Monitoring Without Capacity: Enforcement and Deforestation in the Amazon

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Abstract

This paper examines the effectiveness of satellite monitoring in curbing illegal deforestation in the Brazilian Amazon. Combining high-resolution deforestation maps, real-time alerts, and geo-referenced enforcement data, I estimate both the targeting role of monitoring and its deterrence effects. Monitoring increases inspection probability by roughly one percentage point and lowers deforestation by 2–4% annually. Yet most enforcement actions occur independently of alerts. These findings highlight the limits of monitoring alone and show that stronger institutional capacity is required to translate technological improvements into meaningful deterrence.

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1 Introduction

Monitoring technologies can make law enforcement more effective by helping agencies deploy limited resources in a targeted way. From tax compliance to environmental regulation, governments increasingly invest in tools like satellite imagery or third party data assessments to identify and punish offenders. But monitoring only improves outcomes if it changes enforcement behavior and, ultimately, deters potential offenders. This raises two key questions: To what extent do enforcement agencies use monitoring information to guide inspections? And how much does this targeting improve compliance?

This paper answers these questions in the context of illegal deforestation in the Brazilian Amazon, where nearly all deforestation is illegal and enforcement resources are scarce. Since 2004, Brazil has deployed DETER, a satellite-based system that generates real-time deforestation alerts. These alerts are available to IBAMA, the federal environmental agency, which keeps detailed records of deforestation fines. Combining high-resolution maps of deforestation, real-time alerts, geo-referenced enforcement data, and terrain and weather controls, I build a monthly panel at 4 km x 4 km resolution from 2011–2020 to study how information flows from satellites to enforcement agents—and ultimately affects behavior on the ground.

The value of a monitoring technology depends on whether i) it increases the probability of a penalty for a given budget, and ii) enforcement induces deterrence effects. The first part of the analysis assesses the impact of monitoring information from DETER on enforcement behavior, revealing the extent to which enforcement behavior is targeted based on monitoring. Several aspects may limit how the enforcement agency relies on monitoring to inform its inspection decisions, including the presence of false positive signals, redundancy of monitoring information compared to other information sources, institutional constraints, and monitoring blind spots that offenders can exploit.

I propose a decomposition of enforcement action into targeted and "non-targeted" by isolating the enforcement action that is likely caused by monitoring information. Next, I introduce a framework to estimate and integrate the general and specific deterrence effects of enforcement on deforestation. General deterrence refers to the impact of enforcement probability on illegal behavior, whereas specific deterrence is the effect of enforcement on subsequent illegal behavior. Although the enforcement literature has long acknowledged the conceptual difference between these two effects, studies typically focus on only one of them.

In the context of illegal deforestation in the Brazilian Amazon during the decade 2011-2020, I show that the probability of an enforcement action, conditional on illegal behavior, is approximately 12%. While many polygons of deforestation were detected in real-time by the satellite-based monitoring technology, the detection probability varies with the terrain characteristics, deforestation area, and over time, suggesting that the monitoring system underwent gradual improvements.

Using monthly-level data on alerts and fines within an event study framework, I demonstrate that the probability of enforcement action increases significantly in the few months following an alert. These results show that the enforcement agency targets some enforcement actions based on deforestation alerts. However, approximately half of the additional probability comes from anticipating fines that would likely happen in later periods. Overall, the net effect of alerts on the probability of inspection, conditional on deforestation, is an increase of approximately one percentage point over a baseline probability of 12 percent. This exercise decomposes the probability of inspection into targeted (i.e., alert-driven) and non-targeted inspections, showing that the monitoring tool only marginally increases the risk of penalizing offenders. The impact of alerts is greater in areas with lower expected levels of deforestation, where deforestation alerts are likely to provide more additional or surprising information to the enforcement agency.

Next, I estimate the deterrence effects of inspections on the incidence of deforestation. To estimate the general deterrence effect, I use variation in detection quality as an instrumental variable for the inspection probability. The instrumental variable approach isolates technological variation in monitoring quality by exploiting the variation of detection probability net of terrain characteristics, precipitation, and deforestation size. Such technological variation affects the probability of detection, and therefore the probability of enforcement, providing a quasi-experimental variation on enforcement action. To estimate specific deterrence, I employ an event study approach to assess the impact of enforcement actions on deforestation over time at the grid cell-year level. The findings indicate that a one percent increase in inspection probability saves between 140 and 300 square kilometers of forest or 2-4% of the average yearly deforestation in 2011-2020. Under the more conservative estimate (i.e., 140 square kilometers), the general and specific deterrence effects have roughly equal contributions.

Finally, I use budget data from the enforcement agency at the state-year level to estimate the relative cost of targeted versus non-targeted inspections. The evidence suggests that non-targeted fines cost, on average, approximately 60% more than targeted fines, likely reflecting the fact that non-targeted inspections often yield no fine. This estimate enables me to calculate the number of non-targeted inspections that could occur if the monitoring system were to shut down. Considering this counterfactual, the impact of monitoring by DETER on enforcement probability is likely half a percentage point, and therefore, the deterrence value is even lower than the 2-4% reduced deforestation mentioned above.

Taken together, the findings show that while real-time satellite monitoring improves the targeting and cost-efficiency of enforcement, its effect on overall deforestation is modest. The main constraint is not the quality of monitoring, but the limited responsiveness of enforcement behavior. These results suggest that improving compliance may require not only better information, but stronger institutional capacity to act on it. More broadly, the paper sheds light on the conditions under which monitoring technologies translate into deterrence—and the limits of information-based enforcement in settings with weak state capacity.

Launched in 2004, DETER is widely cited as a breakthrough in Brazilian environmental enforcement, having contributed to the 80% decrease in deforestation rates observed from 2004 to 2012. However, alongside DETER, the federal government enacted several other policies to combat deforestation as part of a program called PPCDAm, including inter-agency collaboration, increased enforcement capacity, and revised penalties. Later updates of PPCDAm included the "priority municipalities" program, which enhanced environmental enforcement in select municipalities.

This paper builds directly on recent evidence that satellite monitoring combined with law enforcement can reduce Amazon deforestation (Assunção, Gandour, and Rocha 2022). While that work showed at the municipal level that greater enforcement causally reduces deforestation, it left open two fundamental questions: does real-time monitoring actually guide enforcement behavior, and how much deterrence does this generate on the ground? I address these questions by combining high-resolution deforestation maps, geo-referenced fines, and real-time alerts in a 4 km × 4 km monthly panel from 2011–2020. This granular approach allows me to decompose enforcement into alert-driven ("targeted") and other ("non-targeted") actions, and to separately identify general and specific deterrence effects. I find that alerts increase the probability of inspection by only about one percentage point over a 12% baseline, leading to a modest 2–4% annual reduction in deforestation. These results reveal that most enforcement remains independent of alerts and that the binding constraint is not the quality of monitoring, but the limited institutional capacity to act upon it. Thus, the contribution of this paper is to show that monitoring technologies, while improving cost-effectiveness, cannot substitute for strong state capacity in achieving large-scale deterrence.

Besides its convenient features for studying law enforcement, tropical deforestation is itself a problem of paramount importance in environmental policy. More than 12% of global greenhouse gas emissions stem from forest destruction (IPCC 2014), mainly because of biomass decomposition and forest fires. In addition, deforestation destroys biodiversity (Fearnside 2021), disturbs regional rain patterns (Leite-Filho et al. 2021, Araujo 2023), and pollutes the local air via deforestation-related fires (see Ferreira 2023 for a survey). While deforestation causes collective and diffuse harm, individual farmers reap private benefits from the agricultural exploitation of deforested areas. From an economic perspective, the externalities generated by deforestation justify governmental actions, such as forest protection policies. Nevertheless, enforcing these policies over vast forest areas can be daunting for enforcement agencies with limited resources and scarce information about offenders' actions.

One way to obtain systematic information about deforestation is by using satellite imagery. Thanks to high-resolution satellite images, deforestation worldwide can be computed accurately. For decades, several research endeavors have mapped deforestation worldwide using 30-m resolution data from Landsat satellites (see Hansen et al. 2013). However, processing and interpreting high-resolution images is computationally intensive and may take several months to conclude (INPE 2019a), making it unsuited for day-to-day decisions about enforcement deployment. Quicker alert-generating instruments based on lower-resolution images prove to be a more effective approach for enforcement purposes. The availability of (quasi-)real-time deforestation alerts can transform the decision-making process of enforcement agencies, allowing them to react quickly and effectively to detected offenses.

This paper contributes to several strands of literature. First, it adds to a growing body of work on the role of monitoring and enforcement in regulatory compliance. Prior studies have shown that satellite-based monitoring programs improve compliance with air pollution standards (Greenstone et al. 2020, Zou 2021), and reduce deforestation (Moffette et al. 2021). Monitoring tools can also improve attendance of school teachers (Duflo, Hanna, and Ryan 2012), deter urban crime (Priks 2015), reduce election fraud (Callen and Long 2015, Enikolopov et al. 2013), and enhance tax compliance through the use of third party data (e.g., Kleven et al. 2011, Pomeranz 2015, and Naritomi 2019). However, most of these studies examine whether monitoring improves compliance, not whether it changes enforcement behavior, one exception being the study of monitoring of absenteeism on audit probability by Callen et al. (2020). I directly study how an agency incorporates monitoring into inspection decisions and how that behavior, in turn, affects compliance.

Second, the paper speaks to the inspection targeting literature, which has a long history in the theoretical enforcement literature (see Andreoni, Erard, and Feinstein 1998). Recent work has begun to explore the value of discretion rules in inspection allocation (e.g., Duflo et al. (2018), Kang and Silveira (2021), Bachas et al. (2021), and Blundell, Gowrisankaran, and Langer (2020)). My analysis offers a new perspective by empirically decomposing enforcement into monitoring-driven ("targeted") and other ("non-targeted") actions data from a large-scale environmental program.

Third, I contribute to the crime and deterrence literature by estimating both general deterrence—how inspection probabilities influence behavior—and specific deterrence—how past enforcement affects future compliance. While both concepts are well established (Becker 1968; Kessler and Levitt 1999; Chalfin and McCrary 2017), most studies estimate only one of these two behavioral effects. The effects of enforcement probability on behavior have been estimated in urban crime (Levitt 1997, McCrary 2002), environmental (Chan and Zhou 2021) and tax settings (Almunia and Lopez-Rodriguez 2018, De Neve et al. 2021). Specific deterrence has been studied in the context of imprisonment and criminal behavior (Kessler and Levitt 1999, Kuziemko and Levitt 2004), as well as in environmental (Dusek and Traxler 2021), and in tax settings (Advani, Elming, and Shaw 2018). I provide a unified empirical framework that identifies and compares both margins using spatially and temporally fine-grained data.

Finally, this paper contributes to a growing body of literature that seeks to understand the role of enforcing command and control policies in combating tropical deforestation. Assunção, Gandour, and Rocha (2022), Vieira, Dahis, and Assunção (2023), and Assunção, Gandour, and Souza-Rodrigues (2019) employ different empirical strategies to investigate how enforcement intensity affects deforestation and forest regeneration. In a similar vein, Assunção and Rocha 2019 and Assunção et al. 2023 evaluate the impact of enforcement on deforestation through the "priority municipalities" program. In contrast to previous literature, this paper is the first to systematically utilize geo-referenced fines, deforestation alerts, and high-resolution maps of deforestation to examine patterns of enforcement and deforestation at a granular geographical level.

The paper proceeds as follows: Section 2 describes the institutional context, Section 3 describes the data, Section 4 discusses the conceptual framework, Section 5 explains the methods, Section 6 presents the results, and Section 7 discusses the benefits of targeting. Section 8 concludes.

2 Background: deforestation in the Amazon forest

The Brazilian Amazon is the world's largest rainforest, with 4 million square kilometers.[1] As a rich repository for biodiversity, a regulator of local rain seasons, and the carbon concentration in the atmosphere, the forest provides vital local and global environmental services. Starting in the late 1980s, awareness about the environmental risks related to the destruction of the forest led to protective legislative action, investments in enforcement activity, and monitoring programs based on satellite data. The 2000s saw several policies centered on monitoring technologies, enforcement capacity, and punishment of offenders (for a historical

[1] The total area of the forest is 6 million square kilometers. Besides Brazil, it spreads over Bolivia, Peru, Ecuador, Colombia, Venezuela, Suriname, Guyana, and French Guyana.

overview, see Souza-Rodrigues 2014, Nepstad et al. 2014, Assunção, Gandour, Rocha, et al. 2015, Ferreira 2023). In 2004, the introduction of the satellite-monitoring system called "DETER" represented a breakthrough in the ability to inspect areas using real-time data on deforestation. DETER is the main source of deforestation alerts in this study, and I discuss it in more detail below. Other relevant initiatives that may have collaborated in reducing deforestation were the Soy Moratorium (Nepstad et al. 2009) and the policy of prioritizing municipalities for enforcement action (Assunção and Rocha 2019, Assunção et al. 2023). By 2023, deforestation has destroyed approximately 23% of the primary forest in the Brazilian Amazon, although approximately 20% of this area has regenerated as secondary vegetation. The accumulated deforestation in the Brazilian Amazon is also much larger than deforestation in the other Amazon countries. For example, accumulated deforestation in Colombia, Peru, Ecuador, and Bolivia, is around 10%, whereas deforestation in Venezuela, Guyana, Suriname, and French Guyana is less than 5% (see Ferreira 2023 for a description of deforestation in other Amazon countries).

2.1 The process of deforestation

Deforestation is the complete clearing of vegetation from an area. Farmers clear forests to convert the land into agriculture or pasture, with timbering or mining as drivers of small-scale deforestation. While historically soybean culture has been the main driver of deforestation, since the mid-2000s, around 80% of deforested areas were converted to pasture for cattle grazing (Nepstad et al. 2009, Nepstad et al. 2014). Conversion of forest to agriculture or pasture is illegal in the Brazilian Amazon forest for environmental protection reasons. Therefore, the economic rationale for deforestation relies heavily on getting away with illegal deforestation, via lack of enforcement action, unclear property rights, and amnesties.

Deforestation occurs in three steps: selective logging, clearing vegetation, and cleaning remaining biomass (INPE 2019a). During selective logging, farmers selectively cut valuable types of timber.[2] After extracting valuable timber, farmers clear trees and other vegetation using mechanized logging and fire. Farmers set fires in forest borders, letting it spread to the forest and damaging the vegetation. Damaged vegetation is easier to clear subsequently via logging activities. The third step usually consists in burning the remaining biomass, which is a technique to fertilize the soil with nutrient-rich ashes (Nepstad et al. 1999).[3]

2.2 Enforcement by IBAMA and PPCDAm

Deforestation is practically banned in the Brazilian Amazon, except for some particular circumstances. Roughly 50% of the Amazonian territory is explicitly designated as Indigenous territory or conservation units, where deforestation is banned. At least 13% consists of public forests (also called "undesignated" public forests), where it is also forbidden to deforest. The remaining areas are privately owned rural properties and are mandated to preserve 80% of their area as forest as "Legal Reserve" under the Brazilian Forest Code. Only 2% to 4% of deforestation was legal in 2020, according to estimates by Azevedo et al. (2020)

[2]In the Brazilian Amazon forest, some valuable types of wood are *ipê*, *jacarandá*, and *mogno*.

