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 three percentage points the inspection probability for offenders, avoiding approximately 450 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), disturbs regional rain patterns (Leite-Filho et al. 2021, Araujo 2023), and pollutes the local air via deforestation-related fires (see Ferreira 2023 for a survey). While deforestation causes collective and diffuse 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.

To understand how real-time monitoring affects enforcement action, . Monitoring technologies can support enforcement agencies in targeting inspections to fight punishable offenses. In a bestcase 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

[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.

then its impact on compliance. I perform the analysis at a precise geographical level, where deforestation, 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

[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.

to inspect areas using real-time data on deforestation. DETER is the main source of deforestation alerts in this study, and I discuss it in more detail below. Other relevant initiatives that may have collaborated in reducing deforestation were the Soy Moratorium (Nepstad et al. 2009) and the policy of prioritizing municipalities for enforcement action (Assunção and Rocha 2019, Assunção et al. 2023). By 2023, deforestation has destroyed approximately 23% of the primary forest in the Brazilian Amazon, although approximately 20% of this area has 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]

[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*.

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

[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).

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

An important landmark in the history of environmental enforcement in the Brazilian Amazon was the "PPCDAm Plan", 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 essentially 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.

[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

2.4 Data

The three main datasets are from two satellite systems managed by the Brazilian Spatial Research Institute (INPE) and the administrative data on fines, namely:

1. the maps from soil coverage system (PRODES), updated yearly
2. the maps of deforestation alerts from the monitoring system DETER, published monthly
3. the administrative dataset of fines from IBAMA

I restrict the dataset to fines related to deforestation of native forests in the Amazonian biome using a string search on the free description of the fines typed by inspectors. More details on the classifications of fines can be found in the Online Appendix. I use the geographical coordinates of deforestation fines to locate the enforcement action at a precise area and link it to measured outcomes. These four datasets can be visualized in the set of figures[9] 2a to 2d. Figure 2a shows the categorization of the land coverage by PRODES as forest, old deforestation, and new (i.e., "last-year") deforestation. Figure 2b overlays this the soil coverage with the fire locations. Figure 2c shows the areas of logging signals in yellow. Finally, Figure 2d shows the points where inspectors produced a fine.

To overlay the maps of soil coverage, logging alerts, and fire alerts in the whole Amazon forest, I rasterized the entire area into 300m level squares. I also added more information at this level, such as the administrative divisions of the Amazon into municipalities and the legal status of the land - private property (from the official rural registry CAR), indigenous land, conservation units, or others. Therefore, at a 300m level of precision, there are several layers of merged information. I then aggregate information at the 15km x 15km cell level.

The 15km x 15 km cell level is the observational unit used in this study. It roughly corresponds to splitting the Amazon forest into 20 thousand equally-sized squares. I include information on enforcement action at the cell level instead of matching the fines' coordinates with the exact locations of the polygons of deforestation or alert. I also compute some other variables at the (15km x 15km) cell level, such as i) the distance from each cell to each of the three main cities of the

[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.

Amazon: Manaus, Cuiabá and Belém, ii) the presence of state roads in the cell (binary variable), iii) the presence of federal roads in the cell (binary variable), and iv) the shortest distance from each cell to a federal road, v) the accumulated share of deforested area in that cell-year, and vi) the size of the forest frontier in the cell[10].

3 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.[11]. 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

[10]By forest frontier I meant the border between native forest and already deforested area.

[11]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.

the value of following real-time alerts as opposed to random fines.

3.1 Computing the fine probability

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 having a positive level of deforestation in a given year, a 15km x 15km 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 (see Appendix figure A1), and yearly additional deforestation seems to be beyond what IBAMA is able to inspect every year, given that only 13% of cells with positive deforestation received a fine.

This probability hides a lot of heterogeneity. Cells that are close to IBAMA's offices, cells that deforest larger areas, or cells that receive real-time deforestation alerts are more likely to be fined. I estimate the following linear probability model to understand the factors which are correlated with fine probability:

$$\begin{aligned} \mathbb{P}(\text{fine}_{it}) = \beta_0 + \beta_1 \text{deforestation alert}_{imt} + \beta_2 \text{fire signal}_{it} \\ + FE_i + \delta_t + \gamma X_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where ε_{it} is a cell-year idiosyncratic error term, assumed to have a conditional mean zero. FE_i are cell fixed effects and δ_t are month dummies. X_{it} is a matrix of controls such as distances to three main cities (Manaus, Cuiabá and Belém), distances to the closest IBAMA office, prices of commodities and IBAMA's budget expenditure. Some specifications also include municipality fixed effects and year fixed effects. The regression is estimated with different samples, including a sample with only areas with positive deforestation. All variables are binary, including deforestation (1 if there was positive deforestation) and alerts, except for the controls and unless specified otherwise. The coefficients of interest are β_1 and β_2, which reflect the additional probability of enforcement given the occurrence of a logging or fire alert, relative to no alert. The main specifications are estimated only for the sample of cells with positive deforestation, that is the areas "eligible" for fines.

The table can be analysed for descriptive purposes but is unlikely to yield causal estimates of the different factors on fine probability. The OLS results can be seen in Table **??**. The probability of an inspection increases by almost 8 percentage points in areas with positive deforestation (Column 1), and 1.5 percentage point if there is fire. Columns 2 and 3 include a dummy for whether both fire and deforestation alerts are observed in the same year, still conditional on "same year deforestation". Almost all cells with a deforestation alert also presented some degree of forest fires, even though the exact overlap of areas is rare. The interaction coefficient therefore captures almost the full effect of deforestation alerts, and makes the effect of forest fire alerts negative but not statistically significant. The other Columns change the sample in which the model is estimated. In Column 4 only priority municipalities are selected. These are municipalities declared as high-priority by the enforcement agency itself. The effect is strongest for this sample, with deforestation alerts increasing by 14 percentage points the probability of a inspection, although the effect of forest fires is still around 1.5 percentage point. Column 5 has all cells that presented some year of positive deforestation in the 2011-2020 period. The effects if alerts are understandably weaker, since alerts may lead the enforcement to areas where there is no deforestation, such that no inspection would be observed. The same is the case in Columns 6 and 7, which include all data, including cells with no deforestation whatsoever. It cannot be ruled out that "false positives" led to inspections, but these would be unsuccessful and not appear in the dataset. This explains why the effects are attenuated once we account for all alerts, including in areas where no deforestation took place.

Clearly there are several factors which influence fine probability, and the real-time monitoring system that produces deforestation alerts. Below I propose a strategy to estimate the causal effect of the real-time deforestation alerts on fine probability, which allows me to understand the contribution of this technology to the enforcement action in the Amazon forest.

3.2 Effect of alerts on fine probability

Identification

As discussed in previous sections, satellites produce several types of alerts to the enforcement agency, and especially fire and deforestation alerts. While deforestation alerts are observed at a month-cell level, they are not an exogenous event, and it is not possible to infer causal effects immediately from a regression of fines on alerts. The reason is that areas that receive alerts are more easily observed by satellites, particularly because they have less cloud coverage and present larger areas of deforestation. Therefore, I propose a differences-in-differences identification strategy to estimate the causal effect of alerts on fines. 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 second one is "non anticipation", which means that the observed outcomes previous to the alert can be interpreted as untreated outcomes.

Estimation

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:

$$P(\text{inspection})_{it} = \sum_{\ell=-6,\ell\neq-1}^{12} \beta_\ell \mathbb{1}\{t - e_i = \ell\} + \delta_t + FE_i + \varepsilon_{it} \tag{2}$$

where ε_{it} is a conditional mean zero error term, and e_i is the month of the an alert event within cell i.[12] $\mathbb{1}\{t - e_i = \ell\}$ 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

[12]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.

"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 2 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 2 makes potentially invalid 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 in particular 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.

I first estimate the event study in equation 2 using OLS, and then I estimate the model using a method robust to biases stemming from problems of staggered designs. To overcome these problems, I follow the approach suggested by Borusyak, Jaravel, and Spiess (2021), which the authors name an "imputation method". The method consists of three steps. In the first step, I estimate the time and cell fixed effects (i.e., the two-way fixed effect model) only using non-treated observations (the union of "never-treated" and the "not yet treated" observations). This yields cell-month specific estimates of the untreated value of the outcome. Then, I extrapolate these estimates to the remaining part of the sample (the sample of observations after treatment has taken place), which is essentially a prediction of individual counterfactuals. Finally, I compute the average treatment effect as the average difference between the realized values of the outcome (fines in this example) and the imputed counterfactual. This procedure avoids making invalid comparisons with cells that have already been treated in the past, thus yielding a meaningful estimate of the ATT in the sense that it is a convex combination of the individual treatment effects.[13]

[13]Additionally to the problem of negative weights, Borusyak, Jaravel, and Spiess (2021) warn that the absence of groups which are "never treated" in the analysis created an identification problem, in which the time fixed effects

Results

The OLS results are shown graphically in Figure 4b. The results for the estimation using the method of Borusyak, Jaravel, and Spiess (2021) are in Figure 4c. In this case, they are qualitatively and quantitatively very similar to the OLS results, suggesting that the problems related to staggered designs are not severe in this particular application. They all 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.

