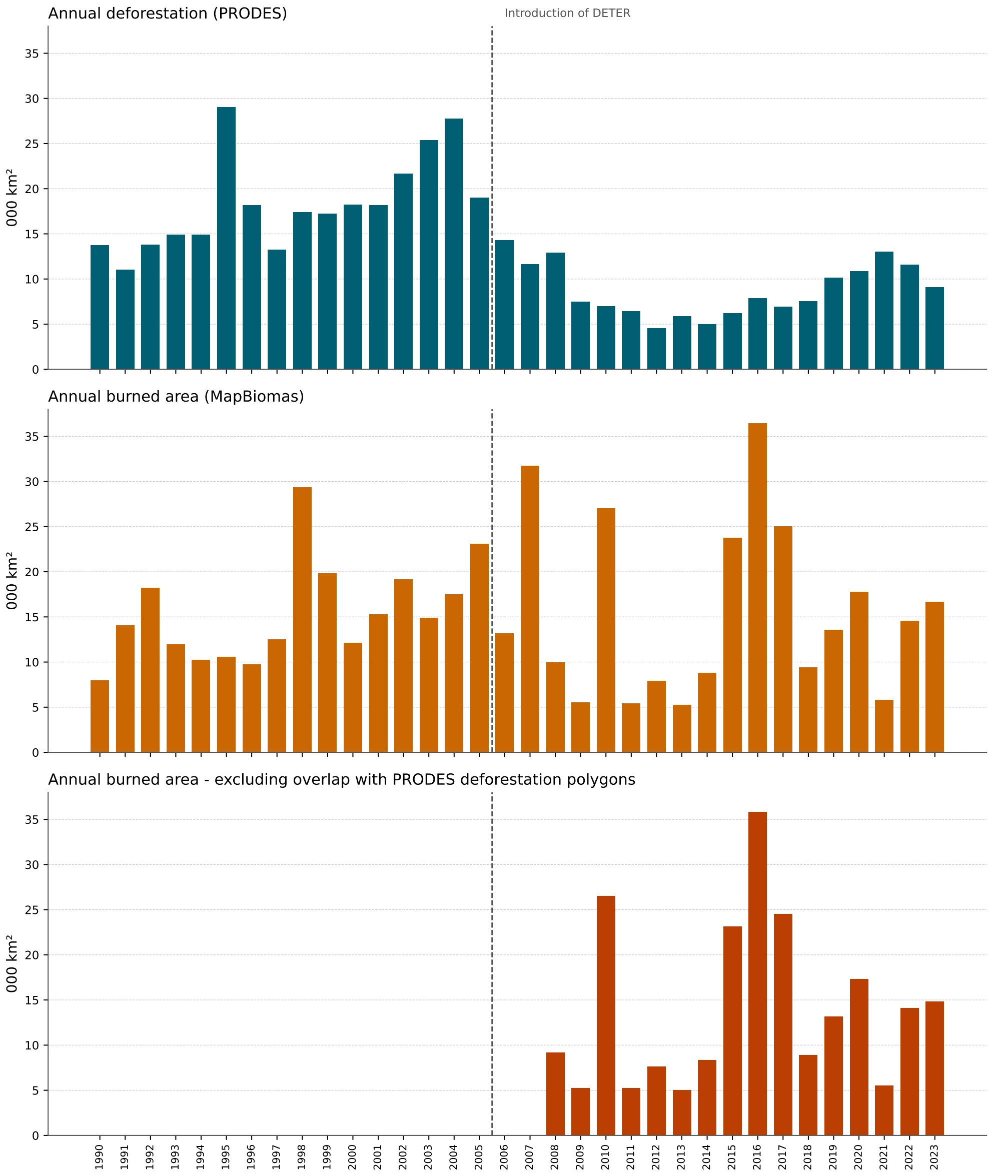
[2]PRODES is the official Brazilian government statistic of Amazon's deforestation rate.

ically after 2004, the burning of vegetated areas showed no comparable decline. The bottom figure also shows that most burned areas were not included in the same year's official deforestation polygons from PRODES. This paper is motivated by understanding what drives the persistence of forest fires despite the decline in deforestation, and whether environmental policy may have contributed to it.

Fire in the Amazon is predominantly intentional. Lightning-ignited fires are uncommon in the Amazon forest due to its humidity. On average, only about 10% of fire events in the region are preceded by a lightning strike (Figure D.1). While climate events, notably El Niño-driven droughts, amplify fire incidence by reducing forest moisture and facilitating spread (Aragão et al., 2018; Valente and Laurini, 2023), fires have remained closely tied to land degradation over the past two decades, with human behavior the critical determinant (Libonati et al., 2021). Because fire use is both intentional and illegal, enforcement incentives are a relevant determinant in this setting.

Different deforestation technologies differ in fundamental ways from an enforcement perspective. First, mechanical clearing and fire-based degradation differ fundamentally in their visibility to DETER satellite monitoring. Clear-cut deforestation involves the rapid and complete removal of forest cover, leaving exposed soil that contrasts sharply with surrounding vegetation. This spectral signature is relatively straightforward to detect via the satellite imagery used for enforcement (Almeida et al., 2022), and mechanical clearing was the dominant form of deforestation in the Amazon from the 1970s through the early 2000s. Fire-based degradation, by contrast, unfolds over multiple years through successive burning cycles: pasture is seeded into partially cleared forest while trees remain standing; cattle are introduced as the forest canopy thins; the pasture is burned in a second year, further clearing what remains; and by the third year, repeated fires have destroyed the original forest cover (Almeida et al., 2022). The result is a far subtler satellite signature than clear-cutting, which can be easily confused with natural variation, posing a significant challenge for satellite detection.

Figure 1: Annual deforestation and forest fires in the Brazilian Amazon, 1990–2023.



Note: Top panel: annual deforestation area recorded by PRODES, the Brazilian government's official annual satellite-based deforestation monitoring program (TerraBrasilis). Middle panel: annual burned forest area from MapBiomas Fogo. Bottom panel: annual burned forest area net of any overlap with that same year's PRODES deforestation polygons — available only from 2008 onward, since polygon-level PRODES data don't exist for earlier years. The vertical dashed line marks 2004, when the DETER real-time deforestation alert system was introduced. Deforestation trends downward after the mid-2000s while burned area does not track it closely; across 2008–2023, only 2–11% of burned forest area overlaps officially mapped deforestation.

Another critical asymmetry between the two technologies concerns legal attribution. Whereas mechanical clearing can be unambiguously attributed to human activity, fire has a positive natural probability of occurrence. Brazilian law requires that a causal nexus be established between an individual's action and a specific fire before sanctions can be applied (Brasil, 2012), and satisfying this standard requires extensive investigation (IBAMA, 2010). This legal burden of proof is substantially lower for mechanical clearing, making fire not only harder to detect but also harder to punish even when detected.

Anecdotal evidence suggests that farmers strategically exploit this constraint. There is anecdotal evidence of farmers coordinating simultaneous ignitions across multiple properties, effectively overwhelming investigative capacity and rendering individual attribution nearly impossible (Peron, 2024; Machado, 2019; Girardi, 2024). With these considerations in mind, in section 3 I formalize a model of deforestation technology choice under differential enforcement risk.

2.2 The DETER Monitoring System

The Brazilian Forest Code requires property owners in the Amazon to maintain 80% of their land as native vegetation, and illegal deforestation, regardless of the technology used, constitutes an environmental infraction subject to administrative and criminal sanctions (Brasil, 2012). IBAMA (Brazilian Institute for the Environment and Renewable Natural Resources) is the federal agency responsible for monitoring and enforcing these rules, with authority analogous to a national environmental police force. Sanctions range from fines to property embargoes, which carry severe economic consequences, including loss of access to rural credit and exclusion from the supply chains of major meatpacking companies (Girardi, 2024).

The enforcement of such regulation, however, has been severely constrained by the geographic scale and remoteness of the Amazon region. In response, in 2004, PPCDAm introduced

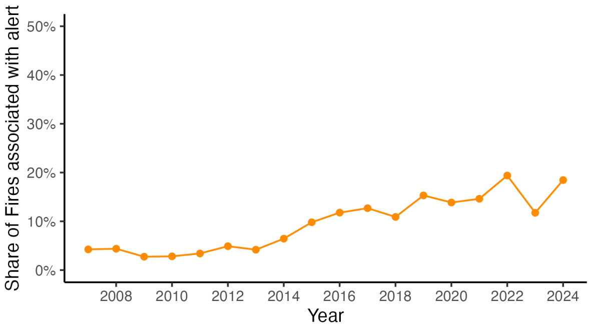
DETER (Real-Time Deforestation Detection System), a near-real-time satellite monitoring system that detects changes in forest cover and triggers alerts for on-the-ground enforcement by IBAMA. Evidence suggests that DETER was central to the post-2004 decline in clear-cut deforestation (Assunção et al., 2023a).

DETER first generation (2006-2015) DETER's trial phase was introduced in 2004, but it became fully operational in 2006. In its initial version, the system relied on near-daily MODIS imagery to detect deforestation events exceeding 25 hectares. The system operated on an exclusion mask — previously mapped deforestation from PRODES, non-forest areas, and hydrographic features — so that only new alterations to forest cover could generate alerts (Almeida et al., 2022). This first generation had two critical blind spots. First, it missed all clearing events below 25 hectares — in this sub-threshold range, DETER detected only 0.05% of total deforested area (Diniz et al., 2015). Second, and key for this paper, it was nearly blind to fire-based degradation, with burning vegetation generating almost no alerts (Figure 2a). Evidence suggests that at least the first blind spot was strategically explored. Baragwanath and Shinde (2025) show that the average size of deforestation patches declined after DETER's introduction, consistent with land users adjusting their behavior to remain below the detection threshold. Fire, which leaves a qualitatively different spectral signature than mechanical clearing, offered an additional margin of evasion that the system was technically unable to flag.