[3]The practice of destroying and then burning vegetation is known as *slash-and-burn*.

and Valdiones et al. (2021). The main legal instruments regulating deforestation in Brazil are the Criminal Environmental Law of 1998, the Forest Code of 2012, and a Presidential Decree of 2008. Penalties for farmers caught committing deforestation include high fines (about 1 thousand USD per hectare), seizure of equipment and goods, an economic embargo on the deforested land, and even imprisonment.

The federal enforcement agency, IBAMA, is the government body in charge of environmental law enforcement in the Amazon forest. Municipal and state authorities may play a subsidiary role in environmental law enforcement. Fighting deforestation is IBAMA's main activity in the Amazon region. In the decade from 2011 to 2020, IBAMA fined 23 thousand deforestation infractions, out of a total of 75 thousand environmental fines imposed by IBAMA in the Amazon region. IBAMA has access to real-time monitoring information on fires and logging and uses it to deploy enforcement personnel on the ground. There are 30 IBAMA units in the Amazon forest, from where enforcement agents leave to perform law enforcement field operations. Operations sometimes require the use of helicopters, as well as support from state police.

An important landmark in the history of environmental enforcement in the Brazilian Amazon was the "PPCDAm Plan," a federal government task force launched in 2004 to reduce illegal deforestation. One of the most noticeable features of the PPCDAm was the creation of a monitoring system with the production of real-time alerts based on satellite images. However, PPCDAm was a general push to tighten enforcement and reduce deforestation, and included an increase in budget resources for IBAMA, and myriad related policies. Primary deforestation abated in the years following the launching of PPCDAm, and reached in 2012 its lowest levels in more than 20 years. For its apparent success, PPCDAm also sparked an active research agenda to understand the impact of its individual policies to fight deforestation, such as the tightening of rural credit to non-compliant farmers (Assunção et al. 2020), the prioritization of "blacklisted municipalities" (Assunção et al. 2023), and the impact of fines on deforestation (Assunção, Gandour, and Rocha 2022).

2.3 Satellite systems

Satellite systems are used to *measure* and *monitor* deforestation in the Brazilian Amazon. The *measurement* of deforestation takes place once a year (see INPE 2019b for a technical description). Using images at a 30m x 30m resolution, the Brazilian National Institute for Spatial Research (INPE) categorizes the land cover entire territory of the Amazon forest as native forest, deforestation, water bodies, or clouds. This system is the source of the official measurement of yearly deforestation in Brazil. The measurement takes place once a year at the end of July, which is when clouds are very dispersed, maximizing visibility. Processing the data takes six to eight months to be concluded (INPE 2008). The result is a complete map of the Amazon forest with the land cover corresponding to late July. The yearly measurement is not a suited for real-time monitoring, since it only measures deforestation once a year and takes several months to be published.

The main tool for monitoring deforestation in the Amazon is the system DETER. Launched in 2004, DETER sends daily deforestation alerts to the enforcement agency. The monitoring program DETER produces deforestation alerts based on rapid degradation of forest ceilings. Degradation can be the result of fires, but the deforestation alerts do not capture active fires. In practice, it captures situations of natural forest degradation, fire-induced degradation, and also active logging of the forest. DETER has been a major breakthrough in law enforcement in the Brazilian Amazon, but its ability to detect deforestation with deforestation alerts was relatively low in the early years, with a large number of false positives.

The sample period used in this paper is the decade from 2011 to 2020. During this period, the program progressed substantially in its capacity to flag deforestation areas correctly in real time. Figure 1 shows the probabilities of detecting in real-time the deforestation polygons measured by PRODES, for different years and deciles of polygon size. The figure illustrates that DETER is consistently better at detecting large polygons, and that for any given size, the detection probability increased over time. In 2015, DETER started integrating higher-resolution satellite data, and DETER-B became fully operational in 2017. The improvement in detection of smaller polygons is visible in Figure 1.[4]

The monitoring system DETER has the same methodology as the yearly measurement system PRODES (INPE 2019a), but uses higher-frequency, lower resolution images. The production of alerts is made by technicians at the National Institute for Spatial Research, and is not automated. The technicians use computers to exclude areas covered by clouds and areas that were already previously deforested, based on the measurement system PRODES. From this stage, the technicians monitor the images of the whole Amazon, aided by estimates of land cover at each pixel done via a Linear Spectral Mixing Model (Diniz et al. 2015). These technicians are independent from the enforcement agency.

3 Data

The three main datasets used in the analysis are the following: i) the yearly deforestation maps from the PRODES system, ii) the monthly maps of deforestation alerts from the monitoring system DETER, and iii) the geo-referenced deforestation fines from IBAMA. The yearly deforestation maps measure the realized amount of illegal deforestation obtained only months after deforestation is concluded, the deforestation alerts measure the real-time information available to the enforcement agency, and the fines reflect the penalties imposed via a field inspection.[5]

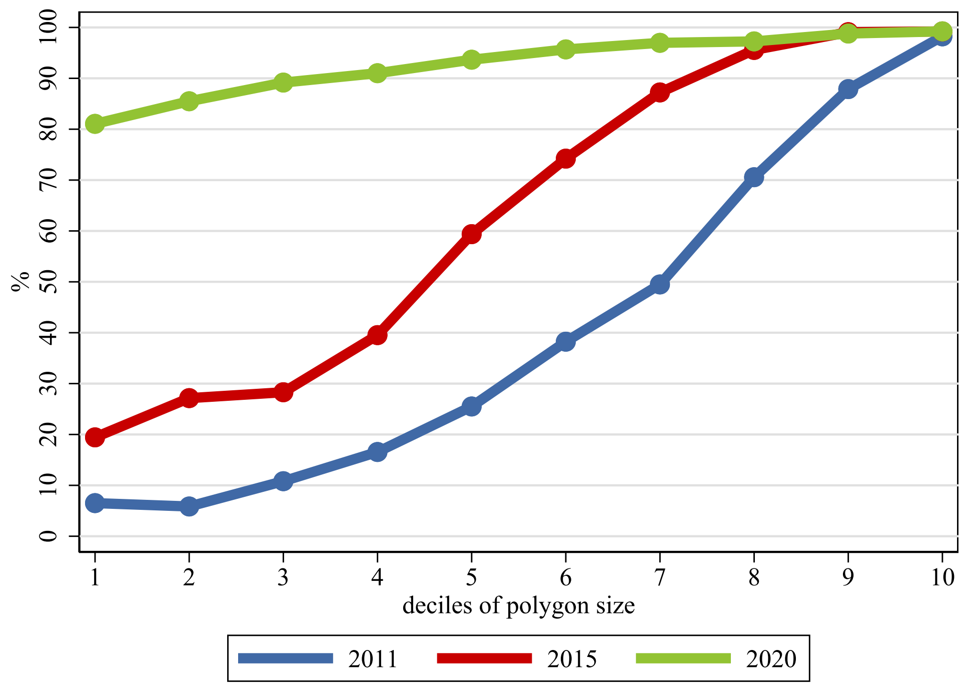
I restrict the dataset to fines related to deforestation of primary forest using a string search on the description of the fines typed by inspectors. Since 2011, nearly all the deforestation-related fines possess geographic coordinates, which allows a more precise analysis enforcement action relative to previous studies, which mainly aggregate fines at the municipality level. For this reason, the time span of the study includes data from 2011 to 2020.

To overlay the maps of deforestation, deforestation alerts, and fines, in the whole Amazon forest, I used the 30m raster of deforestation from PRODES and aggregated it at the level of a 4 km cell-sized grid. The

[4]DETER initially based on 250m-resolution images from the satellite Terra, and since 2017, DETER-B started using 60m-resolution images from the satellites CBERS-4 and IRS. Terra is a NASA satellite, CBERS-4 is a Chinese-Brazilian satellite and IRS stands for Indian Remote Sensing Satellite. DETER-B also started distinguishing alerts for different types of events on the ground, such as forest degradation, mining, selective logging, and burned areas.

[5]In the Appendix, I provide examples of these datasets in the set of Figures A.1a to A.1c. To produce these figures, I took an area of approximately 30 thousand square kilometers, corresponding to a "scene" of the Landsat satellite, in the northern state of Pará in the year 2016.

Figure 1: Probability of Real-Time Alerts by Size of Deforestation Polygon



Note: This graph describes the evolution of the real-time monitoring quality of DETER over time, for different sizes of deforestation polygons measured by PRODES every year. Based on the history of unique polygons of PRODES from 2011-2020, deciles by polygon size were constructed. The figure depicts the share (in percentages) of polygons that overlapped with an alert in the respective year of deforestation, and within each decile. The figure shows the evolution of detection ability for each decile over the years 2011, 2015, and 2020. NB: In 2017, DETER was restructured to incorporate satellite imagery of much higher resolution, and was renamed as DETER-B.

DETER alerts are polygons, and I rasterize them at the 4 km grid level. Finally, I assign the deforestation fines to the nearest grid cell centroid based on the fines' coordinates.

These three datasets are crucial to study the role of monitoring information to shape enforcement and deterrence. The high-resolution yearly mapping of deforestation corresponds to the "true" incidence of offenses, enabling the separation from offense and monitoring alerts. Moreover, inferring inspections from fines can be problematic because inspections yield no fine and are not observed in that dataset. However, among areas with positive deforestation, the absence of fines is likely to truly indicate absence of enforcement action. Therefore, the complete mapping of deforestation allows me to interpret variation within grid cells with positive deforestation as variation in inspections. Most of the analysis is done conditional on grid cells with positive deforestation at least once in the 2011-2020 period, as measured by PRODES. Summary statistics by year for the main variables are displayed in Table A.1 for cells with at least one year of positive deforestation, and in Table A.2 for cells with positive deforestation per year.

I also added the following set of geographic characteristics at the level of grid cell: the municipality, land tenure status (private property, Indigenous land, conservation unit. public forests, and land reform settlements), soil suitability for soy, cassava, and cacao (from FAO), caloric suitability (Özak 2015), altitude and terrain ruggedness, presence of water bodies, presence of state and federal roads, distance to the city of Cuiabá, and distance from the nearest IBAMA office. These variables are fixed at the cell level.

Finally, I compute the share of accumulated deforestation at the cell level based on PRODES, cloud coverage from DETER, and monthly precipitation (i.e., rainfall), all of which vary at the cell-year level. Cloud data from DETER is only available until 2017 and used in robustness analysis only, as explained below. More details on the datasets are given in the Appendix A.

4 Conceptual framework

The enforcement problem illustrated in this paper is whether to target enforcement action based on monitoring information. A targeted strategy means that the enforcement agency acts upon a signal sent by the monitoring system. If the monitoring system does not produce many false positives, a targeted strategy provides a cost-effective way to find and sanction offenders. In contrast, a non-targeted strategy means that enforcement action is random or based on diffuse sources of information. The non-targeted approach tends to be more expensive in the sense that some enforcement actions yield no deterrence and no sanctions. In general, conditioning action on meaningful signals is a cost-effective strategy that maximizes pressure on offenders for a given budget, thus maximizing deterrence.

In the following sections, I empirically decompose the enforcement agency's action against deforestation in Brazil into "targeted" and "non-targeted" and study the heterogeneity of the share of "targeted" inspections. This exercise allows me to tease out how important monitoring is to determine enforcement action in the Brazilian Amazon. In the Appendix, I discuss some theoretical reasons why an enforcement agency may not find it optimal to target enforcement fully even if targeted inspections are cheaper.[6]

The next part of the study, which studies the deterrence effects, requires a framework to integrate general and specific deterrence effects. As mentioned earlier, there are two conceptually different effects of enforcement: the effect of increased punishment probability (general deterrence), and the effect of punishment itself on subsequent behavior (specific deterrence). I propose the following simple framework, in which π denotes the probability of (targeted) inspections conditional on a real-time alert at a particular location, and f denote the history of past fines at that location. The amount of deforestation chosen by agents at that location is $d(\pi, f)$. The aggregated amount of deforestation in the Amazon in a period t is denoted:

$$D(\pi_t, f_t) = p(d_t)\bar{d}_t \tag{1}$$

where $p(d_t) \equiv \mathbb{P}(d_t > 0)$ is the extensive margin of this problem, denoting the number of areas that

[6]In the Appendix, I demonstrate that even though targeted inspections are cheaper, an agency may choose to conduct non-targeted inspections in equilibrium if it prioritizes "catching" offenders. This objective is compatible with the existence of specific deterrence effects, which only materialize when offenders are punished. This argument is developed in a simple static model with discrete actions between an agency and an offender in Appendix B, and in a two-period model with continuous actions in Appendix C. In both cases, the agency faces a trade-off from targeting: on the one hand, it is cheaper and allows for more deterrence; on the other hand, more deterrence means that it is harder to catch offenders using monitoring.

choose to have positive deforestation and thus become eligible for punishments, and $\bar{d}_t \equiv \mathbb{E}[d_t | d_t > 0]$ is the intensive margin, expressed in the mean deforestation area in areas with positive deforestation.[7] Over T periods of time, accumulated deforestation is denoted by $\sum_t^T D(\pi_t, f_t)$.

A marginal increase in π_t in one single period generates general deterrence effects in period t and specific deterrence effects in future periods, as follows:

$$\frac{\partial \sum_t^T D(\pi_t, f_t)}{\partial \pi_t} = \underbrace{\frac{\partial p(d_t)}{\partial \pi_t}\bar{d}_t + p(d_t)\frac{\partial \bar{d}_t}{\partial \pi_t}}_{\text{A: general deterrence}} + \underbrace{\left(d\pi_t p(d_t) + \pi_t \frac{\partial p(d_t)}{\partial \pi_t}\right)}_{\text{B: } \Delta \text{ number fines}} \underbrace{\sum_t^T \frac{\partial \bar{d}_t}{\partial f_t}}_{\text{C: sp. deterrence}} \tag{2}$$

The general deterrence effects contain the impact of π_t on the extensive and intensive margins, which could be estimated from the data using exogenous variation in π_t. The specific deterrence effect reflects the impact of π_t on the number of fined areas times the impact on future average deforestation, which can potentially last for several years.

The goal of the following sections is twofold. First, I decompose the policy rule chosen by IBAMA in terms of targeted (by alerts) and non-targeted inspections and estimate the impact of the alerts system on the overall probability of inspections. Then, I estimate the general and specific deterrence effects, feeding the estimates into the formula given by Equation 2. This exercise provides a fairly complete assessment of the impact of the monitoring system on the incidence of offenses.

5 Methods

5.1 Impact of Alerts on Enforcement

In this section, I empirically study the effect of the real-time monitoring system for Amazon deforestation on the actions of the Brazilian environmental enforcement agency, aiming to decompose the share of enforcement action caused by the monitoring information, as opposed to actions that occur regardless of monitoring. I assume the enforcement agency can sanction offenders without real-time alerts, but they would not have real-time information on the offenders' actions. In practice, the agency can fine offenders at the early stages of deforestation, when the alert system could not produce alerts, or at later stages, when deforestation is likely larger than at the point of alert. As argued in the previous section, it is reasonable to expect that credible monitoring signals affect enforcement action (targeting), but there are reasons to expect that the agency does not fully target its inspections.