Placebo tests

Table 7 summarizes the OLS results and includes other specifications testing the effect of other real-time satellite information as placebo tests. Column 1 shows the effect of the occurrence of a deforestation alert on the probability of an inspection. Prior to the occurrence of the alert, there is no difference between the enforcement probability of areas that received an alert and areas that received no deforestation alert, despite having positive amounts of deforestation. Column 2 and Figure 5a show the effect of real-time alerts of forest fires on the probability of fines. They suggest a strong correlation between forest fires and inspection probabilities. However, there are clear differences between areas with or without fires prior to the first alert that the forest is burning, such that the differences between areas with an alert and without an alert cannot be causally attributed to the alert. When one considers any fire alerts, including fires that started outside of forest, as in Column 3 and Figure 5a, there is a more compelling case to suggest that fire alerts lead to enforcement action, but again the differences arise prior to the first alert. These correlations are driven by the fact that fires often happen in the process of deforestation, such that many of the fire alerts are probably happening in the proximity of areas with deforestation alerts, which were

cannot be identified from an alternative model in with time trends. The treatment effect estimates with this method happen to be simply the difference between observed outcomes and predicted counterfactuals. This means that there is no "error" term estimated next to the treatment effect, raising the question of how to estimate the variance of the estimator. As shown in Borusyak, Jaravel, and Spiess (2021), the variance of the estimator relied on the variance of these individually computed treatment effects, as well as on the error term o the estimation of the two-way fixed effect model (which is done with only the untreated part of the sample).

shown to have a strong effect on enforcement. In fact, fire alerts bear really no weight in the decision of the enforcement agency: when comparing areas with deforestation and fire versus areas with deforestation with no fire, excluding all areas that also had a deforestation alert, a flat curve appears (Figure 5b)

Other placebo tests can be done using other types of real-time alerts produced by satellites, but which are unrelated to large scale deforestation, such as "selective logging" alerts (*desmatamento seletivo*) and "mining alerts" (*mineração*). Though these activities also encompass destruction of forest, they do so at a smaller scale than deforestation aimed at converting forest to pasture or agriculture. As a consequence, these alerts should not have any effect in altering probability of inspection for deforestation, and can be used as a placebo test to verify whether the effect observed for deforestation alerts is really specific to that kind of information. Indeed, that is clearly what is observed in Columns 4 and 5 of Table 7 and Figures 6a and 6b. In summary, only deforestation alerts have a causal effect on enforcement action, with fire alerts being correlated but not causing increases in inspection probability.

3.3 Decomposing the effect of monitoring in the fine probability

The probability of inspections for offending cells can be decomposed as follows, using the Law of Total Probability:[14]

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

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:

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

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

This decomposition allows us to understand how much of the overall enforcement action can be attributed to the alerts. These fines are "additional" to the baseline inspections, which would have occurred regardless of the alerts. To understand the role of real-time monitoring in the overall enforcement risk, 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. This allows me to 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. The share of fines caused by alerts is $s \equiv \frac{\sum_{\ell=0}^{8} \beta_\ell \times \#\text{alerts}}{\#\text{fines in areas with alerts}} \approx 1/3$. 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. A fraction $s \approx 1/3$ of the fines is due to real-time monitoring, and I use this fraction to apportion the part of the 22% yearly fine probability to real-time monitoring. This is an approximation, but it seems to be the most natural way to apportion the probability that an areas gets fined in a given year using monthly level estimated ATTs. The consequence is that out of the 22% yearly probability of fine for areas with deforestation and alerts, 7 percentage points are due to the real-time monitoring system, and 15 percentage points are the baseline probability, captured by cell and month fixed effects.

$$\underbrace{\mathbb{P}(\text{fine})}_{\textbf{13\%}} = \underbrace{\mathbb{P}(\text{fine}|\text{no alert})}_{\textbf{6\%}} \underbrace{\mathbb{P}(\text{no alert})}_{\textbf{60\%}} + \left(\underbrace{\mathbb{P}(\text{fine}(0)|\text{alert})}_{\textbf{15\%}} + \underbrace{ATT}_{\textbf{7\%}} \right) \underbrace{\mathbb{P}(\text{alert})}_{\textbf{40\%}}$$

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 (15%), 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 3 percentage points ($ATT \times \mathbb{P}(\text{alert}) = 7\% \times 40\%$). This represents a substantial amount of the overall fine probability, especially given that it is the part that is due to a single source of information: the real-time monitoring system DETER.

The results of this decomposition exercise can be seen in Figure 8a. In the next section I estimate the impact that this 3 percentage point increase in fine probability has on deforestation reduction.

3.4 Mechanism: why following real-time alerts matters for 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:

$$\begin{aligned}\text{fine characteristic}_{imt} = \beta &+ \alpha_0 \text{deforestation alert}_{imt} + \alpha_1 \text{deforestation alert}_{imt-1} \\ &+ \alpha_2 \text{deforestation alert}_{imt-2} + \alpha_3 \text{deforestation alert}_{imt-3} + FE_m + \delta_t + \varepsilon_{it}\end{aligned} \tag{3}$$

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 8 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 8 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 8. 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.

4 Farmers' responses to inspections

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". In the context of deforestation, this would be captured by agents' behavior after punishment.

The general and specific deterrence effects are 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 do that, I propose a simple framework to understand how they interact.

Formally, call p_t the probability of inspection in year t, $N(p_t)$ the resulting number of offending farmers, $d_t(p_t, f)$ the average deforestation areas by offending farmers, which is a function of the probability of inspections p_t and the history of inspections f. The variable f codes whether the farmer was inspected in period 0. The share p_t of farmers who have been inspected deforest less up to three years later,[15] whereas those who have not been inspected continue deforesting as before. The four year accumulated deforestation is:

$$D = \sum_{t=0}^{3} N(p_t) d_t(p_t, f)$$

Suppose there is a marginal increase in p_0 (the inspection probability at period 0), lasting only one period. Then the impact of this marginal increase on a four-year period of deforestation D is:

[15] Three years is an arbitrary time horizon.

$$
\begin{aligned}
\frac{dD}{dp_0} &= \sum_{t=0}^{3} \frac{dN}{dp_0} d_t(p_t) + N(p_t)\Big(\frac{\partial d_t}{\partial p_0} + \frac{\partial d_t}{\partial f}\frac{df}{dp_0}\Big) \\
&= \frac{\partial N}{\partial p_0} d_0(p_0) + N(p_0)\frac{\partial d_0}{\partial p_0} + \sum_{t=1}^{3} N(p_t)\frac{\partial d_t}{\partial f}\frac{df}{dp_0} \\
&= \underbrace{\frac{\partial N}{\partial p_0} d_0(p_0) + N(p_0)\frac{\partial d_0}{\partial p_0}}_{\text{general deterrence effect}} + \underbrace{\Big(dp_0 N(p_0) + p_0\frac{\partial N}{\partial p_0} d_0(p_0)\Big)\sum_{t=1}^{3}\frac{\partial d_t}{\partial f}}_{\text{specific deterrence effect}}
\end{aligned}
\tag{4}
$$

The second equality comes from the fact that the probability of inspection only changes in period 0, and therefore does not affect p_1, p_2, p_3. The third equality comes from the fact that only $f = 1$ only for those that are inspected. Since only $p_0N(p_0)$ are inspected in period 0, then $dp_0N(p_0) - p_0\frac{\partial N}{\partial p_0}$ are inspected in that period as a result of a marginal increase in p_0.

The first part of the decomposition refers to the general deterrence effect, the ex ante reduction in deforestation resulting from an increase in inspection probability. There is an extensive margin response (the change in the number of cells having any level of deforestation) and an intensive margin response (the change in the deforested area within these cells). To understand the magnitude of deforestation reduction in the Amazon forest as a result of an increase in fine probability, we need to estimate the behavioral responses, which are the derivatives in the equation 4.

4.1 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.[16] 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 of areas where deforestation takes place. As is typically the case in the crime literature (see, for

[16]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.

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 an instrumental variable.