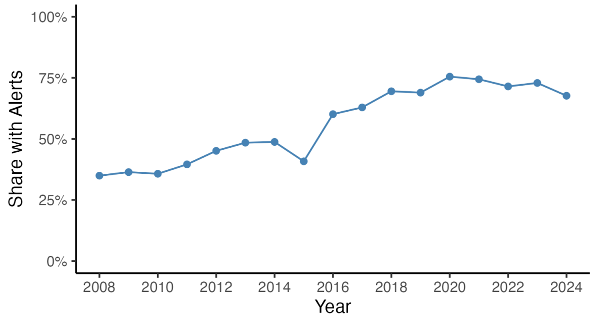
DETER second generation (post-2015) In 2015, INPE introduced DETER-B, which uses higher-resolution imagery (Diniz et al., 2015; Valeriano et al., 2016). DETER-B extended detection to events as small as 3 hectares and, critically, added the capacity to identify fire scars alongside mechanical clearing [3]. Visual image interpretation by trained

[3]With DETER-B, alerts are organized into two groups: deforestation warnings (clear-cut deforestation, deforestation with remaining vegetation, and mining) and degradation warnings (degradation, geometric selective logging, disorganized selective logging, and forest fire scars). Polygons initially mapped as degra-

Figure 2: DETER detection rates for fire versus deforestation, 2007–2024



(a) **Share of fire events with a coincident DETER alert.** For each year, the percentage of MODIS-detected fire events that coincided with a DETER system alert.



(b) **DETER's detection rate of PRODES-confirmed deforestation.** For each year, the percentage of PRODES-confirmed deforestation area that received a corresponding DETER alert.

Note: Deforestation refers to PRODES's official end-of-year deforestation measurement. Panel (a)'s share remains well under 20% throughout the sample, especially reflecting DETER's blind spot for fire-based clearing prior to 2015. Panel (b)'s share rises from roughly 35% (2008) to about 75% by the early 2020s, reflecting improving detection accuracy for mechanical clearing, notably after DETER-B's 2015 upgrade.

analysts remains foundational to both generations, reflecting a deliberate institutional choice to minimize false positives (Soler et al., 2021). The reliance on human visual interpretation and the associated learning process helps explain progressive improvement in the system's accuracy (Figure 2b).

I explore two features of the DETER system in my empirical strategy. First, a constraint affecting both generations: the system can only detect forest disturbances in areas not obscured by clouds. Cloud cover systematically delays the interval between a deforestation event and a satellite alert, and, in turn, reduces the likelihood of on-the-ground enforcement (Section 2.3 explains in detail why this is the case). For this reason, following Assunção et al. (2023a), I use cloud cover as an instrument for enforcement intensity: municipalities with higher cloud cover were less likely to receive timely enforcement, providing exogenous variation in the likelihood of punishment for mechanical clearing. Crucially, under the first generation, cloud cover affected only the enforcement of mechanical clearing — fire was already undetectable regardless of cloud conditions, so the instrument isolates variation in clear-cut enforcement alone. Second, I exploit the shift from the first to the second generation, which reduced the detectability gap between mechanical clearing and fire[4]. Together, these two sources of variation allow me to identify whether satellite detection shaped the relative attractiveness of fire as a land-clearing strategy.

dation can be reclassified as deforestation in subsequent monitoring cycles, allowing the system to capture progressive forest loss over time.

[4]Reduced but did not fully close the gap since (i) as shown in Figure 2a, the detection accuracy of fire events improved post-2015 but is still significantly lower than the accuracy of mechanical clearing; and (ii) *de facto* legal punishment remained relatively more challenging with fire.

2.3 Importance of near-real-time enforcement response to a deforestation event

The severity of sanctions that environmental law enforcement can apply in Brazil depends critically on the timing of the response to a deforestation event (Assunção et al., 2023a). Prior to DETER, enforcement officers had difficulty locating and accessing new deforestation hotspots in a timely manner, since the identification of new clearings relied either on IBAMA's capacity to accurately anticipate spatial deforestation patterns or on reports received via a hotline. By the time officers reached a deforested area, the window for applying the most binding penalties had typically closed. Even if officers were able to correctly identify and locate the responsible parties, their ability to impose the costliest penalties ultimately depended on catching offenders on the spot. For example, if law enforcement officers find heavy machinery, such as tractors, on site in a deforestation hotspot, they can impose an immediate and severe financial loss on the offender by seizing and destroying it (Assunção et al., 2013).

The adoption of near-real-time satellite-based monitoring through DETER changed this dynamic. The system's inability to detect deforestation through cloud cover only lengthens the interval between a deforestation event and an alert. Hence, new deforestation events will eventually lead to an alert. However, the key aspect that underlies my instrument is that a short gap between detection and enforcement makes caught-in-the-act operations more likely. IBAMA can now quickly locate and act on areas with recent deforestation. In summary, this enhances law enforcement's ability to catch offenders and impose binding sanctions.

3 Theoretical framework

The following simple model presents the idea of substitution between deforestation technologies, which informs my main empirical approach. Consider a profit-maximizing farmer endowed with a fixed amount of land L [5]. The land is partitioned between:

$$L = l_p + l_f \tag{1}$$

where l_p is the amount of land under agricultural production and l_f is the land kept as forest. Under the Brazilian forest code, the farmer must keep 80% of their parcel as native vegetation, such that $\bar{s}_f = 0.8$ where $s_f \equiv l_f/L$.

Compliance therefore implies $l_p = (1 - \bar{s}_f)\,L = 0.2\,L$. The farmer's problem is to decide whether to comply and have $\bar{s}_f$ or to expand production by converting forested land, i.e. to set $s_f < \bar{s}_f$.

Production

Given productive land l_p, the farmer chooses the level of a composite input h (fertilizer, labour, machinery, etc.) to maximise the flow of land rent:

$$R(l_p) \;=\; \max_{h \geq 0} \Big[p\,A\,f(l_p,\, h) \;-\; q\,h \Big], \tag{2}$$

where p is the output price, A is total factor productivity, $f(\cdot)$ is a production function satisfying standard regularity conditions ($f_h > 0$; $f_{hh} < 0$), and q is the unit cost of the input h.

Deforestation choice

A farmer who chooses to violate the Forest Code must also choose how to clear the additional forested land. Let $t \in \{\textit{fire},\, \textit{cut}\}$ index the available clearing technologies. The key institutional feature exploited in this paper is that the two technologies differ in their detectability by Brazil's DETER satellite monitoring system.

[5] The model set-up was heavily inspired by Lee and Barrett (2001).

Assumption 1 (Differential detection risk)**.** *The probability of enforcement conditional on illegal clearing is strictly lower for fire-based clearing than for mechanical cutting:*

$$\theta_{\mathit{fire}} \;<\; \theta_{\mathit{cut}}, \qquad \theta_t \in [0,1]. \tag{3}$$

This assumption reflects the fact that DETER's first-generation system (2004–2015) detected the spectral signatures of clear-cuts but was unable to distinguish fire-related deforestation. Because detection by DETER is the primary trigger for on-the-ground inspections by IBAMA, a lower θ_t implies a lower expected enforcement burden.

The detection probability θ_t depends on satellite visibility, which is in turn obstructed by cloud cover $c \in [0,1]$:

$$\theta_t \;=\; \theta_t(c), \qquad \frac{\partial \theta_t}{\partial c} < 0. \tag{4}$$

Under DETER's first generation:

$$\partial \theta_{\mathit{fire}} / \partial c = 0 \tag{5}$$

$$\partial \theta_{\mathit{cut}} / \partial c < 0 \tag{6}$$

Farmer's Problem

Compliance

A farmer who complies with the Forest Code has $s_f = \bar{s}_f$ and earns:

$$\Pi_{\mathit{comply}} \;=\; R^{*}\Big((1-\bar{s}_f)\, L\Big). \tag{7}$$

Violation with Fire

A farmer who chooses to deforest illegally using fire sets $s_f < \bar{s}_f$, converting $\Delta l = (\bar{s}_f - s_f)L > 0$ hectares of forest to agricultural land. Fire-based clearing carries two costs:

(i) Expected punishment cost. With probability θ_{fire} the illegal clearing is detected, triggering a sanction $F > 0$ (fine, embargo, or both):

$$\text{Expected punishment cost} \;=\; \theta_{\mathit{fire}} \cdot F.$$

(ii) Fire spread damage. Unlike mechanical cutting, fire carries a risk of uncontrolled spread. This imposes a damage cost proportional to the area cleared by fire and to a fire spread parameter $\gamma \geq 0$:

$$D \;=\; \gamma\,\Delta l \;=\; \gamma\,(\bar{s}_f - s_f)\,L. \tag{8}$$

In this set-up, D is borne by the farmer (e.g. fire escapes to productive land). Note that D is increasing linearly with the burned area Δl.

The fire-deforestation payoff is:

$$\Pi_{\mathit{fire}} \;=\; R^*\Big((1 - s_f)\,L\Big) \;-\; \theta_{\mathit{fire}} \cdot F \;-\; \gamma\,(\bar{s}_f - s_f)\,L. \tag{9}$$

Violation with Mechanical Clearing

A farmer who deforests using mechanical clearing faces no spread-damage cost ($\gamma = 0$), but faces strictly higher detection and punishment probability:

$$\Pi_{cut} \;=\; R^*\Big((1 - s_f)\,L\Big) \;-\; \theta_{cut} \cdot F. \tag{10}$$

Deforestation technology choice

Given that the farmer has chosen to deforest an amount Δl, they will choose $t = fire$ if:

$$\Pi_{\mathit{fire}} > \Pi_{cut} > \Pi_{comply} \tag{11}$$

The first inequality implies that:

$$\left(\theta_{cut} - \theta_{\mathit{fire}}\right) \cdot F \;>\; \gamma\,\Delta l. \tag{12}$$

Condition (12) means that the farmer uses fire when the expected fine savings from lower detectability exceeds the fire spread cost.

Determinants of deforestation technology choice Fire-based deforestation becomes relatively more attractive when:

(i) The detection gap $(\theta_{cut} - \theta_{\mathit{fire}})$ is larger

(ii) The sanction F is larger—stronger enforcement raises the comparative advantage of the low-detection technology;

(iii) The spread risk γ is smaller—small fire damage makes fire relatively more profitable;

(iv) The amount of illegal clearing Δl is smaller—fire damage cost is lower for marginal conversions.

My empirical work is motivated by these theoretical predictions. In light of prediction (i), I first examine the change in deforestation behavior following the introduction of DETER in Section 5. I argue that the first satellite generation increased the detection gap by raising θ_{cut}. I also test a change in behavior induced by DETER post-2015. The Introduction of DETER's second-generation system, which gained fire-detection capability post-2015, should shrink the detection gap ($\theta_{cut} - \theta_{fire}$), reducing the incentive to use fire.

