Satellites and Fines:
Using Monitoring to Target Inspections of Deforestation

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Abstract

Effectively fighting deforestation requires monitoring of vast areas, which is possible thanks to satellite imagery. However, satellite monitoring can only reduce deforestation if three conditions are met: the monitoring alerts must be informative, the enforcement agency must use them to target inspections, and farmers must respond to enforcement action by doing less deforestation. This paper quantifies the contribution of real-time monitoring in deforestation reduction using detailed satellite and administrative data in the Brazilian Amazon forest. It studies the whole chain of events from the production of a deforestation alert to its effect on deforestation. It first documents an improvement in the monitoring system's ability to detect infractions in real-time. Then it estimates the impact that real-time alerts have on deforestation inspections. Finally, it estimates the impact of inspections on deforestation using an instrumental variable approach and an event study. Overall, the real-time alerts increase by two percentage points the inspection probability for offenders, avoiding approximately 430 square kilometers of deforestation per year.

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1 Introduction

One of the challenges for law enforcement agencies is to target enforcement resources smartly to maximize their deterrence effect. This problem is particularly challenging because offenders are likely to hide their behavior and avoid enforcement if they can. Monitoring technologies help enforcement agencies observe offenses, albeit often imperfectly, providing valuable information to decide the deployment of resources. Despite its promising potential, monitoring technologies may fail to deliver their promises because of technical and behavioral barriers within the enforcement agency. For example, the information brought by a monitoring technology may be poor or redundant to the knowledge already at the agency's disposal, or agencies may resist to automating practices by machines and algorithms, thus reducing the impact of monitoring on deterrence. Moreover, to the extent that monitoring changes enforcement behavior, the impact on compliance hinges on offenders' responses to enforcement action.

This paper aims to document how monitoring technologies shape (or do not shape) enforcement action, and their resulting impact on regulatory compliance. It studies this problem by investigating law enforcement against illegal deforestation in the Brazilian Amazon forest. This context is particularly suitable to study how monitoring affects enforcement action. The main reason is that it is possible to observe separately, in the data, i) the extent of infractions, measured at high resolutions with satellite data but only computed once a year, ii) the monitoring information at disposal of the enforcement agency, also produced by satellites but at a lower resolution and higher frequency than the measurement of infractions, and iii) and the location of enforcement action. The separation of these three layers - almost-perfect observation of infractions, monitoring information, and enforcement action - is an almost unique feature in studies of crime and enforcement, which are often plagued by the lack of observability of the infraction itself except when monitoring technologies or enforcement agents detect it.

Besides its convenient features to study the law enforcement problem, the fighting 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). Deforestation liberates the carbon stored in the trees' biomass to the atmosphere through forest fires or decomposition, aggravating climate change. In addition, deforestation destroys biodiversity (Fearnside 2021), dis-

turbs 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 harms, individual farmers reap private benefits from agricultural or timber exploitation of deforested areas. The tension between the individual benefits and the social costs of deforestation calls for governmental action, 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 with a high degree of certainty, usually yearly and 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 be concluded (INPE 2019a), making it unsuited for day-to-day decisions about enforcement deployment. For enforcement purposes, algorithms have been developed, using lower resolution images than the Landsat images, to generate (almost) real-time information about deforestation, which could be more actionable for enforcement agencies. The availability of real-time deforestation alerts can transform the decision-making rule of enforcement agencies, allowing them to react fast and effectively to detected offenses, thereby raising the probability of penalty for potential offenders, and hopefully reducing the overall level of illegal activity. But for all that to happen, the enforcement agency must incorporate the new information into its decision-making, using it as a rule to target enforcement resources. This paper studies to which extent the Brazilian enforcement agency does that, and how that affects deforestation.

Real-time monitoring information can be useful for enforcement action against illegal deforestation because enforcement agents may stop ongoing deforestation processes, preventing it from spreading to larger areas. For example, in the case of the Brazilian Amazon forest, enforcement agents can apprehend equipment used to deforest, and even arrest offenders. On the other hand, in the case of deforestation, enforcement agents do not need to act immediately if the offender can be contacted at any time, as could be the case if the property owner is known or the area is used for economic development.

Monitoring technologies can support enforcement agencies in targeting inspections to fight punishable offenses. In a best-case scenario, monitoring technologies provide new and accurate

information, thereby changing the behavior of enforcement agents. However, in the worst-case scenario, monitoring information is redundant to other information sources already available to inspectors and does not affect inspection selection. Finally, the third factor is the impact of inspections on offenses. Offenders may be undeterred by inspections and consequently not change their behavior even in the presence of monitoring. In the end, monitoring technologies are only helpful if they affect appraisal selection and reduce offenses. To assess the value of real-time monitoring, one must estimate how real-time information causes enforcement action and how enforcement action affects illegal behavior. That is, in a nutshell, the roadmap for this paper.

I study the effect of a real-time monitoring technology on environmental enforcement deforestation and deforestation in the context of the Brazilian Amazon forest. In this forest, almost all deforestation is illegal (Valdiones et al. 2021), and a single federal enforcement agency does most law enforcement action, inspecting and punishing offenders. In 2004 the Brazilian government launched a monitoring program to produce real-time deforestation alerts based on satellite images. The system is touted as a breakthrough in Brazilian environmental enforcement, and there is evidence that real-time monitoring helped reduce deforestation (Assunção, Gandour, and Rocha 2022). This paper builds on the pioneering effort by Assunção, Gandour, and Rocha (2022), but goes beyond by proposing a framework to compute the value of the real-time monitoring system in terms of reduced deforestation.

I merge the yearly measurement of deforestation, the real-time monitoring alerts, and georeferenced fines, and other geographical data, creating a balanced panel over the decade 2011 to 2020. As alluded previously, the yearly measurement is an accurate measure of deforestation, computed independently from the real-time monitoring technology or inspections. The ability to observe the degree of offenses is not always the case in other applications in the crime literature, where offenses are only observed if victims report them or if enforcement agents carry out inspections. The fact that deforestation is measured in an accurate way is a crucial asset to understand the quality of monitoring and the behavior of the enforcement agency in this paper.

To assess the quality of the deforestation alerts produced by the monitoring system, I overlay the maps of yearly deforestation with the monitoring alerts to the monitoring system's detection rate and its share of false-positive alerts. To my knowledge, this analysis is the first systematic and independent assessment of the quality of this monitoring system. The results show that the

production of deforestation alerts by the monitoring system improved substantially in quality over the years 2011-2020. Furthermore, the comparison of real-time deforestation alerts with the yearly deforestation maps revealed a substantial improvement in detection rates, with a relatively low level of false positives. The increase in detection rate was due to improvements in the satellite image resolution and the technical capacity to monitor the images in real-time by experts.

Next, I study how the real-time alerts impact the behavior of the enforcement agency. I use a monthly-level event study to estimate the causal impact of a real-time deforestation alert on the probability of a fine. The results show that the enforcement agency explicitly uses the deforestation alerts to decide its inspections. Indeed, the inspection probability almost doubles when the agency receives a deforestation alert, while the inspection probability barely changes for other types of satellite alerts, such as fire alerts. Moreover, the share of alerts-driven fines in the enforcement agency's portfolio doubled in the period, reflecting a transformation in the inspection selection strategy with a more significant role for the monitoring system.

Finally, I estimate the impact of inspections on farmers' decisions to deforest. I decompose the behavioral responses of farmers into two parts: the effect on deforestation of changes in the inspection probability (general deterrence) and the effect of punishment over time (specific deterrence). The distinction between general and specific deterrence is well-known in the crime literature, but studies usually estimate either one or another.

To identify the general and specific deterrence effects separately, I use two different identification strategies. First, to identify the general deterrence effect, I exploit variation in the monitoring system's ability to detect deforestation in an instrumental variable approach. Cloud coverage blocks the view from satellites, making it impossible to generate real-time alerts, and therefore less likely to receive an inspection. The exclusion restriction is that cloud coverage only affects the incentives of farmers through its impact on the probability of an inspection. The results show that areas with more cloud coverage have less deforestation fines and show higher deforestation on the extensive (i.e., are more likely to have any deforestation) and intensive margin (i.e., deforest larger areas on average).

Furthermore, I used an event study design to estimate the specific deterrence effect, which enabled me to compute the dynamic effects of punishment several years after it happened. The two effects combined provide a complete picture of the effect of enforcement on deforestation.

Inspected areas are 10% less likely to display any level of deforestation even three years after the inspection occurred.

In summary, a one percent increase in inspection probability saves almost 150 square kilometers of forest or 2% of average yearly deforestation levels. In a conservative computation, the satellite increased the inspection probability by three percentage points every year for farmers, saving almost 450 square kilometers of forest per year and one thousand square kilometers in a decade. This number is an estimate of the value of the real-time monitoring system in terms of avoided deforestation. Moreover, the monetary value of avoided carbon emissions from deforestation are about 20 times as large as the opportunity costs of agricultural output in the Amazon forest. The benefits also far outweigh the budget of the monitoring and enforcement agencies.

1.1 Related literature

This paper contributes to four strands of literature: i) the effect of monitoring and enforcement on compliance, ii) inspection selection, and iii) tropical forest deforestation. It also adds to the growing literature in economics using geo-referenced satellite data to measure outcomes and identify causal effects (see Donaldson and Storeygard 2016 for a review).[1]

The literature on monitoring and enforcement has highlighted the importance of monitoring information to induce regulatory compliance. Satellite-based monitoring programs had substantial positive impacts on compliance with air pollution environmental regulation in China (Greenstone et al. 2020) and US (Zou 2021).[2]. Nevertheless, the availability of information *per se* cannot explain compliance: monitoring can only affect incentives if the information is used to sanction offenders[3]. I contribute to this literature by studying the relationship between monitoring and enforcement, and then its impact on compliance. I perform the analysis at a precise geographical level, where defor-

[1]Examples range from tax compliance (Casaburi and Troiano 2016) to environmental economics, in particular tropical forest deforestation (Burgess, Costa, and Olken 2019, Assunção, Gandour, and Rocha 2022, Souza-Rodrigues 2019, among others) and forest fires (Balboni, Burgess, and Olken 2021).

[2]A parallel of monitoring can be also made with tax evasion, where the presence of third-party reporting also bridges the information gap between enforcement agency and taxpayers. Several papers have provided evidence of the role of third-party reporting in inducing tax compliance in Denmark (Kleven et al. 2011), Chile (Pomeranz 2015) and Brazil (Naritomi 2019).

[3]For example, in the issue of CCTV cameras, an extensive review by Welsh and Farrington (2009) has shown mixed evidence on their role in preventing crime. Ashby (2017) shows how the information produced by the cameras is effectively used to solve different types of crime, which helps explain the variety of effects of CCTVs on deterring crime.

estation, alerts and inspections are observed. In the context of deforestation in Brazil, Assunção, Gandour, and Rocha 2022 show that municipalities that receive additional fines caused by better monitoring visibility reduce deforestation one year later, suggesting a strong specific deterrence effect in areas that receive additional punishments. I expand on that paper's approach to estimate the effect of satellite visibility on the decision to deforest (general deterrence), and by proposing a framework to integrate general and specific deterrence to assess the total deterrence value of the Brazilian monitoring system.

The most invaluable aspect of the datasets used is that it allowed me to separately observe deforestation, monitoring alerts and inspections. In several settings, the outcome cannot be observed independently of monitoring or audits, such as tax evasion. The independent measurement of deforestation allowed me to compute monitoring detection rates by overlaying the alerts maps with deforestation maps. As a consequence, it is possible to study with precision what causes detection rates to fail and how detection rates influence audit selection. Inspection selection is an important topic in the enforcement literature, which has been largely studied in the game theoretical literature (see Andreoni, Erard, and Feinstein 1998 for a review in tax compliance) but less so in the empirical literature. Duflo et al. (2018), Kang and Silveira (2021), and Bachas et al. (2021) have shed light on the value of discretion in inspection selection. Blundell, Gowrisankaran, and Langer (2020) estimate the value of an "escalation" strategy in terms of compliance with environmental regulation.

Furthermore, this paper is unique to estimate both general and specific deterrence effects, and proposing a framework to integrate them in the evaluation of the monitoring system. The distinction between general deterrence and specific deterrence is well-known in the crime literature (Chalfin and McCrary 2017). General deterrence effects have been in the analytical framework of economists at least since Becker (1968), representing how agents internalize punishment probability in their decision-making. Effects of punishment probability on behavior has been estimated in urban crime (Levitt 1997, McCrary 2002), environmental (Chan and Zhou 2021) and tax compliance settings (Almunia and Lopez-Rodriguez 2018, De Neve et al. 2021), to name a few examples. Specific deterrence was first recognized as "incapacitation" effects of punishments such as imprisonment (Kessler and Levitt 1999, Kuziemko and Levitt 2004), but the concept has been applied to understand the effect of punishment on behavior more generally, also in environmental (Dusek and

Traxler 2021) and in tax settings (Advani, Elming, and Shaw 2018).