The instrumental variable that provides the exogenous variation on fine probability is *cloud coverage* at the cell level. This instrumental variable was first proposed by Assunção, Gandour, and Rocha (2022), who also used it to estimate the causal impact of fines on deforestation. Cloud coverage blocks temporarily the visibility of a cell, making it impossible for optimal sensors in satellites to produce images of the forest. This feature is a major limitation of the real-time monitoring system DETER, and provide therefore variation in the timing of the deforestation alerts, and consequently on the enforcement agency's ability to inspect and punish offenders on time.

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 three main cities in the Amazon forest (Manaus, Belém, and Cuiabá), and dummies for the presence of indigenous territory, conservation units, 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. Finally, in some specifications, I control for commodity prices of soy and ox (aggregate and year-specific) and prices of vegetal coal and wood (state-year specific).

The model is estimated with Two-Stage-Least-Squares using only areas with positive deforestation in the period 2011-2020. The standard errors are clustered at the cell level, thus allowing for autocorrelation of the unobserved error between different years.

Results

Table 9 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 deforestation 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.[17]

4.2 Specific deterrence: dynamic effects of fines

Identification and estimation

[17] 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.

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 3.

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:

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

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 3, 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 9b. 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.[18] 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.[19] 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 neighbor-

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

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

ing municipalities.

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 10a 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.

4.3 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 4. 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. I thus obtain the following areas of avoided deforestation:

$$
\begin{aligned}
\frac{dD}{dp_0} &= \underbrace{\frac{\partial N}{\partial p_0} d_0(p_0) + N(p_0)\frac{\partial d_0}{\partial p_0}}_{\text{general deterrence effect}} + \underbrace{\left(dp_0 N(p_0) + p_0 \frac{\partial N}{\partial p_0} d_0(p_0)\right) \sum_{t=1}^{3} \frac{\partial d_t}{\partial f}}_{\text{specific deterrence effect}} \\
&= \overbrace{5000 \times (-0.009)}^{\frac{\partial N}{\partial p_0}} \times \overbrace{1}^{d(p_0)} + \overbrace{5000}^{N} \times \overbrace{1 \times (-0.019)}^{\frac{\partial d}{\partial p_0}} \\
&+ \Big(\underbrace{0.01 \times 5000}_{dp_0 N(p_0)} + \underbrace{0.13 \times 5000 \times (-0.009)}_{p_0 \frac{\partial N}{\partial p_0} d_0(p_0)} \Big) \times \underbrace{3 \times (-0.08)}_{\sum_{t=1}^{3} \frac{\partial d_t}{\partial f}} \\
&= \underbrace{-140}_{\text{gen. deterrence}} \quad \underbrace{-10}_{\text{sp. deterrence}} \quad = -150
\end{aligned}
$$

A one percent increase in inspection probability would reduce yearly deforestation by approximately 150 square kilometers a year. This area represents approximately 1.2% of the deforestation level in 2020 (12 thousand square kilometers) and 2% of the average deforestation in 2011-2020 (7 thousand square kilometers).

As computed in section 3, the treatment effects of the monitoring system represent approximately three 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 450 square kilometers of saved forest by year, or 6% of the average yearly deforestation in the decade.

5 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?

5.1 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:

$$\text{expenditure}_{it} = \beta_0 + \beta_1 \text{alerts\_inspections}_{it} + \beta_2 \text{no\_alerts\_inspections}_{it} + \delta_t + FE_i + \varepsilon_{it} \quad (7)$$

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 11 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).

5.2 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.[20] The harm caused by these emissions in terms of climate change are estimated from 30 to 100 USD.[21] 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.

6 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.

[20] 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/

[21] 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.

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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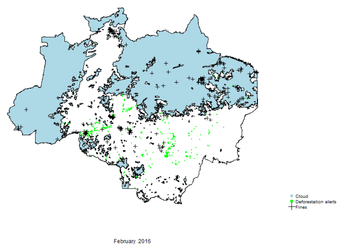
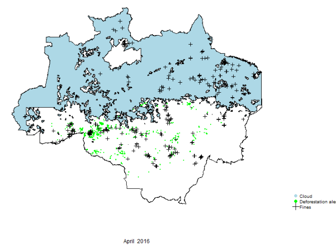
FIGURES

F1. Datasets



(a) January



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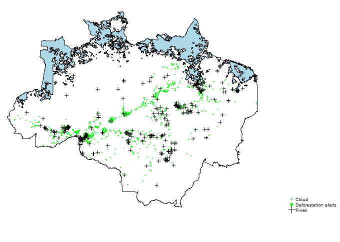

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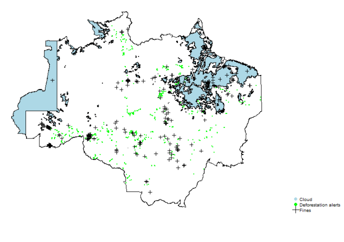
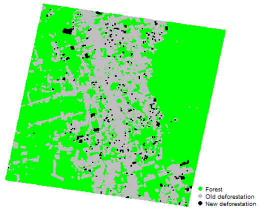


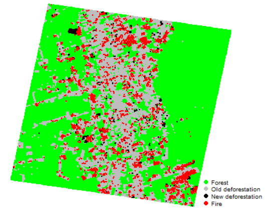
(d) October

Figure 1: Real time information on the Amazon forest

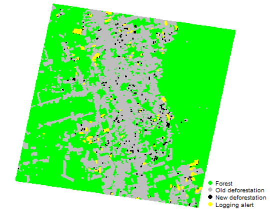
The following figures provide examples of maps used in the analysis. The square represented is an area of approximately 30 thousand square kilometers in the Brazilian Amazon forest, in the state of Pará. The picture corresponds to the year 2016, defined according to the PRODES methodology, that is, from August 2015 to July 2016. The PRODES image represents the state of the soil coverage on August 1st 2016. The logging alers, fire alerts and fines maps represent all the events that took place in the twelve month period from August 2015 to July 2016. The data from PRODES, logging alerts (DETER) and fires were obtained from the Brazilian National Institute for Space Research (INPE). The fines stem from the administrative dataset on environmental infractions of IBAMA, and refer exclusively to “deforestation” fines.



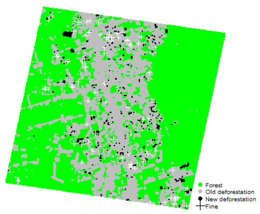
(a) Measurement satellite (PRODES)



(b) Fires (Queimadas)



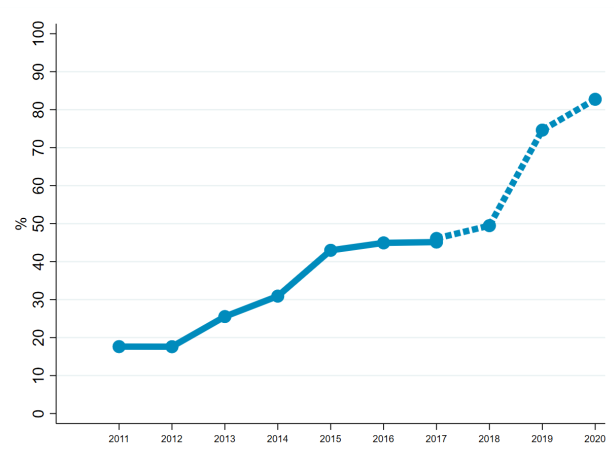
(c) Logging alerts (DETER)



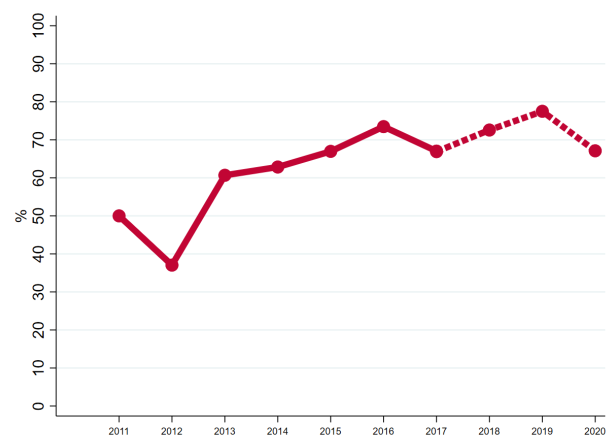
(d) Deforestation fines (IBAMA)

