DETERring Deforestation in the Brazilian Amazon: Environmental Monitoring and Law Enforcement

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Abstract

This paper evaluates the impact of law enforcement and monitoring on deforestation. It focuses on DETER, a satellite-based system for real-time detection of deforestation, which is the key tool for targeting law enforcement activities in the Brazilian Amazon. DETER cloud coverage, which limits satellite visibility, is shown to be correlated with environmental fines. Cloud coverage is then used as a source of exogenous variation in the number of fines for the estimation of the effect of monitoring on deforestation. Deforestation observed from 2007 through 2011 was 75% smaller than it would have been in the absence of fines. More stringent monitoring had no impact on municipality-level agricultural production.

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1. Introduction

The economic aspects of law enforcement have garnered much attention since the seminal work of Becker (1968). Legislation, rules, and regulations - in large part established and enforced by the state - govern an increasingly wide range of activities, determining sanctions that differ substantially across sectors, firms, and individuals. Understanding offenders' responses to changes in law enforcement is thus crucial to addressing the legislation and regulation design problem. Documenting the effect of law enforcement on illegal behavior is not, however, an easy task (Cameron (1988), Levitt (1997, 2002), McCrary (2002), Di Tella and Schargrodsky (2004) and Draca et al. (2011)).

Additional challenges arise when focusing on law enforcement for the protection of natural resources. Nearly 20% of global greenhouse gas emissions is attributed to tropical deforestation (Stern (2008), MMA (2012)), with extensive forest clearings in Indonesia and the Brazilian Amazon accounting for most of the acceleration in global deforestation rates observed through the mid-2000s (Hansen and DeFries (2004), Hansen et al. (2008)). Concerns regarding the potential impacts of large-scale deforestation - which include, but are not limited to biodiversity loss, water quality and availability, and climate change - increasingly push for greater protection of rainforests. A wide range of environmental law enforcement instruments are currently available to states, but in-depth understanding of the efficacy of these instruments is still scan. Burgess et al. (2012) investigate how competition among bureaucrats affects deforestation in Indonesia, where environmental law enforcement occurs via a relatively decentralized institutional set-up. The authors show that, as the number of political jurisdictions increases, so does the number of bureaucrats with the potential to facilitate illegal logging in a province, as predicted by a Cournot model.

This paper studies the highly centralized environmental monitoring and law enforcement scenario of the Brazilian Amazon, the world's largest rainforest. In Brazil, which holds 60% of the Amazon Forest, the forest originally occupied over 4 million square kilometers – an area equivalent to almost half of continental Europe. Today, around 80% of the Brazilian Amazon remains covered by native vegetation. Protecting the Amazon from illegal deforestation and enforcing environmental regulation in the region is a challenge as immense as the forest itself. Yet, the pace of forest clearings appears to have lost momentum in recent years. Amazon deforestation rates escalated in the early 2000s, but after peaking at over 27,000 square kilometers in 2004, decreased sharply to about 6,500 square kilometers in 2011 (INPE (2012)). In this study, we assess the role played by stricter environmental monitoring and law enforcement to this recent Amazon deforestation slowdown.

In 2004, the Brazilian government adopted a new approach towards Amazon conservation policy, integrating actions across different government institutions and proposing novel procedures for monitoring of forest clearings. One of the key changes introduced at this time was the implementation of the Real-Time System for Detection of Deforestation (DETER). DETER is a satellite-based system that captures and processes georeferenced imagery on Amazon forest cover in 15-day intervals. These images are used to identify deforestation hot spots and issue alerts signaling areas in need of immediate attention, which then serve as basis for targeting of law enforcement activity. With the adoption of the new remote sensing system, the Brazilian environmental authority was able to better identify, more closely monitor, and more quickly act upon areas with illegal deforestation activity.

Was this change in forest conservation policy effective in containing forest clearings in the Amazon? How did it influence deforestation paths? Did it affect agricultural production? We answer these questions by quantifying the impacts of Amazon monitoring and law enforcement efforts in Brazil, using an instrumental variable approach to address the well-known law enforcement and crime endogeneity problem (Cameron (1988)). In our context, this problem can be stated as follows: because the allocation of law enforcers typically targets areas under greater risk of deforestation, the correlation between the presence of law enforcers and forest clearings is jointly determined by the deterrent effect of law enforcement and the risk-based targeting strategy. Estimation of the causal effect of monitoring and law enforcement on deforestation therefore hinges on successfully disentangling the impact of these two determinants. The literature documents different ways for isolating these effects, particularly in a context of police force and crime. Examples include Levitt (1997), who identifies the causal effect of police on crime by using electoral cycles as an instrument for police presence, and Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), and Draca et al. (2011), who explore isolated events (such as a terrorist attack) as exogenous sources of variation in police presence.

Our analysis draws on this literature, using an exogenous source of variation in the allocation of environmental authority resources and personnel to capture the impact of monitoring and law enforcement on Amazon deforestation. As the satellite used in DETER is incapable of detecting land cover patterns in areas covered by clouds, no deforestation activity is identified in these areas and, thus, no alerts are issued. Monitoring personnel therefore have a lower probability of being allocated to such areas. We exploit this characteristic of DETER to derive an empirical strategy that uses DETER cloud coverage as an instrument for the intensity of law enforcement activity. Because rainfall and temperature are correlated with cloud coverage, our estimations include data on observed local precipitation and temperature, and thereby only consider cloud coverage variation that is orthogonal to rainfall and temperature. The total number of fines applied at the municipality level serves as a proxy for local intensity of law enforcement.

Using a 2007 through 2011 panel of 526 municipalities in the Brazilian Amazon Biome, we show that the number of fines systematically varies with DETER cloud coverage, even after controlling for precipitation, temperature, other relevant observable variables, and municipality fixed effects. Through two-stage estimation we show that an increase in the number of fines applied in a given year significantly reduces forest clearings the following year.

The effects are not only statistically significant, but quantitatively relevant. In a counterfactual exercise, we estimate that, after the adoption of DETER-based monitoring, increased intensity of law enforcement helped avoid approximately 62,000 square kilometers of Amazon forest clearings from 2007 through 2011. Compared to deforestation actually observed during this period, which totaled 41,500 square kilometers, our estimates indicate that recorded deforestation was 60% smaller than it would have been in the absence of the policy change. In an analogous exercise, we estimate that, in a hypothetical scenario in which law enforcement was entirely absent from the Amazon (as captured by the complete absence of environmental fines), an additional 129,000 square kilometers of Amazon forest would have been cleared from 2007 through 2011. In this case, observed deforestation was 75% smaller than total estimated deforestation for the period.