The empirical approach to this decomposition is summarized as follows. The probability of sanctioning offenders without alerts, or "baseline probability," depends on the location and follows a different seasonality from the alerts' incidence. The agency's reaction to real-time information would provide an empirical signature in the form of short-term deviations from the seasonal trend in enforcement action. I interpret this deviation as the causal effect of the alert.

[7] The history of fines f_t is a vector of binary variables denoting the past incidence of fines $f_t = \{f_{t-1}, f_{t-2}, ...\}$.

The analysis uses finely geo-referenced data on fines and deforestation alerts at the monthly level in a 4km x 4km grid. Although the object of interest is enforcement action, or inspections, I only observe the incidence of fines, which is trivially equal to zero in grid cells containing no infractions. Therefore, I restrict the sample to grid cells with positive levels of deforestation, that is "non-compliant cells." Restricting the data allows me to interpret the variation in fines as a variation in inspection efforts. In other words, among cells with deforestation, I can interpret the absence of fines as absence of inspections.[8]

I describe how the overall yearly probability of inspection rises in non-compliant areas when the monitoring system produces deforestation alerts. Next, using an event study approach, I use monthly data to estimate the causal impact of alerts on enforcement action probability. The probability of inspections conditional on positive deforestation is decomposed as follows, using the Law of Total Probability:

$$\mathbb{P}(\text{inspection}) = \underbrace{\mathbb{P}(\text{inspection}|\text{no alert})\mathbb{P}(\text{no alert})}_{\textbf{probability without alerts}} + \underbrace{\mathbb{P}(\text{inspection}|\text{alert})\mathbb{P}(\text{alert})}_{\textbf{probability with alerts}}$$

Using year-cell data, I interpret that an inspection occurs when the cell has a positive number of deforestation fines in the year. Similarly, the cell has an alert if at least one alert is emitted for that cell during the year. The unconditional probability of an inspection in 2011-2020 was approximately 12%, the probability of an inspection conditional on no alert (but still positive deforestation) was 9%, and the probability conditional on an alert was 22.4%. Approximately 30% of cells with positive deforestation received an alert during the period. Notice, however, that cells with alerts tended to have much larger deforestation areas, so the incidence of alerts is highly dependent on the underlying sizes of deforested areas within a grid cell.[9]

I further decompose the probability of an inspection conditional on alert as a baseline level of fines, denoted $\mathbb{P}(\text{inspection}(0)|\text{alert})$, plus the effect of alerts, which is the average treatment effect on treated cells, denoted ATT:

$$\mathbb{P}(\text{inspection}|\text{alert}) = \underbrace{\mathbb{P}(\text{inspection}(0)|\text{alert})}_{\textbf{baseline/counterfactual probability}} + ATT \tag{3}$$

This decomposition allows us to understand how much of the overall enforcement action can be attributed to the alerts. These fines are "additional" to the baseline inspections, which would have occurred regardless of the alerts. As already mentioned, the main assumption underlying this exercise is that the unique feature of the alerts is the timing of the information.

[8] Formally, the probability of a fine in any given cell i and period t is $\mathbb{P}(\text{fine}) \equiv \mathbb{P}(\text{inspection \& deforestation}) = \mathbb{P}(\text{inspection}|\text{deforestation})\mathbb{P}(\text{deforestation})$. Using data on fines to infer enforcement action, compliant areas (i.e., areas with zero deforestation) become useless to understand the behavior of the enforcement agency, since fines are trivially equal to zero in these areas. By interpreting that the absence of fines in non-compliant cells indicates absence of inspection, this approach implicitly rules out corrupt behavior.

[9] In principle, deforestation can be punished in later years. However, more than 80% of deforestation fines by IBAMA happen in areas with positive new levels of deforestation in the same year. Within a grid cell with deforestation there can be several fines in different months, possibly due to multiple offenders operating within the same cell in the same period. As noted, the 12% figure refers to the share of cells with deforestation that received at least one fine.

In this setting, the incidence of an alert is a "treatment," and the outcome is a fine, which reflects an inspection. I assume the underlying trend in fine probabilities among treated cells can be retrieved from untreated cells (i.e., cells with deforestation but no alert) and not-yet-treated cells. Under this parallel trends assumption and the assumption that the exact timing of alerts is uncorrelated with other sources of information, the deviations from the trend of fine probability identify the causal effect of alerts.

The analysis takes the form of an event study at the month-cell level, reflected in the following regression:

$$P(\text{inspection})_{it} = \sum_{\ell=-6,\ell\neq-1}^{12} \beta_\ell \mathbb{1}\{t - e_i = \ell\} + \delta_t + FE_i + \varepsilon_{it} \tag{4}$$

where each observation is a cell i in period t (month-year), and ε_{it} is a conditional mean zero error term. In the expression, e_i is the month of the alert event within cell i. $\mathbb{1}\{t - e_i = \ell\}$ is an indicator function that takes value 1 when the period t is ℓ months distant from the event date e_i. The set of all $\mathbb{1}\{t - e_i = \ell\}$ is a matrix containing binary vectors that refer to the lags and leads relative to the alert date.

There are several cases of alerts and fines that happen consecutively over two or more months for the same cell. The empirical exercise only considers as an "event" an alert that has not been preceded by another alert for at least five months. Moreover, the inspection outcome is a fine not preceded by another fine for twelve months so that the effects can be interpreted as the probability of an inspection within a year. This restriction also makes it easier to convert the results of the month-level analysis into a year-level analysis.

To estimate equation 4, I stack each event containing four months before the alert, the month of the alert, and twelve months after the alert, in similar way as in the study of minimum wage laws by Cengiz et al. (2019). This procedure allows me to duplicate observations that are useful for the estimation of different events, for example when single grid cell has alerts separated by ten or twelve months. Finally, I also include in the dataset the observations of grid cells that had no alerts despite having positive deforestation. Equation 4 is a two-way fixed effects model, and estimation by OLS yields a differences in differences estimator for the coefficients β_ℓ. The standard errors are multi-way clustered in four grids of 1^o (approximately 110 km) around each cell as in Barsanetti and Ferreira (2025), thus allowing for different degrees of geographic and time autocorrelations of the unobserved error term.

The OLS estimator of the two-way fixed effects model identifies the ATT under the assumptions of parallel trends and no anticipation of treatment. However, in this setting, given that the treatment occurs in different moments across events (i.e., the treatment is "staggered"), the OLS estimator may provide biased estimators of the ATT in the presence of heterogeneous treatment effects, as highlighted by a recent literature (Wooldridge 2021, Borusyak, Jaravel, and Spiess 2024). In the results section, I include robustness analyses using imputation method proposed by Borusyak, Jaravel, and Spiess 2024 and Wooldridge 2021, henceforth JW/JBS. Other robustness analyses are introduced together with the results.

5.2 Estimating General Deterrence

The general deterrence effect is the effect of inspection probability on deforestation. As before, I use data on fines to estimate the inspection probability at a cell-year level, using only cells with positive deforestation.

This analysis is performed at the cell-year level.

Although inspection probability can be inferred from the data on realization of fines, the correlation between fines and deforestation is unlikely to reflect a causal relationship because of endogeneity issues. As is typically the case in contexts of illegal behavior (see, for example, Levitt 1997), enforcement efforts tend to be more intense in areas with a higher incidence of offenses because the enforcement agency has prior knowledge about offense hotspots and deploys efforts accordingly.

To estimate the causal effect of inspection probability on deforestation, I use the variation in monitoring quality of the system DETER as an instrumental variable for fines. As mentioned in the Background section, DETER's detection probability has increased consistently over time and varies across space. DETER's ability to detect deforestation polygons in quasi-real time varies according to terrain characteristics, sunlight, and technology. Such variation in detection probability is orthogonal to determinants of deforestation, such as costs, prices, and market access. Therefore, visibility or technology-related changes in DETER's ability to detect deforestation polygons provide quasi-experimental variation for fine probability, identifying the general deterrence effect.

Computing quasi-real-time detection probability is possible by overlaying polygons of deforestation from PRODES with DETER alerts. This implies that detection probability can only be computed near areas with positive deforestation, as measured by PRODES, limiting the geographic scope of the analysis. Moreover, to ensure that the detection measure satisfied the exclusion restriction, one must abstract from features that affect detection while being related to deforestation decisions: the size of the deforestation area (i.e., larger polygons are mechanically easier to detect) and terrain characteristics, both fixed and changing (the area of forest and precipitation).

To ensure maximum coverage of the measure of detection probability in the dataset, I measure detection probability as the share of detected deforestation polygons within a distance of 80km from each grid cell, comparing polygons of PRODES (yearly measurement) and DETER (real time monitoring). To shut down the aforementioned confounding factors, I restrict the measurement to polygons of sizes between 0.09 to 0.1 hectare, which is the interval with the highest density of deforestation polygons. To control for other confounding characteristics that may affect detection and deforestation, in the empirical analysis I control for cell fixed effects and cell-year measures of precipitation and accumulated deforestation. I test the robustness of the results to alternative definitions of detection probability, by computing it within a smaller radius and using a Gaussian kernel.

In summary, the technological aspect of monitoring quality is obtained by i) calculating the detection probability for a fixed size of deforestation polygons, and ii) controlling for grid cell fixed effects, accumulated deforestation, and precipitation in each grid cell-year. By abstracting from variations in polygon size, terrain characteristics, and weather patterns, this variation likely fulfills the assumptions of exogeneity and exclusion restriction needed for identification.

The model is estimated with Two-Stage-Least-Squares using only areas with positive deforestation in the period 2011-2020. The standard errors are multi-way clustered in four grids of 1^o (approximately 110 km) rotated around each grid cell. The two stages are described in equation 5:

$$
\begin{aligned}
y_{it} &= \beta_0 + \beta_1 \pi_{it} + \beta_x X_{it} + \gamma_i + \delta_t + \epsilon_{it} \\
\pi_{it} &= \alpha_0 + \alpha_1 Z_{it} + \alpha_x X_{it} + \theta_i + \eta_t + \varepsilon_{it}
\end{aligned}
\tag{5}
$$

where y_{it} is the outcome (deforestation in hectares or a binary variable indicating positive deforestation) computed in grid cell i and year t, π_{it} is the probability of an inspection conditional on positive deforestation, X_{it} is a vector of the two relevant varying controls described above (accumulated deforestation and precipitation), Z_{it} is the probability of detecting a small polygon within a 80 km radius, γ_i and θ_i are grid cell fixed effects, δ_t and η_t are year fixed effects, and ϵ_{it} and ε_{it} are independently distributed error terms.

The equation relating π_{it} to Z_{it} is the first stage, estimated using a binary outcome denoting that the cell had a deforestation fine in a particular year. The fitted values are then used in the second stage, which is the structural equation relating the outcome y_{it} to π_{it}. The estimation of the intensive margin is straightforward, as it only includes grid cells with positive deforestation. However, estimating the extensive margin, where the outcome is the probability of positive deforestation, requires extrapolating the first stage to a broader set of observations that were not used in the estimation of the first stage. I use the coefficients estimated in the first stage, including the fixed effects, to predict π_{it} for observations that had zero deforestation but had positive deforestation at some point during the 2011-2020 period.

5.3 Estimating Specific Deterrence

The specific deterrence effect is the effect of punishment on the subsequent behavior of farmers. It affects a smaller number of farmers than the general deterrence effect, which is the effect of punishment probability. To identify the causal effect of inspections on deforestation over time, I use an event study approach like the one used to estimate the effect of alerts on enforcement action. Here, the event is a deforestation fine and the outcome is deforestation measured by PRODES, and the observation level is a grid cell-year. I use grid cells with positive levels of deforestation at some point in the 2011-2020 period, thus including some observations with zero deforestation in some years. I estimate the equation below using OLS:

$$
y_{it} = \sum_{\ell=-3}^{5} \beta_\ell \mathbb{1}\{t - e_i = \ell\} + \delta_t + FE_i + \varepsilon_{it} \tag{6}
$$

where y_{it} is the outcome in cell i and year t.

This expression is a two-way fixed effects model like the one in Equation 4. As discussed when explaining the event study for enforcement action, the coefficients β_ℓ estimated by OLS is difference-in-differences estimator, which estimates the ATT under the assumptions of parallel trends and no anticipation. However, given the staggered nature of the treatment, this estimator may be biased in the presence of heterogeneous treatment effects. Like in the previous event study at the cell-month level, I show the OLS results and present the estimated coefficients according to the imputation method by JW/BJS as a robustness test.

6 Results

6.1 Impact of Monitoring Alerts on Enforcement Action

The first set of results explains how the monitoring alerts affect the behavior of the enforcement agency. Figure 2a describes the data, depicting the mean probability of a fine in each month around an alert (solid line) and counterfactual observations constructed with weighted means of not-yet-treated and untreated (i.e., no alert) grid cells (dashed lines). As explained earlier, I only consider the earliest fine within 12 months. The constructed counterfactuals are weighted as the means of the probability of a fine using the distribution of time periods (months and years) for the relative periods of the treated group. This descriptive graph shows that among treated grid cells, every month's baseline probability of a fine is around 1.3% and increases in the first few months following an alert. The probability of a fine among never-treated cells is very low, likely because these cells have small deforestation areas.

Figure 2b shows the OLS results for the two-way fixed effects model with stacked events, where each point is an estimated coefficient and the dashed lines show the 95% confidence intervals. As suggested by the descriptive figure just above it, this figure shows a strong and immediate effect of alerts on the probability of a fine in the cell where the alert occurs. As soon as the alert appears, the cells with the alert become immediately one percentage point more likely to receive an inspection, and then two points more likely in the two months after the alert. However, coefficients between the fifth and the tenth months are negative, suggesting that the alert's effect is to anticipate fines that would have occurred later. The effects completely disappear by the eleventh month after the alert.

The average net effect of an alert on the probability that a grid cell receives a fine is positive, despite the negative effects between the fifth and the tenth months. On average, an alert raises the probability of a fine by 2 percentage points from a baseline of 19%, representing an increase of 11% in the probability of enforcement action. The effects accumulated up to the third month after the alert amount to approximately 4 p.p., so the anticipation effect corresponds to approximately half the immediate response of enforcement to alerts. The results of the two-way fixed effects model are almost identical to the results based on the imputation method by JW-BJS, as shown in Appendix Figure A.2.

These results suggest that the additional aggregate enforcement risk generated by the monitoring system is small. Given that among observations with a fine the effect is approximately 2 percentage points, and this group corresponds to 30% of grid cells with positive deforestation, the effect of alerts on the aggregate probability of inspection is .7 percentage points (or 1.5 percentage points without considering the anticipated fines). Overall, it seems that around 8% of IBAMA's inspections are caused by the alerts system DETER.