Figure 2: Main datasets

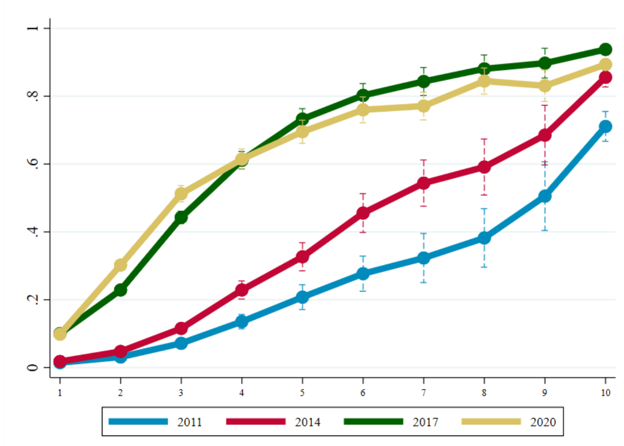
F2. Alert probabilities



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



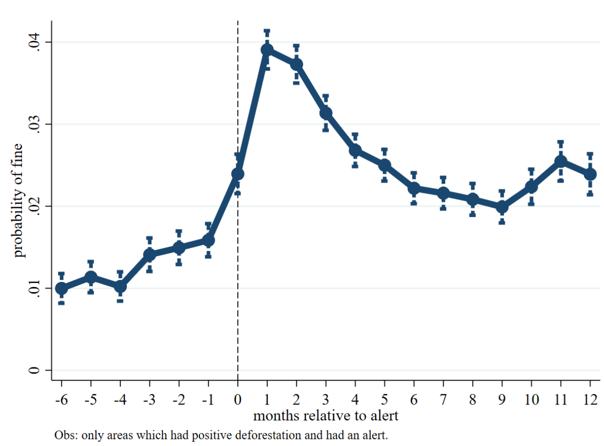
(b) Share of deforestation alerts that were declared deforestation $\mathbb{P}(\text{deforestation}|\text{alert})$



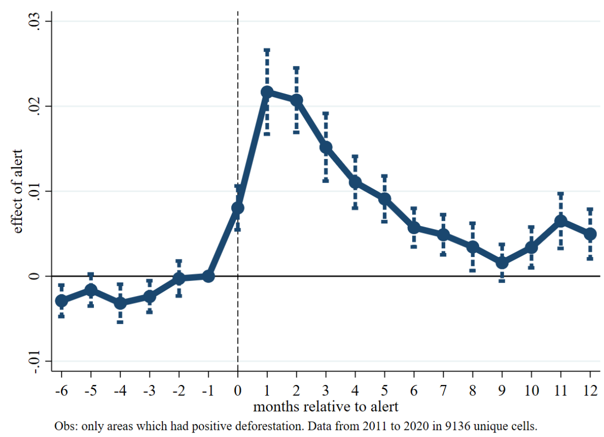
(c) Share of detected deforestation by size decile of deforestation areas and year

Figure 3: Monitoring quality

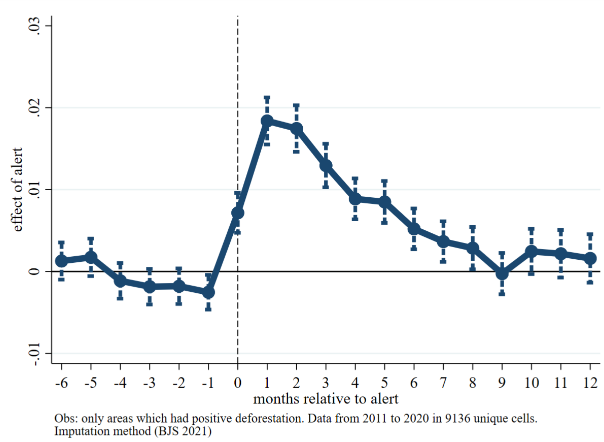
F3. Results - inspection probability and alerts - Event study



(a) Mean outcome (probability of fine) by months relative to deforestation alert

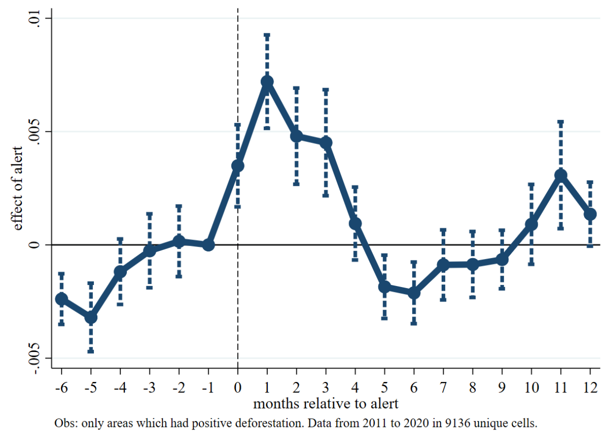


(b) Treatment effects on probability of fine by OLS

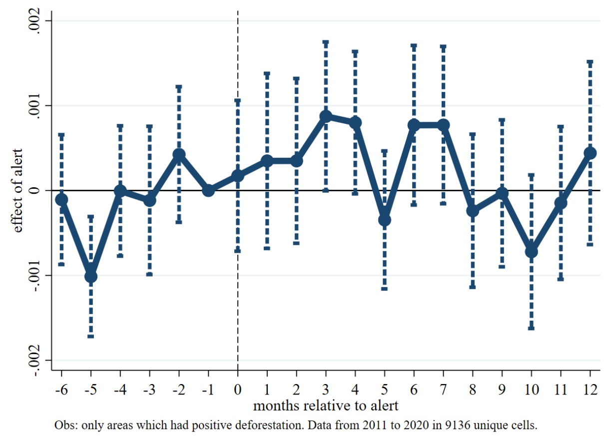


(c) Treatment effects on probability of fine using imputation method (Borusyak, Jaravel, and Spiess 2021)

Figure 4: Effects of deforestation alerts on probability of fine

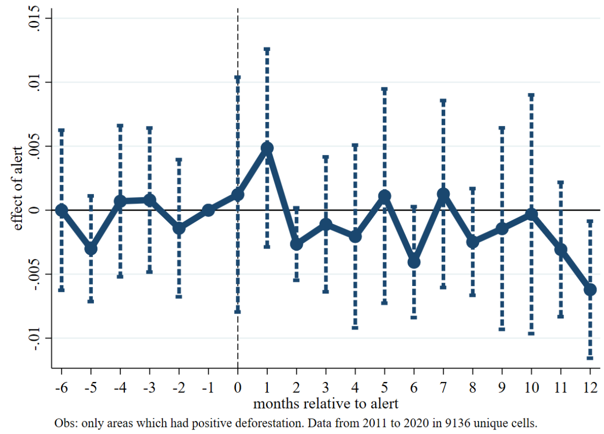


(a) Treatment effects of forest fires alerts on probability of fine

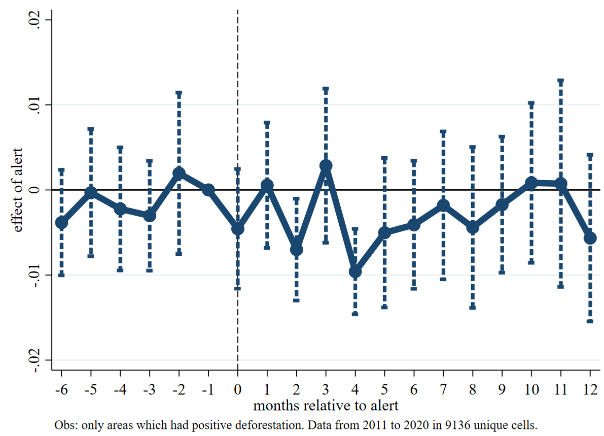


(b) Treatment effects of forest alerts on probability of fine (excluding areas with deforestation alerts)

Figure 5: Fire alerts



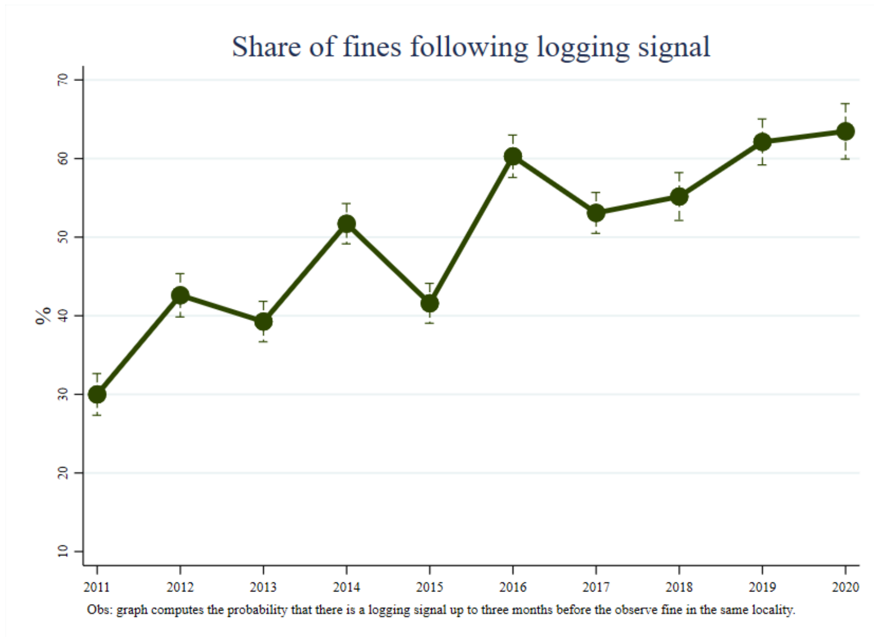
(a) Treatment effects of mining alerts on probability of fine