Items (ii) and (iii) motivate my future empirical work. Concerning (ii), I will check for differential responses to sanctions F - comparing between low (fines) and high (property embargoes) sanctions. On item (iii), I will analyze farmers' responses to extreme weather conditions, looking at behavioral responses to droughts and wind patterns.

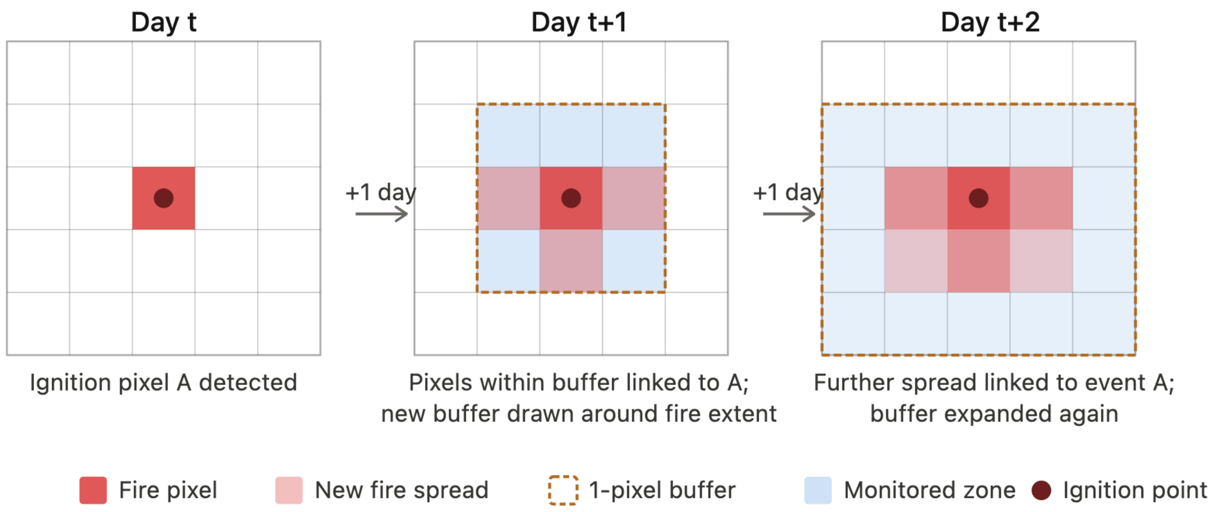
4 Data

4.1 Fire data

I use the MODIS Terra Thermal Anomalies and Fire product to calculate the municipal burned area and count fire ignitions for each municipality. The product presents 1km gridded information on pixels where fire was detected for every 24-hour period. The dataset tracks fire hotspots from 2000 to the present. For this paper, I tracked the burned area and number of fire ignitions instead of using MODIS hotspots directly. I chose to include the tracking of ignitions because the "conversion" of fire ignitions into fire spread depends on climate variables, such as average temperature and soil moisture. Therefore, the number of ignitions better reflects individuals' intentional decision to start a fire.

To calculate the number of individual fire ignition events in this dataset, I use the procedure proposed by Balboni et al. (2024). The procedure tracks daily MODIS fire observations across time to determine the ignition and spread of each fire event. For each pixel A_t, or a contiguous cluster of pixels with fire observed on day t, a 1-pixel buffer is created around it. All pixels inside this buffer with fire on day $t+1$ are considered to be a continuation of fire A_t. In the presence of cloud cover, the procedure uses the next day's observation. On day $t+1$, a new buffer is created around the new extension of A_t. All pixels with fire within this buffer on day $t+2$ are treated as a continuation of fire A_t. This process is iterated across each day so I can link each fire-detected pixel to a specific event. Figure 3 presents a visual scheme of this process. For comparison, I also use fire hotspot data from INPE. INPE (Brazil's National Institute for Space Research) uses data from several satellite sensors to track fires in Brazil.

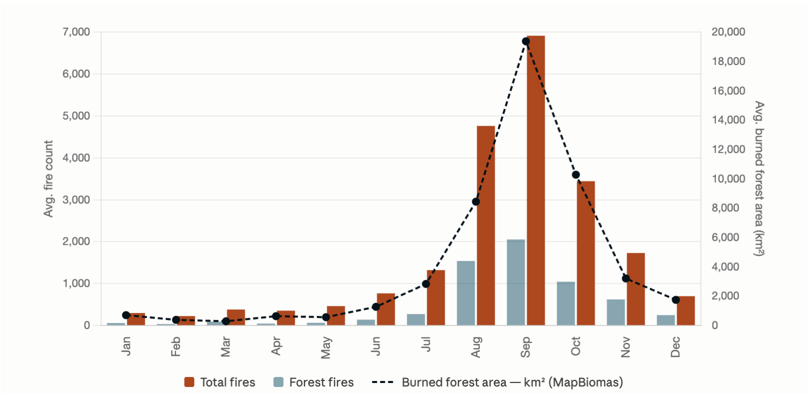
Figure 3: Representation of the fire hotspot-to-ignition-point linking algorithm



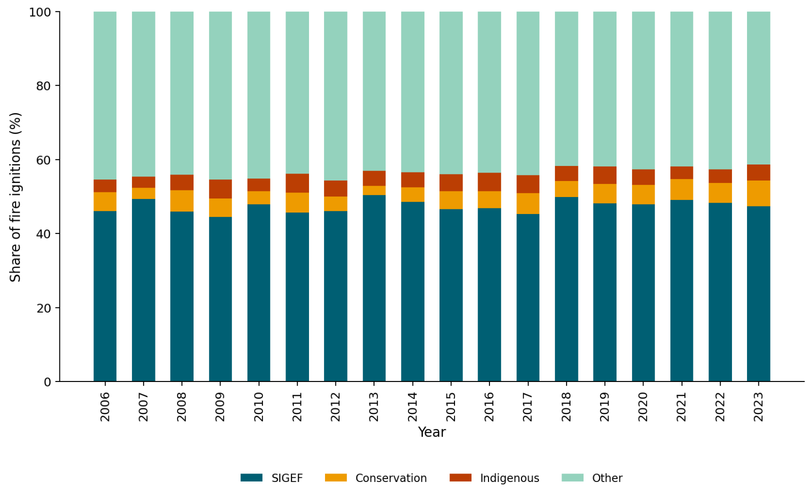
Note: Schematic of the procedure (following Balboni et al., 2024) used to convert daily MODIS fire-pixel detections into discrete ignition events.

Figure 4a shows the seasonality in fire occurrence in the region. Fire activity follows a pronounced dry-season pattern, peaking sharply in August and September before declining through the wet season (November–April). Forest fires account for a minority of total fire counts in all months. Figure 4b shows the distribution of the fire ignitions within different tenure regimes. Fires are concentrated in properties with full title (in the SIGEF database) or in public lands/non-fully titled areas (others). Conservation units and indigenous lands held a small portion of the ignitions during the post-DETER period.

Figure 4: Fire ignition patterns: monthly trends and property-level details of occurrence.



(a) Monthly patterns



(b) Location of fire occurrence

4.2 Environmental Law Enforcement data

As in Assunção et al. (2023a), I will use fines issued by IBAMA as a proxy for environmental enforcement presence. Unfortunately, there is no data on the exact deployment or tracking of IBAMA's agents' work. Fines are the best proxy, as they indicate that agents were present at a site and could hold a violator accountable. The information on fines includes the type of infraction, the issuance date, and the municipality. I use the detailed crime-type description in the data to distinguish deforestation-related fines.

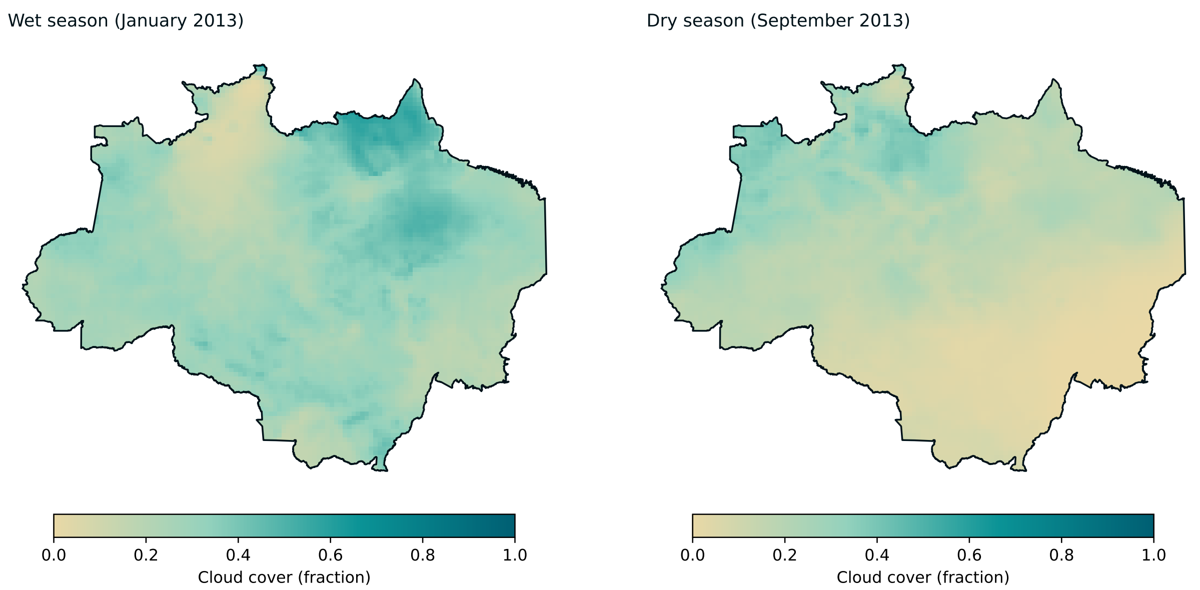
4.3 Cloud cover

My empirical strategy follows Assunção et al. (2023a) in using cloud cover as an instrument for satellite-based environmental monitoring. When clouds obstruct DETER's satellite view of deforestation scars, the probability of detecting and prosecuting illegal deforestation falls exogenously, generating plausibly random variation in enforcement intensity across municipalities and months.