These results indicate that monitoring and law enforcement activities have a substantial deterrent effect on deforestation activity. Moreover, they highlight the crucial role played by the real-time monitoring and law enforcement system. Given Brazil's institutional setup, the environmental authority has greater capacity to apply severe penalties for illegal deforestation when it catches deforesters red-handed. This is particularly relevant for some of the legal sanctioning instruments available to the authorities – namely the establishment of embargoes and seizure of production goods, tools, and material – whose applicability depends on law enforcers being able to identify the responsible party and having access to seizable items. Although Brazilian environmental legislation allows for punishment of past deforestation, once an area has been cleared, it becomes a small part of the enormous contingent of illegally cleared land in Brazil. Effective punishment of illegal deforestation in such areas, where land and production property rights are unclear, has proven to be far more limited. The adoption of DETER-based monitoring and targeting of law enforcement significantly increased the government's capacity to identify and reach deforestation activity as it happens, thereby also increasing its ability to punish illegal deforestation.

We also perform a back-of-the-envelope cost-benefit analysis, comparing a conservative estimate (upward biased) of the annual cost of Amazon monitoring and law enforcement with the estimated annual monetary benefits of preserving the forest and thereby avoiding carbon dioxide emissions. We find that the break-even price of carbon in this conservative scenario is 0.76 USD/tCO_2.[1,2] Compared to the price of 5.00 USD/tCO_2 commonly used in current applications, these figures suggest that the presence of an active monitoring and law enforcement authority in the Amazon has the potential to yield significant net gains.

To address another cost dimension of stricter monitoring and law enforcement, we investigate potential adverse effects on municipality-level agricultural production. Our estimates suggest that the more stringent monitoring and law enforcement efforts had no significant impact on local agricultural GDP. Combined, our results show that DETER-based monitoring and law enforcement played a crucial role in curbing Amazon deforestation, and thereby containing carbon dioxide emissions, without adversely affecting municipality-level agricultural production.

This paper speaks to four different strands of literature. First, our results contribute to the literature on the deterrent effects of law enforcement. This literature often explore circumstances that are very context-specific for making the appropriate causal inference, forcing authors to resort to additional assumptions for the extrapolation of their results. Di Tella and Schargrodsky (2004) use the increase in police determined by the terrorist attack on the main Jewish center in Buenos Aires to estimate the impact of police on crime. Klick and Tabarrok (2005) also assess the crime-police relationship, using terror alert levels in Washington, DC. In both studies, inference is indirect, since the authors do not use data on the intensity of enforcement activity. Draca et al. (2011), on the other hand, use detailed data on police deployment and explore increased security presence following the 2005 London terrorist attack. Although Draca et al. (2011) consider a less restricted context in comparison to Di Tella and Schargrodsky (2004), their results are still associated to terror attacks. By contrast, our strategy allows us to identify a causal effect of environmental authority presence on illegal behavior within a broader empirical context. Our strategy uses information for the entire Amazon, ensuring that our estimates are computed based on data for all areas where the problem is actually relevant. In this sense, our identification strategy is closer to the one suggested in Levitt (1997). However, as pointed out by McCrary (2002), results in Levitt (1997) are not statistically significant at standard levels of significance.

Second, this study is also related to the environmental monitoring and law enforcement literature. Most studies in this literature refer to plant-level environmental performance, as captured by standard emissions or accidental discharges (Epple and Visscher (1984), Magat and Viscusi (1990), Anderson and Talley (1995), Eckert (2004), Gray and

[1]Estimations are based on a conversion factor of 10,000 tC/km^2 (36,700 tCO_2/km^2), as established in DPCD/MMA (2011).

[2]This exercise uses the avoided deforestation results from the simulation in which law enforcement is entirely absent from the Amazon region to account for the deterrent effect of monitoring and law enforcement as a whole, and not only that of the policy change.

Shadbegian (2005), Shimshack and Ward (2005), Earnhart and Segerson (2012)).[3] Our paper addresses a different dimension of environmental monitoring and law enforcement, focusing on the impact on deforestation.

Third, there is a substantial stream of literature documenting the impact of long-run socioeconomic drivers of deforestation activity in the Brazilian Amazon, including population, road density, and agroclimatic characteristics (Reis and Margulis (1991), Reis and Guzmán (1994), Pfaff (1999), Chomitz and Thomas (2003)). However, there is still scarce empirical evidence on the immediate drivers of the sharp decrease in Amazon deforestation observed starting in the mid-2000s. Hargrave and Kis-Katos (2010) find a negative relationship between fine intensity and deforestation in the Amazon, but do not adequately address endogeneity issues in their work. Assunção et al. (2012) estimate that, even when controlling for commodity prices and relevant fixed effects, conservation policies introduced in the second half of the 2000s helped avoid over 60,000 square kilometers of forest clearings in the Amazon. This paper complements their findings by identifying that the adoption of the satellite-based monitoring system was particularly effective in curbing Amazon deforestation, as compared to other recent conservation efforts adopted in Brazil.

Finally, other studies have explored the relationship between income and forest preservation, but no consensus has been established in the literature. Cropper and Griffiths (1994) and Panayotou (1995) find no significant relationship between the two, while Antle and Heidebrink (1995) document a positive relationship between afforestation and income, but only for income levels above a certain threshold. Foster and Rosenzweig (2003) provide evidence of there being no relationship between forest cover and economic growth in open economies, but a positive relationship in closed ones. From a general perspective, our results contribute to the debate about the relationship between economic growth and the environment (Grossman and Krueger (1995), Arrow et al. (1996)).

The remainder of this paper is organized as follows. Section 2 describes the institutional context, as well as Amazon monitoring and law enforcement policies implemented within the PPCDAm framework. Section 3 details the empirical strategy used to identify the causal effect of police presence on deforestation. Section 4 introduces the data and descriptive statistics. Section 5 discusses results for the impact of DETER cloud coverage on the number of fines, the effect of the number of fines on deforestation, and the potential relationship between conservation policies and agricultural production. It also presents some robustness checks. Section 6 concludes with final remarks.