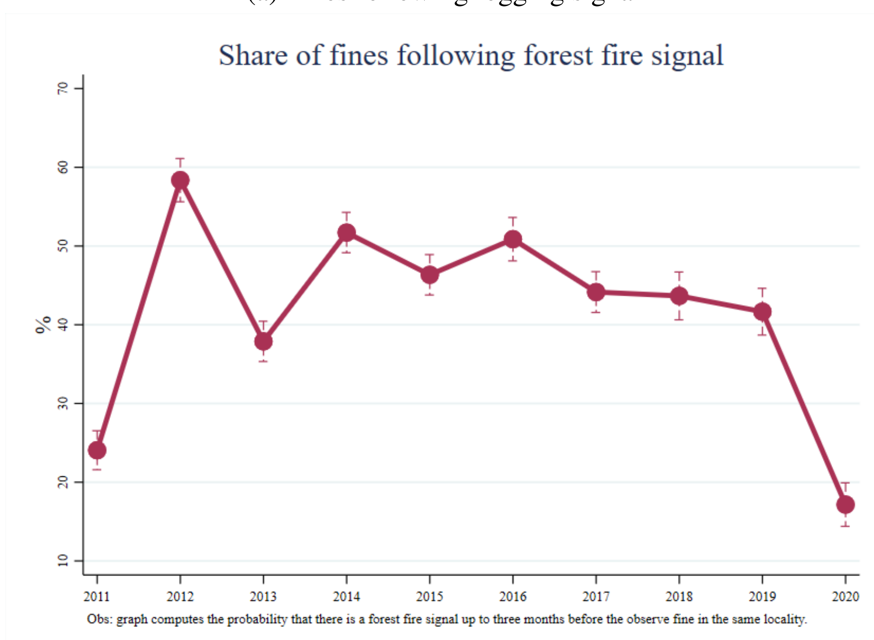
(b) Treatment effects of forest fires alerts on probability of fine

Figure 6: Placebo tests

F4. Share of fines following a real-time satellite alert

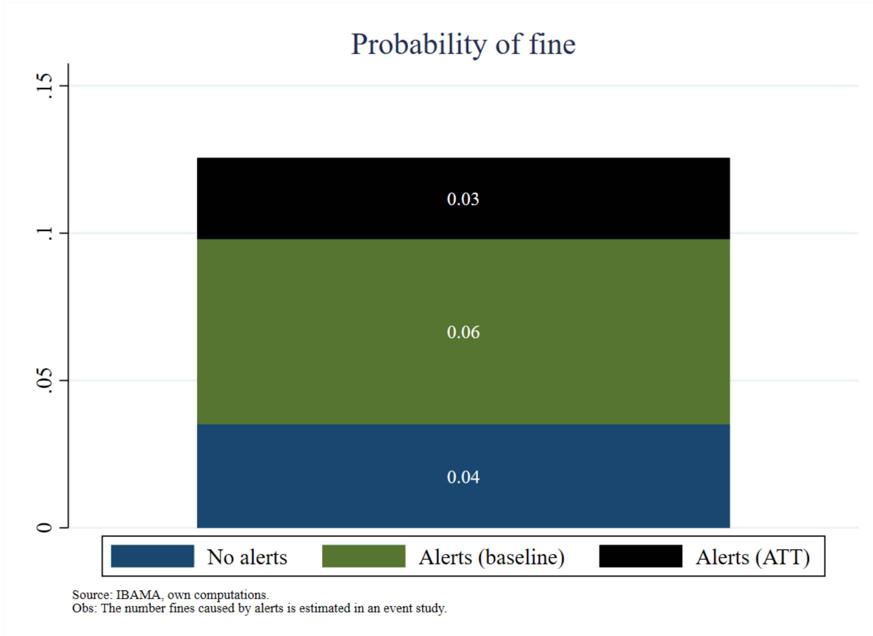


(a) Fines following logging signal



(b) Fines following fire signal

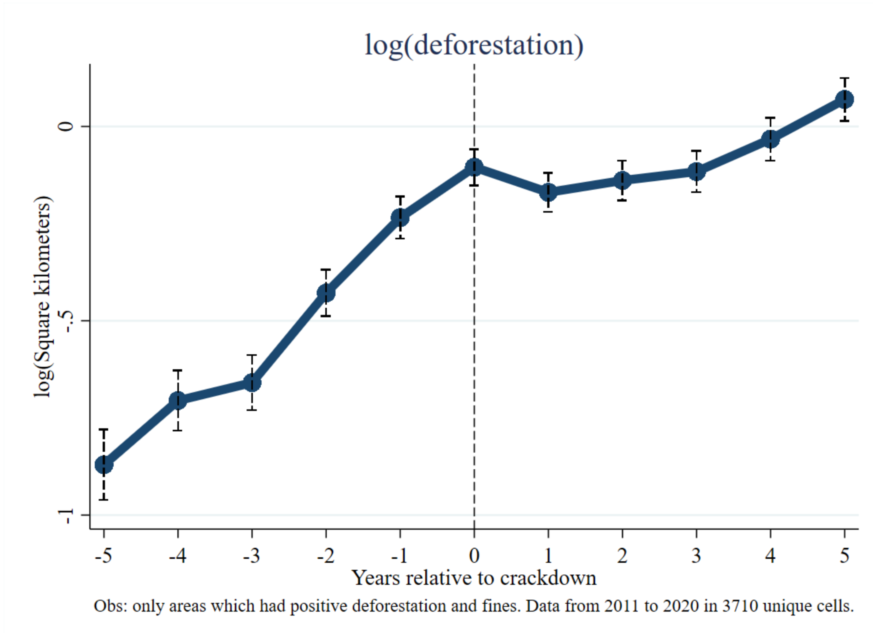
Figure 7: Targeting using monitoring alerts