The paper contributes to the deforestation literature by exploiting the satellite and administrative data in a novel way, and by studying the incentives to use fire in deforestation. This paper is the first to systematically use geo-referenced fines, logging alerts, and fire alerts in a single framework to explain patterns of enforcement and deforestation at a detailed geographical level. Assunção, Gandour, and Rocha (2022) has also studied the role of real-time monitoring on deforestation, using cloud coverage as an instrument for environmental fines at the municipality-year level. Building on that insightful work, I compute the detection probability of the logging monitoring system over time and show how this improvement has affected enforcement strategy and then deforestation patterns. Assunção, Gandour, and Souza-Rodrigues (2019) use logging signals directly as proxies of enforcement and show that they increase the probability of forest regeneration. Other papers have studied the impact of enforcement on deforestation by studying the policy of "priority municipalities" (Assunção and Rocha 2019 and Assunção et al. 2023), and incentive-based approaches to fight deforestation (see Jayachandran et al. 2017 for a study of initiatives in developing countries). Souza-Rodrigues (2019) discusses potential efficiency gains from moving to a more incentive-based approach, using a structural model of deforestation.

2 Background: deforestation in the Amazon forest

The Brazilian Amazon is the world's largest rainforest, with 4 million square kilometers.[4] 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 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 deforesta-

[4]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.

tion 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 been partly recovered 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 (see INPE 2019a for a detailed description). In the first step, selective logging, farmers selectively cut valuable types of timber.[5] 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).[6]

In this highly humid area, fires do not emerge naturally. Instead, farmers set fires to clear veg-

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

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

etation as a preparation or sequel to logging. Fires aggravate the concerns involving deforestation because they introduce additional environmental risks. First, forest fires inflict irreversible damage on tropical vegetation, which lacks natural defenses against fires (Nepstad et al. 1999, Gillespie 2021). Second, fires severely impair local air quality, with damaging effects on human health (see Reddington et al. 2015 for a study in Brazil and Sheldon and Sankaran 2017, Jayachandran 2009 for Indonesia). Thirdly, fires spread easily to neighboring areas, sometimes getting out of control in catastrophic ways. Forest fires damage vegetation, pollute the air, and emit greenhouse gases even when the areas are not ultimately logged. Official inventories of greenhouse gases often fail to account for forest fires because their methodologies focus on deforestation (Alencar, Nepstad, and Diaz 2006). Controlling fires is costly, consisting of building barriers and monitoring the fire.[7]

2.2 Enforcement by IBAMA and PPCDAm

Deforestation is banned in the Brazilian Amazon, except for some particular circumstances. Regarding land tenure, 50% of the Amazonian area is indigenous territory (1.16 million square kilometers) or conservation units (1.2 million square kilometers). At least 13% (roughly half a million square kilometers, according to Azevedo-Ramos et al. 2020) consists of public forests (also called "undesignated" public forests). It is forbidden to deforest in any of these areas. The remaining areas are privately owned rural properties and are mandated to preserve 80% of their area as forest. Only 2% to 4% of deforestation was legal in 2020, according to estimates by Azevedo et al. (2020) 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. The use of fires is also tightly regulated in the region. Under authorization and following safety procedures, the law authorizes fires for agricultural purposes, but all forest fires are illegal. Penalties for farmers caught committing deforestation include high fines (about 1 thousand euros per hectare), seizure of equipment and goods, an economic embargo on the deforested land, and even imprisonment. The use of fire in deforestation is supposed to increase penalties. The law is quite severe against offenders but is not always enforced.

The federal enforcement agency, IBAMA, is the government body in charge of environmental

[7] In the year 2020 in the Brazilian "Pantanal", fires covered 3.9 million hectares during the months of July and August, which represents 26% of the total area of the biome (Leal Filho et al. 2021).

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", which consisted in a task force in the federal government launched in 2004 to improve enforcement against illeal 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, which I explain in more detail below. 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 for the enforcement agency.[8] 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* the forest. DETER has been a major breakthrough in law enforcement in the Brazilian Amazonia, but its ability to detect deforestation with deforestation alerts was relatively low in the early years, with a large number of false positives. In the period used in this paper, the decade of 2011 to 2020, the program progressed substantially in its capacity to flag deforestation areas correctly in real time, as documented later in this paper. DETER also started distinguishing alerts for different types of events on the ground. Today, besides the deforestation alerts, DETER produces alerts for forest degradation, mining, selective logging, and fire scars.

The monitoring system DETER uses 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 automatized. 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). The technicians in charge of monitoring the forest and producing the alert are independent from the enforcement agency, and there is no prioritization of monitoring areas in case of shortages of personnel or computing capacity.

2.4 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

[8]DETER initially based on images from the satellite Terra, and since 2017 using images from the satellites CBERS-4 and IRS. Terra is a NASA satellite, CBERS-4 is a Chinese-Brazilian satelliten and IRS stands for Indian Remote Sensing Satellite. To distinguish from its first phase (2004-2017), the program is now named DETER-B

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.

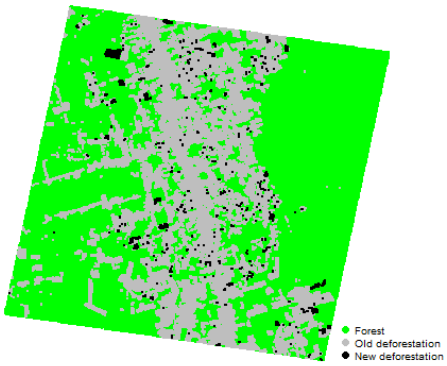
These three datasets are exemplified in the set of figures 1a to 1c.[9] Figure 1a shows the categorization of the land coverage by PRODES as forest, old deforestation, and new (i.e., "last-year") deforestation. Figure 1b shows the areas of logging signals in yellow. Finally, Figure 1c shows the points where inspectors recorded a fine.

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

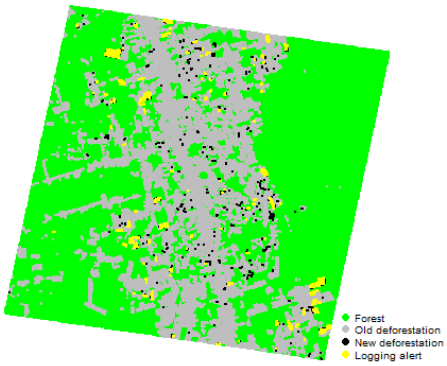
To overlay the maps of deforestation, deforestation alerts, and fines, in the whole Amazon forest, I used the 30m raster of deforestation from PRODES and aggregated it at the level of a 4 km cell-sized grid. The DETER alerts are polygons, and they are rasterized at the 4 km level. The deforestation fines are provided as points with a latitude and longitude, and I allow a fine to correspond to any grid cell centroid at a maximum of 5 km from the recorded coordinates.

On top of these three main datasets, I also added the following set of geographic characteristics at the level of 4 km grid cell: the municipality of the grid cell, and land tenure status of the grid cell (private property from the official registry CAR, indigenous land from FUNAI, conservation unit from INPE, non-designaged forest from INPE, and land reform settlements from INCRA), soil suitability for soy (from FAO), altitude and terrain ruggedness, presence of water bodies, presence of state and federal roads, distance to the city of Cuiaba (as a proxy for proximity to the "deforestation frontier"), and distance from the nearest IBAMA office (as a proxy for enforcement cost). All these variables are fixed at the cell level. Finally, I compute the share of accumulated deforestation at the cell level, which varies at the cell-year level. This variable allows to distinguish between cells that are close to exhausting the amount of forest, and which mechanically would not present any degree of additional deforestation, nor of enforcement action.

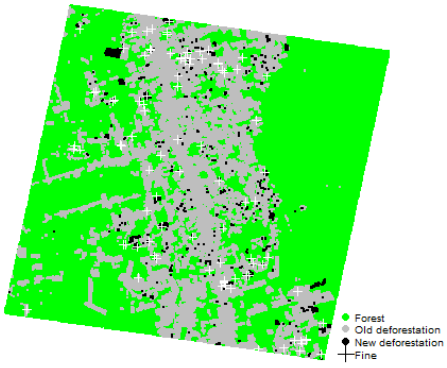
[9]To produce these figures, I took an area of approximately 30 thousand square kilometers, corresponding to a "scene" of the Landsat satellite, in the northern state of Pará in the year 2016.



(a) Measurement satellite (PRODES)



(b) Logging alerts (DETER)



(c) Deforestation fines (IBAMA)

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

3 Conceptual framework

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.

Inspections are valuable to the extent that they affect farmers' decisions to deforest. The classical model of crime in economics, first proposed by Becker (1968), posits that agents decide whether to commit a crime based on the probability of punishment. In this model, the credible risk of punishment is enough to deter agents from engaging in unlawful activities. This effect came to be known in the crime literature as "general deterrence" effect. In the context of deforestation, this effect would translate to farmers refraining from deforestation when the probability of being caught is high enough.

Besides the general deterrence effect, another way enforcement can deter crime is by affecting the future behavior of punished agents. One classic example is imprisonment, which incapacitates agents from committing a crime, reducing the future crime incidence. The effect of punishment itself on agents' future behavior is known as "specific deterrence effect" or "incapacitation effect." Empirically, the incapacitation effect is observable in agents' behavior after experiencing punishment. The general and specific deterrence effects are thus theoretically different and can be thought of as "ex ante" and "ex post" effects of punishment. Understanding the full impact of enforcement on agents' behavior requires accounting for both behavioral responses.

To illustrate the trade-offs faced by an enforcement agency when choosing the amount of targeting, one can imagine an inspector game between potential offenders and an agency. The agent derives some utility Y from the illegal action, but suffers f when caught. The agency suffers a damage d if an offense takes place, regardless if the offender was caught or not. However, catching the offender yields a benefit θ to the enforcement agency, which could be interpreted as incapacitation effects of punishment (reducing the potential of agents to continue inflicting damages d to

the agency) or incentives of bureaucrats. To adapt to the setting of illegal deforestation, I assume that the agency has three strategies: no audit, audit ("random audit"), or audit conditional on a random signal ("targeted audit"). The random signal occurs with probability s if the agent chooses to offend, but with probability 0 if there is no offense. Audits cost c to the agency.

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

Table 1: Payoff matrix (Agent on top, agency on the bottom of each cell)

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

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 pi_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 enforce-

ment 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.

The existence of general and specific deterrence effects can also affect the incentives of enforcement agencies to target their inspections based on monitoring information. Monitoring data are a potential cost saver for enforcement agency because monitoring allows the agency to carry out actions only conditional on credible indications of offenses. In the context of deforestation, credible monitoring alerts allow conservation agencies to send field inspectors only to areas where infractions are known to be taking place. From this perspective, one might to conclude that resource-constrained enforcement agencies should only act as a response to monitoring alerts, thus maximizing the probability of penalty conditional on alerts and minimizing field inspections that lead to no punishment. In sum, agencies should only run targeted inspections. However, full targeting of inspections might not be an optimal policy choice for the enforcement agency when specific deterrence effects are important. The existence of specific deterrence effects means that the agency can also benefit from punishing offenders, thus generating a trade-off between the general deterrence created by targeting and the number of punishments guaranteed by random inspections.

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. In Appendix **??**, I derive the optimal choice of targeting and random inspections in a two-period model that has a convex s. 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.

These theoretical considerations had the goal of convincing the reader that monitoring technologies may interact in complex ways with the agency's objectives and the agents' incentives. It is, therefore, reasonable that agencies choose interior solutions of targeted versus non-targeted inspections, as opposed to only doing targeted inspections. In what follows, I describe how to create an empirical model that provides a characterization of the amount of targeting and deterrence generated by IBAMA's use of real-time deforestation alerts in the Brazilian Amazon.

Following the notation introduced above, π_T denotes the probability of inspections conditional on a real-time alert, which happens with probability s. All the other inspections are lumped in the category of non-targeted or random inspections, with probability π_R. In practice, it is unlikely that inspections are truly random, and can be motivated by beliefs about deforestation formed through other means than the real-time monitoring alerts. However, to illustrate the role of real-time alerts, I assume that the targeted inspections display a specific empirical signature that allows to identify π_T from π_R.