[3] Gray and Shimshack (2011) provides a recent survey of this literature.

2. Institutional Context

Since its creation in February 1989, the Brazilian Institute for the Environment and Renewable Natural Resources (Ibama) has been responsible for environmental monitoring and law enforcement in Brazil. It both operates as an environmental police force, investigating environmental infractions and applying administrative sanctions, and executes environmental policy actions concerning environmental licensing, quality control, and impact, as well as the generation and spread of environmental information. As the country's leading figure in environmental monitoring, Ibama plays a central role in the control and prevention of Amazon deforestation.

The strengthening of command and control has been a key policy effort of the Brazilian Ministry of the Environment (MMA) since the mid-2000s. Launched in 2004, the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) marked the beginning of a novel approach towards combating deforestation in the Brazilian Amazon. It integrated actions across different government institutions and proposed innovative procedures for monitoring, environmental control, and territorial management. Changes to command and control constituted an important part of the PPCDAm's tactical-operational strategy. One such change was the major leap forward in remote sensing-based Amazon monitoring capacity brought about by the implementation of DETER. Figure 1 shows how deforestation is captured by DETER in satellite imagery. The system, capable of detecting deforested areas larger than 25 hectares, portrays forested and deforested areas in different colors, such that, for any given location, recent images are compared with older ones to identify changes in forest cover. The imagery is prepared and distributed in the form of georeferenced digital maps, which are then used to locate deforestation hot spots and issue alerts signaling areas in need of immediate attention.

[Figure 1 about here.]

Since its implementation in 2004, DETER has been heavily used to target law enforcement activities in the Amazon. Prior to the activation of the real-time remote sensing system, Amazon monitoring depended on voluntary and anonymous reports of threatened areas. This made it very difficult for Ibama to identify and access deforestation hot spots in a timely manner. Yet, with the adoption of DETER, Ibama was given speedier access to recent georeferenced data, and was thus able to better identify and more quickly act upon areas with illegal deforestation activity.

The PPCDAm also promoted institutional changes that enhanced command and control capabilities in the Amazon. Ibama sought to improve the qualification of its personnel through the establishment of stricter requirements in its recruitment process. This led to an increase in both the number and quality of monitoring personnel. Additionally, Ibama's law enforcement efforts gained greater legal support with the passing of Presidential Decree 6,514 in July 2008, which reestablished directives for the investigation of environmental infractions and application of sanctions. The decree determined the administrative processes for sanctioning environmental crimes in more detail than had been previously incorporated in legislation, which increased both the clarity and speed of such processes. It also regulated the use of both old and new instruments for the punishment of environmental fines, including fines, embargoes, seizure and destruction of production goods, tools and material, and arrest, among others. Last, but not least, the decree established the public release of a list identifying landowners of areas under embargo. These measures not only increased the robustness of sanctions and the safety of law enforcement agents, but also brought greater regulatory stability to the administrative processes for the investigation and punishment of environmental crimes.

Another relevant command and control effort of the late 2000s was the signing of Presidential Decree 6,321 in December 2007, which established the legal basis for singling out municipalities with intense deforestation activity and taking differentiated action towards them. These municipalities, selected based on their deforestation history, were classified as in need of priority action to prevent, monitor, and combat illegal deforestation. Exiting the list of priority municipalities was conditioned upon significantly reducing deforestation. In addition to concentrating a large share of Ibama's attention and monitoring efforts, priority municipalities became subject to a series of other administrative measures that did not necessarily stem from command and control policy. Examples include, but are not limited to, harsher licensing and georeferencing requirements, revision of private land titles, compromised political reputation for mayors of priority municipalities, and economic sanctions applied by agents of the commodity industry. Consequently, the impact of being added to the list of priority municipalities could be broader than that of increased monitoring and law enforcement. Our empirical analysis takes this potentially broader impact into consideration.

Overall, the policy efforts adopted starting in the mid-2000s improved, intensified, and more accurately targeted command and control efforts in the Brazilian Amazon. This paper aims at measuring the impact of the more stringent DETER-based monitoring and law enforcement policy on deforestation. To do this, we must isolate the effect of other relevant potential drivers of the deforestation slowdown, particularly that of the priority municipalities policy, which involved sanctions unrelated to command and control.

3. Empirical Strategy

This section describes the empirical strategy used to identify the causal effect of Ibama's presence on Amazon deforestation. As we only observe an equilibrium situation – the number and value of fines applied by Ibama once the environmental crime has already been committed – we face a serious problem of simultaneity in addition to the usual empirical problems of omitted variables. We follow the literature on the effect of police presence on crime in aiming to address endogeneity.

The majority of studies concerning the environment and law enforcement attempt to solve the endogeneity problem by estimating the impact of the lagged enforcement variable on current environmental outcome (Magat and Viscusi (1990), Shimshack and Ward (2005), Shimshack and Ward (2008)). In our case, this means capturing the effect of the number of environmental fines applied by Ibama in year $t-1$ on deforestation recorded in year t. For literature comparison purposes, we test this type of specification in our empirical investigation. However, we do not consider this method to be a satisfactory solution to the endogeneity problem, because it is not robust for a potential persistence of deforestation activity.

We propose a new strategy to tackle endogeneity. As explained in Section 2, Ibama allocates its monitoring personnel based on alerts issued by DETER. Due to DETER's inability to detect land cover patterns beneath clouds, law enforcers have a lower chance of being allocated to areas that are covered by clouds during remote sensing, even if deforestation activity is occurring in these areas. We therefore argue that average annual DETER cloud coverage at the municipality level is a source of exogenous variation in the presence of law enforcement personnel in Amazon municipalities. Thus, we use DETER cloud coverage as an instrument for Ibama presence, as proxied by the number of environmental fines applied in each municipality by the Brazilian environmental police authority.

Is this a valid instrument? If so, it must be uncorrelated with the error term in the deforestation equation, conditional on all observable variables. There are two relevant scenarios in which this condition would be violated in our empirical setup: (i) if there is correlation between cloud coverage and other geographical characteristics, which, in turn, may be correlated with deforestation; and (ii) if there is correlation between DETER cloud coverage and cloud coverage affecting the satellite used to measure annual Amazon deforestation. The availability of relevant observable variables and the use of fixed effects help make the case for our instrument's validity.