I use two sources of cloud cover data. I have access to DETER's operational cloud cover information, which records the fraction of each municipality's area obscured by clouds in each month. However, a key limitation of the DETER cloud measure is in the post-2015 period, when DETER transitioned to its second phase. The second phase uses AWiFS sensors on the Indian ResourceSat-2 and CBERS-4/4A satellites, but cloud cover information is only available for the latter.

For this reason, to have a consistent cloud cover measure from 2007 to 2024, I also use ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts. Unlike plain satellite images, reanalysis data combines satellite, ground observations, and models to fill in gaps and give full coverage. ERA5 provides gridded atmospheric reanalysis fields at a monthly frequency, derived from a numerical weather model that assimilates global observational data, yielding complete spatial and temporal coverage by construction. ERA5, among other reanalysis datasets, exhibits the best correlation with MODIS for cloud cover Wu et al. (2023), while minimizing smoke contamination relative to MODIS. Optical satellite instruments such as DETER can misclassify dense smoke plumes from fires as cloud cover, which would introduce a spurious correlation between the instrument and fire activity—the very outcome of interest. ERA5 cloud fields are derived from atmospheric reanalysis rather than optical imagery, making them less sensitive to aerosol or smoke loading (as tested in Section 5.4). For these reasons, I use ERA5 low-level cloud cover as my preferred instrument in baseline specifications. Figure 5 displays the average monthly cloud cover calculated from ERA5 low-level data, which is the primary instrument for enforcement in my empirical analysis.

Figure 5: Spatial variation in cloud cover across the Brazilian Legal Amazon: wet versus dry season



Note: Panels show ERA5 monthly-mean low cloud cover (fraction of grid-cell area) for January 2013 (wet season) and September 2013 (dry season) — the same product used as the preferred instrument in Section 4.3. The black outline marks the Brazilian Legal Amazon; darker blue indicates higher cloud fraction. Cloud cover is higher and more spatially uniform in the wet season and drops sharply, especially in the south and east, during the dry/fire season. Source: ERA5 reanalysis, Copernicus Climate Data.

Table 1 shows that DETER cloud cover and ERA5 low-cloud measurements are highly associated. This close relationship suggests that variation in the DETER instrument mostly reflects true meteorological cloud cover rather than smoke-induced misclassification. This table also shows that the instrument's power is concentrated in low-level cloud cover, the layer most relevant to DETER's optical detection range and least likely to be contaminated by smoke aerosols, which typically rises to medium and high altitudes. Figure D.2 shows the variation in the cloud cover variables across the seasonal cycle, including during the fire season months (July–October) when smoke contamination is most likely to appear.

Table 1: Association between cloud cover variables

	DETER cloud cover		
	(1)	(2)	(3)
ERA5 low cloud	0.9909***		
	(0.0296)		
ERA5 high cloud		0.3490***	
		(0.0179)	
ERA5 total cloud			0.3946***
			(0.0189)
R^2	0.64215	0.62982	0.63042
Observations	159,785	159,785	159,785
Municipality fixed effects	✓	✓	✓
Year-month fixed effects	✓	✓	✓

Note: OLS regressions of DETER's operational cloud cover measure (share of a municipality's area obscured by clouds in a given month) on three ERA5 reanalysis cloud cover measures, estimated separately: low-level cloud cover (col. 1), high-level cloud cover (col. 2), and total cloud cover (col. 3). Municipality and year-month fixed effects included; standard errors clustered by municipality in parentheses.

An evidence concern regarding the cloud cover data is whether smoke from fires affects it. In Appendix A.2, I show evidence that smoke contamination does not pose a significant problem for the cloud cover measurements used.

4.4 Other sources

Land-use data I use the MapBiomas Brazil land-cover product to track pre-fire land cover information. This allows me to differentiate between fires in agricultural and forest areas.

I transform PRODES plot-level deforestation data into a monthly measure of forest-clearing disturbances. I use this data as the denominator in my outcome of interest: the fraction of burned forest relative to the fraction of cleared forest. Section A.1 details how I extract this monthly data. Because of data limitations, PRODES plot-level information is available only starting in 2008. Therefore, the empirical analysis starts in 2008 rather than 2007 when I use this data.

Weather controls My rainfall data comes from CHIRPS. All additional weather controls come from the ERA5 reanalysis product. Table C.1 presents a summary of the main variables used in the empirical analysis.

5 Empirical framework

5.1 Deforestation technology substitution effect

Understanding how environmental law enforcement affects land-clearing behavior is challenging because of the endogeneity between monitoring efforts and illegal land-clearing activities. Enforcement should be present in areas under deforestation pressure, but it may also deter illegal behavior, so closely monitored areas might experience less illegal deforestation.

To overcome this reverse-causality problem, I propose using the instrument for environmental law enforcement introduced in Assunção et al. (2023a). The instrument leverages the fact that DETER, the near-real-time deforestation alert system, is the primary resource for triggering on-the-ground enforcement in the Brazilian Amazon. Clouds limit the system's capacity to detect clearings. As a result, cloud coverage acts as a random factor in the presence of enforcement. I will use this to examine how farmers respond to enforcement, measured by fines issued in a given location and instrumented by cloud coverage.

For my estimates, I construct a municipality-month panel from 2008 [6] to 2023, covering both of DETER's monitoring phases. I estimate the following first stage:

$$E_{it} = \alpha_i + \omega_t + \theta \text{DETERclouds}_{it} + \gamma \mathbf{X_{it}} + \epsilon_{it} \tag{13}$$

where E_{it} is the number of deforestation-related fines in municipality i in month-year t. DETERclouds_{it} is the average cloud coverage in municipality i in year t. In my preferred specification, I use the ERA5 cloud cover data. $\mathbf{X_{it}}$ is a set of monthly municipal-level weather controls, which includes lagged and cumulative variables (more details in Section B.1). α_i is a municipality fixed effect and ω_t is a month-year fixed effect. The second stage is given by:

$$ln\left(\frac{F_{it}}{C_{it}}\right) = \psi_i + \lambda_t + \beta \hat{E}_{it-1} + \delta \mathbf{X_{it}} + \epsilon_{it} \tag{14}$$

where $ln\left(\frac{F_{it}}{C_{it}}\right)$ is the municipal-level log of the ratio between the burned forest area (F_{it}) and the clear-cut area (C_{it}). The coefficient β will be positive if enforcement, instrumented in the first stage, has a substitution effect on the two deforestation technologies.

$\hat{E}_{mt-1}$ is the number of deforestation-related fines in municipality i in month-year t instrumented by cloud coverage in the first stage. ψ_i is a municipality fixed effect, λ_t is a month-year fixed effect, and $\mathbf{X_{it}}$ is the same set of municipal-level weather controls as in my first stage.

[6] DETER was introduced in 2004 but became fully operational only in 2006. Cloud cover data is only consistently available from March 2007. Further, the analysis only begins in 2008 since I can only generate the monthly deforestation data starting from this year.

5.2 Effect across the different DETER generations

I exploit the transition between DETER's monitoring phases as a shock to the fire-detection likelihood farmers face. DETER's second generation, introduced in 2015, extended detection capabilities to include fire-based clearing. This reduced, though not eliminated (as shown in Figure 2a), the technological blind spot that created substitution incentives under the first generation. If farmers were strategically substituting toward fire under DETER-1, we would expect the positive effect of enforcement on fire use to attenuate under DETER-2, when fire became detectable.

To formally test this potential shift with the introduction of the new detection capability, I define an indicator D_t equal to one for months from August 2015 onward—the start of the operational rollout of DETER-B's fire-detection capability—and zero otherwise. I then instrument both enforcement and its interaction with D_t, estimating the first stage:

$$E_{it} = \alpha_i + \omega_t + \theta_1 \text{DETERclouds}_{it} + \theta_2 \left(\text{DETERclouds}_{it} \times D_t\right) + \gamma \mathbf{X_{it}} + \epsilon_{it} \tag{15}$$

and the corresponding second stage:

$$ln\left(\frac{F_{it}}{C_{it}}\right) = \psi_i + \lambda_t + \beta_1 \hat{E}_{it-1} + \beta_2 \left(\hat{E}_{it-1} \times D_t\right) + \delta \mathbf{X_{it}} + \epsilon_{it}, \tag{16}$$

where $\hat{E}_{it-1}$ and $\hat{E}_{it-1} \times D_t$ are both instrumented, using DETERclouds_{it} and $\text{DETERclouds}_{it} \times D_t$ respectively. In this specification, β_1 captures the effect of enforcement on the fire-clearing mix under DETER-1, when fire fell outside the system's detection capability. The coefficient β_2 captures how this effect changes once fire-based clearing becomes detectable: if farmers' substitution toward fire was driven by DETER-1's blind spot, closing that gap should attenuate the enforcement effect, so the substitution hypothesis predicts $\beta_2 < 0$. All other variables are as defined in Equations 13 and 14.

5.3 Effect across different time exposure windows

Equation (14) relies on a one-month window of exposure to enforcement. However, deterrence likely operates through a gradual process of learning rather than immediate behavioral adjustment. A farmer's decision to use fire in land-clearing depends on their perceived risk of detection and punishment, a belief that is shaped by accumulated exposure to enforcement in their municipality over time. Hence, a single month of exposure to enforcement might be insufficient for this learning process to take place if information about enforcement activity diffuses gradually through social networks. For this reason, I examine how my results change across different temporal exposure windows.