Regarding the impact on the amount of deforestation, I assume that agents choose an optimal amount of deforestation $d(\pi_t, f)$ which is a function of the probability of inspection π_t at time t and their history of past experienced fines $f = \{f_{t-1}, f_{t-2}, ...\}$. Notice that it can be optimal for agents to choose $d_t = 0$ as a response to economic conditions (e.g., high cost of deforestation in a given location) or enforcement (π_t or f). The aggregated amount of deforestation in the Amazon in one period is denoted:

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

or $\sum_t^T D(\pi_t, f)$ over T periods of time. Where $p(d_t) \equiv \mathbb{P}(d_t > 0)$ is the extensive margin of this problem, denoting the number of areas that 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 area of deforestation chosen in areas with positive deforestation. An increase in π_t affects the both margins, meaning that the number of areas that do deforestation may change as a result. Consequently, the number of areas that receive a fine is affected by the impact on the extensive margin. The areas that are fined change their amount of deforestation in the future due to the

specific deterrence or incapacitation effect. Formally, the impact of a marginal increase in π_t for one period on $\sum_t^T D(\pi_t, f)$ is:

$$\frac{\partial \sum_t^T D(\pi_t, f)}{\partial \pi_t} = \underbrace{\frac{\partial p(d_t)}{\partial \pi_t}\bar{d}_t + p(d_t)\frac{\partial \bar{d}_t}{\partial \pi_t}}_{\textbf{general deterrence effect}} + \underbrace{\left(d\pi_t p(d_t) + \pi_t \frac{\partial p(d_t)}{\partial \pi_t}\right) \sum_t^T \frac{\partial \bar{d}_t}{\partial f_t}}_{\textbf{specific deterrence effect}} \tag{2}$$

The general deterrence effects contains the impact of π_t on the extensive and intensive margins, both of 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 next sections is twofold: first, to decompose the terms of the policy rule chosen by IBAMA as $\pi = \pi_R + s\pi_T$, and then understand how increases in $s\pi_T$ (and hence π) affect deforestation using equation 2. This exercise provide a fairly complete assessment of the impact of the monitoring system on the incidence of an offense.

4 Monitoring and inspection selection

How does the Brazilian environmental agency use satellite alerts to decide which areas to inspect? I answer this question using geo-referenced data on fines and deforestation alerts at the monthly level. This section aims to quantify the importance of deforestation alerts in Brazilian enforcement action against deforestation. It is unclear to which extent real-time monitoring alerts have an effect on enforcement action since the enforcement agency can also carry out inspections in the absence of satellite inspections, based on helicopter surveillance, denunciations by citizens, regular patrolling, or other types of non-coded information. In Brazil, the real-time monitoring system DETER is touted as a breakthrough in enforcement, and here I assess how much of IBAMA's enforcement action are caused by it.

In this section, I compute the probability of a fine in areas with deforestation, and decompose this probability to how much of it is caused by real-time deforestation alerts. To do that, I use geo-referenced information on fines, true measured deforestation, and the satellite-based deforestation alerts at the 15km x 15km cell level. To estimate inspection selection, I restrict the sample to areas with positive levels of deforestation, that is, non-compliant areas. Restricting the data is necessary

to interpret variation in the fines as variation in inspection efforts. Fines only reflect enforcement in areas that are "eligible" for them, that is, areas with positive levels of offenses.[10]. Among non-compliant cells, observed variation in fines can be interpreted as variation in enforcement action. I describe how the overall yearly probability of inspection rises in non-compliant areas, when satellites produce logging or fire alerts in the same areas. Next, I use monthly data to estimate the causal impact of alerts on enforcement action probability, using an event study approach. I then discuss the value of following real-time alerts as opposed to random fines.

4.1 Decomposing the fine probability

The probability of inspections for offending cells can be decomposed as follows, using the Law of Total Probability:[11]

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

The objects in this expression are easily computed from the data, and as already mentioned, the probability of fine in the Amazon forest in the studied period was 13%. The probability of a fine (i.e., a positive number of fines in the year) in areas that receive an alert was 22%, but this value is not the causal effect of alerts. Indeed, this probability is decomposed in a baseline level of fines in areas that receive alerts, which I denote $\mathbb{P}(\text{fine}(0)|\text{alert})$ borrowing from the potential outcomes literature, and the average causal effect of alerts, denoted ATT:

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

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

[10] 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.

[11] All expressions below are conditional on the cells having positive deforestation, that is, the cell is an "offending cell".

occurred regardless of the alerts.

The probability of inspections in the Amazon forest in the 2011-2020 was 13% in the decade from 2011 to 2020. This means that conditional on a positive level of deforestation, a 4km x 4km cell had a 13% probability of receiving at least one deforestation fine in the same year. In principle, deforestation can be punished at later dates, even years after the offense has been committed. However, this seems to be rare: more than 80% of deforestation fines by IBAMA happen in areas that have positive new levels of deforestation in the same year.[12]

The conditional probability of inspection in a cell, given that the cell contains illegal deforestation, depends on the allocation decisions of the enforcement agency. This allocation decision depends, in turn, on the agency's information set and preferences. In this exercise, I propose to evaluate the role of real-time monitoring information on the probability of enforcement in an area with deforestation, and decompose the action of IBAMA into alerts-driven or not alerts-driven. The challenge of causally assigning an enforcement action to an alert is that alerts may be correlated with other sources of information that would allow the agency to carry out enforcement even in the absence of alerts. Although the agency may have accurate predictions about the geographic dispersion of future deforestation, and obtain additional information through patrolling or reports, the monitoring system provides quasi-real-time data that would not be available otherwise. Therefore, the unique feature of the alerts is the timing of the information. To the extent that the agency reacts to this information to target enforcement, the exact timing of the alert should affect the timing of enforcement relative relative to a situation without the alert.

This strategy relies on the trends of fines in different areas, and identifies as a causal effect any deviation from parallel trends which follows from an alert. Exploiting the panel dimension of the data, it is possible to recover the average treatment effect on the treated (i.e., the cells which received alerts) by the evolution of the number of fines before and after alerts with the evolution of fines in the same period for cells that did not receive any alert. This is the differences-in-differences approach. This strategy identifies the average treatment effect on the treated under two mains assumptions. The first one is "parallel trends", meaning that in the absence of alerts, the number of fines would evolve on average the same way for cells with and without alerts. The

[12] Within a grid cell with deforestation there can be several fines in different months, notably because different offenders may be deforesting around the same time. As noted, the 13% figure refers to the share of cells with deforestation that received at least one fine.

second one is "non anticipation", which means that the observed outcomes previous to the alert can be interpreted as untreated outcomes.

The analysis is done in the form of an event study at the month-cell level. I pool every cell at the monthly level to create a balanced panel of cell i and month t. Furthermore, I only consider cells which have displayed positive levels of deforestation at some point in the decade, because these are areas where a fine could be produced. I then estimate 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 ε_{it} is a conditional mean zero error term, and e_i is the month of the an alert event within cell i.[13] $\mathbb{1}\{t - e_i = \ell\}$ 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.

As mentioned above, only observations which presented positive deforestation were included. Therefore, this estimation captures the effect of an alert in spurring enforcement action in an area which is "eligible" for fines, with or without monitoring alerts. Indeed, many cells had positive levels of deforestation but did not have deforestation alerts, making them a group of comparable "never treated" cells. Among treated cells, the treatment date varies from one place to the other, partly because deforestation happens in different moments in time, or because cloud coverage delays detection of deforestation by the monitoring systems.

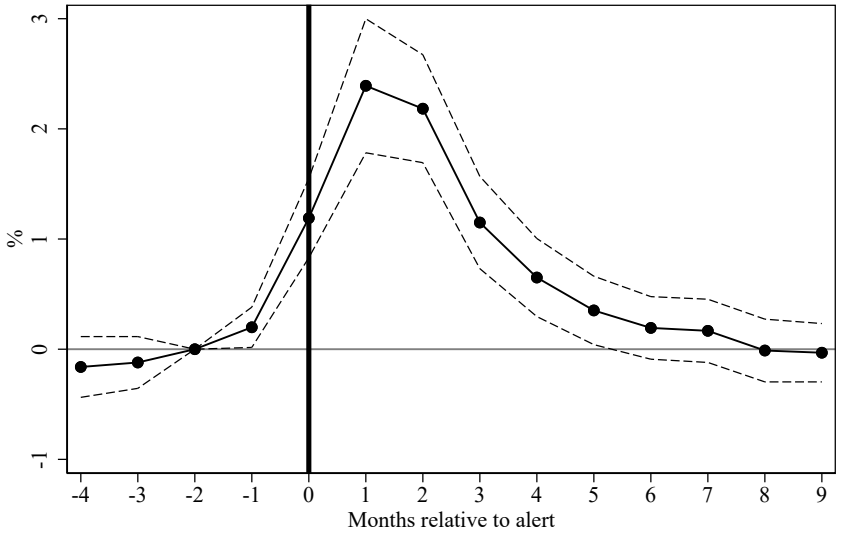
Estimation of equation 4 by OLS can identify the average effect of alerts on the probability of fines under some strict assumptions. Indeed, omitting the first lag ($\ell = -1$) in the estimating equation means that each β_ℓ is a weighted average of all differences-in-differences parameters. Normally, the differences-in-differences strategy identifies the average treatment effect on the treated under the assumptions of parallel trends and no anticipation (see Wooldridge 2021 for a detailed discussion). However, as highlighted by a recent literature (see Callaway and Sant'Anna 2020, De Chaisemartin and d'Haultfoeuille 2020, Goodman-Bacon 2021, Borusyak, Jaravel, and Spiess 2021, Sun and Abraham 2021), OLS estimation of equation 4 makes potentially invalid

[13] Deforestation usually spans over several months, and one single area may present several successive alerts. For this reason, I only consider as an "alert event" only the alert that takes place after four months without alerts in the same cell.

differences-in-differences comparisons, in the sense that they subtract values of outcomes that may include treatment effects, even when the parallel trends and no anticipation assumptions are true. This happens when estimating treatment effects in settings in which the treatment date varies across groups, as is the case here. In short, one should be careful not to compare treated observations with other treated observations.

The aforementioned literature has suggested several solutions to this problem, all of them amounting to an estimation method that uses only non-treated observations as a comparison group for treated observations. One approach that ensures this is to recreate the dataset by stacking events one over the other, as in Cengiz et al. (2019). That way, each event (i.e., deforestation alert) is treated separately and contains a number of lags and leads. This simple and intuitive approach mechanically guarantees that every event contains non-treated observations, which are used to take the first difference. I also include "never-treated" observations in the dataset, consisting of monthly observation of grid cells that had deforestation but did not have the event of a deforestation alert. The inclusion of these never treated observations is important to estimate the time fixed effect included in the model. This procedure avoids making invalid comparisons with cells that have already been treated in the past, thus yielding a meaningful estimate of the ATT.

Figure 2: Event study: Impact of Alerts on Fines



Accumulated Treatment Effects: 8 p.p. (± 1.9), over a baseline value of 37% (increase of 22%).
N = 0.85 million
64.98 thousand alerts in 28.06 thousand unique grid cells, plus 26.80 thousand grid cells with no alerts.

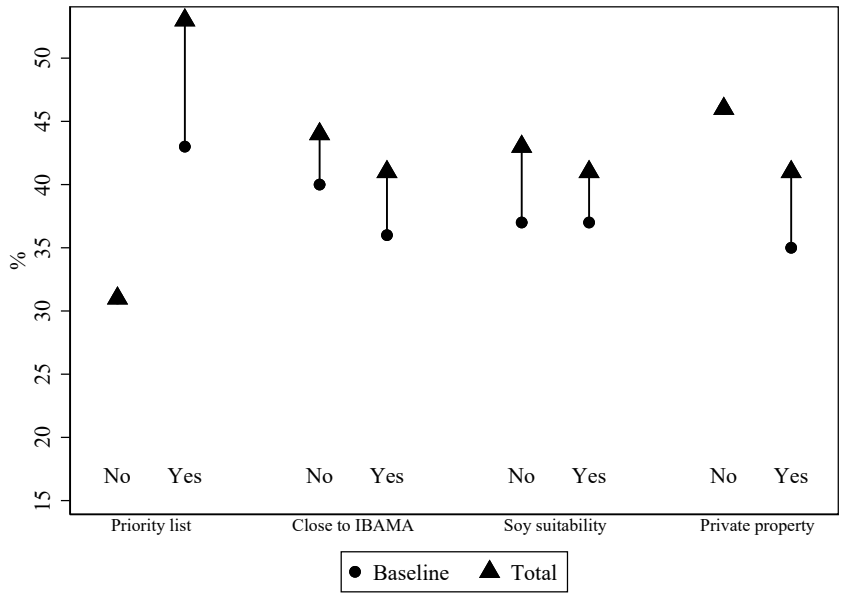
The OLS results are shown graphically in Figure 2. They show a strong and immediate effect

of alerts on the probability of a fine in the cell where the alert was produced. 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. The effect fades out over time and disappears after nine months. The fact that the effect is never negative means that the effect of the alerts is not merely an anticipation of fines which would take place anyways later in time. Alerts produce *additional* fines which would not have taken place otherwise.