We address the first scenario by using rainfall and temperature data compiled by Matsuura and Willmott (2012) to control for precipitation and temperature at the municipality level in all our specifications. There is still the concern about the relationship between cloud coverage and soil types which, for instance, could affect production outcomes and thereby deforestation. However, soil types change very slowly with time and our time window is very small (2007-2011)[CITAR A EMBRAPA AQUI]. Therefore, we control for fixed effects, which completely solve the problem about the relationship between cloud coverage and soil type.

The second scenario merits a more detailed discussion. Annual Amazon deforestation is recorded by INPE's Project for Monitoring Deforestation in the Legal Amazon (PRODES) based on interpretation of satellite imagery. Much like the satellite used in DETER, the one used in PRODES suffers from an inability to detect forest clearings beneath cloud coverage. Potential correlation between DETER cloud coverage and PRODES cloud coverage therefore raises an important concern. We use two complementary approaches to tackle this issue. First, we control for PRODES cloud coverage, such that our coefficients are estimated considering only DETER cloud coverage that is orthogonal to PRODES cloud coverage. Second, we explore the fact that PRODES collects imagery between the 1st of June and the 29th of August of a given year, while DETER collects imagery every 15 days. We conduct a robustness check by replacing our original instrument with a measure of average DETER cloud coverage that excludes data from the PRODES period of remote sensing. Specifications using this alternative instrument also include PRODES cloud coverage as a control.

Having controlled for precipitation, temperature, PRODES cloud coverage, and fixed effects, we argue that the only remaining channel through which DETER cloud coverage could be correlated with deforestation is that of the allocation of Ibama law enforcement resources.

Our strategy also considers other potential causes of concern. First, because deforestation has been shown to be strongly correlated with agricultural commodity prices, we control for relevant crop and cattle prices. We follow Assunção et al. (2012) and include prices for both the previous year and the first semester of each current year. Second, we control for priority municipalities and protected areas to account for other relevant conservation policies that were introduced during our period of interest. As the way these environmental policies are allocated is endogenous, we control for them only in a robustness check exercise. Finally, there are important municipality and time fixed effects that could influence both deforestation and monitoring and law enforcement. We take advantage of the panel structure of our data to control for these fixed effects.

In our first stage, the estimation equation is given by:

$$Fines_{it} = \beta_1 DETERclouds_{it} + \sum_k \beta_k X_{itk} + \alpha_i + \phi_t + \epsilon_{it} \tag{1}$$

where $Fines_{it}$ is the number of environmental fines applied by Ibama in municipality i and year t; $DETERclouds_{it}$ is average annual DETER cloud coverage for municipality i and year t; X_{it} is a vector of controls including rain, temperature, PRODES cloud coverage, agricultural commodity prices, and other conservation policies; α_i is the municipality fixed effect; ϕ_t is the year fixed effect; and ϵ_{it} is the idiosyncratic error.

In our second stage, we include the lagged number of fines and, thus, lagged values for DETER cloud coverage. As we intend to capture DETER cloud coverage that is correlated with the allocation of law enforcers, but uncorrelated with deforestation through all other channels, we must also control for lagged precipitation. No lags are included for the other variables. Hence, the estimation equation is given by:

$$Deforestation_{it} = \gamma_1 Fines_{i,t-1} + \sum_k \gamma_k X_{itk} + \quad + \psi_i + \lambda_t + \xi_{it} \tag{2}$$

where $Deforestation_{it}$ is the normalized deforestation increment in municipality i and year t; $Fines_{i,t-1}$ is instrumented by $DETERclouds_{i,t-1}$; ψ_i is the municipality fixed effect; λ_t is the year fixed effect; and ξ_{it} is the idiosyncratic error. X_{it} are as in equation 1, but now lagged precipitation and temperature is used to put them in the same window of fines and cloud coverage.

Standard errors in all specifications are clustered at the municipality level, making them robust to heteroscedasticity and serial correlation (Bertrand et al. (2004)).

4. Data

Our empirical analysis is based on a 2007 through 2011 municipality-by-year panel data set.[4] The initial sample includes all 553 municipalities located partially or entirely within the Amazon Biome. Lack of data for 6 municipalities imposes a first sample restriction. As variation in forest cover is required for the normalization of our main dependent variable (normalized annual deforestation increment – see detailed description of variable construction below) and also because we are using municipality fixed effects, the sample is further restricted to municipalities that portray such variation [5]. The final sample comprises 526 municipalities.

The following sections describe our variables of interest and present some descriptive statistics.

4.1. Deforestation

We define deforestation as the annual deforestation increment – the area of forest cleared over the twelve months leading up to August of a given year. Thus, the annual deforestation increment of year t measures the area of forest, in square kilometers, deforested between the 1st of August of $t-1$ and the 31st of July of t. Deforestation data are built from satellite-based images that are processed and publicly released by

[4] As discussed in Section 3, our strategy uses lagged DETER cloud coverage as an instrument for the lagged number of environmental fines. Because DETER cloud coverage data is only available starting in 2006, our sample must begin in 2007.

[5] All municipalities without deforestation variation have zero deforestation for all years. They are also municipalities where the forest cover is very small, four square kilometers in average

PRODES/INPE. The annual data capture total forest area cleared at the municipality level in a twelve-month period.

Sample municipalities exhibit a significant amount of cross-sectional variation in deforestation due to heterogeneity in municipality size. We therefore use a normalized measure of the annual deforestation increment to ensure that our analysis considers relative variations in deforestation increments within municipalities. The variable is constructed according to the following expression:

$$Deforestation_{it} = \frac{ADI_{it} - \overline{ADI}_{it}}{sd\left(ADI_{it}\right)} \tag{3}$$

where $Deforestation_{it}$ is the normalized annual deforestation increment for municipality i and year t; ADI_{it} is the annual deforestation increment measured in municipality i between the 1^{st} of August of $t-1$ and the 31^{st} of July of t; and $\overline{ADI}_{it}$ and $sd\left(ADI_{it}\right)$ are, respectively, the mean and the standard deviation of the annual deforestation increment calculated for each i over the 2002 through 2011 period.[6] We use the log of ADI_{it} as dependent variable in alternative specifications to test whether results are driven by our choice of normalization technique.