I estimate the following first stage for each monthly temporal window h, where $h \in \{1, 2, \ldots, 12\}$, with i indexing municipality and t the month-year period:

$$\bar{E}^h_{it} = \beta_h \, \overline{\text{DETERclouds}}^h_{it} + \boldsymbol{\gamma}_h \bar{\mathbf{X}}^h_{it} + \boldsymbol{\delta}\mathbf{X}_{it} + \alpha_i + \omega_t + \varepsilon_{it} \tag{17}$$

where

$\bar{E}^h_{it} = \frac{1}{h}\sum_{s=1}^{h} E_{i,t-s}$	average number of deforestation fines in i in past h periods,
$\overline{\text{DETERclouds}}^h_{it} = \frac{1}{h_{it}}\sum_{s=1}^{h} \text{DETERclouds}_{i,t-s}$	average cloud cover in past h months,
$\bar{\mathbf{X}}^h_{it} = \frac{1}{h}\sum_{s=1}^{h} \mathbf{X}_{i,t-s}$	rolling average of weather controls over the past h months,

and $\mathbf{X}_{it}$ are the contemporaneous weather controls. α_m is a municipality fixed effect and ω_t is a month-year fixed effect. The matched rolling weather controls $\bar{\mathbf{X}}_{it}^h$ absorb collinearity between cloud cover and seasonal climate patterns over the enforcement window. For each horizon h, I estimate a matched second stage:

$$\mathrm{F}_{i,t+1} = \theta_h \hat{\bar{E}}_{it}^h + \boldsymbol{\gamma}_h \bar{\mathbf{X}}_{it}^h + \boldsymbol{\delta}\mathbf{X}_{it} + \psi_i + \lambda_t + \epsilon_{it} \tag{18}$$

where $\hat{\bar{E}}_{it}^h$ is the h-month rolling average of fines instrumented by the rolling cloud cover average from equation (17), $\bar{\mathbf{X}}_{it}^h$ is the rolling average of weather controls over the same window, and $\mathbf{X}_{it}$ are contemporaneous weather controls. Municipality fixed effects ψ_i and month-year fixed effects λ_t are included in all specifications. This yields a sequence of causal estimates $\{\hat{\theta}_h\}_{h=1}^{12}$, tracing out how the effect of cumulative enforcement exposure on fire use evolves as the temporal window shifts.

5.4 Threats to identification

Exclusion restriction I argue that the exclusion restriction — that cloud cover affects fire incidence only through its effect on enforcement — holds after controlling for rain, temperature, and humidity. These weather controls absorb three direct channels through which cloud cover could affect fire use independently of enforcement: a "wet fuel" channel (rain), a "moisture content" channel (humidity), and a "flammability" channel (temperature). A further concern is that cloud cover is correlated with the dry season in the Amazon, which is precisely when fire incidence peaks. My month-year fixed effects absorb aggregate seasonal patterns common across municipalities, while municipality fixed effects absorb time-invariant local differences in fire and cloud seasonality. Together, these controls isolate within-municipality variation in cloud cover that is orthogonal to predictable seasonal fire patterns.

One remaining potential channel is that cloud cover could directly affect farmers' propensity to use fire by signaling reduced satellite visibility, inducing more fire use independently of whether enforcement actually decreases. I argue this channel is unlikely to be quantitatively important, as farmers are unlikely to observe cloud cover at the precision needed to time fire-setting. Conditional on weather controls and fixed effects, cloud cover is therefore plausibly a pure measure of satellite opacity, affecting fire use only through its effect on DETER's detection capacity and the enforcement it triggers.

Instrument relevance Table 2 shows variations in my first-stage estimates across different cloud-cover measurement leads and lags. Contemporaneous and lagged cloud cover — for both DETER and ERA5 low cloud instruments — have a statistically significant negative correlation with the number of fines within a municipality. Crucially, lead cloud cover has no statistically significant effect on fines, providing a clean falsification: if cloud cover were proxying for some omitted variable correlated with enforcement, we would expect future cloud cover to predict current fines, which it does not. Additionally, ERA5 total cloud cover has no statistically significant effect on fines (column 7), reinforcing my use of ERA5 low cloud cover as the preferred instrument. Figure D.3 displays the association between cloud cover leads and lags on the number of fines issued by IBAMA. First-stage F-statistics are reported in all second-stage tables and exceed the conventional threshold ($F > 10$) for instrument strength.

Table 2: First-stage estimates: cloud cover leads and lags on enforcement fines

Dependent Variable:	Number of Fines						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
DETER cloud coverage $_t$	-0.0867***		-0.0447***				
	(0.0214)		(0.0153)				
DETER cloud coverage $_{t-1}$		-0.1064***	-0.0809***				
		(0.0233)	(0.0204)				
DETER cloud coverage $_{t+1}$			-0.0313				
			(0.0190)				
ERA5 low cloud $_t$				-0.5536***		-0.2033*	
				(0.1510)		(0.1175)	
ERA5 low cloud $_{t-1}$					-0.6119***	-0.4517***	
					(0.1476)	(0.1262)	
ERA5 low cloud $_{t+1}$						-0.1469	
						(0.1307)	
ERA5 total cloud $_t$							0.0712
							(0.0560)
Fixed-effects							
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
R^2	0.19094	0.19155	0.19566	0.18798	0.18881	0.18844	0.18775
Observations	159,785	159,019	150,286	164,649	163,876	163,103	164,649

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: OLS regressions of the number of deforestation-related fines issued in a municipality-month on cloud cover at different leads and lags: DETER cloud coverage (cols. 1–3) and ERA5 low/total cloud cover (cols. 4–7). Municipality and year-month fixed effects included; standard errors clustered by municipality in parentheses. Contemporaneous and one-month-lagged cloud cover are negatively and significantly associated with fines under both measures. Lead cloud cover (col. 3, t+1) and ERA5 total cloud cover (col. 7) are not significant — the lead result serves as a falsification check on the exclusion restriction.

Smoke contamination A potential threat to instrument validity is that smoke from fires could contaminate my cloud cover measurements, introducing a mechanical correlation between the instrument and the outcome. I address this concern directly in Section A.2. I show that the association between fire ignitions and cloud cover is negative and very small, and the within-municipality R^2 of fire ignitions on cloud cover is close to zero, ruling out meaningful smoke-driven contamination of the DETER and ERA5 cloud cover measurements.

6 Main results

Deforestation-technology substitution effects Table 3 presents the main instrumental variables estimates. Column (1) presents the effect on the log ratio between burned forest area and mechanically cleared area. The estimated coefficient $\hat{\beta} = 2.023$ ($p < 0.01$) is positive, indicating that municipalities receiving more enforcement fines in the previous month subsequently substitute away from mechanical clearing towards fire. The coefficient implies that one additional fine issued in the prior month is associated with an approximate 656% increase in the ratio of burned to mechanically cleared area. This is a large response, suggesting that the substitution margin goes well beyond a simple hectare-for-hectare swap. One possibility is that, unlike mechanical clearing, fire does not allow for a precise clearing area, so farmers may over-clear or decline to control the extent of the burned area once they turn to fire. Another possibility is that a hectare of burned area is not a perfect substitute for a hectare of mechanically cleared land, so producers may need to burn substantially more area than they would otherwise have cleared mechanically to achieve a comparable outcome.

The estimate in column (2) considers the log burned area, also estimated via IV. Column (3) shows the corresponding estimate on the log land clearing area. For the IV estimates, the first-stage F-statistics confirm instrument relevance. The ERA5 low cloud specification has a first-stage F-statistic of 35.12. Column (4) shows the OLS estimates for comparison. The IV estimates (2) and (3) indicate a positive and statistically significant increase in the burned fire area and an imprecise estimated change in the cleared area. The OLS estimate in column (4) is substantially attenuated at 0.0057, consistent with attenuation bias expected when enforcement is endogenous to deforestation activity.

Table 3: IV estimates of enforcement effects on fire and clearing outcomes

Dependent Variables:	log(ratio)	log(Fire)	log(clearing)	log(ratio)
Model:		IV		OLS
	(1)	(2)	(3)	(4)
Variables				
Enforcement (fines_{t-1})	2.023***	2.347***	0.3245	0.0057
	(0.6770)	(0.6962)	(0.4349)	(0.0041)
Fixed-effects				
Municipality FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Fit statistics				
F-test (1st stage)	35.122	35.122	35.122	-
Observations	92,245	92,245	92,245	92,245
Climate controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Two-stage least squares estimates of the effect of environmental enforcement (deforestation fines, instrumented by cloud cover per Equation 13) on land-clearing outcomes the following month. Col. (1): log ratio of burned forest area to mechanically cleared area, IV. Col. (2): log fire ignitions, IV. Col. (3): log mechanically cleared area, IV. Col. (4): log ratio outcome, OLS. Municipality and year-month fixed effects and weather controls included; standard errors clustered by municipality.

Change in DETER's fire detection capacity I test if the introduction of a fire-detection capability to DETER in 2015 changed the relative advantage of using fire. Hence, I check whether, post-2015, the enforcement-induced substitution effect shifts. I instrument both the level of enforcement fines and its interaction with a post-August 2015 indicator using cloud cover and its interaction with the same indicator. This yields two endogenous variables instrumented by two excluded instruments, with first-stage F-statistics of approximately 18 and 16, respectively. Table 4 reports the results. The coefficient β_1 captures the effect of enforcement on fire ignitions in Phase 1 (pre-August 2015), when DETER could detect mechanical clearing but was blind to fire-based degradation. The coefficient β_2 captures how this effect changed after DETER-B introduced fire detection capability.

Table 4: Effect heterogeneity across DETER generations

Dependent Variable:	log(ratio)	
	Full sample	Excl. Bolsonaro (<2019)
Model:	IV	
	(1)	(2)
Variables		
$\beta_1 : Enforcement(fines_{t-1})$	4.805	3.810***
	(3.239)	(1.442)
$\beta_2 : Enforcement(fines_{t-1}) *$ Phase 2	-2.915	-2.516*
	(2.836)	(1.468)
Fixed-effects		
Municipality FE	Yes	Yes
Year-Month FE	Yes	Yes
Fit statistics		
F-test (1st stage), Enforcement (fines_{t-1})	30.809	18.029
F-test (1st stage), Enforcement (fines_{t-1}) $*$ Phase 2	43.770	16.167
Observations	141,417	92,245
Climate controls	Yes	Yes
Municipality FE	Yes	Yes
Year-Month FE	Yes	Yes

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: IV estimates of enforcement's effect on the log fire-to-clearing ratio, allowing the effect to differ between DETER's first generation (fire-blind, through July 2015) and second generation (fire-aware, from August 2015), per Equation 16. Enforcement (fines_{t-1}) is the Phase 1 (before August 2015) effect; the interaction term is the change in that effect after August 2015. Col. (1) uses the full 2007–2023 sample; col. (2) excludes 2019 onward, when IBAMA enforcement collapsed for political reasons under the Bolsonaro administration. Municipality and year-month fixed effects and weather controls included; standard errors clustered by municipality in parentheses.