The results suggest that, on average, the event of a deforestation alert on a grid cell with deforestation triggers an increase in the probability of fines up to 8 months after the alert's date. The accumulated increase in the increase in probability is 9 percentage points, representing a 24% increase over the baseline monthly probability of a fine of 38% among the grid cells with deforestation that received an alert. At the yearly level, these probabilities are smaller because areas with fines tended to receive fines in several months, whereas other areas would not have received any fine.

The effect of alerts on IBAMA's enforcement action does not seem to vary noticeably across different geographic characteristics. Figure 3 shows the baseline and total (i.e., plus effect of alert) probability of fines across four potential heterogeneity dimensions: priority list (a list of municipalities designated as priority by IBAMA), proximity to IBAMA (above or below the median), soy suitability (above or below the median), and presence of private property in the grid cell. Being in a priority municipality is associated with a probability of fine that is twice as large as being in a non-priority municipality, and the treatment effect seems to be stronger as well. However, the other heterogeneity dimensions do not seem to matter nearly as much.

Figure 3: Heterogeneity of effects of alerts on enforcement probability



4.2 Decomposing the effect of monitoring on the fine probability

As discussed earlier, the enforcement action that can be causally attributed to the monitoring system is only a part of the enforcement action done by IBAMA, since IBAMA also relies on other sources of information that may complement or overlap with the monitoring system. To understand the role of real-time monitoring in the overall enforcement risk, I use the estimated treatment effects and apply it to equation 3. I aggregate the monthly causal effects estimated in the event study in the previous section up to the nine-th month after the event date, which is when the average effect seems to disappear. understand what is the share of fines in areas with alerts which were effectively caused by the alerts, which is easily computed by dividing the alerts-caused fines by the total fines in areas that had alerts. As described in Figure 2, the treatment effect of an alert increases the number of fines relative to the baseline by approximately 24%. Therefore, the share of fines caused by alerts is $\frac{\sum_{\ell=0}^{8} \beta_\ell \times \#\text{alerts}}{\#\text{fines in areas with alerts}} \approx 1/5$. This share is computed using the monthly data estimation, and is a useful tool to translate the results into yearly data.

Using yearly information (the level at which deforestation is measured), we know that areas with deforestation *and* alerts had a 22% probability of receiving at least one fine.The simplest way to apportion the yearly probability of fines using the monthly ATT is by assuming that 1/5

of the 22% is is due to the monitoring technology, though this is only a plausible approximation. The consequence is that out of the 22% yearly probability of fine for areas with deforestation and alerts, approximately 4.5 percentage points are due to the real-time monitoring system, and 17.5 percentage points are the baseline probability, captured by cell and month fixed effects.

$$\underbrace{\mathbb{P}(\text{fine})}_{13\%} = \underbrace{\mathbb{P}(\text{fine}|\text{no alert})}_{8\%}\underbrace{\mathbb{P}(\text{no alert})}_{60\%} + \Big(\underbrace{\mathbb{P}(\text{fine(0)}|\text{alert})}_{17.5\%} + \underbrace{ATT}_{4.5\%}\Big)\underbrace{\mathbb{P}(\text{alert})}_{40\%}$$

The contribution of the real-time monitoring system to the probability of fine is captured by the last term, which multiplies the ATT by the probability of having deforestation and alert. Notice that not all fines happening in areas with alerts are deemed additional. To a great extent (17.5%), IBAMA would be able to impose fines on farmers in those areas, even in the absence of alerts. The decomposition of the probability reveals the following: in the decade 2011 to 2020, a cell with positive deforestation had a 13% probability of receiving at least one fine in the same year of deforestation, and the part that is due to the monitoring system is approximately 2 percentage points ($ATT \times \mathbb{P}(\text{alert}) = 4.5\% \times 40\%$).

5 Deterrence responses to inspections

5.1 General deterrence: effect of inspection probability

Identification and estimation

The general deterrence effect is the effect of changes in fine probability on deforestation. I use data on fines to estimate the fine probability at a cell-year level, using only cells with positive deforestation.[14] It is possible to estimate the probability of a fine (conditional on positive deforestation) using observable variables in a first stage, and then use the fitted probabilities to estimate the effect of fine probability increases on deforestation in a second stage.

However, it is likely that the probability of fines is correlated with unobserved characteristics

[14] As explained previously, fines are trivially equal to zero in areas with no deforestation. For that reason, these areas should be excluded, since they convey no meaningful information about the inspection efforts by the enforcement agency.

of areas where deforestation takes place. As is typically the case in the crime literature (see, for example, Levitt 1997) enforcement efforts tend to be more intense in areas with higher crime incidence because the enforcement agency has knowledge about what are the hotspots of crime and deploys enforcement efforts accordingly. This means that there is a potential endogeneity problem in the fine probability. To overcome this problem, it is necessary to estimate the probability in the first stage using an instrumental variable (or "excluded variable"), that is, a variable that shifts fine probability but does not affect directly the decisions of farmers to deforest areas. A valid instrument then captures exogenous variation in the probability of fines, which can then be used to estimate the impact of fine probability on deforestation in the second stage.

I estimate the following two-equations model:

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

where the first equation is the structural equation relating the outcome to the probability π_{it} of fines, and the second equation is a linear probability model of fine probability π_{it} as a function of observables X_{it} and Z_{it}, where Z_{it} is a set of instrumental variables.

X_{it} are control variables common to both stages. Some of them are time-invariant and at the cell level: dummy variables for deciles of distances to the city of Cuiabá, distances to the nearest IBAMA office, soy suitability, altitude, ruggedness, and dummies for the presence of indigenous territory, conservation units, land reform settlements, non-designated (i.e. non "reserved") public forest, presence of water bodies, and roads (federal or state). I also control have cell-year deciles of the share of deforested area. I choose to include the controls as dummies of deciles to allow for potential non-linear relationships between the outcome and these variables. Controlling for the share of deforested area is particularly important because yearly deforestation rates may depend on how much forest is still standing in an area.

The monitoring system DETER has two features that generate exogenous shifts in enforcement action, and therefore, can be validly used as instrumental variables. The first one is the fact that satellite-based monitoring using optical imagery is impossible in the presence of clouds.[15] Areas

[15] Assunção, Gandour, and Rocha (2022) use lagged cloud cover at the municipality level to estimate the impact of enforcement on deforestation.

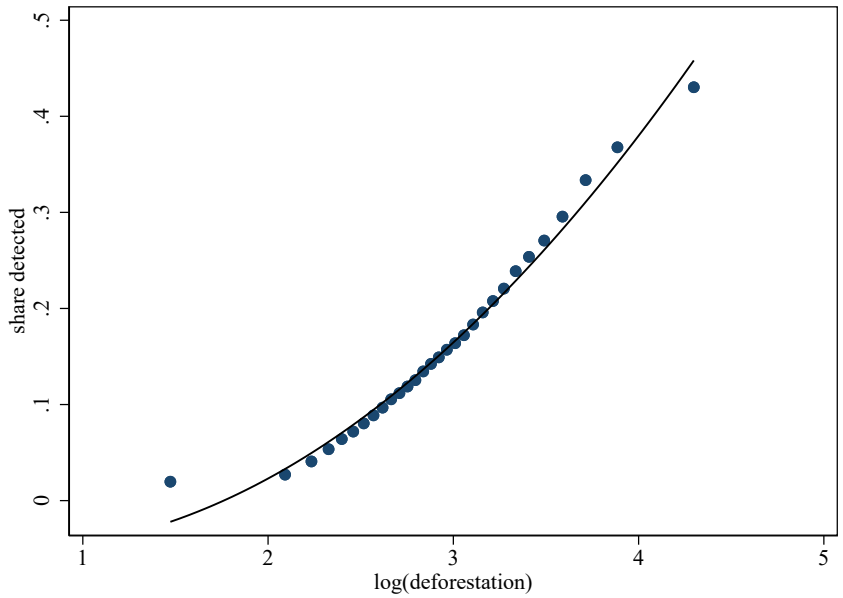
that are covered by cloud for a large part of the year are therefore shielded from monitoring, which should be associated with lower incidence of fines and higher amounts of deforestation. For each 4 km x 4 km grid cell-year, I compute which ones were covered for more than 50% of the year. Therefore, this instrument is a binary variable.

The second feature of the monitoring tool that generates a shift in enforcement is the detection capability. Even when clouds are absent, DETER may not detect the presence of deforestation polygons, likely due to its use of low resolution imagery or other optical distortions that reduce the system's ability to produce alerts. Whereas the size of deforestation is a choice by offenders, detection also depends on visibility conditions that are outside of their control, and which can be used as exogenous shifters of enforcement. Measuring detection capability requires some steps, because we can only know the probability of detection conditional on actual realizations of deforestation. Moreover, larger polygons of deforestation are mechanically easier to detect. To gauge a measure of detection capability that can be used as an exogenous shifter for enforcement, I assume (and verify) that the probability of real-time detection (that is, the production of an alert) conditional on a particular size of realized deforestation follows is well approximated by a third order polynomial:

$$\mathbb{P}(alert_{it}) = \gamma_0 + \gamma_1 \log(deforestation_{it}) + \gamma_2 \log(deforestation_{it})^2 + \theta X_{it} + \xi_{it} \qquad (6)$$

Where xi_{it} is the unobserved detection capability. As can be observed from Figure 4, the probability of real-time detection by DETER follows a remarkably regular pattern as a function of deforestation size (measured by PRODES). The detection probability $\mathbb{P}(alert_{it})$ is computed as the share of detection within the neighboring cells within a 100 km radius, excluding the cell itself. The regression of the share of detection on a third level polynomial of the deforested area plus geographic controls generates a predicted error term $\hat{\xi}_{it}$. The error term of this regression stands for deviations in detection probability net of the role played by the deforestation polygon's size and geographic controls, thus approximating a pure "detection quality" measure, which can be used as instrumental variable.

Figure 4: Detection probability of DETER conditional on deforestation areas



The two instruments used in this exercise are directly related to the functioning of the monitoring system. Cloud coverage measures instances in which the monitoring system is "shut down", whereas detection quality measures its ability to detect deforestation in real-time when it is running. The validity of the instrumental variable approach rely on the exogeneity and exclusion restriction assumptions. The use of exogenous geographic controls has the purpose of making the exogeneity assumption more plausible, as some areas are likely consistently covered by clouds or have better detectability conditions, which is likely correlated with underlying geographic characteristics. The exclusion restrictions for the two instruments is a plausible assumption, since the instruments are specific to the functioning of the monitoring system and have little or no relationship with economic conditions.

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) around each cell, thus allowing for geographic and time autocorrelation of the unobserved error term.

Results

Table 2 summarize the results for the regressions of the intensive (d_{it}) and extensive margin ($\mathbb{P}(d_{it} > 0)$). Overall, enforcement probability displays a substantial effect in reducing deforesta-

tion along both margins. The table shows, for each outcome, the OLS regression, the 2SLS results, the first stage (using fines as outcome), and the reduced form (the direct effect of the instrument on the outcomes). The samples are different for the two outcomes because I only considered cells with positive deforestation levels for the intensive margin effect. In contrast, for the extensive margin, I considered all cells that had deforestation at some point in the decade from 2011 to 2020.

Columns 1 and 5 show the OLS regressions of deforestation on fines, showing a strong positive correlation both for the intensive and extensive margin, as expected. Columns 2 and 6 show the responses to exogenous increases in the probability of fines. A percentage increase in the probability of fines reduces deforestation areas by 1.9%, and reduces the probability of an area having deforestation by 0.9%. The first stage is strong, as shown in columns 3 and 7, suggesting that intensively cloudy cells-years were less likely to receive fines. Finally, to corroborate the robustness of the results, the direct effect of the instrument on the outcome, on Columns 4 and 8, is positive. This means that cloudier areas have more deforestation than non cloudy areas.

All the results are conditional on a rich set of controls, such as distances from the three main Amazonian cities, distances from the closest IBAMA office, presence of roads, presence of indigenous land, presence of conservation parks, and the percentage of accumulated destroyed forest within the cell-year.[16]

[16]The continuous controls (distances and percentage of destroyed forest) were included as dummies of the deciles of the underlying variable. This choice is intended to allow for non-linearities in the relationship between these controls and other variables.