For any given municipality, cloud coverage during the period of remote sensing may prevent the PRODES satellite from capturing land cover imagery. Forest areas that were cleared in a given year, but were blocked from view by clouds during remote sensing, are not incorporated into that year's deforestation increment figure. These areas are only accounted for when they eventually show up on PRODES imagery. Variables indicating PRODES cloud coverage and unobservable areas, both of which are made publicly available by PRODES/INPE, are included in all regressions to control for measurement error.

4.2. Law Enforcement

We use the total number of fines applied as sanctions for environmental crimes in each municipality as a measure of the intensity of monitoring and law enforcement at the municipality level. The data are publicly available from Ibama.

It is worth highlighting that the knowingly low collection rates for environmental fines applied in Amazon municipalities do not interfere with our analysis (Hirakuri (2003), Brito and Barreto (2008), Barreto et al. (2008), Brito (2009)). These fines are often accompanied by other sanctioning instruments that are more binding, such as seizure and destruction of production goods, tools and materials, and embargoes of production

[6] We take advantage of available municipality-level deforestation data for non-sample years to calculate the mean and the standard deviation of the annual deforestation increment in a longer panel. For comparison, we also estimate all specifications using the mean and standard deviation over the 2007 through 2011 period for the normalization of our dependent variable.

areas. Because panel data for the use of these instruments are not available, we use the number of fines as a proxy for command and control efforts as a whole. Essentially, we are interested in exploring fines as a means of capturing the effect of environmental police (Ibama) presence – not of the sanctioning instrument itself – on deforestation.

To maintain consistency across our panel data, we consider the PRODES year – August 1$^{\text{st}}$, $t-1$ through July 31$^{\text{st}}$, t – as the relevant unit of time in our sample. Thus, for each municipality, the total number of fines in a given year captures all fines applied in that municipality in the twelve months leading up to August of that year.

4.3. Cloud Coverage

As explained in Section 2, georeferenced data on deforestation activity produced by DETER are used to identify deforestation hot spots and issue alerts that serve to target law enforcement activity. Figure 2 shows examples of maps containing both cloud coverage and alerts captured by DETER. In addition to portraying the high degree of within-year variation in DETER cloud coverage, the figure also clearly illustrates DETER's inability to detect land cover pattern in areas covered by clouds – typically, no deforestation activity is captured and no deforestation alerts are issued in these areas. This supports our perception that the allocation of Ibama personnel is directly affected by DETER cloud coverage, such that law enforcers are less likely to be present in areas that are systematically under greater cloud coverage.

[Figure 2 about here.]

We are interested in exploring how DETER cloud coverage affects Ibama presence in the Amazon. To do this, we use georeferenced data from DETER/INPE that map cloud coverage over the Amazon throughout the year. When visibility is at least partial, these maps show exactly which areas were covered by clouds (see Figure 2). When visibility is too precarious to derive information about land cover, however, no map is produced – we assume DETER cloud coverage to be complete in this case. We use the 15-day periodical data to calculate, for each sample municipality and year, average DETER cloud coverage for that municipality and year both in absolute (square kilometers) and relative (share of total municipality area) terms. Again, the relevant unit of time is the PRODES year. We use this constructed variable as an instrument for the intensity of law enforcement activity in each Amazon municipality.

We note that although DETER was implemented in 2004, the first georeferenced DETER maps to be made publicly available refer to 2006. This implies our sample must start in 2007.

4.4. Additional Controls

We include a series of variables to control for other potentially relevant determinants of deforestation, namely rainfall, temperature, agricultural commodity prices, and other conservation policies.

First, there is no consensus in the literature as to how deforestation and precipitation are related. On the one hand, forest clearings are often concentrated in dry seasons, when it is easier to penetrate and burn the forest. On the other hand, the cutting down of forests may itself affect the region's microclimate and precipitation patterns (Negri et al. (2004), Aragão et al. (2008), Saad et al. (2010)). Although understanding this relationship in detail is out of the scope of this paper, we include a measure of total precipitation in each sample municipality to account for the effect of rainfall on forest clearing activities. We do so by using annual precipitation data compiled by Matsuura and Willmott (2012), who draw on worldwide climate data to calculate a regular georeferenced world grid of estimated precipitation over land. Their estimations are based on a variety of sources for geographic extrapolations of rainfall data collected at weather stations. Using this georeferenced grid, we estimate total precipitation in each municipality according to the following rule: (i) for municipalities that overlap with only one grid node, we use the precipitation value for that grid node as municipality precipitation; (ii) for municipalities that overlap with two or more grid nodes, we consider all node values and use their average precipitation as municipality precipitation; (iii) for municipalities that have no overlap with any grid nodes, we take the area of a 28-kilometer buffer around the municipality and consider the average precipitation of all grid nodes that fall within this buffer area as municipality precipitation; and (iv) for the few municipalities whose 28-kilometer buffer do not overlap with any grid nodes, we use the precipitation value for the nearest grid node as municipality precipitation.[7]

Data on temperature is also compiled by Matsuura and Willmott (2012) and is constructed in the same way as the rainfall data.

For the third set of controls, we consider agricultural commodity prices, which have been shown to be drivers of deforestation (Panayotou and Sungsuwan (1994), Barbier and Burgess (1996), Angelsen and Kaimowitz (1999), Assunção et al. (2012)). As agricultural prices are endogenous to local agricultural production and, thus, local deforestation activity, we must construct output price series that capture exogenous variations in the demand for agricultural commodities produced locally. As argued in Assunção et al. (2012), agricultural commodity prices recorded in the southern Brazilian state of Paraná are highly correlated with average local crop prices for Amazon municipalities. We follow the authors and collect commodity price series at the Agriculture and Supply Secretariat

[7] Buffer size was chosen based on the size of grid nodes – 28 kilometers is equivalent to half the distance between grid nodes.

of the State of Paraná (SEAB-PR). The set of commodities includes beef cattle, soybean, cassava, rice, corn, and sugarcane.[8]

The Paraná price series are used to build two price variables. The first, an annual index of crop prices, is constructed in three steps. In step one, we calculate nominal annual prices by averaging nominal monthly prices for each calendar year and culture. Annual prices are deflated to year 2000 Brazilian reais and are expressed as an index with base year 2000.