In column (1), I present results considering the entire sample period (2008 -2023), with the log ratio of burned area to mechanically cleared area as an outcome. My results are noisy, and I find no statistically significant effect of substitution pre-2015 (β_1) or a difference in fire use between DETER's phases (β_2).

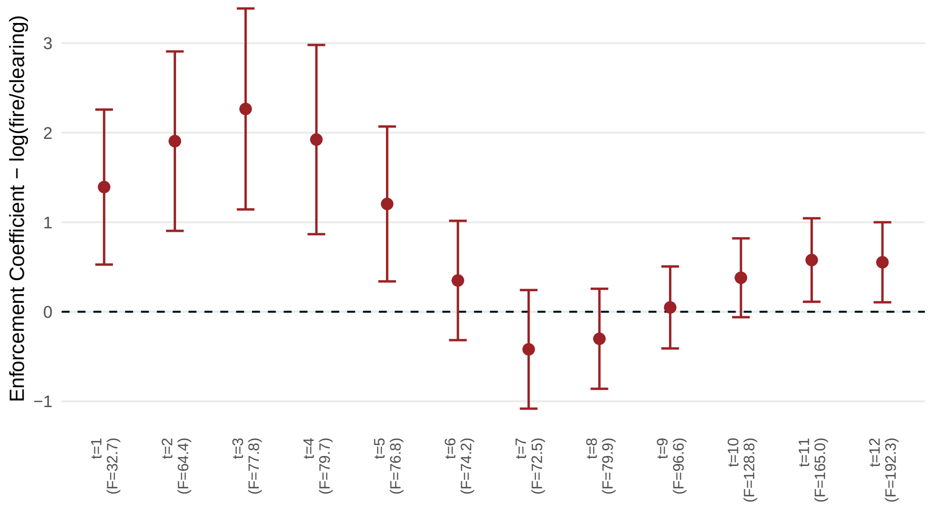
In column (2), I conduct the same estimate but on the sample excluding the Bolsonaro administration years (starting in 2019), when enforcement collapsed for political rather than monitoring-related reasons[7]. In this estimate, the Phase 1 effect is 3.810 ($p < 0.01$), consistent with the main results in Table 3. Phase 2 effect is $\hat{\beta}_2 = -2.516$ ($p < 0.1$).

Two features of these results are worth noting. First, the attenuation in the enforcement-fire coefficient ($\beta_2 < 0$) is consistent with a reduction in the detection gap between mechanical clearing and fire. As shown in Figure 2a, fire detection accuracy improved substantially after 2015 but remained well below that of mechanical clearing throughout Phase 2. Under the theoretical framework in Section 3, this is consistent with DETER's second generation shrinking the detection gap $\theta_{cut} - \theta_{fire}$. Still, the Phase 2 effect remains positive and statistically significant, ruling out the interpretation that DETER-B fully eliminated substitution incentives. This is consistent with institutional evidence that the criminal punishment for fire use remains substantially more difficult than that for mechanical clearing, due to a legal attribution problem even when fire scars are detected. Hence, at least in this margin, fire-based land clearing retains a residual enforcement advantage.

Cumulative exposure effect Figure 6 displays the estimated coefficients considering the cumulative exposure to fines from Equation (18). I find a positive and statistically significant effect of enforcement exposure on fire-to-clearing substitution across most exposure windows within a 12-month period. Across all exposure windows, the cloud cover instrument remains relevant (F>10).

[7] During the Bolsonaro administration, IBAMA's budget and staff were cut dramatically, causing a sharp decline in enforcement activity unrelated to satellite monitoring technology. Including these years conflates political enforcement shocks with the monitoring channel this paper studies.

Figure 6: Effect of enforcement on the fire-clearing ratio across exposure windows



Note: Each point shows the IV coefficient (with 95% CI) on log(fire ignitions/clearing area) from a separate regression using a rolling average of enforcement fines over the prior h months, for h = 1 to 12 (Equation 18). First-stage F-statistics for each window are reported in parentheses on the x-axis. Municipality and year-month fixed effects and weather controls included.

6.1 Robustness checks

Effect on fire ignitions Table 5 presents the main instrumental variable estimates considering the entire 2007-2023 period and using the count of fire ignitions as an outcome. Columns (1) and (2) report the IV estimate of the raw fire count. Column (3) shows the corresponding OLS estimate for comparison.

The IV estimates indicate a positive and statistically significant effect of enforcement on subsequent fire ignitions. The coefficient in column (1) is 3.342 ($p < 0.01$), implying that a one-unit increase in the number of enforcement fines issued in the prior month is associated with approximately 3.3 additional fire ignitions in the current month. The OLS estimate in column (3) is substantially attenuated at 0.120, consistent with attenuation bias expected when enforcement is endogenous to deforestation activity.

The first-stage F-statistics confirm instrument relevance. The ERA5 low cloud specification (column 1) has a first-stage F-statistic of 50.9. The DETER cloud cover specification (column 2) yields a lower F-statistic of 12.7. The weaker first stage under the DETER instrument is unsurprising, given the discussion in Section 4.3 — DETER cloud cover likely exhibits measurement noise after 2015, when the transition to the second-generation satellite system introduced a dual-sensor regime that could not be fully addressed with the available data.

Table 5: Main IV Estimates

Dependent Variable:	Fire ignitions (count)		
Model:	IV		OLS
	(1)	(2)	(3)
Variables			
Enforcement (fines$_{t-1}$)	3.342***	2.899***	0.1196***
	(0.9309)	(1.089)	(0.0324)
Fixed-effects			
Municipality FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
F-test (1st stage)	50.995	12.725	
Observations	148,416	143,835	148,416
Instrument	ERA5 low cloud$_{t-1}$	DETER cloud$_{t-1}$	—
Climate controls	Yes	Yes	Yes

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Alternative fire data Table 6 replicates the main specification using INPE's fire count data as the dependent variable. The results are qualitatively unchanged; however, the coefficient of interest is substantially larger. INPE's data uses a different methodology to measure fire incidence - it measures hotspots rather than ignitions - hence, the effect magnitudes should not be directly comparable with what I present in Table 5.

Table 6: Alternative IV estimates using INPE fire hotspot data

Dependent Variables:	Fire ignitions (count)		
Model:	IV		OLS
	(1)	(2)	(3)
Enforcement (fines$_{t-1}$)	38.33***	38.38***	0.8720***
	(7.904)	(12.09)	(0.2712)
Fit statistics			
F-test (1st stage)	50.995	12.725	
Observations	148,416	143,835	148,416
Instrument	ERA5 low cloud$_{t-1}$	DETER cloud$_{t-1}$	—
Climate controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: IV (cols. 1–2) and OLS (col. 3) estimates of enforcement's effect on fire activity, using INPE's fire hotspot count — rather than the paper's main MODIS-derived ignition-event count — as the dependent variable. Col. (1) instruments with lagged ERA5 low cloud cover; col. (2) instruments with lagged DETER cloud cover. Municipality and year-month fixed effects and weather controls included; standard errors clustered by municipality in parentheses.

Poisson Regression My data have a large share of zero observations; approximately 85 percent of municipality-month observations record no fire activity. For this reason, I estimate my main specification using a Poisson pseudo-maximum-likelihood (PPML) IV estimator, which accommodates count data with excess zeros. Results are presented in Table 7. My outcome of interest is statistically significant only when using the ERA5 product in my cloud-cover instrument (Column 1).

Table 7: IV Poisson Estimates

Dependent Variables:	Fire ignitions (count)	
Model:	IV Poisson (CF)	
	(1)	(2)
Variables		
Enforcement (fines$_{t-1}$)	25.4525***	12.8384
	(9.3715)	(8.2201)
Fixed-effects		
Municipality FE	Yes	Yes
Year-Month FE	Yes	Yes
F-test (1st stage)	24.995	11.154
Observations	141,940	137,488
Instrument	ERA5 low cloud$_{t-1}$	DETER cloud$_{t-1}$
Climate controls	Yes	Yes

Bootstrapped SEs (200 reps) clustered at municipality level in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Control function approach: Wooldridge (2002). F-stat from linear first stage.

Note: IV Poisson pseudo-maximum-likelihood (PPML) estimates of enforcement's effect on fire ignition counts, addressing the roughly 85% share of zero-valued municipality-month observations. Estimated via a control-function approach (Wooldridge, 2002). Col. (1) instruments with lagged ERA5 low cloud cover; col. (2) with lagged DETER cloud cover. Bootstrapped standard errors (200 replications), clustered by municipality, in parentheses; first-stage F-statistics from the corresponding linear first stage.

7 Policy implications and conclusion

Environmental regulation and enforcement might induce unexpected behavioral responses. Understanding these responses is key to improving existing policies and designing better incentives to achieve intended conservation goals. Here, I presented the first evidence on the impacts of deforestation-related regulation and monitoring on deforestation technology choice. My work focuses on the Brazilian Amazon, a central conservation priority that has suffered from persistent forest fires even as successful environmental policies have reduced deforestation rates since 2005.

The key finding of this paper is evidence of a strategic substitution from mechanical to fire-based clearing in response to the introduction of DETER, a near-real-time satellite monitoring system. As previous work has shown (Baragwanath and Shinde, 2025), farmers respond strategically to the monitoring technology they face. Here, I discuss a novel margin of substitution: from mechanical to fire-based forest clearing.

Using cloud cover as an instrument for enforcement, I find that one additional fine issued in the prior month is associated with an approximate 656% increase in the ratio of burned to mechanically cleared area. Using fire ignitions as an outcome, I found that a one-unit increase in deforestation fines in a given municipality-month is associated with 3.3 additional fire ignitions in forest-covered areas the following month. These results are consistent with my theoretical prediction that DETER created an enforcement gap between fire-based and mechanical-based clearing due to its technical detection limitations. My results hold across different enforcement exposure windows and fire measurements.

When looking at the effect of introducing DETER's second generation, which added fire detection capability, my results are mixed. I find evidence that the second generation reduced the mechanical-to-fire substitution effect, indicating a smaller advantage to fire-based deforestation. But these results hold only when I exclude the Bolsonaro presidency years. Indeed, the lack of effect makes sense given that Bolsonaro reduced IBAMA's budget and undermined its capacity to use DETER as a tool for targeted enforcement Rodrigues (2022). Hence, the result is unsurprising, as the enforcement gap between fire-based and mechanically based clearing became irrelevant.