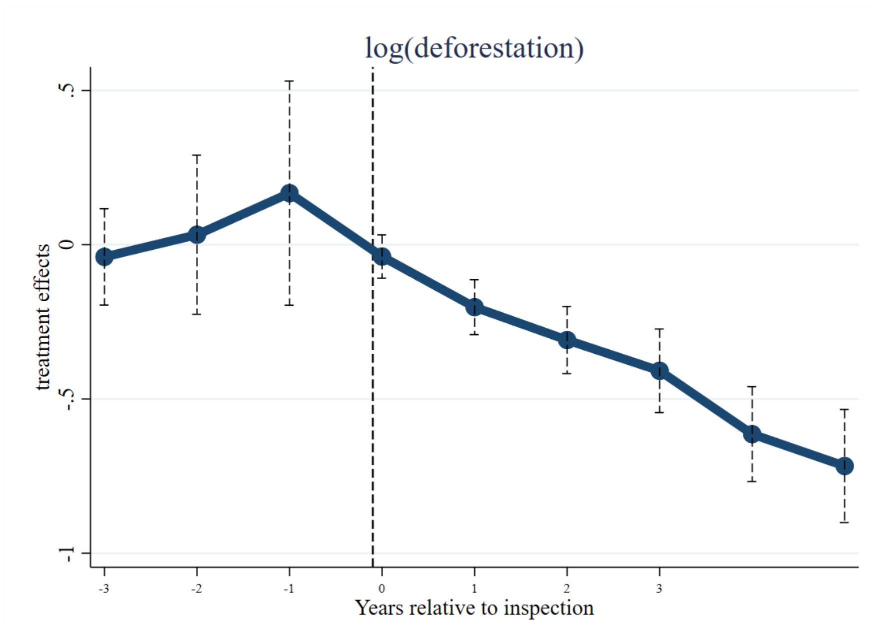
(a) Inspection probability

Figure 8: Fines caused by alerts

F5. Event Study of Deforestation and Fines

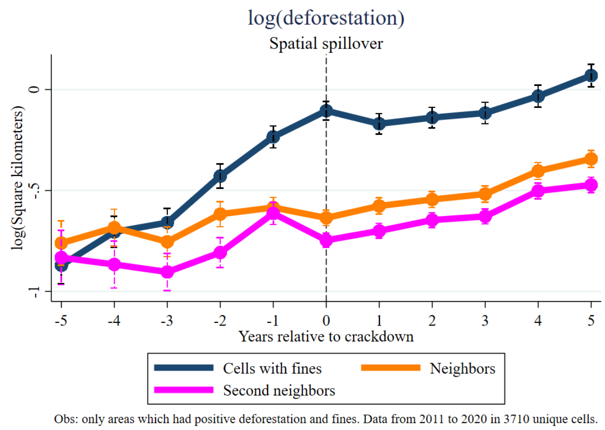


(a) Mean outcome (log deforestation) by year relative to inspection year

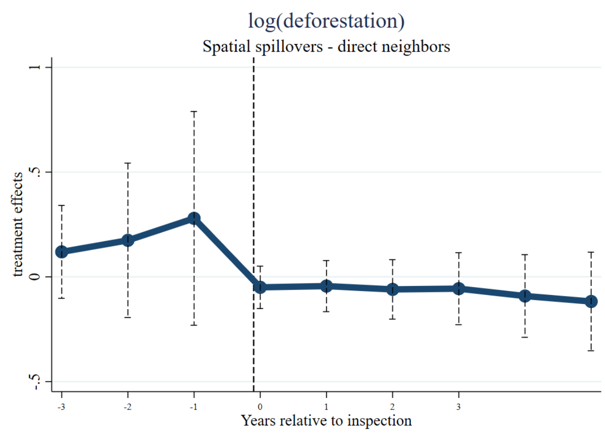


(b) Treatment effects using imputation method (Borusyak, Jaravel, and Spiess 2021)

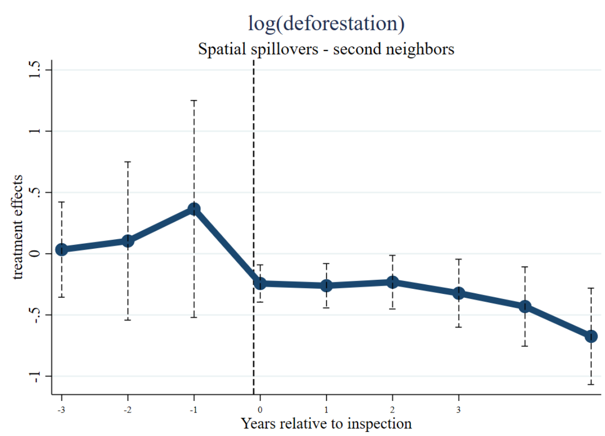
Figure 9: Deforestation and inspections



(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 10: Spatial spillovers

TABLES

T1. Data sources

Table 1: Main datasets used and sources

NAME OF DATASET	DESCRIPTION	TIME	GEOGRAPHICAL LEVEL	SOURCE
Fire signals (Queimadas)	Fire events in the Amazon forest detected by satellites.	Daily (2011-2020)	Geo-referenced points	Satellites Terra, Aqua and NPP (from 2013), compiled by INPE (Queimadas)
Logging signals (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	Yearly (measured in July of each year)	Geo-referenced polygons	Data from satellite Landsat, interpreted and compiled by INPE.

Table 2: Auxiliar datasets and sources

NAME OF DATASET	DESCRIPTION	TIME	GEOGRAPHICAL LEVEL	SOURCE
Prices of wood and coal	Prices in Brazilian Real (BRL) of 2020 of wood (*“madeira em tora”*) and vegetal coal (*“carvão vegetal”*).	Yearly (2011-2019)	State-level averages	IBGE, Vegetal Extraction Surveys
Prices of soy and cattle	Prices in Brazilian Real (BRL) of 2020 of 60kg of soy (*“soja industrial”*) and cattle (*“boi em pé arroba”*).	Monthly (2011-2018)	National averages	Agricultural Secretariat of the State of Paraná
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.	Geo-referenced polygon.	INPE (TerraBrasilis)
Road infrastructure	State and federal roads in the Brazilian Amazonia.	Fixed over time.	Geo-referenced lines.	MapBiomas
Private rural properties	Areas of private properties in the official public registry (*Cadastro Ambiental Rural*).	Fixed over time.	Geo-referenced polygons.	CAR, Ministry of Agriculture of Brazil
Budget execution of environmental	Expenditures in BRL 2020 by the Amazonian units	Yearly (2015-2020)	By state.	Federal Government of Brazil, (http://transparencia.gov.br)

T2. Regression tables - Behavior of the enforcement agency

Table 3: Outcome: detection probability

	(1)	(2)	(3)	(4)
DETER B dummy		0.382***		
		(0.0225)		
% year cloud coverage	-0.109			
	(0.0954)			
up to 20% fire	0.00727	0.0387***	0.0387***	0.0144
	(0.0152)	(0.0102)	(0.0102)	(0.00997)
20% to 50% fire	0.0148	0.0358***	0.0358***	0.0144
	(0.0143)	(0.00949)	(0.00949)	(0.00932)
50% to 80% fire	0.0472***	0.0564***	0.0564***	0.0439***
	(0.0130)	(0.00955)	(0.00955)	(0.00947)
80% to 100% fire	0.0698***	0.0673***	0.0673***	0.0669***
	(0.0131)	(0.0105)	(0.0105)	(0.0104)
Size of polygon	0.105***	0.0351***	0.0351***	
	(0.00970)	(0.00467)	(0.00467)	
Size squared	-0.00599***	-0.000855***	-0.000855***	
	(0.00107)	(0.000249)	(0.000249)	
2012.year	-0.104***	-0.0793***	-0.0793***	-0.0818***
	(0.0350)	(0.0268)	(0.0268)	(0.0263)
2013.year	-0.00737	0.0253	0.0253	0.0226
	(0.0375)	(0.0250)	(0.0250)	(0.0246)
2014.year	0.173***	0.191***	0.191***	0.187***
	(0.0284)	(0.0246)	(0.0246)	(0.0242)
2015.year	0.262***	0.288***	0.288***	0.284***
	(0.0288)	(0.0232)	(0.0232)	(0.0229)
2016.year	0.304***	0.349***	0.349***	0.346***
	(0.0379)	(0.0223)	(0.0223)	(0.0220)
2017.year	0.363***	0.0136	0.395***	0.390***
	(0.0295)	(0.0117)	(0.0225)	(0.0222)
2018.year		-0.107***	0.274***	0.271***
		(0.0130)	(0.0227)	(0.0223)
2019.year		-0.0886***	0.293***	0.261***
		(0.00925)	(0.0225)	(0.0222)
2020.year		0	0.382***	0.347***
		(.)	(0.0225)	(0.0222)
Log size				0.120***
				(0.00451)
Intercept	0.444***	0.420***	0.420***	0.480***
	(0.0543)	(0.0204)	(0.0204)	(0.0199)
N	9881	18639	18639	18639
r2	0.423	0.389	0.389	0.404

Obs: ***1% **5% *10% significance levels. Linear probability model of detection probability by monitoring

Table 4: Outcome: probability of inspection

	(1)	(2)	(3)	(4)	(5)	(6)
Positive deforestation				5.715***	6.235***	5.393***
				(7.18)	(7.62)	(5.07)
Positive deforestation X 2012	-4.833***	0	1.475	-3.129***	-3.850***	
	(-5.24)	(.)	(0.92)	(-3.52)	(-4.32)	
Positive deforestation X 2013	2.055	0	14.04***	2.428*	2.690**	
	(1.52)	(.)	(5.67)	(1.96)	(2.09)	
Positive deforestation X 2014	-1.357	1.656	10.69***	-0.722	-0.950	0
	(-1.12)	(0.95)	(4.02)	(-0.64)	(-0.82)	(.)
Positive deforestation X 2015	2.835*	6.400***	18.13***	3.619***	3.824***	4.811***
	(1.87)	(3.66)	(5.53)	(2.71)	(2.67)	(4.08)
Positive deforestation X 2016	-2.602**	0.665	7.323***	-1.671	-1.399	-0.445
	(-2.24)	(0.42)	(3.00)	(-1.59)	(-1.25)	(-0.43)
Positive deforestation X 2017	-0.727	2.979**	9.909***	0.543	0.388	1.432
	(-0.70)	(2.04)	(5.40)	(0.55)	(0.38)	(1.21)
Positive deforestation X 2018	-3.000***	0.839	6.550***	-2.060*	-1.717	-0.797
	(-2.73)	(0.56)	(2.99)	(-1.90)	(-1.56)	(-0.61)
Positive deforestation X 2019	-3.767***	1.261	5.432***	-2.165**	-2.675***	-1.757
	(-3.64)	(1.21)	(3.07)	(-2.10)	(-2.60)	(-1.57)
Positive deforestation X 2020	-6.202***	0	3.794***	-4.660***	-4.896***	-4.014***
	(-7.26)	(.)	(3.25)	(-5.55)	(-6.06)	(-3.74)
State road	1.356	1.357	-0.682	1.040	0.959	0.994
	(1.61)	(1.55)	(-0.60)	(1.56)	(1.62)	(1.51)
Size of forest border	0.349***	0.338***	0.520***	0.321***	0.337***	0.323***
	(9.11)	(8.26)	(7.89)	(9.26)	(9.74)	(8.81)
Indigenous territory	-1.304	-0.690	0.616	-1.322**	-0.961**	-0.884**
	(-1.30)	(-0.66)	(0.47)	(-1.99)	(-2.48)	(-2.12)
Conservation unit	-2.047**	-1.929*	-1.760	-1.768**	-0.671*	-0.714*
	(-2.09)	(-1.82)	(-1.61)	(-2.39)	(-1.74)	(-1.79)
prioritylist	3.357	0.475	0	3.446*	2.237*	1.148
	(1.17)	(0.14)	(.)	(1.69)	(1.85)	(0.81)
expenditureindex		7.730**				1.718
		(2.29)				(1.49)
Sample	Same year deforestation	Same year deforestation	Priority municipalities	Some year deforestation	All data	All data
Mun. Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	51657	37139	40263	93624	198819	139310
R2	0.173	0.184	0.207	0.160	0.175	0.181