Table 2: Treatment effects estimation on observed actions

	log(deforestation)				P(deforestation>0)			
	OLS	ITT	First Stage	2SLS	OLS	ITT	First Stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fine	0.326***			-1.969***	0.168***			-0.969***
	(0.0260)			(0.620)	(0.0104)			(0.251)
Detection quality		-0.402***	0.225***			-0.114***	0.118***	
		(0.153)	(0.0364)			(0.0334)	(0.0204)	
Cloud cover		0.0675***	-0.0225**			0.0134*	-0.0140**	
		(0.0249)	(0.0104)			(0.00781)	(0.00561)	
N	207275				689064			
Cragg-Donaldson F	527.61				886.3			
Mean deforestation	30.43				.3			
Mean fine	.11				.1			
Mean cloud	.4				.4			
Mean quality	0				0			

Obs: * 0.10 ** 0.05 *** 0.01 significance levels. This table shows the estimates of general deterrence effects for intensive and extensive margins using cloud cover for more than half a year as instrument. The first four columns show the results for the intensive margin, measured as the log of deforestation (in hectares) among the cells that presented positive deforestation in a given year. The last four columns show the analysis for the probability of having positive deforestation in a given year, and uses sample the cells that presented positive deforestation at some point between 2011 and 2020. The table shows four types of regressions: the OLS coefficient of fines on the outcome, the intention to treat (ITT) of the instrument (more than half-year cloud cover) on the outcome, the first stage regression of the instrument on the probability of a fine, and finally the two-stage least squares (2SLS) regression using cloud cover for more than half a year as instrument. All regressions include year fixed effects and controls for deciles of altitude, ruggedness, distance from Cuiaba, distance from Ibama, soy suitability, land tenure dummies (Indigenous reserves, private farm, land reform settlement, conservation unit, non-designated forest), a dummy for the presence of roads, and a dummy for the proximity to water bodies. Standard errors are computed using a multi-way cluster of 1^o around each cell.

5.2 Specific deterrence: dynamic effects of fines

Identification and estimation

The specific deterrence effect is the effect of punishment on the behavior of farmers. It affects

a smaller number of farmers than the general deterrence effect, which is the effect of punishment probability. In deforestation, the specific deterrence effect is the change in farmers' behavior *after* an inspection, and caused by the inspection. To identify the causal effect of inspections over time, and in particular distinguish it from time-specific shocks, I use an event study approach like in section 4.

To estimate the specific deterrence effect, I restrict the sample only to those areas that received enforcement action at least once in 2011-2020. Thus subsampling the data, I circumvent the endogeneity issue regarding the inspection decisions since there is no comparison between inspected with non-inspected areas. I estimate the average effect of inspections on inspected (average treatment effect on the treated) using an event study design, where I exploit variation in the timing of the inspections. The assumption that allows this strategy to identify the effect of inspections is a parallel trends assumption. The assumption means that inspected areas would have evolved like non-inspected areas in the absence of an inspection.

I rely on an event study approach, where the "event" is an inspection in a cell. The event occurs in different years for each cell, and the objective is to understand the causal effect of an inspection in several periods relative to the event date, similar to what was done in the analysis of signals and inspections in the previous section. It is possible to see how deforestation evolves relative to the event date. To estimate the specific deterrence effects of inspections, the challenge is, as usual, to find the correct comparison group for the treated cells. The differential timing of inspections gives an opportunity to compare similar areas. Using only the areas that were treated at some point, it is always possible to have some observations that were not yet treated and use them as controls for those that were already treated. Standard practice would lead to an estimation via OLS of an equation like the following:

$$y_{it} = \sum_{\ell=-3}^{5} \beta_\ell \mathbb{1}\{t - e_i = \ell\} + \delta_t + FE_i + \varepsilon_{it} \tag{7}$$

Where the inspection date is denoted by e_i, and which symbolizes the date t in which cell i receives the inspection. As explained in Section 4, estimating this equation via OLS, using only the cells that received an inspection at some point, implies making before and after comparisons between groups. This makes no distinction if the cell used as control has already been treated in the

past. As highlighted by recent research, this may be a big problem of the so called two-way fixed effects model for estimating treatment effects: if the control cell has already been treated in the past, its values may be carrying a treatment effect, which is given a negative weight in the estimation of the treatment effect. Therefore I estimate the effects using the imputation method proposed by Borusyak, Jaravel, and Spiess (2021), which avoids invalid comparison between treated groups with other treated groups.

Results

The treatment effects of the deforestation areas is depicted in figure 6b. The treatment effect is negative and increasing in size in periods after the treatment. The reason is that the outcome stabilizes after the inspection, whereas it was accelerating in the years before. The counterfactual scenario is therefore that the outcome would continue accelerating, which yields a growing treatment effect. It is probable that the linear trend is only a good approximation for the counterfactual in the first few years after the inspection occurs, but it does allow for an estimation of the treatment effects in these years. The results show that the treatment effect can only be distinguished from zero from the second year on-wards, when treated cells show 0.3 square kilometer less deforestation than the counterfactual. In the accumulated three years, the treatment effect is approximately 0.7 square kilometer of forest saved on average.

Spatial spillovers

It easy to estimate the event study explained above to capture potential spatial spillovers of fines. Spillovers could be a threat to the estimation of the treatment effects in the preceding sections, since it is assumed that non-treated cells are unaffected by treatment. Two types of spatial spillovers could occur: contagion and leakage.[17] If there is contagion, neighboring farmers may realize that neighboring areas were fined and become more compliant, and this implies that the impact of fines is even greater than the estimated above. On the other hand, if there is leakage, offenders could disperse from areas that suffered enforcement intervention and commit crimes in other areas.[18] In the context of deforestation in the Amazon forest, Assunção, Gandour, and Rocha (2022) and Assunção et al. (2023) have found small contagion effects of enforcement in neighboring municipalities.

[17]The terminology is borrowed from Assunção, Gandour, and Rocha (2022)

[18]This effect is also known as "displacement effect" and has been documented recently in the urban crime literature (Blattman et al. 2021)

I estimate the same event study to look for any effect of a fine on all the neighboring cells, and to second-order neighbors. Figure 7a shows the evolution of deforestation in every year relative to the date of the fine. The blue line shows the evolution for the cells that received the intervention, and the discontinuity in the increasing trend reflects the treatment effects that were discussed above. The neighboring cells (both direct and second-order neighbors) have a lower level of deforestation overall, which is not surprising, since the enforcement agency acts more intensively in areas with large deforestation. Moreover, these neighboring areas show a weak upward trend in deforestation, but no noticeable change in this trend after their neighbor received a fine. Estimation of the treatment effects using the imputation method shows that there is indeed no treatment effect distinguishable from zero, though there the period preceding the fine shows a slight acceleration. Therefore, the results qualitatively confirm previous findings (Assunção, Gandour, and Rocha (2022) and Assunção et al. (2023)) suggesting that enforcement leads to small reductions in deforestation in neighboring areas.

5.3 Overall effect of inspections on deforestation

After these steps, it is finally possible to compute the impact of increases in fine probability on deforestation by using equation 3. I use 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 20 thousand 4 km x 4 km cells) and the average area of deforestation $d_0(p_0)$, which was 30 hectares. The estimated parameters are the increase in the probability of enforcement dp_0, estimated at 2 percentage points, the extensive margin effect of enforcement risk $\partial N/\partial p_0$, estimated at approximately -1%, the intensive margin effect of enforcement risk $\partial d_0/\partial p_0$, estimated at apprximately -2%, and the specific deterrence effect, estimated at approximately 8 hectares less deforestation every year. I thus obtain the following areas of avoided deforestation for an increase of dp_0 in the probability of enforcement:

$$
\begin{aligned}
\frac{dD}{dp_0} &= \underbrace{\frac{\partial N}{\partial p_0} d_0(p_0) + N(p_0)\frac{\partial d_0}{\partial p_0}}_{\text{general deterrence effect}} + \underbrace{\left(dp_0 N(p_0) + p_0 \frac{\partial N}{\partial p_0} d_0(p_0)\right) \sum_{t=1}^{3} \frac{\partial d_t}{\partial f}}_{\text{specific deterrence effect}} \\
&= \overbrace{20000 \times (-0.01)}^{\frac{\partial N}{\partial p_0}} \times \overbrace{0.3}^{d(p_0)} + \overbrace{20000}^{N} \times \overbrace{1 \times (-0.02)}^{\frac{\partial d}{\partial p_0}} \\
&+ \left(\underbrace{0.01 \times 20000}_{dp_0 N(p_0)} + \underbrace{0.13 \times 20000 \times (-0.01)}_{p_0 \frac{\partial N}{\partial p_0} d_0(p_0)} \right) \times \underbrace{3 \times (-0.08)}_{\sum_{t=1}^{3} \frac{\partial d_t}{\partial f}} \\
&= \underbrace{-174}_{\text{gen. deterrence}} \quad \underbrace{-42}_{\text{sp. deterrence}} = -216
\end{aligned}
$$

A one percent increase in inspection probability would reduce yearly deforestation by approximately 216 square kilometers a year. This area represents approximately 1.8% of the deforestation level in 2020 (12 thousand square kilometers) and 3% of the average deforestation in 2011-2020 (7 thousand square kilometers). As computed in section 4, the treatment effects of the monitoring system represent approximately two percentage points in the overall yearly probability of fines in the Amazon forest. Therefore, the value of this system in terms of reduced deforestation probably lies in the ballpark of 430 square kilometers of saved forest by year, or 6% of the average yearly deforestation in the decade.

6 Cost benefit analysis

This paper has so far shown that the enforcement agency has extensively used the monitoring alerts to direct its inspections, which in turn reduced deforestation and forest fires. The use of monitoring alerts has meant a change in the way the enforcement agency targets its inspections. What was the value of this shift in terms of inspection resources saved and welfare gains?

6.1 Inspection costs

I used administrative data on operational expenditures (not including wages) in the Amazon forest to estimate the average cost of a deforestation inspection from 2011-2020. The data is available

separately for each of the nine states of the Amazon forest, but it does not distinguish expenditure with deforestation inspections from other operations. I distinguish the deforestation inspections between those that followed a deforestation alert, and those that did not follow an alert, and estimate their costs using a linear regression model, as follows:

$$\text{expenditure}_{it} = \beta_0 + \beta_1 \text{alerts_inspections}_{it} + \beta_2 \text{no_alerts_inspections}_{it} + \delta_t + FE_i + \varepsilon_{it} \quad (8)$$

Where β_1 is an estimate of the average marginal cost of an inspection following an alert and β_2 the average marginal cost of an inspection not following any alert, while δ_t are year fixed effects, and FE_i are state fixed effects. These fixed effects capture other year-specific enforcement activities or state-specific expenditure levels.

The results in table 8 show that the inspections following alerts seem to be considerably less costly than inspections not following alerts. The first column, without any year of state fixed effects, shows that the marginal inspection following alert cost around 7 thousand BRL (1.7 thousand USD), whereas the marginal inspection not following an alert cost 16 thousand BRL (4 thousand USD), more than twice as much. Including year fixed effects, in the second column, does not change much the results and keeps the proportion of the two costs. The third column includes also state fixed effects, which reduces the marginal costs of both inspections by half, but again keeps the proportion between them.

In short, an inspection strategy that follows monitoring alerts seems to be more cost efficient than using other methods to select inspections. The reason is likely to be that inspections without alerts depend on more investigation and attempts before finding an offender to punish. The monitoring system provides the information in real-time, which is almost always correct as shown in section **??**. It is therefore cheaper to base inspection selection on them, which is what IBAMA increasingly did. Indeed, since 2014, the operational expenditures of IBAMA in the Amazon forest dropped by 40% (43 million BRL to 25 million BRL), whereas the number of deforestation inspections dropped by 20% (from 935 in 2014 to 730 in 2020).

6.2 Welfare costs and benefits of reducing deforestation

To compute the value of saved forest, I focus solely on the its carbon content, abstracting from the impact of deforestation on biodiversity loss, rain seasons and air quality. On average, deforestation of one hectare in the Amazon forest leads to approximately 560 tonnes of CO2 emissions.[19] The harm caused by these emissions in terms of climate change are estimated from 30 to 100 USD.[20] This substantial benefit accrues globally, whereas some costs and benefits are born locally by Brazilians. In particular, the non-deforested areas have an opportunity cost of economic activities that could be carried out. Using data from the Brazilian Agricultural Survey, I compute that in the Amazon forest, the average value of agricultural output per square kilometer is approximately 100 thousand USD per year, which is approximately 5% of the welfare benefits using 30 USD as the social cost of carbon.