This paper has first-order implications for designing enforcement and punishment of illegal fire use in the tropics. My paper highlights both the technical and legal challenges of tracking and punishing fire use relative to mechanical clearing methods. Despite DETER's continuous advances in mechanical-clearing detection over the years, advances in near-real-time fire-scar detection have not kept pace, and the detection capacity has remained consistently lower - around 20% for fire versus nearly 75% for mechanical clearing in 2023. Still, even as the system detection gap shrinks with technological advances, this will likely be insufficient given the legal framework in the Brazilian Amazon, which requires proving the intent to use fire to issue fines and proving that a crime has taken place. This latter problem will remain at the crux of designing an adequate legal framework to regulate illegal fire use even as technology advances.

This paper has limitations that prevent it from addressing some important caveats in the substitution story. I have access only to IBAMA's fines and no information on the active deployment of monitoring forces. Hence, I cannot tell whether IBAMA systematically targets areas where mechanical clearing is taking place because the likelihood of issuing a fine there is higher, or whether places with fires are being monitored but fines cannot be issued. Although this does not change my story, since my instrument is statistically relevant, my results and discussion might not be capturing the nuances of the enforcement story. Another important caveat is that my theoretical model assumes fire-based and mechanical-based clearing are pure substitutes, when in reality they can often operate as complements. To address this concern, I separate pure fire-based from pure mechanically-based clearing by excluding overlaps in burned areas from my monthly PRODES deforestation measurements.

Fire is one of the compounding disturbances that could push the Amazon past an ecological tipping point and impose severe health externalities. My results show that this persistence is not purely a matter of land-clearing incentives but rather a consequence of the enforcement regime itself. To reduce the persistence in Amazon fires, closing the enforcement gap between mechanical-based and fire-based clearing should be a priority for the next generation of enforcement design. As climate change raises fire risk through higher temperatures and drier forests, this enforcement gap is likely to become even more consequential.

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Appendices

A Data

A.1 Monthly PRODES data

PRODES records the official Brazilian government statistic for year-to-year deforestation. Since 2008, PRODES releases deforestation polygons and assigns the deforestation to a monitoring year running from August of year $t-1$ to July of year t, with no information on which month within that window the clearing occurred. To construct a monthly deforestation measure, I combine PRODES's annual data with an independent, higher-frequency measure of clearing derived from Landsat surface reflectance.

For each municipality and each PRODES monitoring year, I take PRODES's confirmed deforestation polygons (excluding non-forest, hydrographic, and other non-deforestation classes retained in the raw product) and assign each polygon to a municipality using its representative point. Summing polygon area by municipality-year recovers the same annual total used elsewhere in the paper; this quantity, $D_{i,t}$, is treated as authoritative.

To distribute $D_{i,t}$ across the twelve months of monitoring year t, I use a separate Landsat-based clearing measure constructed independently of PRODES. For each municipality-month, I build cloud-masked median Landsat surface-reflectance composites and flag pixels undergoing a new transition from forest cover (MapBiomas Collection 9) to bare soil: pixels with a Bare Soil Index (BSI) above 0.05 in the current month that were below threshold in the prior month, and with a Normalized Burn Ratio difference (dNBR) below 0.27 — the low-severity burn threshold in Key and Benson (2006) — to exclude fire-related clearing. Aggregating flagged pixels by municipality-month yields $L_{i,\tau}$, Landsat-detected clearing area for municipality i in calendar month τ.

For each municipality-year, I compute month τ's share of that municipality's total Landsat-detected clearing within the corresponding PRODES monitoring window,

$$s_{i,\tau} = \frac{L_{i,\tau}}{\sum_{\tau' \in t} L_{i,\tau'}}, \tag{19}$$

and allocate PRODES's annual total accordingly,

$$D_{i,\tau} = D_{i,t} \times s_{i,\tau}. \tag{20}$$

PRODES therefore continues to determine the total amount of deforestation attributed to each municipality-year; the Landsat measure is used only to determine the within-year timing of that total. In the 8,713 municipality-years with PRODES-recorded deforestation between 2008 and 2023, Landsat detected at least some clearing signal in every case. By construction, summing $D_{i,\tau}$ over the twelve months of monitoring year t exactly reproduces $D_{i,t}$.

The resulting municipality-month series displays the seasonal pattern expected from prior descriptions of land clearing in the region: deforestation is concentrated in the dry season, rising from a low of roughly 0.2 km^2 per municipality-month in the January–March wet season to a peak of 3.8 km^2 in September, before declining through the remainder of the year. This pattern is consistent with the timing of fire ignitions in the Brazilian Amazon, and lends some independent support to using Landsat-derived timing as a proxy for within-year deforestation timing.

A limitation is worth noting. Landsat's ability to detect a land-cover transition in a given month depends on the availability of a sufficiently cloud-free scene; months with persistent cloud cover could mechanically register fewer detections independent of the true rate of clearing. This concerns the within-year *timing* of deforestation, not its level: because PRODES continues to set the municipality-year total, any distortion from uneven scene availability affects only how that fixed total is allocated across months, not the total itself.

A.2 Clouds and smoke

A key concern is the extent of smoke contamination in my cloud cover measurements. As a first test, I check for the direct correlation between cloud cover and fire ignitions, controlling for municipality and time fixed effects in Table A.8. The association of fire ignitions with cloud cover is negative and very small (cloud cover measurements range from 0-1), ruling out the possibility that fires increase cloud cover through smoke contamination. Additionally, the inclusion of fire ignitions barely shifts the regression's R-squared, meaning that it adds very little explanatory variation relative to the regression with just year-month and municipality fixed effects, which further corroborates my argument that fire ignitions are unlikely to meaningfully contaminate my cloud cover measurements.

Table A.8: Within-municipality cloud cover variation

Dependent Variables:	DETER Cloud Cover		ERA5 Low Cloud Cover	
	(1)	(2)	(3)	(4)
Variables				
Fire ignitions (count)		-0.0006***		-0.0005***
		(0.0001)		(8.31×10^{-5})
Fit statistics				
R^2	0.62237	0.62265	0.76887	0.77092
Within R^2		0.00075		0.00884
Observations	159,785	159,785	164,649	164,649
Municipality FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: OLS regressions of two cloud cover measures — DETER cloud cover (cols. 1–2) and ERA5 low cloud cover (cols. 3–4) — on the count of fire ignitions in the same municipality-month, with and without the fire-ignitions regressor. Municipality and year-month fixed effects included. Fire ignitions carry a small but statistically significant negative coefficient on both measures, and including them barely moves the R^2 (within-R^2 of 0.0008–0.009), indicating little smoke contamination of the cloud cover instrument.

A potential concern is that ERA5 cloud cover may be correlated with fire activity through smoke contamination. I test this directly by regressing ERA5 cloud cover on CAMS EAC4 organic matter aerosol optical depth — the primary biomass-burning smoke proxy — controlling for municipality and year×month fixed effects, as well as local meteorological conditions (rainfall, temperature, relative humidity). The coefficient on organic matter AOD is 0.002 (p=0.73), providing no evidence that ERA5 cloud cover is systematically driven by smoke. The instrument's variation is meteorological, not fire-driven.

Table A.9: Correlation between aerosol optical depth and cloud cover

Dependent Variable:	ERA5 Low Cloud Cover		
Model:	(1)	(2)	(3)
Variables			
Organic Matter Aerosol	-0.0023		
	(0.0069)		
Black Carbon Aerosol		-0.0527	
		(0.0343)	
Total Aerosol			-0.0002
			(0.0058)
Observations	72,846	72,846	72,846
R^2	0.86655	0.86659	0.86655
Climate controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note:OLS regressions of ERA5 low cloud cover on three CAMS EAC4 aerosol optical depth measures, each a proxy for smoke from biomass burning: organic matter aerosol (col. 1), black carbon aerosol (col. 2), and total aerosol (col. 3). Weather controls and municipality/year-month fixed effects included; standard errors clustered by municipality in parentheses.

B Estimates: details and robustness

B.1 Weather controls

Fire and clearing activity respond to weather on more than one time scale: a farmer's decision to burn in a given month depends not only on that month's rainfall and temperature, but on the accumulated dryness of vegetation and soil built up over the preceding weeks. To capture both the immediate and the accumulated effect of weather, my specification includes a common set of contemporaneous and lagged municipality-month climate controls. For rainfall and temperature, I include three terms: the contemporaneous municipality-month value, a one-month lag, and a three-month backward-looking cumulative measure. Formally, for municipality i in month t,

$$\text{Rain\_cum3}_{i,t} = \sum_{s=0}^{2} \text{Rain}_{i,t-s}, \qquad \text{Temp\_cum3}_{i,t} = \frac{1}{3}\sum_{s=0}^{2} \text{Temp}_{i,t-s}.$$

Rainfall's cumulative term is a rolling three-month *sum*, capturing total precipitation received over the current and two preceding months, which serves as a proxy for soil moisture and fuel wetness. Temperature's cumulative term is instead a rolling three-month *average*, since the relevant channel is sustained warmth and its effect on vegetation dryness rather than accumulated heat. Both the lag and the cumulative terms are computed within each municipality's own monthly time series.

For relative humidity, I include the contemporaneous value and a one-month lag, following the same logic: current humidity affects immediate fire risk, while the prior month's humidity captures residual vegetation moisture.

This lag and cumulative structure lets the specification distinguish a transient weather shock (e.g., an unusually dry month that has not yet had time to affect vegetation) from a persistent drought pattern that meaningfully raises fire risk. Omitting this distinction risks misattributing to enforcement the variation in fire activity driven by seasonal drought dynamics correlated with both fines and fire outcomes.