In step two, we calculate a weighted real price for each crop according to the following expression:

$$PPA_{itc} = PP_{tc} * A_{ic,2004-2005} \tag{4}$$

where PPA_{itc} is the weighted real price of crop c in municipality i and year t; PP_{tc} is the Paraná-based real price of crop c in year t; and $A_{ic,2004-2005}$ is the share of municipal area used as farmland for crop c in municipality i averaged over the 2004 through 2005 period.[9] The latter term captures the relative importance of crop c within municipality i's agricultural production in years immediately preceding the PPCDAm. It serves as a municipality-specific weight that introduces cross-sectional variation in the commodity price series.

In the third and final step, we use principal component analysis on the weighted real crop prices to derive the annual index of crop prices. This technique allows price variations that are common to the five selected crops to be represented in a single measure. As the resulting index maximizes the price variance, it represents a more comprehensive measure of the agricultural output price scenario for this analysis than the individual prices themselves.

The second price variable is an annual index of cattle prices, which is derived analogously to PPA_{itc}. As land pasture is not observable, $A_{ci,2004-2005}$ is the ratio of heads of cattle to municipal area in municipality i averaged over the 2004 through 2005 period. Although most of our variables are constructed to fit the PRODES year time frame, agricultural price series are expressed in calendar years.

Finally, we include controls for other relevant conservation policies implemented during the sample period. In particular, we account for total protected area in each municipality, including both conservation units and indigenous lands, and priority municipalities. As discussed in Section 2, priority municipalities were subject not only to stricter command and control, but also to other administrative measures with a poten-

[8]Soybean, cassava, rice, and corn are predominant crops in terms of harvested area in the Legal Amazon. Although not a predominant crop in the region, sugarcane is also included to account for concerns about the recent expansion of Brazilian ethanol biofuel production. Together, the five crops account for approximately 70% of total harvested area averaged across the 2000s.

[9]Variables on annual harvested area at the municipality level are constructed based on data from the Municipal Crop Survey of the Brazilian Institute for Geography and Statistics (PAM/IBGE).

tially deterrent effect on deforestation. By including controls for these municipalities in our estimations, we ensure that the effect of changes in Ibama presence (captured via changes in the number of fines) is isolated from the effect of the other administrative measures adopted in priority municipalities.

4.5. Trends and Descriptive Statistics

Stringency of law enforcement in the Amazon, as captured by the number of environmental fines, was on the rise since the early 2000s. Figure 3, which shows trends for the municipality-level average number of fines and deforestation from 2002 through 2011, illustrates this. While the average annual number of fines by municipality grew nearly sevenfold from 2002 through 2008, average annual deforested area declined by almost half in the same period. In the following years, the number of fines decreased alongside deforestation. Yet, the endogeneity problem discussed in Section 3 also affects the trends shown in Figure 3 – less deforestation implied less need for fines.

[Figure 3 about here.]

Table 1 presents the means and standard deviations for the variables used in our empirical analysis. The figures show that average DETER cloud coverage is high. Agricultural prices and production were rising during the period of interest, which could have pushed for greater deforestation via incentives to convert forest areas for agricultural activity. The extent of protected areas during the period show only minor variation from year to year.

[Table 1 about here.]

5. Results

This section presents results for first and second stage estimations, counterfactual exercises, and robustness checks.

5.1. Cloud Coverage, Monitoring, and Law Enforcement

We start by assessing the impact of average annual DETER cloud coverage on the presence of law enforcers at the municipality level, using the number of fines applied in each municipality as a proxy for Ibama presence in that municipality. Coefficients presented in Table 2 indicate that an increase in DETER cloud coverage significantly reduces the number of fines applied by Ibama as punishment for environmental infractions. Column 1 presents OLS coefficients estimated in a specification lacking controls. Columns 2 through 4 show coefficients estimated in specifications with the following controls: rainfall, temperature, PRODES cloud coverage, and non-observable areas during period of PRODES remote sensing (column 2); municipality and time fixed effects (column 3); current and lagged cattle prices, and current and lagged crop prices (column 4); priority municipality status, and percentage of municipality area occupied by protected areas (column 5). Coefficients remain negative and significant at a 5% significance level in all specifications. Quantitatively, taking tcolumn (4) as our main specification, a 10 percentage point increase in DETER cloud coverage, which represents an increase of 17% in DETER cloud coverage, implies an average reduction of 1.17 in fines, which is equivalent to a 13.5% decrease in the total number of fines for our period of interest. Results suggest that DETER cloud coverage is strongly correlated with the number of fines applied by Ibama. This finding validates the first stage of our empirical strategy and indicates that our instrument is not weak.

[Table 2 about here.]

5.2. Monitoring, Law Enforcement, and Deforestation

Having shown that DETER cloud coverage and Ibama presence in Amazon municipalities are correlated, we move on to evaluate the impact of law enforcement efforts on deforestation. Coefficients shown in Table 3 capture the effect of the number of fines applied by Ibama on deforestation at the municipality level. Columns 1 presents results for fixed effects regressions estimated by OLS using normalized deforestation as dependent variable. Column 2 repeats the specification of previous column using 2SLS estimation with lagged DETER cloud coverage as an instrument for the lagged number of fines. Column 3 repeats Column's 2 specification and estimation technique using the log of deforestation increment as an alternative dependent variable.

Results for OLS estimation suggest that, for a given year, the total number of fines in a municipality does not significantly affect deforestation the following year. Coefficients estimated using instrumental variable specifications, however, show that OLS results are biased. The use of the lagged law enforcement variable in OLS specifications did not adequately solve the endogeneity problem that affects the estimation of the causal impact of police presence on crime. By contrast, 2SLS results indicate that, when instrumented by average annual DETER cloud coverage, a greater number of fines in a given year will significantly reduce deforestation the following year. This is evidence that more stringent monitoring and law enforcement effectively curb deforestation. These results are consistent with specifications that use the log of the deforestation increment as an alternative dependent variable, indicating that our main results are not driven by our choice of normalization.[10]

[10]The normalization in Column 2 is done using deforestation data from 2002 to 2011. Coefficients estimated using deforestation datar over the 2007 through 2011 period are consistent with those shown. These alternative results are not reported in this paper, but are available from the authors upon request.