The small average contribution of real-time monitoring to IBAMA's actions may be due to the agency's rich knowledge of deforestation hot spots. If the alerts are redundant to IBAMA's information set, they would not increase the audit probability; their only effect would be shifting the enforcement action over time. To test this hypothesis, I conjecture that IBAMA possesses a sophisticated knowledge of deforestation hotspots based on geographic characteristics and past deforestation patterns. I predict deforestation in a given year t using a random forest model that uses lagged deforestation up to two years before t, plus the following grid-level characteristics: distance from the nearest IBAMA office, distance from Cuiabá, potential yield for cacao, soy, and cassava, caloric potential, altitude, ruggedness, share of water, 50-km proximity to rivers, land tenure (Indigenous reserve, conservation unit, private land, land reform settlements, or public forests), roads, and precipitation. The prediction is done for the set of grid cells that showed some positive deforestation in 2011-2020.

I estimate the event study for different deciles of "predicted" deforestation. If the informational novelty of alerts matters, the impact should be stronger for areas where IBAMA expected the least deforestation to occur. Corroborating this hypothesis, Figure 3a shows large effects of alerts on inspection probability in areas where the random forest model predicts low levels of deforestation. This result suggests that DETER's information is redundant to IBAMA's alternative available sources, so IBAMA only responds strongly to alerts when the information is novel. Indeed, illegal deforestation is spatially persistent, allowing accurate prediction of hotspots even without monitoring.

Another dimension of heterogeneity is by deforestation area. If the agency prioritizes targeting for larger offenders (for whom specific deterrence may be stronger), cells with larger offenses would have more targeting. I perform a heterogeneity analysis using deciles of realized deforestation. Figure 3b shows that the baseline probabilities increase monotonically with size, suggesting that IBAMA deploys enforcement action in areas with more severe offenses regardless of alerts. The effects of alerts relative to the baseline are largest at the first, fifth, and tenth deciles of deforestation size, but the tenth decile has the largest difference (6 p.p.). Finally, Appendix Figure A.3 shows greater effects for "priority list municipalities," but no heterogeneity by proximity to IBAMA, soy suitability, and presence of private property.

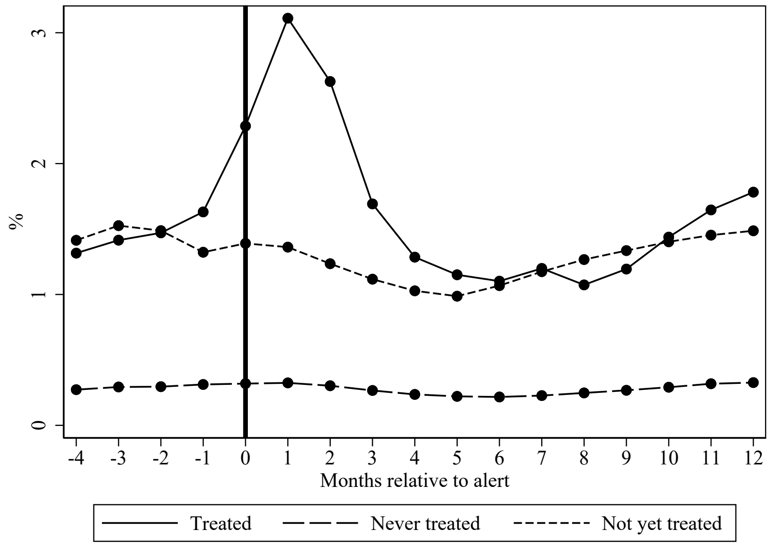
Robustness: The results above rely on the assumption that the monitoring system provides uniquely-timed information on deforestation, meaning that the agency could not know about deforestation at the particular month in which the alert occurs. This assumption is reasonable in the context of the Amazon, an extensive area where it is costly to find out about deforestation in real time absent remotely-sensed techniques. However, it could be the case that the alerts occur at roughly the same time deforestation starts, and that the agency learns about it at roughly the same time through independent means.

To test that, I propose a robustness test that estimates the event study using alerts that likely happen with at least one month delay, thus isolating the "information" aspect of the alert from the action on the ground. I re-estimate the event study using only alerts whose month was preceded by a cloud-covered month, in which the system was unable to detect activities on the ground. If it is true that the agency is reacting to deforestation instead of the alert, we should see a much reduced effect among these "delayed" alerts.

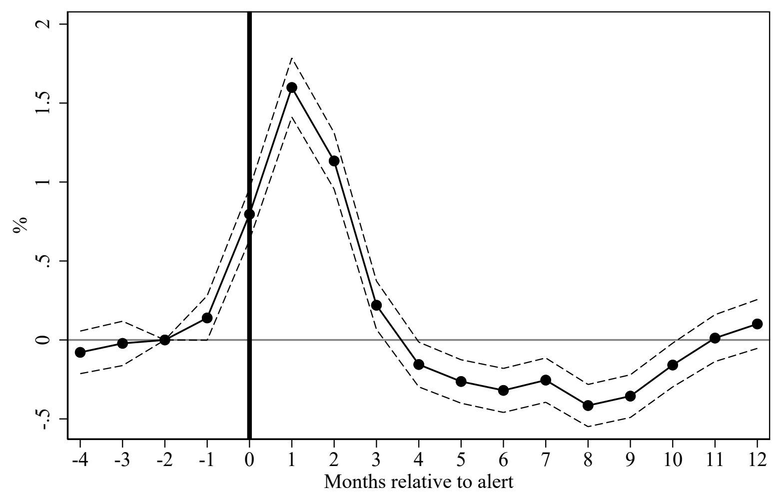
The results are shown in Figure A.4a, and indicate that the average accumulated effect of the alert is much greater among the delayed alerts than among all alerts. In general, there is an increase of 7 p.p. in the probability of a fine in the 12 months after the alert, over a baseline probability of 17%, which is much higher than the average effect of 2 p.p. over a baseline of 19% found in the whole sample. Although the two samples are different, this result strongly suggests that the response of enforcement to the alert reflects the additional information given by the alert instead of a coincidence of the timing of the alert with some other information source available to the enforcement agency.

Figure 2: Effects on the Probability of Inspections

(a) Descriptive Means of Probability of Inspection



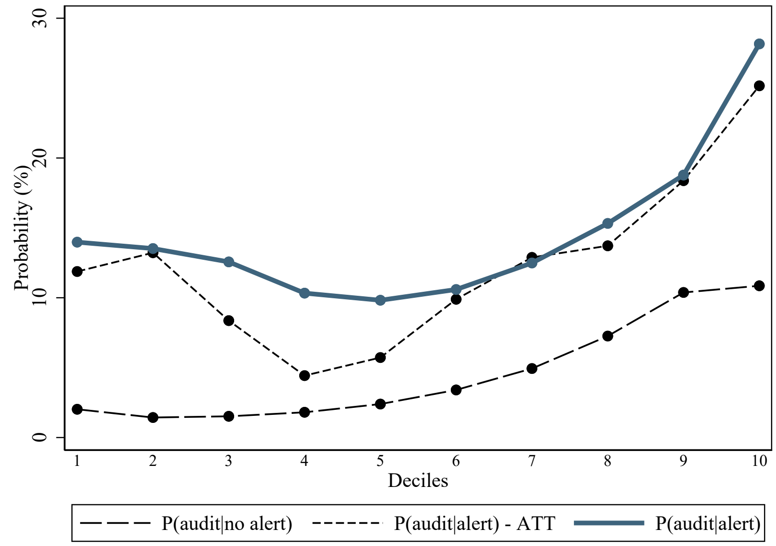
(b) Impact of Alerts on Inspections – OLS Estimates



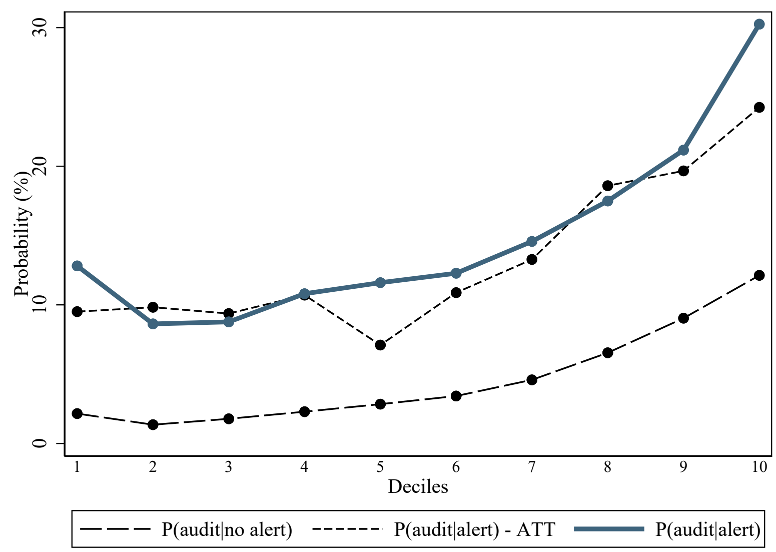
Note: Panel (a) depicts the mean hectares of deforestation within a 4km $\times$ 4km grid cell that received a fine in the 2011-2020 period. The continuous line shows the average deforestation in years relative to the fine (I use the earliest fine within 12 months in cases of multiple fines). To compute the average deforestation in the "not yet treated" and "never treated" (i.e., not fined) grid cells, I computed the average deforestation for these groups in each year, and constructed a weighted average using the distribution of months-years for the periods around the alert identified for the treated group. Panel (b) shows the OLS coefficients for the event study described by Equation 4 using stacked events plus the monthly observations of never treated grid cells. Only grid cells with positive deforestation are included in the analysis. Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.

Figure 3: Heterogeneous effects on the Probability of Inspections

(a) Heterogeneity Based on Deciles of Predicted Deforestation



(b) Inspection probabilities by decile of deforestation area



Note: Panels (a) and (b) depicts the decomposed probabilities of an audit for grid cells with and without alerts for different deciles of predicted deforestation (a) and realized deforestation (b). All grid cells used in the estimation have positive deforestation. The deciles of predicted deforestation are computed based on a random forest model of deforestation where past deforestation and terrain characteristics were used as predictors. The long dashed lines represent the mean probability of an audit conditional on no alert and the respective decile. The probability of an audit conditional on an alert is shown in the solid blue line, whereas the short dashed black line shows the baseline probability of an audit in grid cells with alert excluding the effect of the alert (ATT) estimated by OLS as the event study described by Equation 4. Each point in the panels come from separate regressions where the sample was restricted to observations within the respective decile.

Finally, I test whether the results are driven by cells with multiple alerts in a row. As mentioned earlier, an "event" is considered as the earliest alert in a 5 month period, so repeated alerts are not considered as new events. If an area is repeatedly getting alerts, it may attract the agency's attention for many different reasons, and the results above could be driven by these cases. To address that concern, I first note that 54% of the events in the data contain only one alert, and 90% contain four or fewer alerts within an interval of 12 months of one another. I estimate the event study with the cases of one single alert.

The results for the event study estimation of cases with one single are shown in Figure A.4b. It shows that the effect among those cases is much larger than the average effect including events with multiple alerts, with an increase of 4 p.p. over a baseline probability of 13%, whereas the main results indicate an increase of 2 p.p. over a baseline of 19%. This result suggests that the effects estimated in this exercise indeed come from the informational value of the monitoring alerts, and that areas with multiple alerts also have a higher baseline enforcement probability that likely stems from other information sources.

6.2 General Deterrence: Effects of Inspection Probability

Table 1 summarize the results for the general deterrence estimation, using probability of detection as an instrument for enforcement action. The analysis is done at the grid cell-year level. Column 1 shows the results of the first stage, that is, the impact of detection probability ($P(detection)$) on the probability of a fine or inspection, using only grid cells with positive deforestation. The measure of detection probability is the share of detected polygons of 0.09 to 0.1 hectare within a 80 km circle around each grid cell. The first stage shows that increases in detection probability are strongly associated with higher fines, conditional on grid cell fixed characteristics, year fixed effects, and the two time-varying confounding factors discussed earlier: accumulated deforestation and precipitation. The variable is highly predictive of enforcement action, consistent with the previous finding that the enforcement agency relies on the monitoring system to determine enforcement, at least to some extent. The Cragg-Donald Wald F-statistic is 95.5. The first stage shows that the changes in detection probability across space and time contributed to shifting enforcement risks.

Using this quasi-experimental variation as an instrument for enforcement, I estimate the impact of enforcement probability on deforestation, on the intensive and extensive margin. Columns (2), (3), and (4) show regressions results for the intensive margin, in hectares of deforestation among cells with positive deforestation, denoted d_{it}. These regressions use the same sample used for the first stage, that is, the sample of cells with positive deforestation. Column (2) presents the OLS results, with a coefficient of 2.1 on fine, suggesting a positive correlation between deforestation and fine incidence. This result is consistent with the analysis of enforcement deployment done above, which revealed that the agency systematically deploys more enforcement in areas of higher levels of deforestation. Column (3) shows the 2SLS results after instrumenting for fines with the detection probability. The coefficient on fines is -41.1, which means that an increase in 1 percentage point in the probability of fine reduces average deforestation by 0.4 hectare in cells with positive deforestation. Column (4) shows the intention-to-treat (ITT) effect of the instrument on the outcome, with a coefficient of -5.2 on fines. All these coefficients are significant at the 0.01 level, and standard errors are clustered at four grids of 1^{o} (approximately 110 km) around each cell to allow for spatial auto-correlation of error terms.

Columns (5), (6), and (7) show the results for the extensive margin, that is the probability that cells had positive deforestation, denoted $\mathbb{P}(d_{it} > 0)$. For this exercise, I expand the sample to include cells that had zero deforestation, but restrict the exercise to those cells that had at least one year with positive deforestation in the 2011-2020 period. This procedure allows me to extrapolate the results from the first stage and predict fine probabilities in these observations with zero deforestation, since the grid cell fixed effects are computed for these cells.[10] The qualitative results for the extensive margin are the same as for the intensive margin, though the results are statistically weaker. Column (5) shows the OLS results, showing a positive correlation between fines and the probability of positive deforestation. This result means that cells with a fine were 7% more likely to have positive deforestation, conditional on cell characteristics and year fixed effects. However, as exposed by Column (6), an exogenous increase in fine probability due to higher monitoring detection probability reduces deforestation probability. A 1 percentage point increase reduces by 0.4% the probability that a grid cell does deforestation, a result that is significant at the 10% level only. Column (7) shows the ITT estimate, which is also negative and significant only at the 10% level.

Overall, the evidence shows that enforcement probability reduces deforestation along both intensive and extensive margins. Given that the monitoring system has an effect on enforcement action, variation in monitoring quality provides quasi-experimental variation to estimate the effect of enforcement on the outcomes of interest. These results beg the question of how farmers can respond to year-to-year variations in enforcement effort, given that it is implausible that they adjust their beliefs about enforcement probability based on location-specific satellite monitoring quality. A likely mechanism is that farmers learn about enforcement risk by observing or learning about enforcement action happening in surrounding areas. Vieira, Dahis, and Assunção (2023) provide evidence that enforcement action in a given private property affects neighboring properties' likelihood of engaging in deforestation, suggesting that agents can learn about probabilities in the course of a year and adjust their behavior. In particular, within a 4km x 4km grid cell there may be several neighboring properties. Moreover DETER's alerts are made public (often with a lag of a month), and some farmers may observe alerts happening in their neighborhoods as credible indication that the monitoring system is working effectively.