C Tables

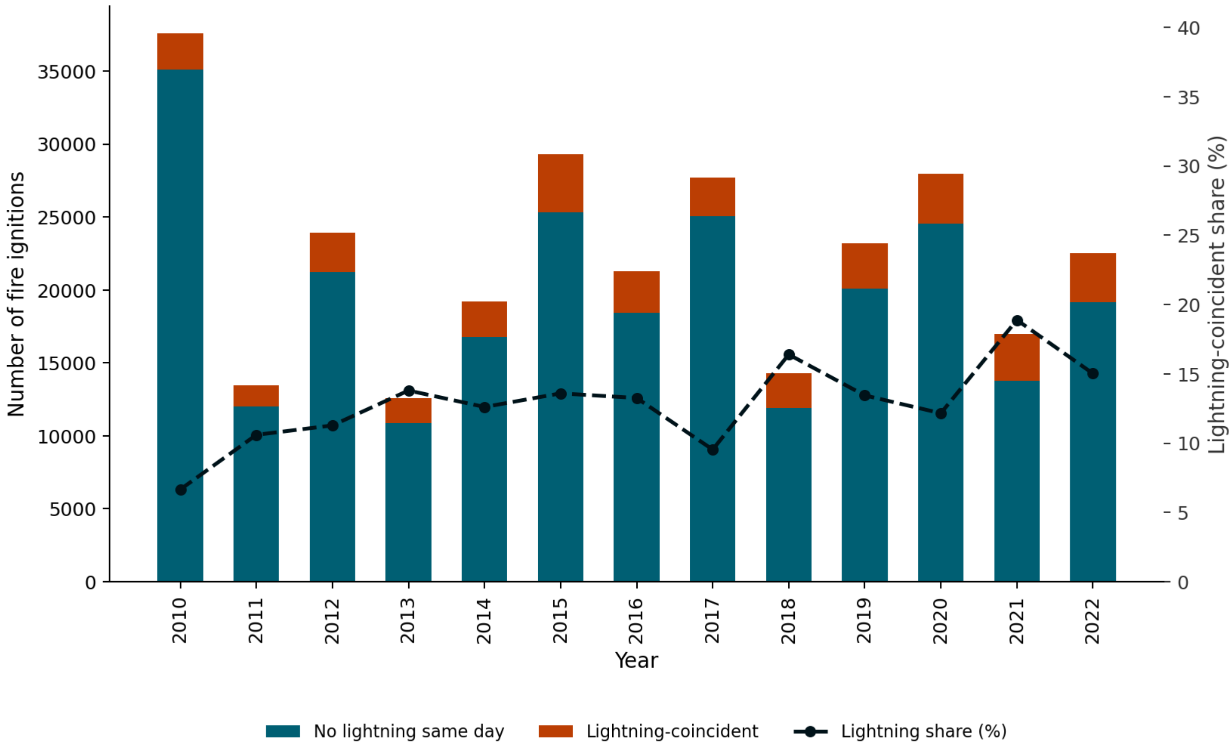
Table C.1: Municipality-level monthly variables: summary statistics

Variable	Mean	SD	Min	Max	Source
Fire ignitions (count)	0.680	4.769	0.000	408.000	FIRMS
Enforcement (fines)	0.263	2.000	0.000	166.000	Ibama
ERA5 low cloud cover (municipal share)	0.173	0.115	0.000	0.639	ERA5 global reanalysis
DETER cloud cover (municipal share)	0.298	0.391	0.000	1.000	INPE
Rainfall (mm)	159.340	135.131	0.000	890.732	CHIRPS
Mean temperature (°C)	26.263	1.497	19.481	32.752	ERA5 global reanalysis
Relative humidity (%)	75.028	12.907	26.368	93.262	ERA5 global reanalysis

N = 164,649 municipality-month observations.

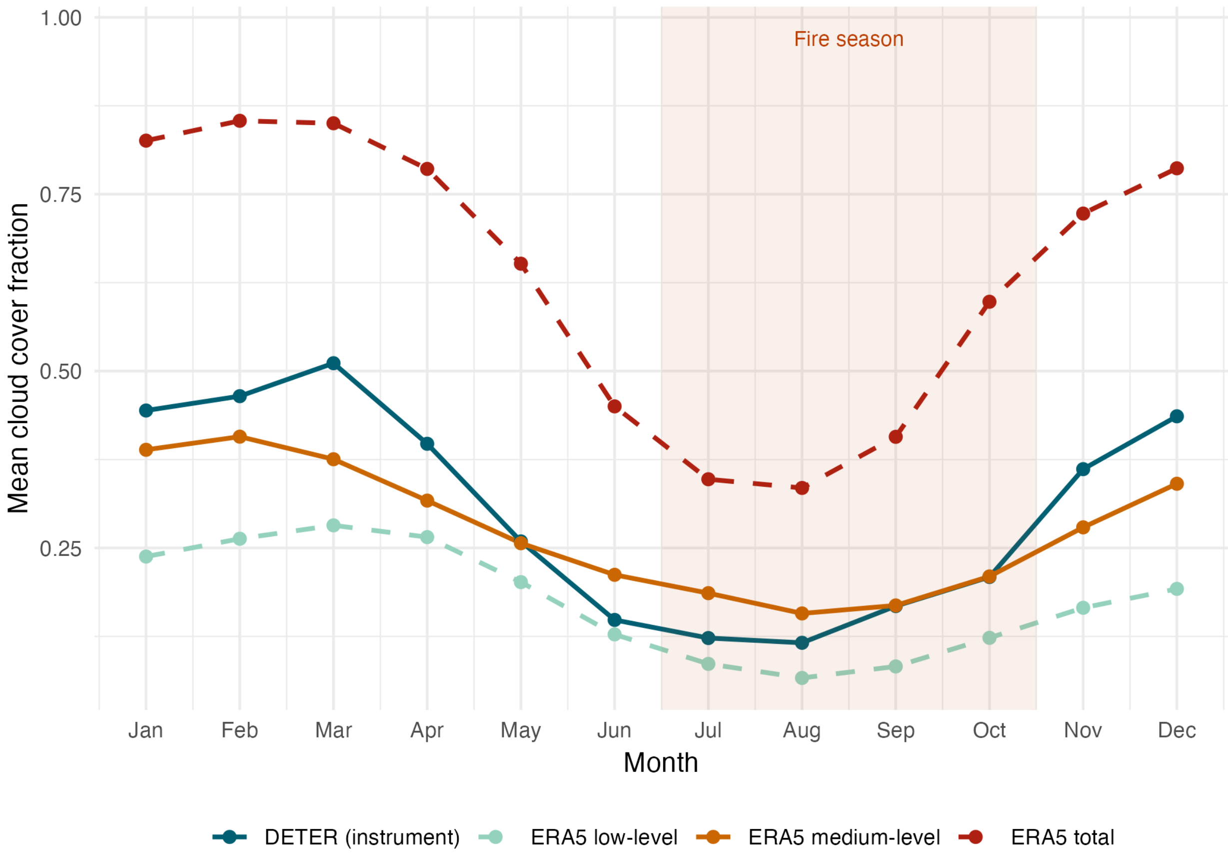
D Figures

Figure D.1: Lightning-coincident versus likely human-caused fire ignitions in the Amazon, 2010–2022



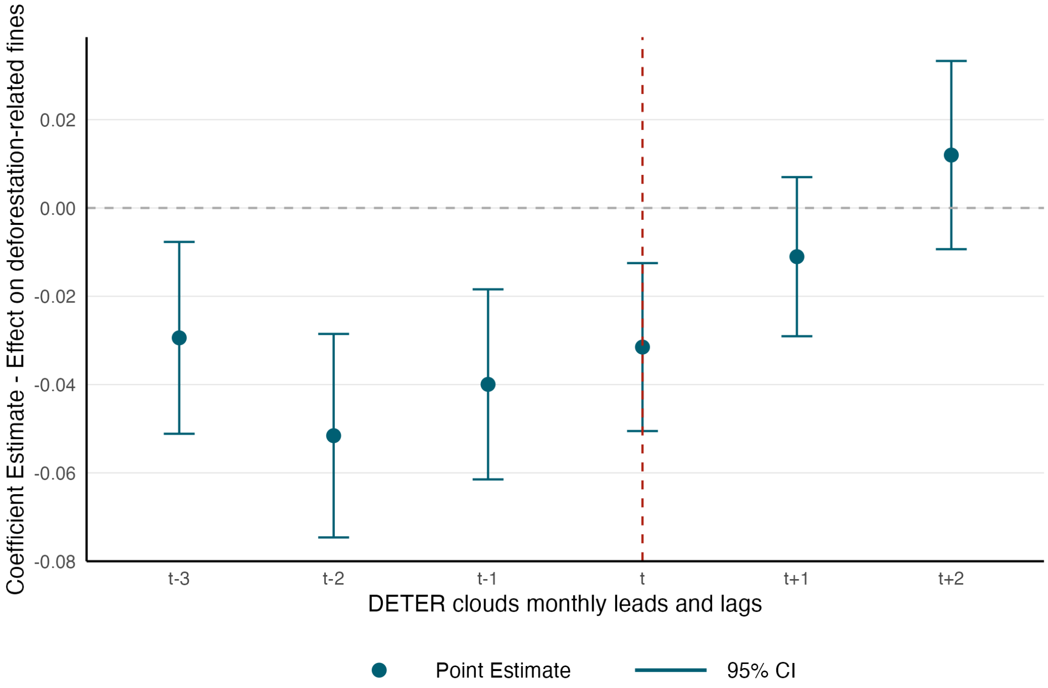
Note: orange) and those with no same-day lightning (teal); the dashed line (right axis) shows the lightning-coincident share. A fire is classified as lightning-coincident if the WWLLN Global Lightning Climatology records a positive stroke density in the same 0.5° grid cell on the same calendar day as the ignition. Because WWLLN detects only about 30% of global lightning strokes, the lightning-coincident share should be treated as a lower bound.

Figure D.2: Comparison of cloud cover products across the seasonal cycle



Note: Mean monthly cloud cover fraction, pooled across years, for four measures: DETER's operational instrument, ERA5 low-level cloud cover, ERA5 medium-level cloud cover, and ERA5 total cloud cover. The shaded region marks the fire season (roughly June–October). All four measures decline heading into the dry/fire season and rise again afterward; DETER's cloud cover tracks the ERA5 low-level measure most closely among the ERA5 series.

Figure D.3: Robustness check: cloud cover instrument, leads and lags



Note: Coefficient estimates (with 95% CI) from separate regressions of deforestation-related fines on DETER cloud cover at monthly leads and lags from t-3 to t+2, controlling for municipality and year-month fixed effects. Cloud cover from t-3 through t is negatively and significantly associated with fines; cloud cover at t+1 and t+2 shows no significant association, supporting the exclusion restriction.