[Table 3 about here.]

To better understand the magnitude of this effect, we conduct two counterfactual simulations to estimate total sample deforestation in hypothetical scenarios that differ from the observed reality. In the first simulation, we assume that the annual number of fines in each municipality from 2007 through 2011 was equal to that observed in 2003, the year immediately preceding the launch of the PPCDAm. In doing so, we recreate a scenario in which monitoring and law enforcement policy stringency remained unchanged after the implementation of the PPCDAm. We then estimate the annual deforestation trend for this hypothetical scenario. Table 4 presents both observed and estimated annual deforestation figures. It shows that, had the number of fines remained in the 2003 levels, the Amazon Biome would have seen over 104,000 square kilometers of deforestation from 2007 through 2011. Compared to the 41,500 square kilometers of deforestation actually observed in our sample during this period, results suggest that increased number of fines promoted by more stringent command and control policies preserved over 62,000 square kilometers of forest area.

In the second simulation, we assume that no fines were applied in all municipalities from 2007 through 2011. This scenario captures the complete absence of monitoring and law enforcement in the Amazon. Table 4 again presents both observed and estimated annual deforestation figures. We estimate that, without monitoring and law enforcement activities, over 171,000 square kilometers of forest would have been cleared in the 2007 through 2011 period. Compared to observed deforestation, results indicate that such activities preserved more than 129,000 square kilometers of forest area.

[Table 4 about here.]

This is a very substantial effect in both absolute and relative terms. It shows that command and control policies were effective in curbing deforestation in the Brazilian Amazon. Unlike several other empirical exercises in the police force and crime literature, which mostly explore context-specific circumstances and require additional assumptions for the extrapolations of their results (such as Di Tella and Schargrodsky (2004) and Draca et al. (2011)), our strategy analyzes policies that were actually put into practice in the full extent of our area of interest. This allows us to identify a causal effect of environmental police presence on environmental crimes within the empirical context that is actually relevant for policy design.

Combined, our results yield important policy implications. The impressive deterrent effect of command and control policies was achieved despite the relatively restricted resources (only 3,000 Ibama law enforcement agents) available to cover an area as vast as the Amazon Biome. We also find that the total amount of avoided deforestation attributed to the command and control policy change in a five-year period is almost as large as the impact of a whole set of conservation policies (including monitoring and law enforcement efforts) introduced in the second half of the 2000s (see Assunção et al. (2012)). Although the counterfactual estimations in this study are performed in a slightly different five-year window to the one used by the authors, the sheer magnitude of the forest area that was preserved indicates that the relative impact of DETER-based monitoring and law enforcement was far greater than that of other conservation policies implemented under the PPCDAm framework. This does not in any way imply that other policies should not be used to combat deforestation. Rather, it suggests that such policies are complementary to command and control efforts, effectively deterring forest clearings at the margin, while monitoring and law enforcement contain the bulk of deforestation.

In addition, our results indicate that there is substantial value in improving remote sensing-based monitoring. Overcoming DETER's incapacity to see through clouds and obtaining land cover imagery in higher resolutions are two examples of technological advances that could improve law enforcement targeting capability and add significant value to Brazil's conservation efforts. Amazon monitoring has recently been enhanced by the incorporation of Japanese radar technology, capable of detecting land cover patterns beneath cloud coverage. Our results reinforce the need of continuing and amplifying the use of such technologies.

5.3. Cost-benefit Analysis

Our results have shown that command and control policy efforts are effective in curbing deforestation. Yet, are they a cost-effective way of protecting the Amazon? We make a first attempt at answering this question by performing a back-of-the-envelope calculation of the costs and benefits of monitoring and law enforcement in the Brazilian Amazon. In this simplified cost-benefit analysis, we compare the sum of Ibama's and INPE's annual budgets with the estimated monetary benefits of preserving forest areas and thereby avoiding carbon dioxide emissions. In this exercise, we use figures from our second counterfactual simulation to account for the deterrent effect of monitoring and law enforcement as a whole, and not only that of the policy change.

According to our simulation, command and control efforts preserved an average of 25,800 square kilometers of forest area per year between 2007 and 2011. This is equivalent to approximately 950 million tCO_2 per year.[11] Assuming that Ibama's annual budget from 2007 through 2011 was 560 million USD (value of its 2011 budget) and that INPE's annual budget in the same period was 125 million USD (value of its 2010 budget), any price of carbon set above 0.72 USD/tCO_2 would more than compensate the cost of environmental monitoring and law enforcement in the Amazon. Compared to the price of

[11] Estimations are based on a conversion factor of 10,000 tC/km^2 (36,700 tCO_2/km^2), as established in DPCD/MMA (2011)

5.00 USD/tCO_2 commonly used in current applications, these figures suggest that the presence of an active monitoring and law enforcement authority in the Amazon has the potential to yield significant net monetary gains. Indeed, our estimates capture the lower bound of this potential gain. Considering that, in reality, only a share of Ibama's and INPE's budgets is used for Amazon monitoring and law enforcement, our cost-benefit comparison becomes even more striking.

5.4. Timing

In addition to showing that command and control policy curbs deforestation, we are interested in investigating the timing of this effect. Table 5 reproduces the specifications of Table 3 including double and triple lags for the number of fines to test for persistence of the deterrent effect. Coefficients indicate that the impact of fines applied in $t-2$ is weaker than that of fines applied in $t-1$. The number of fines applied in $t-3$ is not significant in any of the specifications. These results suggest that the effect of Ibama's presence in a given municipality dissipates over time. They therefore reinforce the need to sustain continuous command and control efforts in the Amazon to effectively combat deforestation.

[Table 5 about here.]

5.5. Monitoring, Law Enforcement, and Agricultural Production

There is an ongoing debate about whether conservation policies negatively affect economic output. Should the preservation of natural resources occur at the expense of production, there would be a tradeoff between conservation and economic growth. Faced with a choice between the two, it is not obvious what society would hold as a priority. Yet, should it be possible to sustain economic growth while preserving natural resources, this tradeoff would cease to exist (Cropper and Griffiths (1994), Panayotou (1995), Antle and Heidebrink (1995), Grossman and Krueger (1995), Arrow et al. (1996), Foster and Rosenzweig (2003)). In this case, society could pursue these goals jointly. In particular, agricultural producers could operate at the intensive margin of production, increasing production by boosting productivity, instead of expanding production into new – often forested – areas. This productivity growth could more than compensate potential costs of conservation efforts.