In Appendix I present robustness results using two alternative measures of detection probability: i) the share of detected small polygons within a 120 km radius from each cell, and ii) the share of detected small polygons within a 120 km radius, weighted by a Gaussian kernel based on the distance of the polygon to the grid cell's centroid. In both cases, the results are qualitatively identical and quantitatively similar.

[10] One caveat applies here: grid cells that only had one year of deforestation would be singletons and therefore not have its estimated fixed effect, and therefore they are excluded in the extensive margin analysis.

Table 1: General Deterrence Estimates

outcome:	P(fine>0)	deforestation (ha)			P(deforestation>0)		
	First Stage	OLS	2SLS	ITT	OLS	2SLS	ITT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fine		2.108***	-41.12***		0.0665***	-0.365***	
		(0.177)	(10.23)		(0.00318)	(0.134)	
P(detection)	0.126***			-5.186***			-0.0460***
	(0.0204)			(0.916)			(0.0169)
log(accumulated deforestation)	0.0667***	15.46***	18.40***	15.65***	0.180***	0.208***	0.183***
	(0.00351)	(0.181)	(0.732)	(0.182)	(0.00175)	(0.00926)	(0.00175)
log(precipitation)	0.0688***	2.033***	4.623***	1.795***	-0.0143*	0.00957	-0.0155**
	(0.00934)	(0.418)	(0.863)	(0.423)	(0.00773)	(0.0112)	(0.00785)
N	186431	186431	186431	186431	397553	397553	397553
Cragg-Donaldson F	95.48						
Mean deforestation		24.11			11.31		
Mean fine		.13			.09		
Mean detection		.09			.08		

Note: * 0.10 ** 0.05 *** 0.01 significance levels. This table shows the estimates of general deterrence effects for intensive and extensive margins using detection probability as an instrumental variable. The instrument is the proportion of 0.09-0.1 ha deforestation polygons (measured by PRODES) detected in quasi-real time by DETER within a 80km radius from each grid cell. Column (1) shows the first stage results, where the outcome is a binary variable indicating that the grid cell-year received a fine. Columns (2) and (3) show OLS and 2SLS showing the estimation of the correlations between the binary fine variable and deforestation, measured in hectares. Column (4) shows the direct correlation between the instrument and deforestation. Columns (5), (6), and (7) perform the same analyses as Columns (2), (3), and (4), but using a binary variable for positive deforestation as outcome. Columns (1), (2), (3), and (4) are estimated using the set of grid cells-years with positive deforestation only, whereas Columns (5), (6), and (7) include observations with zero deforestation among grid cells that had positive deforestation at least twice in the 2011-2020 decade. All regressions include grid cell and year fixed effects. Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.

6.3 Specific Deterrence

The final set of main results documents the existence of specific deterrence effects from enforcement action against deforestation. These effects are estimated using an event study a with observations at the grid cell-year level, using the earliest fine observed for a grid cell in the 2011-2020 as the treatment event.

Figure 4a describes the data, plotting as a solid line the mean deforestation for treated grid cells in each year relative to the fine. This graph shows that on average, fined grid cells showed a steep acceleration of deforestation that can be detected at least three years before the fine. Immediately following the fine, the average deforestation falls and remains roughly constant for the following years. Like in the analysis of the effect of alerts on enforcement action, I construct descriptive counterfactuals as weighted averages of the mean control observations, using the not-yet-treated and the never-treated observations. The weights are the share of each year (2011, 2012, etc.) in the relative periods (-3, -2, etc.) for the treated grid cells. These descriptive counterfactuals suggest that, in the absence of treatment, the yearly deforestation tends to increase year after year. The upwards trend in yearly deforestation is relatively flat for the never treated cells.

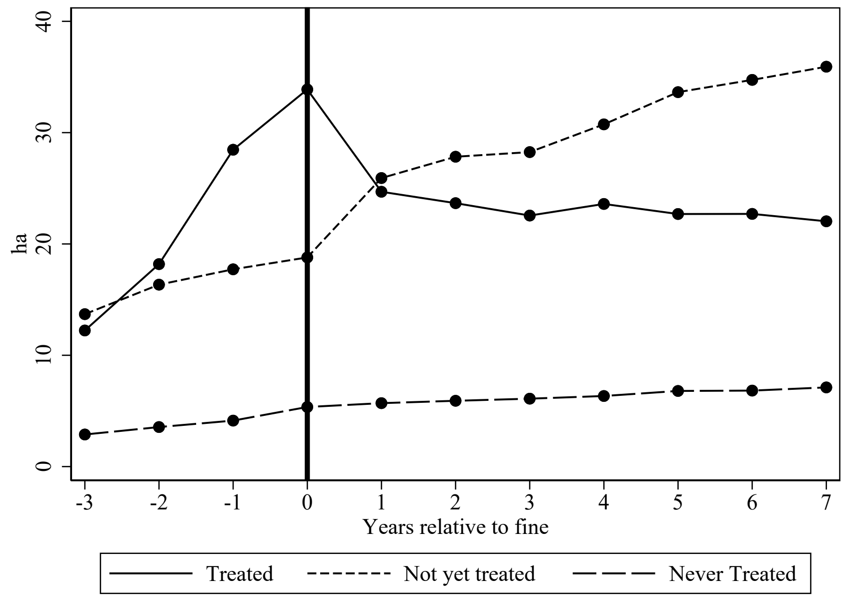
Figure 4b shows the OLS estimates of the two-way fixed effect event study for the specific deterrence effect (Equation 6). The figure shows that the treated units' deforestation drops consistently over time relative to the counterfactual. As suggested by Figure 4a, this reflects the fact that in the counterfactual, deforestation maintains an upwards trajectory, whereas the fine abruptly interrupts that trajectory and keeps deforestation at bay for an extended period of time. The acceleration of forest loss seems to be steeper in years leading to the fine than in other years as suggested both by the descriptive Figure 4a and by the negative, but small, coefficients in periods -3 and -2 in Figure 4b. These results suggest a strong effect in terms of avoided deforestation. The accumulated effects amount to approximately 55 hectares of avoided deforestation over three years, and 175 hectares over seven years. However, the estimated effects over longer horizons such as five or seven years may mechanically increase and should be interpreted with caution. Figure A.5 shows the analogous exercise for the extensive margin, using a binary variable of positive deforestation as outcome.

As a robustness exercise, I also estimate the event study for both margins using the two-step imputation method initially proposed by JW/JBS. This robustness deals with the potential bias arising of applying OLS on the two-way fixed effect model for estimating the ATT, in the presence of staggered treatments and potentially heterogeneous treatment effects. The results are shown in Appendix Figure A.6a for the intensive margin and Appendix Figure A.6b for the extensive margin.

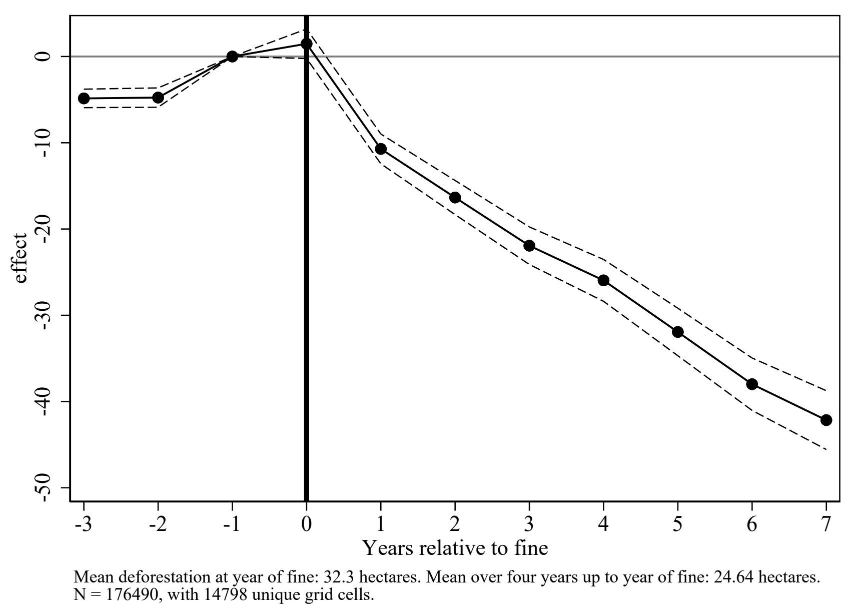
Finally, Appendix Figure A.7 shows a heterogeneity analysis with respect to the fines that mention seized equipments in the fine report. This analysis provides weak suggestive evidence that enforcement action that seizes deforestation equipment elicits a stronger specific deterrence effect, though the difference between the lines is very small and statistically insignificant.

Figure 4: Specific Deterrence Effects

(a) Descriptive Means With Weighted Means for Control Groups



(b) Impact of Inspections on Deforestation (ha) – OLS Estimates



Note: Panel (a) depicts the mean hectares of deforestation within a 4km $\times$ 4km grid cell that received a fine in the 2011-2020 period. The continuous line shows the average deforestation in years relative to the fine (I use the earliest fine in cases of multiple fines). To compute the average deforestation in the "not yet treated" and "never treated" (i.e., not fined) grid cells, I computed the average deforestation for these groups in each year, and constructed a weighted average using the distribution of years for the relative years of the treated group. Panel (b) shows the OLS coefficients for the event study described by Equation 6 using stacked events plus the yearly observations of never treated grid cells. Only grid cells with positive deforestation in at least one year in the 2011-2020 period are included in the analysis. The standard errors are clustered at interlaced grids of approximately 110km around each grid cell.

6.4 Aggregate Effect of Monitoring on Deforestation

The estimations above enable the evaluation of the monitoring system's aggregate impact on the incidence of offense, which I do using Equation 3. On average, the use of monitoring alerts increases the average probability of inspection by a little less than 1 percentage point. The instrumental variable model to obtain estimates of the derivatives of deforestation with respect to the probability of a fine, and then the event study responses for the derivative of deforestation to the realization fine. To complete the computation, it is necessary to use some baseline values of average deforestation and the number of cells with deforestation, which I compute as the averages in the data during the whole period of 2011 to 2020.

The parameters used for the estimation are partly obtained directly from the data, and partly estimated. The parameters obtained from the data are the number of unique cells N with positive deforestation (on average approximately 16.2 thousand 4 km x 4 km cells per year) and the average area of deforestation per grid cell, which was 24 hectares. The estimated parameters are the increase in the probability of enforcement $d\pi_t$, estimated at slightly less than 1 percentage point, the intensive margin effect of enforcement risk $\partial d_t/\partial \pi_t$ is estimated at approximately -0.4 ha per percentage point increase in π_t, the extensive margin effect of enforcement risk $\partial N/\partial \pi_t$, estimated at approximately -0.35% for 1 p.p. increase in π_t, and the specific deterrence effect, estimated at least 55 hectares less deforestation over three years. The parameters are summarized in Table 2.

A one percent increase in inspection probability generates approximately 97 square kilometers of avoided deforestation through general deterrence, mostly (82%) induced by a reduction in the intensive margin of deforestation. The specific deterrence effect is approximately 50 square kilometer of avoided deforestation when we focus on a three-year impact (effect of 55 hectares), but can go up to 160 square kilometers if we aggregate the effects over seven years (effect of 175 hectares). Using the more conservative estimate, the total effect of a one percentage point increase in inspection probability is approximately 150 square kilometers of avoided deforestation per year, corresponding to approximately 1.2% of the deforestation level in 2020 (12 thousand square kilometers) and 2.1% of the average deforestation in 2011-2020 (7 thousand square kilometers). Since the average additional impact of monitoring on enforcement was a little below 1 percentage point, the value of this system in terms of reduced deforestation probably lies between of 150 and 300 square kilometers of saved forest by year, respectively 2.1% and 4.2% of the average yearly deforestation in the 2011-2020 decade.

Table 2: Estimated Coefficients Used to Compute Aggregate Effect of Monitoring on Deforestation

Object	Estimate
π	12%
$d\pi$	1 p.p.
$P(d > 0)$	0.41
$\partial P(d > 0)/\partial\pi$	-0.4
$E[d\|d > 0]$	24
$\partial E[d\|d > 0]/\partial\pi$	-42
ATT	> 55
N	39,755

7 Discussion: Cost Analysis of Targeted Enforcement

The analysis above suggest that the DETER's impact in deterring deforestation is modest. This result stems from several factors. First, much of the information provided by DETER seems to be non-additional, affecting by small amounts the enforcement probability, and often displacing in time enforcement actions. Second, even when IBAMA seems to be targeting actions according to DETER, it does not fully target inspections. The small contribution of the monitoring system can be even smaller if one contemplates the counterfactual situation in which DETER ceased to exist. In this case, the resources used for targeted inspections would be reallocated for non-targeted inspections. Although targeted inspections are likely cheaper than non-targeted inspections, the contribution of DETER would still be attenuated in this scenario. But how much cheaper are the alerts-driven, targeted inspections, relative to non-targeted ones?

To investigated this, I collect expenditure data on enforcement actions by IBAMA in the nine different states of the Brazilian Amazon Biome in the years 2014-2020. Second, I estimate the number of inspections in each state-year that can be assigned to monitoring alerts using state-year specific event studies, i.e., targeted inspections. The hypothesis implies a negative correlation between expenditure and the share of targeted inspections. I assume that the average unit price for non-targeted inspections (p^{NT}) is different than for targeted inspection p^T, especially because not all non-targeted inspections generate a fine. The share of targeted fines is σ, so that total expenditure is:

$$E = n^{\alpha} \times \Big(\sigma p^T + (1-\sigma)p^{NT}\Big)\xi \tag{7}$$

where n is the number of fines, α denotes potential gains of scale from enforcement efforts, and ξ is a random error component. Log-linearizing this expression yields the following regression:

$$log(E) = \beta_0 + \beta_1 log(n) + \beta_2\sigma + \varepsilon \tag{8}$$

where $\beta_0 \equiv log(p^T) + 1 - \frac{p^{NT}}{p^T}$, $\beta_1 \equiv \alpha$, $\beta_2 \equiv 1 - \frac{p^{NT}}{p^T}$, and $\varepsilon \equiv \log(\xi)$.[11] The main hypothesis in this exercise is that $\beta_2 < 0$, or equivalently that $p^{NT} > p^T$.

Table 3 shows the results for regression exercises based on Equation 8. Column 1 only regresses expenditures on fines, showing that one percent increase in fines increases expenditure by 0.7%. Column 2 regresses log expenditure on the share of alert fines, showing that a one percentage point increase in alert-based fines (among all fines in the state) is associated with a reduction of 0.6% in expenditure. Columns 3 includes both regressors, which remain similar to the previous specifications. Column 4 controls for log of deforestation, and column 5 replaces the share of alert fines by the log of the number of alert-driven fines. These results show that while a higher number of fines is associated with more expenditure, a greater share of alerts-based fines is negatively associated with expenditure. The coefficient on the share of alerts-based fines, β_2 is approximately -.6, with slight changes across specifications, indicating that the average expenditure associated with one non-targeted fines is 60% greater than for targeted-fines.