Obs: ***1% **5% *10% significance levels. Linear regression of punishment (binary) on positive deforestation (binary), with year interactions and controlling for several fixed and varying characteristics of the observations, as well as municipality and year fixed effects. Observational level is a 15km x 15km cell-year in the Amazon forest. Standard errors are clustered at the municipality level.

Table 5: Outcome: inspection probability with real-time alerts

	(1)	(2)	(3)	(4)	(5)	(6)
Positive deforestation	0	0	4.616***	0	2.277***	1.887***
	(.)	(.)	(5.32)	(.)	(6.89)	(5.38)
Deforestation alert	12.62***	18.42***	17.56***	12.62***	15.35***	21.63***
	(7.20)	(8.17)	(8.08)	(7.20)	(9.52)	(9.67)
Deforestation alert X 2012	-5.066**		-8.412***	-5.066**	-7.689***	
	(-2.39)		(-3.28)	(-2.39)	(-4.19)	
Deforestation alert X 2013	18.45***		17.15***	18.45***	17.47***	
	(6.23)		(4.44)	(6.23)	(6.18)	
Deforestation alert X 2014	6.473**	0	7.546*	6.473**	6.415**	0
	(2.20)	(.)	(1.83)	(2.20)	(2.44)	(.)
Deforestation alert X 2015	5.370*	-0.960	10.42**	5.370*	6.121**	-0.136
	(1.94)	(-0.36)	(2.58)	(1.94)	(2.42)	(-0.06)
Deforestation alert X 2016	-2.909	-9.000***	-0.711	-2.909	-3.198	-9.254***
	(-1.14)	(-3.50)	(-0.18)	(-1.14)	(-1.38)	(-4.03)
Deforestation alert X 2017	-3.672*	-9.419***	-4.817	-3.672*	-5.217***	-11.18***
	(-1.71)	(-3.88)	(-1.39)	(-1.71)	(-2.81)	(-4.99)
Deforestation alert X 2018	-5.631***	-11.72***	-5.114*	-5.631***	-7.450***	-13.58***
	(-3.03)	(-4.70)	(-1.78)	(-3.03)	(-4.38)	(-5.66)
Deforestation alert X 2019	-7.492***	-13.11***	-6.179**	-7.492***	-8.794***	-14.73***
	(-3.81)	(-5.47)	(-2.18)	(-3.81)	(-4.97)	(-6.66)
Deforestation alert X 2020	-10.98***	-16.86***	-10.79***	-10.98***	-12.27***	-18.32***
	(-5.54)	(-7.70)	(-3.96)	(-5.54)	(-7.19)	(-8.78)
Fire alert	2.346**	2.679**	3.710***	2.346**	1.963***	0.591
	(2.03)	(2.37)	(2.90)	(2.03)	(3.93)	(1.36)
Fire alert X 2012	-3.436**		-4.643***	-3.436**	-2.250***	
	(-2.47)		(-3.12)	(-2.47)	(-3.89)	
Fire alert X 2013	-0.103		0.320	-0.103	-0.771	
	(-0.06)		(0.21)	(-0.06)	(-1.25)	
Fire alert X 2014	0.0585	0	-1.381	0.0585	-1.719***	0
	(0.04)	(.)	(-0.74)	(0.04)	(-2.65)	(.)
Fire alert X 2015	-0.0569	-0.133	-0.745	-0.0569	-0.904	0.790
	(-0.03)	(-0.08)	(-0.35)	(-0.03)	(-1.20)	(1.51)
Fire alert X 2016	0.0114	0.0175	-4.274***	0.0114	-2.157***	-0.527
	(0.01)	(0.01)	(-2.76)	(0.01)	(-3.61)	(-1.08)
Fire alert X 2017	-1.311	-1.533	-1.403	-1.311	-1.645***	-0.0164
	(-0.89)	(-1.00)	(-0.86)	(-0.89)	(-2.62)	(-0.03)
Fire alert X 2018	-3.295**	-3.622**	-4.511***	-3.295**	-2.300***	-0.656
	(-1.97)	(-2.03)	(-2.91)	(-1.97)	(-3.75)	(-1.13)
Fire alert X 2019	-2.381*	-2.853**	-3.992**	-2.381*	-2.425***	-0.903*
	(-1.83)	(-2.20)	(-2.53)	(-1.83)	(-4.22)	(-1.72)
Fire alert X 2020	-1.205	-1.445	-2.964*	-1.205	-2.536***	-0.975*
	(-0.98)	(-1.19)	(-1.84)	(-0.98)	(-4.40)	(-1.87)
Indigenous territory	-0.601	0.0193	0.933	-0.601	-0.643*	-0.540
	(-0.63)	(0.02)	(0.81)	(-0.63)	(-1.84)	(-1.43)

Table 6: Outcome: probability of inspection

	(1) Logging	(2) Forest fire	(3) Fire	(4) Sel. logging	(5) Mining
Lag 6	-0.371***	-0.381***	-0.306***	-0.636**	0.103
	(-4.39)	(-5.14)	(-4.20)	(-1.97)	(0.29)
Lag 5	-0.0293	-0.567***	-0.484***	-0.249	-0.190
	(-0.24)	(-5.64)	(-5.65)	(-0.57)	(-0.84)
Lag 4	-0.133	-0.337***	-0.308***	-0.424	0.0676
	(-1.23)	(-3.49)	(-4.35)	(-0.78)	(0.22)
Lag 3	-0.152	-0.215**	-0.297***	-0.523	0.210
	(-1.51)	(-2.15)	(-3.74)	(-1.15)	(0.66)
Lag 2	-0.00385	-0.0757	-0.120	0.236	-0.0495
	(-0.04)	(-0.81)	(-1.63)	(0.36)	(-0.20)
Lag1					
Alert	1.001***	0.447***	0.220***	-0.650	0.0652
	(6.15)	(4.28)	(2.84)	(-1.30)	(0.13)
Lead 1	2.313***	0.844***	0.477***	-0.208	0.700
	(8.50)	(7.13)	(5.04)	(-0.44)	(1.31)
Lead 2	2.381***	0.595***	0.409***	-0.929**	-0.251
	(10.51)	(4.96)	(3.73)	(-2.02)	(-1.42)
Lead 3	1.860***	0.591***	0.501***	0.472	-0.200
	(8.39)	(4.30)	(4.52)	(0.81)	(-0.83)
Lead 4	1.570***	0.191*	0.322***	-1.503***	0.108
	(8.23)	(1.82)	(3.45)	(-4.69)	(0.19)
Lead 5	1.251***	-0.168	0.0152	-0.717	-0.197
	(7.65)	(-1.62)	(0.18)	(-1.21)	(-0.71)
Lead 6	0.906***	-0.163*	0.00515	-0.700*	-0.334
	(5.78)	(-1.84)	(0.06)	(-1.65)	(-1.32)
Month and year dummies	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes
N	695517	687449	680306	722911	723946
R2	0.0587	0.0567	0.0562	0.0551	0.0548
Share with signal	.03	.06	.07	0	0

Obs: ***1% **5% *10% significance levels. Linear regression of crackdown (binary) periods relative to the earliest signal in a cell-year. Only cells with positive deforestation were used for estimation, since only they can