7 Discussion: the importance of real-time enforcement

Should IBAMA be concerned with real-time monitoring and quick reactions to alerts, as it seems to be? Deforestation is an offense that endures: once it has taken place, it stays. In any case, the offenses are observed by satellite once a year (via the yearly satellite measurement of PRODES) and become known to the enforcement agency. So why not wait and punish the farmers later? IBAMA can go to the place where deforestation took place and punish agents for exploiting an area economically that was illegally deforested. But in practice such late interventions tend to be less likely to succeed, and in particular less likely to inflict costs on offenders. IBAMA agents must find the offender and establish the link between the offense and its author.

The analysis of the timing of fines allows for a comparison between fines that followed alerts and those that did not. Fines that follow alerts up to three months after the occurrence of an alert, or "timely fines", differ from "random fines" in two important dimensions: timely fines tend to punish much larger areas, and are more likely to seize equipment from offenders. These two differences can be seen by estimating the following simple regression model:

[19] This number was computed based on data by the Brazilian Institute for Spatial Research (INPE) over the period 2010-2019. See http://inpe-em.ccst.inpe.br/en/download_en/

[20] The value of 30 USD per ton of CO2 is typically used by authorities such as the US Department of Energy. However, studies may vary regarding the value. Stern (2007) estimates the social cost of carbon at around 85 USD.

$$\text{fine characteristic}_{imt} = \beta + \alpha_0 \text{deforestation alert}_{imt} + \alpha_1 \text{deforestation alert}_{imt-1} + \alpha_2 \text{deforestation alert}_{imt-2} + \alpha_3 \text{deforestation alert}_{imt-3} + FE_m + \delta_t + \varepsilon_{it} \quad (9)$$

where i is the single fine, m is the municipality and t the month. ε_{it} is a conditional mean zero error term, and FE_i is a fixed effect at the municipality level (a level above the cell level) and δ_t stands for month effects. The model is estimated using two outcomes: the share of fines that ended seizing equipment from the offenders, and the size of the deforestation offense, in hectares. Information from seized equipment is obtained from a separate administrative dataset of IBAMA, and merged with the individual fines. Information about the size of deforestation is extracted from a string description of the fines, and in some cases filled explicitly by inspectors in a separate field. Table 7 shows the α coefficients for these two outcomes. Relative to fines that followed no alert or a alert more than four months old, "timely fines" are different across the two characteristics.

Columns 1 to 3 of Table 7 show that the probability of seizing equipment is increased by 1.5-2 percentage points if the fine takes place in the same month of the alert. The older the alert, the lower this probability, and the effect is even negative if the alert is three months old. Adding month fixed effect (column 2) or restricting the sample to priority municipalities (column 3) do not change the effects. The effect is positive and significant as long as the fine occurs in the same month as the alert. Although the effect may seem small, it represents a 20% increase relative to the baseline probability of 8% of a fine seizing the equipment of the offenders.

Regarding the size of the offense, the fines that follow alerts are larger than other fines by around 40 hectares on average, as can be seen in columns 4-6 of Table 7. If the alert happened more than three months before the fine, the difference is much smaller, 16 to 24 hectares larger than fines that did not follow a deforestation alert. The explanation for this large and persistent effect is that alerts are more likely to be produced for larger infractions. As a result, fines that follow alerts tend to go for the larger offenses as well, which is another potential benefit of using monitoring alerts as a rule for deciding where to deploy enforcement.

In this section I showed that the presence of real-time monitoring alerts for logging leads to increased probability of an inspection in an area. Moreover, the increased quality of these alerts has been followed by an increased reliance by IBAMA on these alerts. Fire alerts, on the other

hand, play no substantial role in determining enforcement action. In the next sections I estimate the impact of enforcement on overall compliance (the decision to deforest or not) and then on the choice to use fire in deforestation.

8 Summary and conclusion

This paper has exploited an important improvement in the monitoring of logging in the Amazon forest, and studied its effects on the fights against deforestation. The monitoring system DETER, produces deforestation alerts based on its ability to detect vegetation loss in native forest in the Brazilian Amazonia. 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. Overall this means that farmers doing deforestation in the Amazon forest today is three times more likely to be observed in real time than they were ten years ago. Moreover, the number of false positives by DETER also declined sharply, such that almost all deforestation alerts are correct in the sense that they are later verified as deforested areas.

The consequence of this improvement was that the enforcement risk for farmers went 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. The average yearly probability of a fine in areas with positive deforestation in the period was 13%, of which three percentage points can be causally attributed to the monitoring system. 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 in the probability of inspection reduce the probability of farmers engaging in deforestation by 0.9 percentage point, and reduce the deforested area by 1.9 percentage point. Moreover, the *experience of enforcement* has a lasting impact on the areas that are subject to a crackdown. I document lower levels of deforestation in these areas up to three years after the crackdown.

I compute the benefit of these improvements by computing the costs of targeting inspections

based on the deforestation alerts. This exercise shows that IBAMA is twice more effective with targeted inspections than with non-targeted ones. This means that it is possible to increase inspection probability for farmers simply by using more extensively the deforestation alerts to guide inspections. Moreover, a one percentage point increase in inspection probability reduces deforestation by 150 square kilometer, or about 2% of average yearly deforestation in the last decade. A three percentage point increase thus represents approximately 450 square kilometers of saved forst (or 6% of average deforestation). The welfare benefits of this reduction are likely to outweigh the opportunity costs by more than twenty times.

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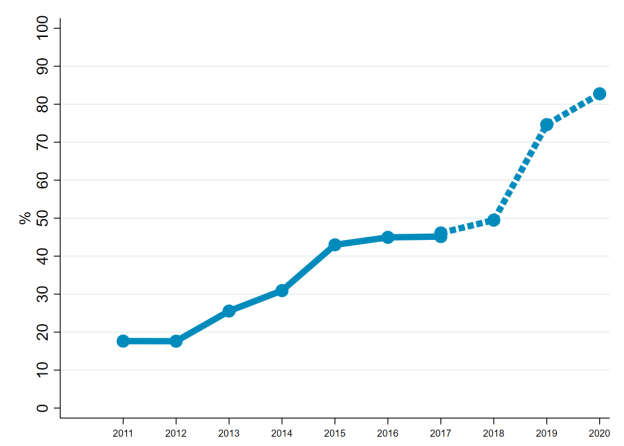
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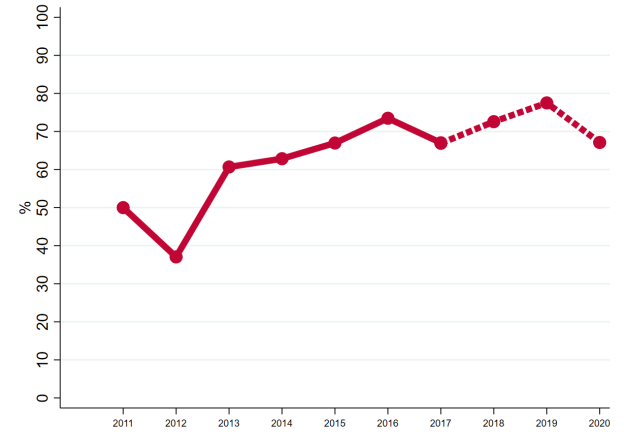
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FIGURES

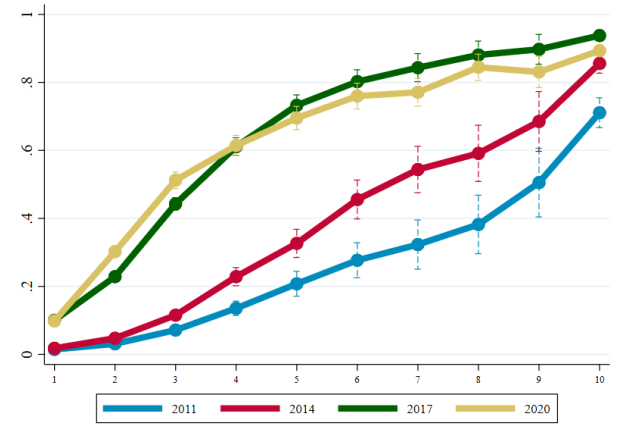
F2. Alert probabilities



(a) Share of detected deforestation by deforestation alerts $\mathbb{P}(\text{alert}|\text{deforestation})$



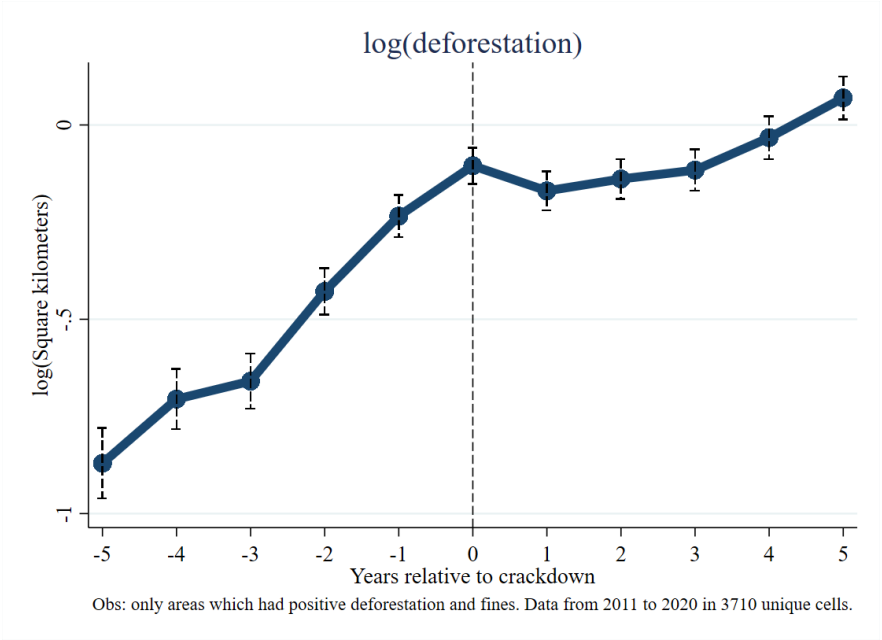
(b) Share of deforestation alerts that were declared deforestation $\mathbb{P}(\text{deforestation}|\text{alert})$



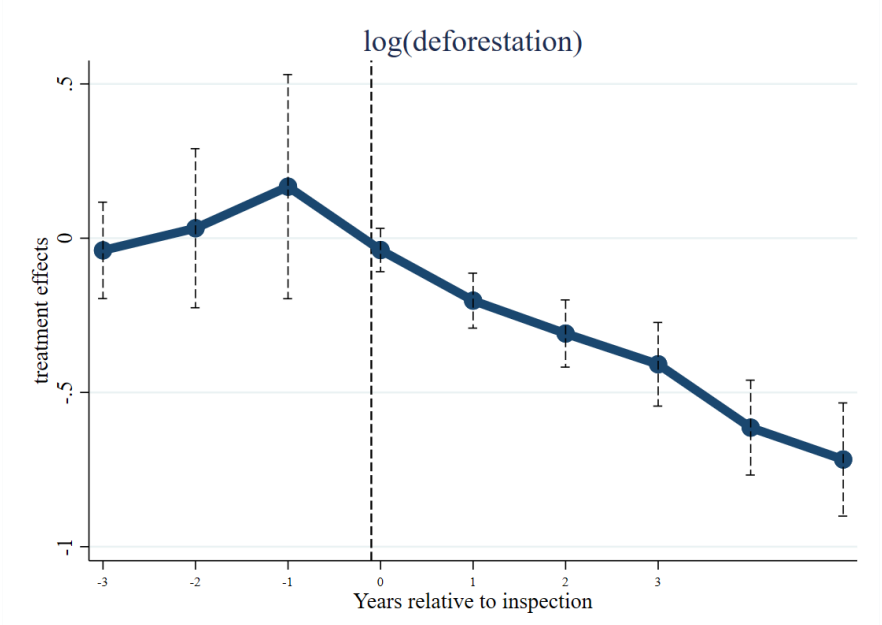
(c) Share of detected deforestation by size decile of deforestation areas and year