Table 3: Analysis of enforcement expenditure by state

	(1)	(2)	(3)	(4)	(5)
Log Total Fines	0.62**		0.50*	0.51*	0.39
	(0.27)		(0.27)	(0.27)	(0.24)
Share Alert Fines		-0.61**	-0.46*	-0.71**	
		(0.24)	(0.25)	(0.33)	
Log Deforestation Area				0.14	0.16*
				(0.11)	(0.08)
Log Alert Fines					-0.09***
					(0.03)
R2	0.93	0.92	0.93	0.94	0.94
N	63	63	63	63	63

Note: This table shows OLS results for a regression of log expenditure (in BRL at January 2020 values) in monitoring expenditure by IBAMA at the state-year level for each of the nine Amazon states in the period 2014-2020. The regressors are the log of the total number of deforestation fines in each state-year, the share of these fines that can be attributed to the monitoring system estimated through the methodology in Section 5, log of deforestation area, and log of the number of alert-caused fines. All specifications include year and state fixed effects to account for nationwide year-specific budget shocks and state-specific characteristics. Robust standard errors (White) are shown in parentheses.

Based on this computation, and assuming that targeted inspections correspond to 1 p.p. in the overall probability of fine conditional on deforestation, I compute the counterfactual probability assuming that all

[11] Log-linearization yields $log(E) = \alpha log(n) + log(\sigma(p^T - p^{NT}) + p^{NT}\Big) + \varepsilon$. In turn, a first order Taylor approximation of $log(\sigma(p^T - p^{NT}) + p^{NT}\Big)$ around $p^T = p^{NT}$, varying p^{NT}, yields: $log(\sigma(p^T - p^{NT}) + p^{NT}\Big) \approx log(p^T) + 1 - \frac{p^{NT}}{p^T} - \sigma\big(1 - \frac{p^{NT}}{p^T}\big)$. Simplifying this expression yields the Equation 8.

resources spent on targeted fines were spent instead on non-targeted inspections. This computation suggests that if all inspections were "non-targeted," the probability of enforcement conditional on deforestation would be $1 - 1/1.6 \approx 0.4$ p.p. lower. Therefore, the additional contribution of monitoring to reducing deforestation is probably as low as 1-2% reduction in illegal deforestation, instead of 2-4% as discussed above. Although this exercise reinforces the idea that the adoption of monitoring technology did little to curb illegal deforestation in the Amazon forest, it also highlights that targeting may represent substantial savings for the enforcement authority. There may be other advantages of targeted inspections that increase their attractiveness, such as the higher probability of seizing equipment of offenders. Overall, targeting inspections based on monitoring information does not seem to be a first order expansion of state capacity in this setting.

8 Summary and conclusion

This paper has exploited the role of monitoring in the enforcement decisions of an agency, and the consequences on deterrence. It used the setting of deforestation monitoring in the Amazon forest, which allows the separate observation of offense levels, monitoring information, and enforcement action. Using different methods, the paper estimates the improvements in detection capacity of monitoring, the impact of monitoring on enforcement action, and the general and specific deterrence effects.

The monitoring system DETER produces deforestation alerts based on its ability to detect vegetation loss in native forest in the Brazilian Amazon. DETER is not a system designed to measure deforestation, but to give real-time alerts about where and when deforestation seems to be taking place. By overlaying the maps of yearly deforestation (measured by the system PRODES) with the deforestation alerts issued by DETER, I document an expressive increase in the probability that an area of deforestation produces an alert over the 2011-2020 decade, reflecting technological improvements in monitoring capacity.

The consequence of this improvement is that the enforcement risk for farmers goes up. I show that IBAMA relies on the deforestation alerts to shape its enforcement strategy, but to a great extent the monitoring technology produces redundant information. I then evaluate how farmers respond to increases in fine probability in order to put a value to the monitoring system in terms of avoided deforestation. I estimate the impact of fines on farmers in two parts. First I estimate the impact of enforcement risk on deforestation, and show that a one percentage point increase in the probability of inspection reduces deforestation via both general and specific deterrence effects.

However, the paper documents a modest increase in the probability of inspections due to monitoring information, and consequently a small overall deterrence effect. The average yearly probability of a fine in areas with positive deforestation in the period was 12%, of which only one percentage point is due to the monitoring system. The resulting reduction in deforestation in the 2011-2020 is estimated at 2-4%. In general, the monitoring technology contributes to reducing deforestation and reducing enforcement costs, but likely does not represent a substitute for expansions in staffing and budget.

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Online Appendix

A Details on Data Management

The three main datasets used in the paper are the following:

- **Deforestation:** the deforestation maps are produced once a year by INPE based on Landsat imagery at 30m resolution, through a program called PRODES. The deforestation measurements for year t refer to the incremental deforestation between August of $t-1$ until July of t. All the other time-specific datasets were adjusted to that definition. INPE makes PRODES data available in raster and vector (shapefile) formats. For most of the analysis, the raster data was used, where the 30m pixels were aggregated at a 4km resolution raster. The polygons of deforestation were used in the computation of monitoring quality, where the size of unique contiguous deforestation polygons is important for the argument. The PRODES program exists since 1988, but the harmonized data is available since 2001. For this study, I used data from 2011 to 2020.

- **Monitoring alerts:** deforestation alerts are produced on a daily basis by INPE based on images from several satellites, through the monitoring program DETER. The data is made available on a monthly basis for the public, and consists of polygons of deforestation alerts. The first phase of DETER lasted from 2004 to 2017 and used 250m resolution imagery to produce alerts in quasi-real time. In 2015, the program was updated to incorporate 60m resolution imagery, and in 2017 the new version was fully operational. The new version was called DETER-B. In this paper, I computed the presence of alerts within the 4km grid, overlaying it with the annual measures of deforestation by PRODES. Moreover, I used the DETER polygons to compute detection probabilities at the polygon level of PRODES to assess the quality of monitoring. Besides deforestation alerts, DETER-B also provides alerts for other infractions, such as fires and illegal mining. However, for the purposes of this study, I only use deforestation alerts.

- **Deforestation fines:** all environmental fines by IBAMA are posted publicly, containing detailed information about the infraction, values, dates, and location. I used a string search within the description of fines for words that designate deforestation, as well as typos and slight variants. Based on this string search, I filtered those environmental fines that concern illegal deforestation, as opposed to other environmental infractions, such as illegal hunting, fishing, animal trade, or lack of environmental licenses for economic activities. The exact latitude and longitude of deforestation fines are available for virtually all fines starting in 2011. This information allows the location of each fine within the 4km grid created for the analysis. For auxiliary analyses, I also merge the data with information on seized equipment, using the fines' unique identifier to cross-reference across other IBAMA databases.

Besides those datasets, I use the following geographic fundamentals in the analysis:

- **Precipitation:** the data on precipitation is based on the methodology of Brocca et al. (2019). The data used in this study is the monthly 10km-resolution raster of precipitation in mm by Parente and Hengl (2022) from 2011 to 2020. The data is based on satellite observations of soil moisture. This information is used in the main analysis.

- **Clouds:** data on monthly cloud coverage is obtained from DETER, but it is only available until 2017. The cloud information indicates areas that could not be monitored during a whole month because of clouds. I compute the area of each grid cell covered by clouds in the analysis. I use this information in a robustness analysis.

- **Altitude and ruggedness:** I use DEM elevation data from CGIAR-SRTM at a 30-arcsec resolution, and compute the average altitude and terrain ruggedness index (TRI) in meters. This information is aggregated at the 4km grid cell level. This information is used in the prediction model of future deforestation.

- **Soil suitability:** I use the FAO-GAEZ model-based estimates of maximum attainable yields of soy, cassava, and cacao under low-input use. The rasters are available at 10km resolution as `https://gaez.fao.org/pages/data-viewer-theme-4` This information is used in the prediction model of future deforestation.

- **Caloric potential:** I use the caloric suitability index of Özak (2015), Galor and Özak (2015), and Galor and Özak (2016), aggregated for each 4 km grid cell. The data is available at `https://ozak.github.io/Caloric-Suitability-Index`. This information is used in the prediction model of future deforestation.

- **Water:** water area within each 4km grid cell stems from the land use mapping by PRODES. This information is used in the prediction model of future deforestation.

- **Land tenure:** I collect land tenure measures compiled by Imaflora, containing information on private land (from CAR and SIGEF), land distribution projects (from INCRA), Indigenous land (from FUNAI), conservation units (from ICMBio), and public forests. This information is used in the prediction model of future deforestation and in heterogeneity analyses.

- **Roads:** I use the 2007 mapping of roads from MapBiomas. This information is used in the prediction model of future deforestation.

Finally, I also incorporated the following administrative data in the analysis:

- **Municipalities:** I use the administrative division of municipalities in Brazil to locate each grid cell into a unique municipality.

- **Priority Municipalities:** I use IBAMA's list of priority municipalities to construct an indicator of which municipalities were priority in which year. I use this information in the prediction model and also in heterogeneity analyses.

- **Location of IBAMA offices**: I use the geo-coordinates of IBAMA offices in the Amazon forest to compute the distance from each grid cell to the nearest IBAMA office. I use this information in the prediction model and also in heterogeneity analyses.

- **Budget of IBAMA**: I downloaded data from budget execution from the Brazilian federal government, available from 2014 onwards. I excluded wages, which are concentrated at the Brasilia office, and computed the operational expenditure per state office in the Amazon forest, to approximate the expenditure that reflects field inspections. I converted the expenditures to 2020 real terms using the Brazilian consumer prixe index IPCA.

Figure A.1: Main datasets (example from Pará, 2016)

(a) Measurement satellite (PRODES)

(b) Logging alerts (DETER)

(c) Deforestation fines (IBAMA)

Notes: Figure A.1a shows the categorization of the land coverage by PRODES as forest, old deforestation, and new (i.e., "last-year") deforestation. Figure A.1b shows the areas of deforestation signals in yellow. Finally, Figure A.1c shows the points where inspectors recorded a fine.

Table A.1: Descriptive Statistics – Time-Varying Variables – Cells with Positive Deforestation Once

Grid cells with positive deforestation at least once

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Deforestation (ha)	8.89	6.84	7.99	7.78	8.69	10.47	10.10	10.21	14.45	13.97
	(15.99)	(14.46)	(15.83)	(15.20)	(16.61)	(17.75)	(17.52)	(17.45)	(20.65)	(20.23)
Share with alerts	0.06	0.06	0.06	0.06	0.11	0.14	0.22	0.19	0.22	0.31
	(0.24)	(0.23)	(0.23)	(0.24)	(0.31)	(0.34)	(0.41)	(0.39)	(0.42)	(0.46)
Share with fines	0.08	0.05	0.10	0.08	0.11	0.09	0.10	0.08	0.07	0.06
	(0.28)	(0.22)	(0.30)	(0.28)	(0.32)	(0.28)	(0.29)	(0.27)	(0.26)	(0.23)
Precipitation	69.08	65.19	66.64	78.89	66.82	54.19	67.94	65.60	68.73	65.38
	(15.81)	(11.85)	(12.27)	(14.40)	(13.54)	(13.36)	(11.82)	(15.12)	(14.91)	(16.76)
Accumulated Deforestation (ha)	613.34	622.03	632.89	643.18	655.66	670.65	684.86	699.55	722.16	744.20
	(503.08)	(503.87)	(505.66)	(506.57)	(507.52)	(508.09)	(507.95)	(506.77)	(503.25)	(500.44)
Share Detection Small Deforestation	0.01	0.02	0.01	0.02	0.02	0.03	0.13	0.14	0.13	0.26
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.09)	(0.08)	(0.09)	(0.13)
N	47311	47311	47311	47311	47311	47311	47311	47311	47311	47311

Note: This table shows the mean and standard deviation (in parentheses) of the time-varying variables used in this study. The unit of observation is a 4 km x 4km grid cell in the Brazilian Amazon biome. Only grid cells that had a positive amount of yearly deforestation in at least one year in 2011-2020 are included.

Table A.2: Descriptive Statistics – Time-Varying Variables – Cells with Positive Deforestation

Grid cells with positive deforestation

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Deforestation (ha)	21.73	21.50	23.29	21.81	23.99	24.20	23.86	23.40	28.04	27.23
	(18.60)	(18.48)	(19.36)	(18.48)	(19.87)	(19.91)	(19.92)	(19.72)	(21.13)	(20.90)
Share with alerts	0.12	0.12	0.13	0.14	0.25	0.28	0.43	0.38	0.39	0.53
	(0.33)	(0.32)	(0.33)	(0.34)	(0.43)	(0.45)	(0.50)	(0.49)	(0.49)	(0.50)
Share with fines	0.12	0.09	0.17	0.13	0.19	0.13	0.14	0.12	0.10	0.08
	(0.33)	(0.29)	(0.38)	(0.34)	(0.39)	(0.34)	(0.35)	(0.32)	(0.30)	(0.27)
Precipitation	70.11	64.87	67.22	80.24	67.66	54.21	68.26	64.75	68.03	64.86
	(16.09)	(11.37)	(11.75)	(14.08)	(13.19)	(12.13)	(10.91)	(12.94)	(13.62)	(15.27)
Accumulated Deforestation (ha)	699.26	692.66	725.20	712.69	738.51	731.40	732.22	710.51	702.76	724.21
	(454.90)	(452.75)	(450.58)	(459.10)	(457.65)	(466.76)	(468.11)	(465.92)	(469.87)	(468.80)
Share Detection Small Deforestation	0.01	0.01	0.01	0.01	0.02	0.03	0.14	0.15	0.14	0.27
	(0.01)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.09)	(0.08)	(0.08)	(0.12)
N	19353	15064	16221	16880	17136	20464	20037	20654	24388	24267

Note: This table shows the mean and standard deviation (in parentheses) of the time-varying variables used in this study. The unit of observation is a 4 km x 4km grid cell in the Brazilian Amazon biome. Only grid cells that had a positive amount of yearly deforestation are included.

B Model of Enforcement Agency and Offenders

The agency cares about deterring offenses. Deterrence is achieved by reducing current offenses (general deterrence) and punishing offenders, generating incapacitation or specific deterrence effects. The agency disposes of a monitoring device that produces signals with a certain probability s and no false positives. The agency chooses between actions a which include no audits ($a = 0$), a random audit ($a = R$), or a targeted audit ($a = T$). Inspections cost c to the agency. The offender can choose to comply or offend. Offending yields an economic benefit Y but risks a fine, which costs f. The agency suffers a welfare cost $-d$ if the agent offends, but gets a benefit θ if it catches and punishes the offender.

The problem to be illustrated in this paper is the choice of targeted versus non-targeted inspections, and their impact on deforestation. Formally, the agency chooses a policy $\pi = \{\pi_R, \pi_T\}$, where π_R is the probability of "random" or "untargeted" inspections, and π_T is the conditional probability of a "targeted" inspection, conditional on a credible signal. The signal happens with probability s such that the ex ante probability of an inspection at a given site is $\pi_R + s\pi_T$. As discussed below, these choices may depend on the resource constraints of the agency, the quality of the signal s, and the impact on the behavior of offenders.

This simple game has no Nash equilibrium in dominant strategies, as can be deduced from the payoff matrix below.