Table 7: Outcome: probability of inspection

	(1)	(2)	(3)	(4)	(5)
	Logging	Forest fire	Fire	Sel. logging	Mining
Lag 6	-0.371***	-0.381***	-0.306***	-0.636**	0.103
	(-4.39)	(-5.14)	(-4.20)	(-1.97)	(0.29)
Lag 5	-0.0293	-0.567***	-0.484***	-0.249	-0.190
	(-0.24)	(-5.64)	(-5.65)	(-0.57)	(-0.84)
Lag 4	-0.133	-0.337***	-0.308***	-0.424	0.0676
	(-1.23)	(-3.49)	(-4.35)	(-0.78)	(0.22)
Lag 3	-0.152	-0.215**	-0.297***	-0.523	0.210
	(-1.51)	(-2.15)	(-3.74)	(-1.15)	(0.66)
Lag 2	-0.00385	-0.0757	-0.120	0.236	-0.0495
	(-0.04)	(-0.81)	(-1.63)	(0.36)	(-0.20)
Lag1					
Alert	1.001***	0.447***	0.220***	-0.650	0.0652
	(6.15)	(4.28)	(2.84)	(-1.30)	(0.13)
Lead 1	2.313***	0.844***	0.477***	-0.208	0.700
	(8.50)	(7.13)	(5.04)	(-0.44)	(1.31)
Lead 2	2.381***	0.595***	0.409***	-0.929**	-0.251
	(10.51)	(4.96)	(3.73)	(-2.02)	(-1.42)
Lead 3	1.860***	0.591***	0.501***	0.472	-0.200
	(8.39)	(4.30)	(4.52)	(0.81)	(-0.83)
Lead 4	1.570***	0.191*	0.322***	-1.503***	0.108
	(8.23)	(1.82)	(3.45)	(-4.69)	(0.19)
Lead 5	1.251***	-0.168	0.0152	-0.717	-0.197
	(7.65)	(-1.62)	(0.18)	(-1.21)	(-0.71)
Lead 6	0.906***	-0.163*	0.00515	-0.700*	-0.334
	(5.78)	(-1.84)	(0.06)	(-1.65)	(-1.32)
Month and year dummies	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes
N	695517	687449	680306	722911	723946
R2	0.0587	0.0567	0.0562	0.0551	0.0548
Share with signal	.03	.06	.07	0	0

Obs: ***1% **5% *10% significance levels. Linear regression of crackdown (binary) periods relative to the earliest signal in a cell-year. Only cells with positive deforestation were used for estimation, since only they can

T3. Importance of acting quickly

Table 8: Characteristics of fines

	(1) Seized	(2) Seized	(3) Seized	(4) Area	(5) Area	(6) 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.

T4. General deterrence

Table 9: General deterrence effect

	$log(d_{it})$				$\mathbb{P}(d_{it} > 0)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	2SLS	First	Reduced	OLS	2SLS	First	Reduced
Fine	0.722***	-1.915**			0.207***	-0.944*		
	(0.0223)	(0.925)			(0.00607)	(0.485)		
Cloudy			-0.0363***	0.0436**			-0.0125***	0.0238***
			(0.00527)	(0.0172)			(0.00326)	(0.00584)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Semester F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean outcome	1.16	1.16	0.16	1.16	0.53	0.53	0.10	0.53
N	34623	34623	34623	34623	65495	65495	65495	65495
R2	0.248	-0.315	0.0979	0.210	0.212	-0.350	0.100	0.199
F-statistic			20.78				15.06	

Obs: ***1% **5% *10% significance levels. The table shows regression results for two outcomes: log of size of deforestation (restricted to areas with positive deforestation) and probability of positive deforestation (restricted to areas that had some deforestation in 2011-2020). For each group there are four regressions. The first one is an OLS regression of the outcome on the occurrence of a fine. The second one is the 2SLS regression using clouds as an instrument. The third one is the first stage, showing the impact of clouds on the probability of a fine. The fourth one is the reduced form, showing the direct impact of cloudson the outcome. The observational level is a 15km x 15km cell-month in the Amazon forest, and only cells with a some positive level of deforestation in the period 2011-2020 were included. The outcome is measured at a yearly level, and divided by 12 to give a monthly interpretation to the regression coefficients. Standard errors are clustered at the 15km x 15km cell level. The regressions include the following controls at the cell level: federal road, state road, indigenous land, conservation unit, distances from Manaus, Cuiaba, Belem, and the closest IBAMA office, and yearly level of accumulated deforestation. The Cragg-Donaldson F-statistic for a test of instrument weakness is shown in the columns of the first stage.

T5. Share fire signal quality

Table 10

	(1)	(2)	(3)	(4)
Logging signal quality	0.158***	0.158***	0.192***	0.148***
	(11.09)	(10.21)	(12.44)	(7.96)
Indigenous land	0.0675	0.0111	-0.233	0.518
	(0.12)	(0.02)	(-0.36)	(0.61)
Conservation unit	-1.492**	-1.939***	-2.920***	-1.988*
	(-2.50)	(-3.18)	(-3.40)	(-1.82)
Priority municipality	4.376***	3.621**	2.531***	
	(2.65)	(2.06)	(3.00)	
Price ox		0.328***	0.255***	
		(12.33)	(9.53)	
Price soy		-0.120***	-0.107***	
		(-2.73)	(-2.59)	
Price coal		-2.355	-0.358	
		(-1.31)	(-0.69)	
Price wood		15.04***	15.84***	
		(2.65)	(3.53)	
Sample	All	All	All	Priority mun.
Mun. Fixed effects	Yes	Yes	No	No
Year dummies	Yes	No	No	No
Unit cell Controls	Yes	Yes	Yes	Yes
Clouds	Yes	Yes	Yes	Yes
N	34462	31036	31108	10264
R2	0.114	0.106	0.0495	0.135

Obs: ***1% **5% *10% significance levels. Linear regression of crackdown (binary) on positive deforestation (binary), logging signals and fire signals, with year interactions and controlling for several fixed and varying characteristics of the observations, as well as municipality and year fixed effects. Observational level is a 15km x 15km cell-year in the Amazon forest. Standard errors are clustered at the municipality-year level.

T6. Costs estimates

Table 11: 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 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.

A Appendix figures

By restricting the sample to areas that received a deforestation fine, it is possible to compute the share of these areas which had deforestation in the same year as the inspection, some year in the sample, or no deforestation detected by satellites. This analysis shows that over 80% of IBAMA inspections occur in the same year of deforestation, with a tiny minority occurring in areas where no deforestation has been detected by satellites. These may be areas in which deforestation was not completed, and there was still some forest left, such that the area was not declared as "deforested" by satellite systems. This finding provides strong evidence that IBAMA's activity is focused on deterring current crime, as opposed to punishing past offenses.

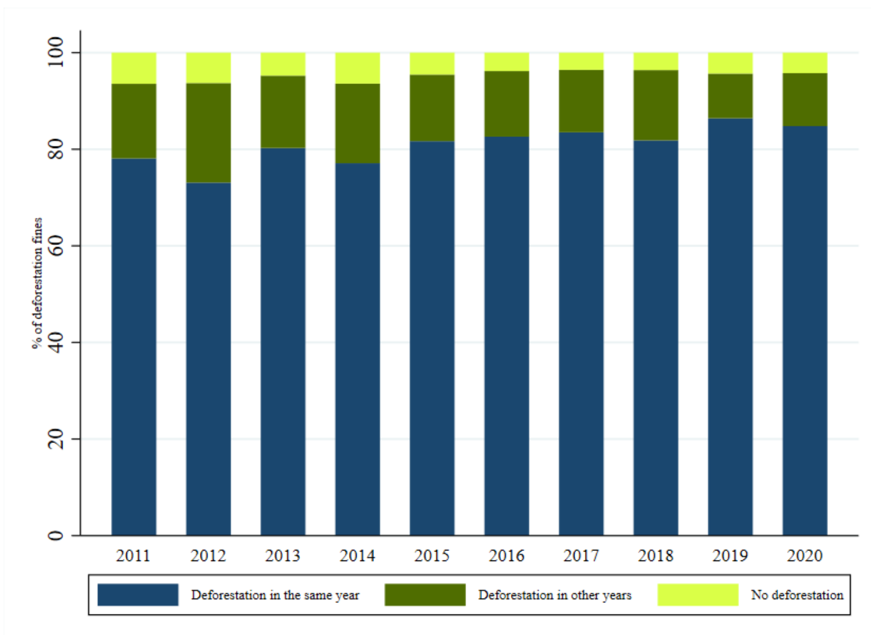


Figure A1: Deforestation in areas with fines