Figure 5: Monitoring quality

F5. Event Study of Deforestation and Fines

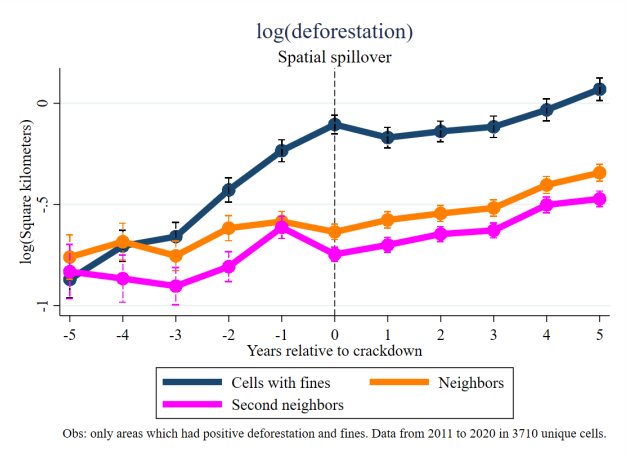


(a) Mean outcome (log deforestation) by year relative to inspection year

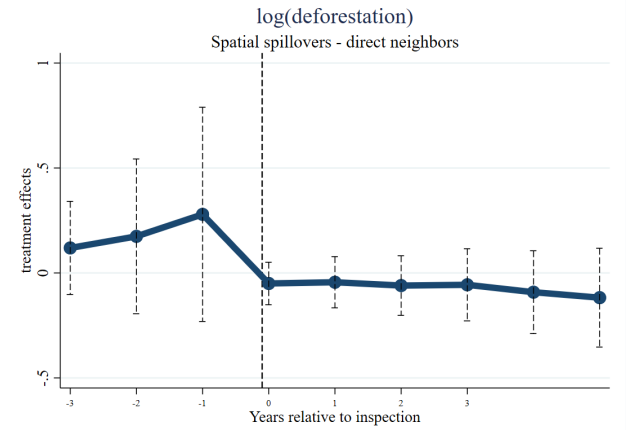


(b) Treatment effects using imputation method (Borusyak, Jaravel, and Spiess 2021)

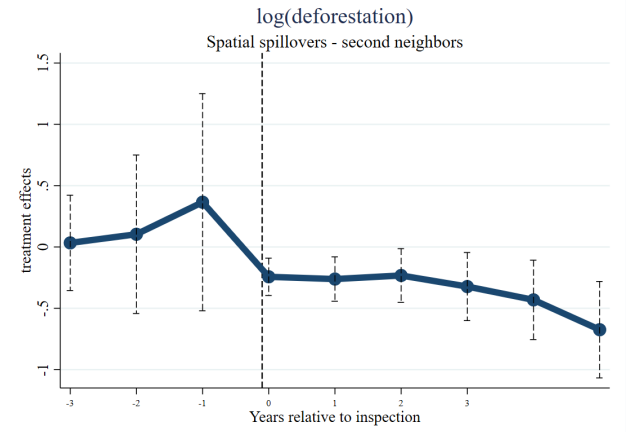
Figure 6: Deforestation and inspections



(a) Average log deforestation in neighboring areas



(b) Treatment effect estimation (BJS 2021) for direct neighbors



(c) Treatment effect estimation (BJS 2021) for second neighbors

Figure 7: Spatial spillovers

TABLES

T1. Data sources

Table 3: Main datasets used and sources

NAME OF DATASET	DESCRIPTION	TIME	GEOGRAPHICAL LEVEL	SOURCE
Deforestation alerts (DETER)	Areas with potential deforestation activity, detected by satellite.	Monthly (2011-2020)	Geo-referenced polygons	Satellites Terra (DETER-A, until 2017) and CBERS (DETER-B, from 2017) and compiled and interpreted by INPE
Cloud coverage (DETER)	Areas with cloud coverage, which inhibit satellite monitoring.	Monthly (2011-2017)	Geo-referenced polygons	Satellites Terra (DETER-A, until 2017) compiled by INPE
Soil cover of Amazon forest (PRODES)	Information about soil cover in every area of the Amazon forest, covering in particular the categories: forest, new deforestation and previous deforestation. PRODES is the official program to measure deforestation in Brazil.	Yearly (measured in July of each year)	Geo-referenced polygons	Data from satellite Landsat, interpreted and compiled by INPE.
Environmental fines	Fines issued by the Brazilian federal environmental authority (IBAMA), and specifically the fines for deforestation.	Daily (2011-2020)	Geo-referenced points	Administrative database of IBAMA

Table 4: Auxiliar datasets and sources

NAME OF DATASET	DESCRIPTION	TIME	GEOGRAPHICAL LEVEL	SOURCE
Indigenous reserves and Conservation Units	Areas of indigenous reserves (or inhabited traditionally but not officially delimited) and conservation units in the Brazilian Amazon.	Fixed over time.	Georeferenced polygon.	INPE (TerraBrasilis)
Road infrastructure	State and federal roads in the Brazilian Amazonia.	Fixed over time.	Georeferenced lines.	MapBiomas
Private rural properties	Areas of private properties in the official public registry (*Cadastro Ambiental Rural*).	Fixed over time.	Georeferenced polygons.	CAR, Ministry of Agriculture of Brazil
Budget execution of environmental agency	Expenditures in BRL 2020 by the Amazonian units of the federal environmental agency IBAMA.	Yearly (2015-2020)	By state.	Federal Government of Brazil, (http://transparencia.gov.br)
Consumer Price Index	Consumer Price Index used to convert monetary values to values of 2020. The index used was IPCA-IBGE.	Monthly (2011-2020)	National level.	IBGE

T2. Regression tables General Deterrence

Table 5: Treatment effects estimation on observed actions

	log(deforestation)				P(deforestation>0)			
	OLS	ITT	First Stage	2SLS	OLS	ITT	First Stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fine	0.330***			-2.882*	0.171***			-0.885
	(0.0256)			(1.505)	(0.0104)			(0.539)
Cloud		0.0722***	-0.0250**			0.0137*	-0.0155***	
		(0.0249)	(0.0108)			(0.00774)	(0.00579)	
N	209955				704800			
Cragg-Donaldson F	179				378.51			
Mean deforestation	30.4				.3			
Mean fine	.1				.06			
Mean cloud	.4				.35			

Obs: * 0.10 ** 0.05 *** 0.01 significance levels. This table shows the estimates of general deterrence effects for intensive and extensive margins using cloud cover for more than half a year as instrument. The first four columns show the results for the intensive margin, measured as the log of deforestation (in hectares) among the cells that presented positive deforestation in a given year. The last four columns show the analysis for the probability of having positive deforestation in a given year, and uses sample the cells that presented positive deforestation at some point between 2011 and 2020. The table shows four types of regressions: the OLS coefficient of fines on the outcome, the intention to treat (ITT) of the instrument (more than half-year cloud cover) on the outcome, the first stage regression of the instrument on the probability of a fine, and finally the two-stage least squares (2SLS) regression using cloud cover for more than half a year as instrument. All regressions include year fixed effects and controls for deciles of altitude, ruggedness, distance from Cuiaba, distance from Ibama, soy suitability, land tenure dummies (Indigenous reserves, private farm, land reform settlement, conservation unit, non-designated forest), a dummy for the presence of roads, and a dummy for the proximity to water bodies. Standard errors are computed using a multi-way cluster of 1^o around each cell.

Table 6: Treatment effects estimation on observed actions

	log(deforestation)				P(deforestation>0)			
	OLS	ITT	First Stage	2SLS	OLS	ITT	First Stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fine	0.326***			-1.806***	0.168***			-0.971***
	(0.0261)			(0.658)	(0.0104)			(0.285)
Detection quality		-0.415***	0.230***			-0.116***	0.120***	
		(0.154)	(0.0371)			(0.0335)	(0.0206)	
N	207275				689064			
Cragg-Donaldson F	910.04				1467.4			
Mean deforestation	30.43				.3			
Mean fine	.11				.1			
Mean quality	0				0			

Obs: * 0.10 ** 0.05 *** 0.01 significance levels. This table shows the estimates of general deterrence effects for intensive and extensive margins using monitoring detection quality as instruments. The first four columns show the results for the intensive margin, measured as the log of deforestation (in hectares) among the cells that presented positive deforestation in a given year. The last four columns show the analysis for the probability of having positive deforestation in a given year, and uses sample the cells that presented positive deforestation at some point between 2011 and 2020. The table shows four types of regressions: the OLS coefficient of fines on the outcome, the intention to treat (ITT) of the instrument (detection quality) on the outcome, the first stage regression of the instrument on the probability of a fine, and finally the two-stage least squares (2SLS) regression using detection quality as instrument. All regressions include year fixed effects and controls for deciles of altitude, ruggedness, distance from Cuiaba, distance from Ibama, soy suitability, land tenure dummies (Indigenous reserves, private farm, land reform settlement, conservation unit, non-designated forest), a dummy for the presence of roads, and a dummy for the proximity to water bodies. Standard errors are computed using a multi-way cluster of 1^o around each cell.

T3. Importance of acting quickly

Table 7: Characteristics of fines

	(1)	(2)	(3)	(4)	(5)	(6)
	Seized	Seized	Seized	Area	Area	Area
Logging signal same month	0.0185***	0.0133**	0.0135*	38.96***	36.73***	39.89***
	(0.00599)	(0.00614)	(0.00686)	(7.541)	(7.585)	(9.729)
L. signal 1 month before	0.00397	0.00149	0.0125	40.69***	42.30***	43.44***
	(0.00687)	(0.00682)	(0.00987)	(7.260)	(7.439)	(9.526)
L. signal 2 months before	-0.00210	0.00153	-0.0125	43.20***	48.39***	46.82***
	(0.00649)	(0.00654)	(0.00854)	(8.274)	(8.784)	(12.10)
L. signal 3 months before	-0.00910	-0.00100	-0.0109	16.90***	24.07***	20.44**
	(0.00592)	(0.00581)	(0.00740)	(6.400)	(7.639)	(8.377)
Sample	All	All	Priority mun.	All	All	Priority mun.
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	No	Yes	No	No	Yes	No
N	11893	11893	6327	11893	11893	6327
R2	0.0720	0.0752	0.0507	0.104	0.106	0.0889
Mean outcome	.08	.08	.08	124.45	124.45	124.45

Note: * 0.10 ** 0.05 *** 0.01 levels of significance. OLS regression of fine characteristics depending on whether they followed a recent logging signal. The two outcomes are the probability that the fine ended with seized equipment from the offenders, and the area (in hectares) of the inspected deforested area. The unit of observation is a 15km x 15km cell at the monthly level. Standard errors are clustered at the municipality level.

T6. Costs estimates

Table 8: Outcome: operational expenditure

	(1)	(2)	(3)
Inspection with alerts	7049.3**	6240.6*	3230.5
	(2983.7)	(3139.1)	(3185.6)
Inspection without alerts	15896.1***	16401.0***	6260.9**
	(2932.8)	(3082.2)	(2433.6)
Year dummies	No	Yes	Yes
State fixed effects	No	No	Yes
N	63	63	63
R2	0.654	0.683	0.935

Obs: ***1% **5% *10% significance levels. Linear regression of operational expenditures of IBAMA on the number of deforestation inspections. The data sources are budget expenditure data for years 2014-2020, in values of Brazilian Real of January 2020 (1 BRL = 4 USD). The deforestation inspections are taken from the administrative dataset on environmental fines, and compared at the month level with the locations of deforestation alerts at a 15km x 15km cell. Inspections are considered to follow an alert if they happen within the same cell at the latest three months after the alert. Standard errors are robust (White) qnd shown in parentheses.

Appendices

A Model

Take the model above, but assuming a representative agent with profit determined by:

$$Y_t = d_t(y - \pi_R - \pi_T s(d_t)) \tag{10}$$

In this model, the first order condition of the agent will give:

$$d_2^* = \frac{y - \pi_R - \pi_T s(d_2^*)}{\pi_T s'(d_2^*)} \tag{11}$$

which implicitly defines:

$$d_2^* = \phi(y, \pi_R, \pi_T) \tag{12}$$

At period 2, d_2^* characterizes the optimal choice for the agent. However, if the agent has received a fine previously, we assume that the agent's marginal cost increases by κ, yielding an optimal value $d_2^{**} < d_2^*$.