Table A.3: Payoff matrix (Agent on top, agency on the bottom of each cell)

		Agent	
		comply	offend
	$a = 0$	0	Y
		0	$-d$
Agency	$a = R$	0	$Y - f$
		$-c$	$-c - d + \theta$
	$a = T$	0	$Y - sf$
		0	$-sc - d + s\theta$

Notice that the agency's action "no audit" $a = 0$ is dominated by "targeted audit" $a = T$ as long as $\theta > c$. We therefore can ignore that strategy when looking for an equilibrium. However, when the agency chooses to audit, the agent would prefer to comply if $Y - f < 0$. But in that case, the agency would have rather chosen "targeted audits". Similarly, if the agency chooses targeted audits, the agent chooses to offend if $Y - sf > 0$, but in that case, the agency would have rather chosen "random audits", allowing them to recover $\theta - c$ for sure instead of with probability s.

A Nash equilibrium in mixed strategies is a set of probabilities δ for offense, and π_R for the probability that the agency audits regardless of a signal, such that agents and the enforcement agency indifferent across their different strategies. The equilibrium probability δ is the one that leaves the agency indifferent between R and T, meaning $-c + \delta(\theta - d) = \delta(s\theta - sc - d)$, so $\delta = c/\big(sc + (1 - s)\theta\big)$. Conversely, the probability

π_R is the one that would make agents indifferent between complying and offending, so $\pi_R(Y - f) = (1 - \pi_R)(Y - sf)$ so that $\pi_R = (Y - sf)/\big(2Y - f(1 + s)\big)$.

This simple model illustrates that even though monitoring signals reduce the cost of enforcement by allowing the targeting of inspections, excessive targeting might have unintended consequences. Excessive targeting would expose the agency to the limitations of the monitoring device, and reduce its ability to obtain benefits from punishing offenders, such as incapacitation effects. Notice that the existence of benefits from punishment is crucial for this results. If the agency did not obtain any benefit θ from punishments, targeted audits would dominate random audits from the agency's standpoint. In this case, we would have a pure or dominant strategy Nash equilibrium that would only depend on whether $Y > sf$, resulting in offense in equilibrium, or $Y < sf$, resulting in compliance in equilibrium.

C Model With Intensive Margin of Offense

There are other considerations that may play an important role in reducing the optimal amount of targeting. One relevant example for the setting in this paper is when the technology of detection s depends on the intensity of the offense. For example, call d the size of a polygons of deforestation d, and let the probability $s(d)$ depend positively on d (i.e. $s'(d) > 0$). Agents now can reduce their probability of punishment by doing marginally smaller amounts of deforestation. Here, I derive the optimal choice of targeting and random inspections in a two-period model that has a convex s (i.e. $s''(d) > 0$). Punishment in the first period generates specific deterrence in the second period, thus reducing the amount of second period deforestation. Since agents care about their second-period profits, they may want to reduce marginally their amount of d , reducing the probability of a signal s more than proportionally, thus allowing offenders to "fly under the radar." This incentive is greater for larger values of π_T, thus affecting the optimal amount of targeting chosen by the agency.

Agent's problem

Assuming a representative agent with payoffs at $t = \{1, 2\}$ determined by:

$$Y_t = d_t(y - \pi_R - \pi_T s(d_t)) \tag{A.1}$$

At period 1, the agent must decide deforestation levels to maximize flow profits plus the expected value of the profits in period 2. The problem is:

$$\max_{d_1} Y_1 + \mathbb{E}[Y_2] \tag{A.2}$$

The state variable at period $t = 2$ is the history of fines in $t = 1$. If the agent receives a fine at $t = 1$, the agent's marginal cost increases by κ. At $t = 2$, the first order condition of the agent will yield:

$$d_2^* = \frac{y - \pi_R - \pi_T s(d_2^*)}{\pi_T s'(d_2^*)} \tag{A.3}$$

which implicitly defines $d_2^* = \phi(y, \pi_R, \pi_T)$. At period 2, d_2^* characterizes the optimal choice for the agent. If the agent receives a fine at $t = 1$, given the higher marginal cost, the optimal value of deforestation is $d_2^{**} < d_2^*$.

At period 1, the choice of d_1 may affect the probability that the agent ends up with $Y_2 = Y_2^*$ or $Y_2 = Y_2^{**}$ through the impact on s_1. Indeed, the probability of a fine in period 1 for an agent with positive levels of deforestation is $\pi_R + \pi_T s(d_1)$. Therefore, the maximization problem in equation A.2 can be rewritten as:

$$\max_{d_1} Y_1 + Y_2^* - (\pi_R + \pi_T s_1)(Y_2^* - Y_2^{**})$$

Yielding:

$$d_1^* = \frac{y - \pi_R - \pi_T\big(s_1 + s_1'(Y_2^* - Y_2^{**})\big)}{\pi_T s_1'} \tag{A.4}$$

where the arguments for s are omitted to economize on notation.

Regulator's problem

The problem for the regulator is to minimize the sum of deforestation in both periods by choosing how much to target inspections based on signals. I allow the regulator to choose different levels of targeting for each period. I show below that this problem does not trivially yield corner solutions, meaning that all the enforcement efforts are targeted or random. The problem can be written as a choice of $\{\pi_R, \pi_T\}$ in the first period, keeping targeting in the second period constant.

$$\begin{aligned} &\max_{\pi_R, \pi_T} -\big(d_1^* + d_2^*\big) + (\pi_R + \pi_T s_1)(d_2^* - d_2^{**}) \\ &\text{s.t.} \qquad \pi_R + \pi_T s_1 + \pi_{R2} + \pi_{T2}\mathbb{E}[s_2] \leq \bar{\Pi} \end{aligned} \tag{A.5}$$

where $\{\pi_{R2} + \pi_{T2}\}$ are the policy parameters in period 2, and $\mathbb{E}[s_2] = s_2^* - (\pi_R + \pi_T s_1)(s_2^* - s_2^{**})$, meaning that it is affected by the choice of π_R and π_T in the first period.

Taking first order conditions yields with respect to π_T yields:

$$\frac{\partial \mathcal{L}}{\partial \pi_T} = -\frac{\partial d_1^*}{\partial \pi_T} + \Big(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\Big)(d_2^* - d_2^{**}) - \lambda\Big(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\Big)(1 - \pi_{T2}(s_2^* - s_2^{**})) \tag{A.6}$$

Whre λ is the Lagrange multiplier. To investigate the sign of this expression, we can check the signs of each of its components. For example, to determine the sign of $\frac{\partial d_1^*}{\partial \pi_T}$, we can totally differentiate the first order condition (Equation A.4) and obtain:

$$\frac{\partial d_1^*}{\partial \pi_T} = -\frac{1}{\pi_T}\frac{s_1 + s_1'(d_1^* + \Delta)}{2s_1' + s_1''(d_1^* + \Delta)} < 0 \tag{A.7}$$

Where $\Delta \equiv Y_2^* - Y_2^{**}$. The formula above is unambiguously negative. Moreover, $1 - \pi_{T2}(s_2^* - s_2^{**}) > 0$ given that π_{T2}, s_2^*, and s_2^{**} all lie between 0 and 1. Therefore, the sign of the first derivative of the Lagrangian depends on the sign of $\Big(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\Big)$. If this expression is positive, increases in π_T imply a greater number of targeted punishments in period 1, which may pressure the organization's budget but reduce deforestation the second period through specific deterrence. Conversely, if this expression is negative, increases in π_T reduce expenditure, but also reduce the number of targeted punishments, since decreases in d_1^* imply an even greater reduction in s_1 such that the agency reduces the overall number of targeted punishments.

The expression $\left(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\right)$ will be negative if and only if $\varepsilon_s > \varepsilon_d^{-1}$, where $\varepsilon_s \equiv \frac{\partial s}{\partial d}\frac{d}{s}$ and $\varepsilon_d \equiv -\frac{\partial d}{\partial \pi_T}\frac{\pi_T}{d}$.

The first order condition with respect to π_R is:

$$\frac{\partial \mathcal{L}}{\partial \pi_R} = -\frac{\partial d_1^*}{\partial \pi_R} + \left(1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_R}\right)(d_2^* - d_2^{**}) - \lambda\left(1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_R}\right)(1 - \pi_{T2}(s_2^* - s_2^{**})) \tag{A.8}$$

Where we have, from the first order condition of the agent's problem:

$$\frac{\partial d_1^*}{\partial \pi_R} = -\frac{1}{\pi_T}\frac{1}{2s_1' + s_1''(d_1^* + \Delta)} < 0 \tag{A.9}$$

Notice further that:

$$\frac{\partial d_1^*}{\partial \pi_R} = \frac{\partial d_1^*}{\partial \pi_T}(s_1 + s_1'(d_1^* + \Delta)) \tag{A.10}$$

Meaning that the impact of random inspection probability on first period deforestation can be greater or smaller than the impact of targeted inspections on deforestation, depending on the magnitude of $(s_1 + s_1'(d_1^* + \Delta))$. However, in the example used for this model, where d and y range from 0 to 1, this value would likely also lie in that interval except for extremely large values of s_1'. Assuming that is the case, it means that the response of deforestation to changes in random audits is negative but *smaller*, in absolute values, than the response to targeted audits. This result is reasonable, given that agents can respond to targeted audits by affecting the probability of signals while still deforesting, whereas in the case of random audits, they can only try to avoid the penalty by doing less or no deforestation at all.

Following that reasoning, it means that the impact of random audits on the number of first period audits will likely be positive, unless s' is very large. In other words, $1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_R} < 0$ if and only if $\varepsilon_s > \varepsilon_d^{-1}(s_1^2 + s_1 s_1'(d_1^* + \Delta))^{-1}$, which is a stricter condition than what is needed for $s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}$ to be negative ($\varepsilon_s > \varepsilon_d^{-1}$). Consequently, we can define three areas depending on the elasticity of s.

- If $\varepsilon_s < \varepsilon_d^{-1}$, then increases in π_R and π_T both have the effect of increasing the number of first period fines.
- If $\varepsilon_d^{-1}(s_1^2 + s_1 s_1'(d_1^* + \Delta))^{-1} > \varepsilon_s > \varepsilon_d^{-1}$, then increases in π_R have the effect of increasing the number of first period fines, but increases in π_T decrease the number of first period fines.
- If $\varepsilon_d^{-1}(s_1^2 + s_1 s_1'(d_1^* + \Delta))^{-1} < \varepsilon_s$, then increases in π_R and π_T both have the effect of decreasing the number of first period fines.

We can write the two first order conditions together as follows:

$$\frac{\partial \mathcal{L}}{\partial \pi_T} = -\frac{\partial d_1^*}{\partial \pi_T}\Theta + s\Theta = 0$$
$$\frac{\partial \mathcal{L}}{\partial \pi_R} = -\frac{\partial d_1^*}{\partial \pi_R}\Theta + \Theta = 0$$

Where $\Theta \equiv (d_2^* - d_2^{**} - \lambda(1 - \pi_{T2}(s_2^* - s_2^{**})))$. Given Equation A.10, we can rewrite the second first order condition, resulting in the following system of two equations as follows:

$$\frac{\partial \mathcal{L}}{\partial \pi_T} = -\frac{\partial d_1^*}{\partial \pi_T}\Theta + s_1\Theta = 0$$
$$\frac{\partial \mathcal{L}}{\partial \pi_R} = -\frac{\partial d_1^*}{\partial \pi_T}(s_1 + s_1'(d_1^* + \Delta))\Theta + \Theta = 0$$

These two equations can be simultaneously equal to zero if and only if:

$$s_1 = (s_1 + s_1'(d_1^* + \Delta))^{-1}$$

Meaning that the solution to this system yields a level of alerts in the first period, s_1^* which solves the following equation:

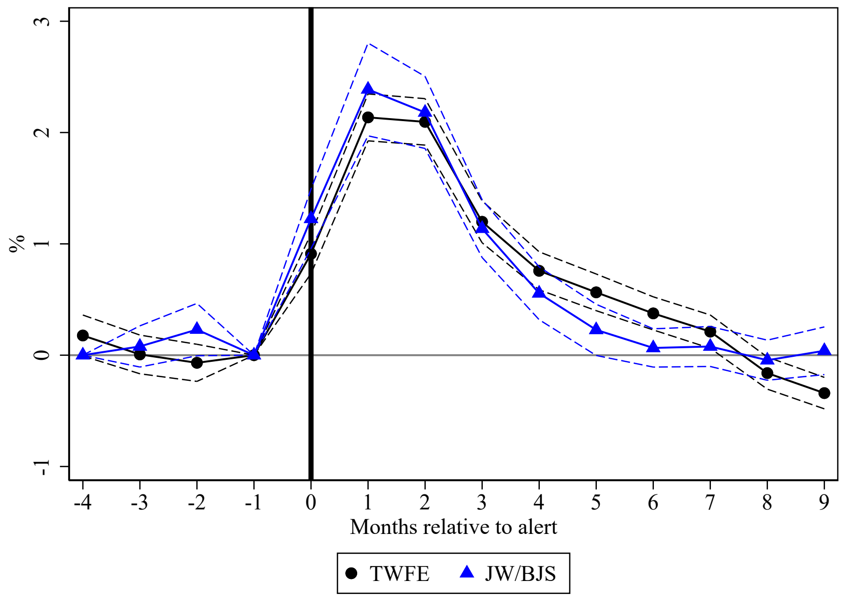
$$s_1^{*^2} + s_1^* {s'}_1^*(d_1^* + \Delta) - 1 = 0$$

The positive roots to this equation would provide a solution to d_1^* that optimizes the government's problem. Replacing that solution into the two first order conditions yields an optimal level of π_T as a function of λ and the parameters. The solution is obtained by using the budget constraint, which defines the values of $\{\pi_T, \pi_R, \lambda\}$ in equilibrium. Although the existence of interior solutions is not always guaranteed in this setting, the problem does not yield trivial results such as "full targeting is always better than some randomization" or vice-versa. The reason lies in the fact that random and targeted audits have contervailing effect on the budget constraint and deterrence. Whereas increasing random audits is costly, it always ensures a greater number of punished offenders. On the other hand, increasing targeted audits is cheaper but may lead to reductions in signal quality, such that the number of punished offenders drops and the agency loses the benefits from punishment, that is, the specific deterrence effects.

Consequently, the problem is non-trivial and has interior solutions where the regulator combines random and targeted audits to maximize its objective function. As in the static game with discrete actions discussed above, the existence of specific deterrence effects is crucial for this result.