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

$$\max_{d_1} Y_1 + \mathbb{E}[Y_2] \tag{13}$$

where 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 13 can be rewritten as:

$$\max_{d_1} Y_1 + Y_2^* - (\pi_R + \pi_T s_1)(Y_2^* - Y_2^{**}) \tag{14}$$

Yielding:

$$d_1^* = \frac{y - \pi_R - \pi_T\big(s_1 + s_1'(Y_2^* - Y_2^{**})\big)}{\pi_T s_1'} \tag{15}$$

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

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. To make the analysis sharper, I assume that the regulator can choose different levels of targeting for each period. This will allow to show how the presence of specific deterrence effects impacts the optimal choice of targeting in the first period, as opposed to the second period, when no such effects exist by definition. The problem can be written as a a choice of $\{\pi_R, \pi_T\}$ in the first period, keeping targeting in the second period constant.

$$\begin{aligned} &\max_{\pi_R, \pi_T} -\big(d_1^* + d_2^*\big) + (\pi_R + \pi_T s_1)(d_2^* - d_2^{**}) \\ &\text{s.t.} \qquad \pi_R + \pi_T s_1 + \pi_{R2} + \pi_{T2}\mathbb{E}[s_2] \leq \bar{\Pi} \end{aligned} \tag{16}$$

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.

We can write the Lagrange of the regulator's problem as follows:

$$\max_{\pi_R, \pi_T} -\big(d_1^* + d_2^*\big) + (\pi_R + \pi_T s_1)(d_2^* - d_2^{**}) - \lambda\Big((\pi_R + \pi_T s_1)(1 - \pi_{T2}(s_2^* - s_2^{**})) + \pi_{R2} + \pi_{T2} s_2^* - \bar{\Pi}\Big) \tag{17}$$

Taking first order conditions yields with respect to π_T yields:

$$\frac{\partial \mathcal{L}}{\partial \pi_T} = -\frac{\partial d_1^*}{\partial \pi_T} + \Big(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\Big)(d_2^* - d_2^{**}) - \lambda\Big(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\Big)(1 - \pi_{T2}(s_2^* - s_2^{**})) \tag{18}$$

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 15) and obtain:

$$\frac{\partial d_1^*}{\partial \pi_T} = -\frac{1}{\pi_T}\frac{s_1 + s_1'(d_1^* + \Delta)}{2s_1' + s_1''(d_1^* + \Delta)} < 0 \tag{19}$$

Where $\Delta \equiv Y_2^* - Y_2^{**}$. The formula above is clearly 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 $\left(s_1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_T}\right)$. 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:

$$\frac{\partial \mathcal{L}}{\partial \pi_R} = -\frac{\partial d_1^*}{\partial \pi_R} + \left(1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_R}\right)(d_2^* - d_2^{**}) - \lambda\left(1 + \pi_T \frac{\partial s_1}{\partial d_1}\frac{\partial d_1^*}{\partial \pi_R}\right)(1 - \pi_{T2}(s_2^* - s_2^{**})) \tag{20}$$

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

$$\frac{\partial d_1^*}{\partial \pi_R} = -\frac{1}{\pi_T}\frac{1}{2s_1' + s_1''(d_1^* + \Delta)} < 0 \tag{21}$$

Notice further that:

$$\frac{\partial d_1^*}{\partial \pi_R} = \frac{\partial d_1^*}{\partial \pi_T}(s_1 + s_1'(d_1^* + \Delta)) \tag{22}$$

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 22, 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 sharp 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.

B Summary statistics

Table A1: Outcomes

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
1 Deforestation (km2)	.2654262	.2106781	.259974	.2467688	.2988944	.353212	.3383303	.3541823	.5350777	.5193492
	(1.02382)	(.8769656)	(1.102042)	(1.004691)	(1.226216)	(1.392089)	(1.277492)	(1.33321)	(1.92843)	(1.968994)
2 % cells with positive deforestation	26.45886	21.84961	23.22584	23.95471	23.37662	25.67018	25.73879	25.58687	29.11051	29.09091
	(44.11247)	(41.3236)	(42.22833)	(42.68175)	(42.32356)	(43.68241)	(43.72056)	(43.6359)	(45.4283)	(45.41928)
3 Deforestation as % of forest	.3290978	.2383326	.308867	.2878339	.3425139	.4060133	.3835201	.3762334	.6863465	.694053
	(1.603958)	(1.081387)	(1.513847)	(1.054278)	(1.320044)	(1.439758)	(1.449726)	(1.360148)	(2.696546)	(2.897824)
4 % of fire in deforestation	22.93893	13.25001	20.85406	12.65349	19.0664	24.42741	19.68144	24.28621	16.53636	17.55187
	(30.83754)	(24.12336)	(29.05567)	(22.97266)	(27.84682)	(29.68453)	(27.69978)	(29.5878)	(24.52846)	(25.23803)
5 Forest fires (km2)	2.413779	.8827375	1.421161	.8892843	1.357776	2.374192	1.555167	2.053755	1.290429	1.594017
	(7.103305)	(2.474242)	(4.278485)	(2.376738)	(3.741547)	(6.362968)	(4.276577)	(5.42448)	(3.792157)	(4.588439)
N	20307	20307	20404	20401	20405	20405	20405	20405	20405	20405

Obs: Mean and standard deviations of the outcome variables used in the study. The unit of observation is a 15km x 15km cell in a given year.

Table A2: Enforcement variables

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Deforestation crackdown	.0519525	.033683	.053715	.0458311	.058319	.0462142	.0508209	.0447929	.0418525	.0357755
	(.2219367)	(.1804163)	(.2254599)	(.2091237)	(.2343515)	(.2099537)	(.2196372)	(.2068541)	(.2002569)	(.1857346)
Total environmental fines*	42.97717	26.36494	49.14207	37.4781	50.90279	42.97597	38.56233	40.96942	35.23814	25.78182
	(64.99281)	(47.37189)	(91.19592)	(71.79812)	(95.46092)	(99.86462)	(69.03695)	(63.65941)	(49.19647)	(40.55786)
Total flora fines*	29.30239	16.41761	37.63325	29.44408	44.49323	35.18388	31.55098	28.66641	26.40553	20.21024
	(48.63064)	(30.18107)	(78.95736)	(60.75993)	(90.26377)	(88.17945)	(62.20887)	(50.82563)	(41.71788)	(35.25489)
Total deforestation fines*	15.24778	8.477295	29.15738	19.39327	27.19063	18.87518	17.18919	15.58405	14.9108	13.77553
	(26.44976)	(16.67455)	(65.55131)	(44.0056)	(52.62172)	(38.36518)	(33.15072)	(29.77979)	(26.36632)	(24.79145)
Deforestation fines	.1180874	.0651007	.1509508	.116759	.1693212	.1297721	.1321245	.1050723	.1020338	.0706199
	(.7757791)	(.5036035)	(1.283648)	(.9478014)	(1.288702)	(1.000499)	(.8513223)	(.7258064)	(.7548953)	(.5010886)
Inspected area - deforestation fines	535.8382	319.1243	545.0786	461.7437	527.1588	591.9043	677.8204	543.893	549.5421	570.0727
	(6286.231)	(4545.979)	(5681.434)	(5527.99)	(5605.993)	(7661.623)	(7966.827)	(6177.925)	(6042.145)	(6683.198)
Share inspected deforestation	1217.815	607.6077	609.9425	770.8841	624.7853	941.0154	997.3306	760.7041	540.3836	587.7106
	(11465.49)	(7718.209)	(5795.383)	(8565.699)	(5377.092)	(10248.96)	(9308.042)	(8947.663)	(6911.589)	(7715.848)
N	20307	20307	20404	20401	20405	20405	20405	20405	20405	20405

Obs: Mean and standard deviations of the enforcement variables used in the study. The unit of observation is a 15km x 15km cell in a given year.

Table A3: Characteristics (controls)

	Fixed	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Distance to Belém (km)	1405.12										
	(680.693)										
Distance to Manaus (km)	876.8191										
	(369.504)										
Distance to Cuiabá (km)	1384.899										
	(535.18)										
Shortest distance to IBAMA (km)	212.9281										
	(129.2514)										
Distance to closest federal road	99.74416										
	(95.41381)										
% with state road	.2870412										
	(.452382)										
% with federal road	.0667437										
	(.2495782)										
% indigenous land	25.23563										
	(40.88788)										
% conservation park	26.71074										
	(41.25416)										
% deforested		.1788433	.1801693	.1831963	.1845236	.1902239	.1917603	.193361	.1950535	.1967795	.1994097
		(.288144)	(.289156)	(.2908991)	(.2918908)	(.2975602)	(.2986323)	(.2997637)	(.3009289)	(.3020107)	(.303517)
% area as forest frontier		.1406703	.1420399	.1473837	.1463392	.1495253	.1517501	.1524734	.1551945	.156986	.1592723
		(.2355864)	(.2373793)	(.2416018)	(.2406238)	(.2437877)	(.2461842)	(.2465821)	(.2492588)	(.250589)	(.2523324)
N	224156	19833	19833	19930	19927	19931	19931	19931	19931	19931	19931

Obs: Mean and standard deviations of the control variables used in the study. The unit of observation is a 15km x 15km cell in a given year.

Table A4: Instruments

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
% area covered with cloud	60.57544	39.00893	33.38096	47.95049	45.95313	36.37062	44.94082	.	.	.
	(16.76757)	(17.78106)	(15.89355)	(21.66128)	(19.6307)	(22.13561)	(18.89225)	(.)	(.)	(.)
% cloud January	92.59623	89.24037	75.15724	56.87693	65.22546	63.80798	78.73978	.	.	.
	(19.03889)	(18.76067)	(32.88083)	(35.27754)	(37.33796)	(38.54224)	(31.05746)	(.)	(.)	(.)
% cloud February	97.57204	64.7845	72.61333	79.3718	66.79065	55.36854	88.79403	.	.	.
	(12.24092)	(35.22684)	(33.88139)	(31.64051)	(37.61581)	(40.6135)	(24.2531)	(.)	(.)	(.)
% cloud March	83.00162	60.85564	61.73267	73.49115	72.75709	74.72589	69.96938	.	.	.
	(20.71694)	(35.43112)	(34.88645)	(30.69811)	(31.50097)	(34.60888)	(33.45851)	(.)	(.)	(.)
% cloud April	69.93829	53.37892	47.26916	66.03577	68.80991	56.64101	66.31811	.	.	.
	(37.05235)	(36.4093)	(36.85641)	(35.50767)	(33.89184)	(41.96188)	(36.08657)	(.)	(.)	(.)
% cloud May	37.95744	36.84292	47.87116	57.77042	59.1328	39.27594	43.97832	.	.	.
	(42.06426)	(35.85012)	(38.14238)	(36.92024)	(40.9706)	(38.97552)	(35.59687)	(.)	(.)	(.)
% cloud June	24.86741	18.61005	23.55973	30.85842	23.68315	21.12761	24.02633	.	.	.
	(34.87022)	(28.84492)	(30.04794)	(39.66283)	(33.8683)	(32.24403)	(34.31461)	(.)	(.)	(.)
% cloud July	8.934099	15.79768	14.78544	17.56279	17.44345	14.05419	13.6497	.	.	.
	(19.21792)	(27.12877)	(26.11981)	(28.2397)	(30.44963)	(25.9672)	(28.79048)	(.)	(.)	(.)
% cloud August	40.23689	3.993289	8.517482	15.54531	6.5673	10.09653	4.804969	.	.	.
	(37.19542)	(13.31091)	(18.78924)	(28.16072)	(19.09563)	(21.81281)	(14.29583)	(.)	(.)	(.)
% cloud September	40.16916	6.050032	4.039638	16.48229	9.423742	6.05813	17.66808	.	.	.
	(29.75331)	(15.12971)	(11.67646)	(26.95425)	(20.96731)	(16.55576)	(26.93725)	(.)	(.)	(.)
% cloud October	68.20777	19.41458	11.78465	31.85862	27.55719	10.94551	16.30834	.	.	.
	(25.56567)	(25.89088)	(19.28267)	(33.88339)	(33.36062)	(24.14709)	(27.69273)	(.)	(.)	(.)
% cloud November	80.48111	49.65245	33.26879	65.66872	52.14124	35.36487	43.76608	.	.	.
	(27.86975)	(30.81676)	(27.99752)	(33.72635)	(32.99355)	(35.6319)	(33.53274)	(.)	(.)	(.)
% cloud December	83.28384	49.5625	0	64.18643	82.27178	49.16998	71.43728	.	.	.
	(29.54058)	(32.49636)	(0)	(28.38874)	(26.2782)	(39.17429)	(29.66008)	(.)	(.)	(.)
Alert quality	3.924026	3.759378	4.78773	6.393847	11.61997	12.94871	18.56592	16.43549	16.90809	20.88673
	(13.85829)	(13.66127)	(15.27722)	(17.60343)	(22.49673)	(22.83537)	(26.65604)	(24.67622)	(24.5471)	(25.74542)
N	20303	20300	20392	20392	20401	20398	20401	5221	5940	5936

Obs: Mean and standard deviations of the control variables used in the study. The unit of observation is a 15km x 15km cell in a given year.