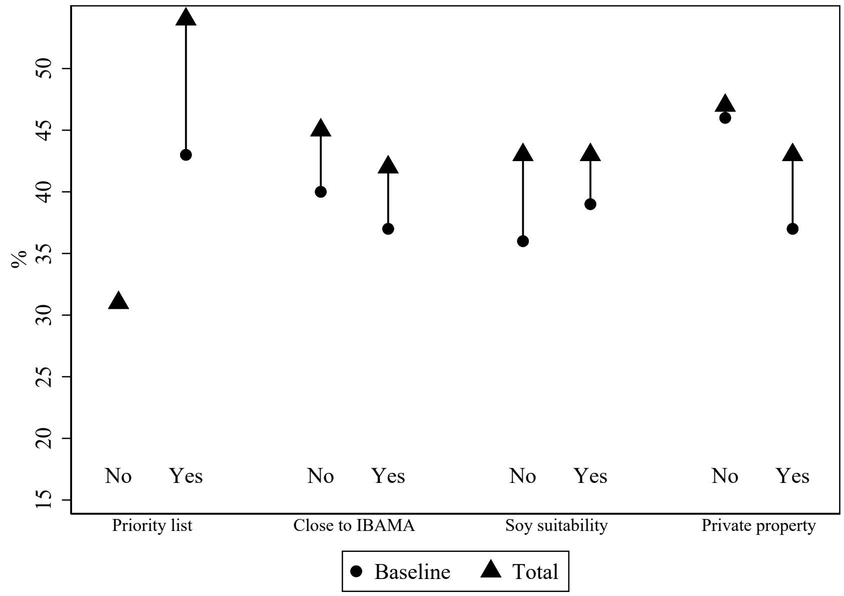
D Additional Results

Figure A.2: Robust Differences in Differences Analysis



Note: This figure shows the estimation results of the event study of deforestation alerts on deforestation fines using OLS (circle markers) and the imputation method proposed by JW/BJS (blue triangle markers) . The unit of observation is grid cell-month, and only grid cells with positive deforestation are considered (as measured yearly by PRODES). Moreover, for grid cells with more than one alert or fine within a few months, we only consider a fine that is not preceded by other fines in at least 12 months, and a unique event is an alert that is not preceded by other alerts in at least 5 months. Standard errors are clustered at four interlaced grid cells of 110 square km around each 4km x 4km grid cell.

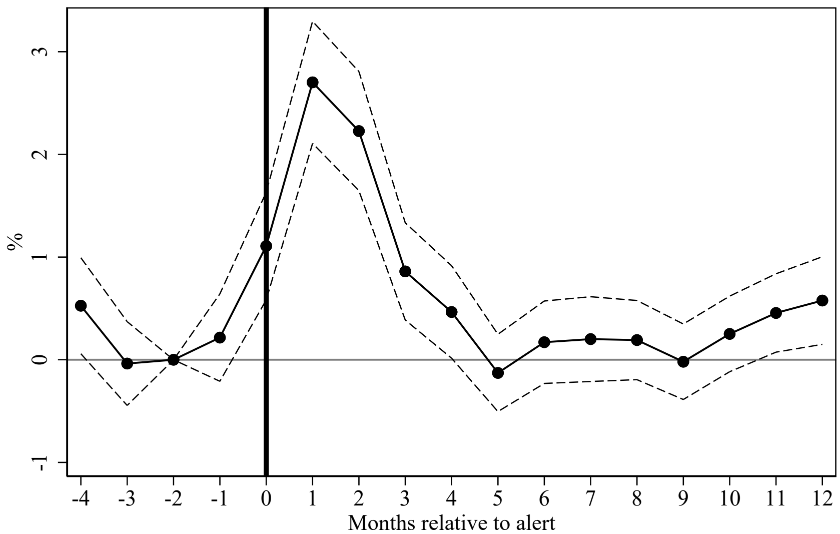
Figure A.3: Heterogeneity of effects of alerts on enforcement probability



Note: This figure show the probability of a fine and the decomposition between baseline and total probability, where the baseline is the total probability minus the estimated ATT using the event study. The figure shows estimates across different heterogeneity dimensions. Priority lists refer to the list of municipalities that are designated as priority by IBAMA in terms of its enforcement mandate. Close to IBAMA divides the grid cells in two groups based on the median distance from the closest IBAMA office, among 30 offices in the Amazon region. Soy suitability divides the grid cells in two groups based on the median of maximum soy yield, from the FAO-GAEZ measure. Private property indicates that the grid cell contains private properties, as observed via CAR/SIGEF.

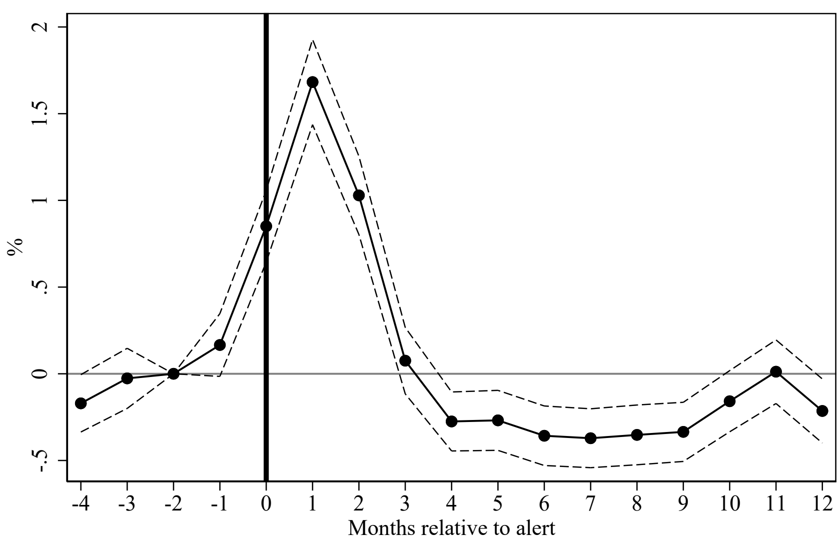
Figure A.4: Robustness Tests

(a) Effects of Alerts for Alerts that Followed a Cloudy Month



Accumulated Treatment Effects: 7 p.p. (± 2.5), over a baseline value of 17% (increase of 41%).
N = 0.12 million
7.23 thousand alerts in 5.89 thousand unique grid cells, plus 59.87 thousand grid cells with no alerts.

(b) Effects of Alerts for Grid Cells with Only One Alert



Accumulated Treatment Effects: 4 p.p. (± 1.8), over a baseline value of 13% (increase of 31%).
N = 0.52 million
34.48 thousand alerts in 23.72 thousand unique grid cells, plus 59.83 thousand grid cells with no alerts.

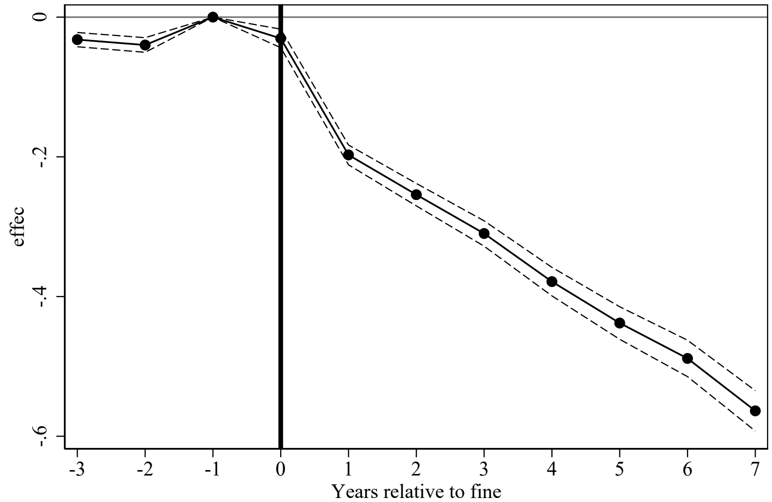
Note: Panel (a) shows the event study results for events where the alert followed a month in which the grid cell was covered by cloud, and therefore invisible to DETER. Panel (b) shows the event study results for events in which no other alert was generated for the same grid cell in the following 12 months. All results are estimated via OLS and standard errors are clustered at four interlaced grid cells of 110 square km around each 4km x 4km grid cell.

Table A.4: Robustness – General Deterrence Estimates

	Panel A: 50 km radius			Panel B: Gaussian weighting		
outcome:	P(fine>0)	deforestation (ha)	P(deforestation>0)	P(fine>0)	deforestation (ha)	P(deforestation>0)
	OLS	2SLS	2SLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Fine		-42.70***	-0.426***		-62.59**	-0.318
		(12.76)	(0.159)		(28.63)	(0.273)
P(detection 50km)	0.0792***					
	(0.0159)					
P(detection Gauss.)				0.0267***		
				(0.00972)		
log(accumulated deforestation)	0.0666***	18.46***	0.212***	0.0671***	19.81***	0.205***
	(0.00350)	(0.894)	(0.0109)	(0.00350)	(1.960)	(0.0185)
log(precipitation)	0.0653***	4.695***	0.0121	0.0617***	5.864***	0.00407
	(0.00923)	(0.978)	(0.0121)	(0.00916)	(1.869)	(0.0180)
N	187142	187142	400193	187474	187474	403133
Cragg-Donald F	62.37			19.75		

Note: * 0.10 ** 0.05 *** 0.01 significance levels. This table shows the estimates of general deterrence effects for intensive and extensive margins using detection probability as an instrumental variable. It shows two panels for two alternative definitions of the instrument. In Panel A, the detection probability is computed as the share of 0.09-0.1 ha deforestation polygons (measured by PRODES) detected in quasi-real time by DETER within a 50km radius from each grid cell. Column (1) shows the first stage results, where the outcome is a binary variable indicating that the grid cell-year received a fine. Columns (2) and (3) show 2SLS results for deforestation in the intensive and extensive margins. In Panel B, the detection probability is the share of 0.09-0.1 ha deforestation polygons (measured by PRODES) detected in quasi-real time by DETER within a 80km radius from each grid cell, but weighted by distance of the polygons to the centroid of the grid according to a Gaussian kernel. Column (4) shows the first stage, and Columns (5) and (6) show the 2SLS results for the intensive and extensive margins of deforestation. All regressions include grid cell and year fixed effects.Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.

Figure A.5: Specific deterrence P($d > 0$)

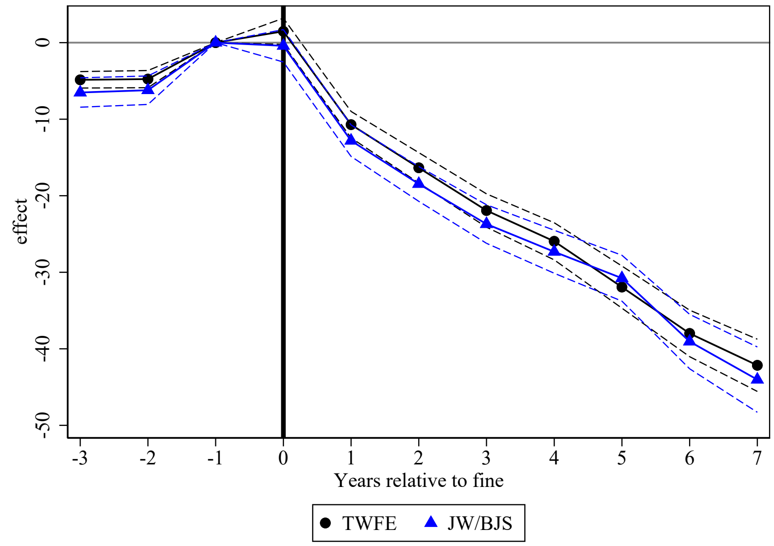


Share with positive deforestation at year of fine: 62%. Share over four years up to year of fine: 57%.
N = 176490, with 14798 unique grid cells.

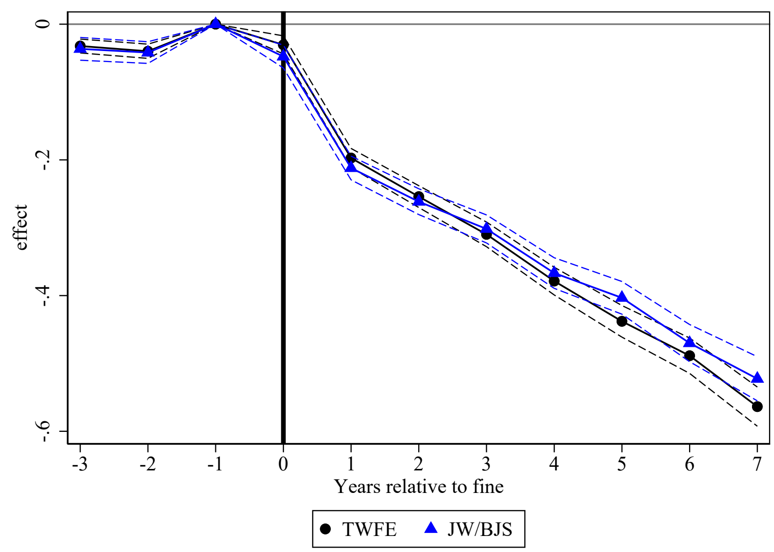
Note: This figure shows the OLS coefficients for the event study described by Equation 6 using stacked events plus the yearly observations of never treated grid cells. The outcome is a binary variable indicating that the grid cell had positive deforestation in a given year. Only grid cells with positive deforestation in at least one year in the 2011-2020 period are included in the analysis. Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.

Figure A.6: Specific Deterrence Effects - Robust Differences in Differences

(a) Specific deterrence hectares

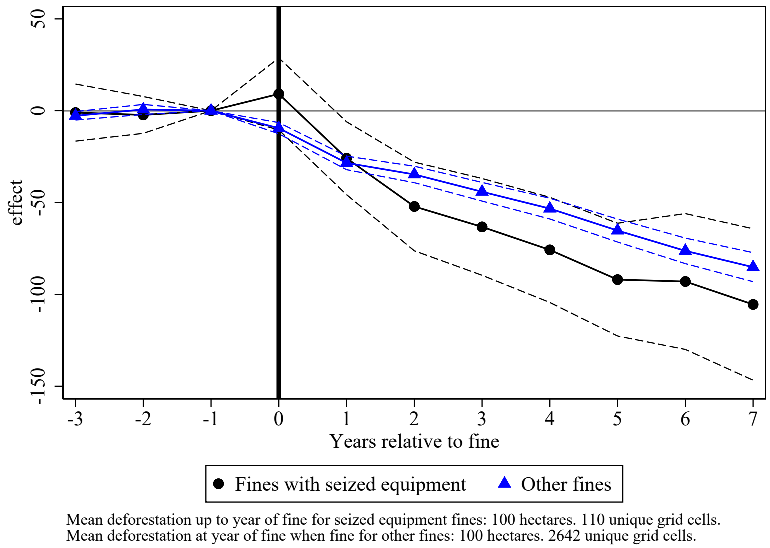


(b) Specific deterrence P($d > 0$)



Note: This figure shows the OLS coefficients for the event study described by Equation 6 using stacked events plus the yearly observations of never treated grid cells. The outcome is a binary variable indicating that the grid cell had positive deforestation in a given year. Only grid cells with positive deforestation in at least one year in the 2011-2020 period are included in the analysis. Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.

Figure A.7: Specific Deterrence Effects – Heterogeneity Analysis – Seized Equipment



Note: This figure shows the OLS coefficients for the event study described by Equation 6 using stacked events plus the yearly observations of never treated grid cells. The outcome is a binary variable indicating that the grid cell had positive deforestation in a given year. Only grid cells with positive deforestation in at least one year in the 2011-2020 period are included in the analysis. Standard errors are clustered using four interlaced grids of 1^o (approximately 110 km) around each 4km x 4km cell.