Bearing this debate in mind, we investigate whether the change in monitoring and law enforcement policies had an adverse impact on local agricultural production. We use two different measures of municipality-level agricultural production: (i) agricultural GDP from Brazilian national accounts, and (ii) crop revenues from PAM/IBGE. Results presented in Table 6 indicate there is no tradeoff between conservation and agricultural production. The evidence therefore suggests that it would be possible to contain forest clearings without significantly compromising local agricultural production.

[Table 6 about here.]

Combined, our findings show that DETER-based monitoring and law enforcement played a crucial role in curbing Amazon deforestation, and thereby containing carbon dioxide emissions, at no apparent cost to local agricultural production. Subsistence agriculture may have been adversely affected by conservation efforts, but this effect cannot be perceived in municipality-level agricultural production. This suggests that it is possible to protect the native forest without significantly interfering with aggregate local agricultural production.

5.6. Robustness Checks

Although our results are generally consistent with the relevant Brazilian institutional context, we run a series of tests to check their robustness. We focus on four potential sources of concern. First, our coefficients could be capturing a spurious effect due to the correlation between PRODES cloud coverage and DETER cloud coverage. Second, our identification strategy relies on the fact that municipalities are comparable after controlling for observable characteristics and municipality and year fixed effects. However, forest cover in early sample years varies significantly across Amazon municipalities. This variation could affect deforestation trends, since the area in which forest clearings can still take place decreases with decreasing forest cover. This could potentially have driven our results. Third, deforestation increment levels in early sample years could also be determinants of municipality-level deforestation patterns. If higher municipality deforestation in the first years of the sample are indicative of areas with more intense economic growth, this baseline difference could result in different deforestation trends over time. Finally, deforestation and the number of fines could be both related to other environmental policies, although our instrumental variable technique mitigates this concern.

Specifications in Table 7 tackle these issues in four sets of robustness checks. First, in Column 1, we recalculate average DETER cloud coverage excluding the PRODES remote sensing period, as explained in Section 3.

Second, in column 2, we restrict our sample to municipalities that had over 50% of forest cover in 2003, the year immediately preceding the PPCDAm. In municipalities where comparatively less forest remains, the dynamics of deforestation may be very different from that in municipalities where forest cover is still high. We also test this in column 3, controlling for a trend determined by the initial percentage of deforested area in each municipality (an interaction between a linear trend and initial deforested area). Should our results have been driven by a natural convergence in deforestation rates between municipalities with greater and smaller deforested areas, this test would yield insignificant coefficients.

Third, in column 4, we run a similar test to that of column 3, but instead of using the initial value of deforested territory, we use the initial value of deforestation increments. The economic dynamics of municipalities with higher deforestation increments could be very different from the dynamics of those with smaller deforestation increments. Note that, in this case, we are analyzing initial annual deforested increments; in the previous case, we were assessing initial cumulated share of deforested area in each municipality. Differences in economic dynamics could imply very different trends in deforestation increments and potentially have driven our results. We therefore also control for a trend that depends on initial deforestation increments (an interaction between a linear trend and initial deforestation increment).

Finally, we run the main specification controlling for other environmental policies, namely for priority municipality status and the percentage of municipality territory covered by protected areas.

The coefficients for the number of fines in Table 7 remains negative and significant in all specifications. Overall, the robustness of our results supports the specifications chosen for our main regressions, as well as the interpretation of our findings.

[Table 7 about here.]

6. Final Comments

Climate change and biodiversity concerns have pushed tropical deforestation into occupying a position at the top of the global policy debate priority list. Understanding deforestation in the Brazilian Amazon and how to most efficiently prevent it is therefore currently a matter of first-order importance not only for Brazil, but for the global community.

This paper investigates the effects of a key command and control policy change on Amazon deforestation. We show that the strategic use of advanced satellite technology and the intensification of monitoring, alongside improvements in law enforcement activity, significantly contributed to the 2000s Amazon deforestation slowdown. We find that command and control has been particularly effective in curbing deforestation compared to other recent Amazon conservation efforts. Increased presence of police force in the Amazon accounts for the preservation of 59,500 square kilometers of forest area from 2007 through 2011.

Our results also shed light on the potentially adverse effects of conservation policies, particularly on the supposed tradeoff between economic growth and preservation of natural resources. We show that command and control policies adopted in the second half of the 2000s had no significant impact on municipality-level agricultural production. Overall, command and control appears to play a crucial role in the curbing of Amazon deforestation at no apparent cost to agricultural production.

Finally, a simple cost-benefit analysis suggests that the gains derived from reduced deforestation more than compensate monitoring and law enforcement costs. This reinforces the case for promoting preservation of the native forest via command and control efforts, and for continuing to make improvements in monitoring and law enforcement technology where possible.

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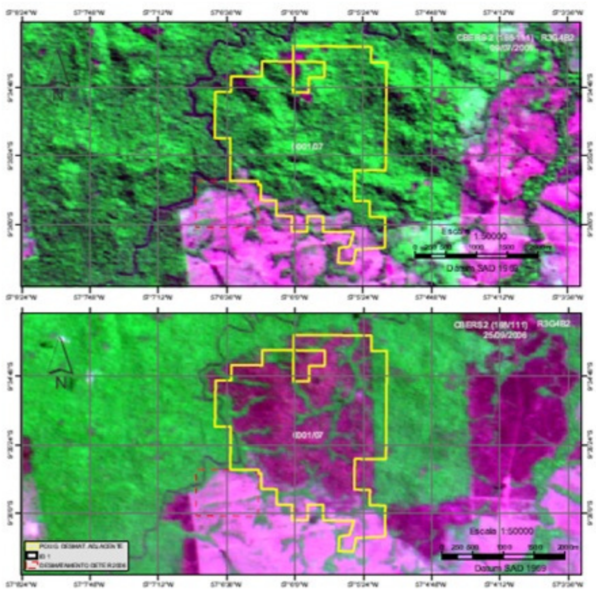
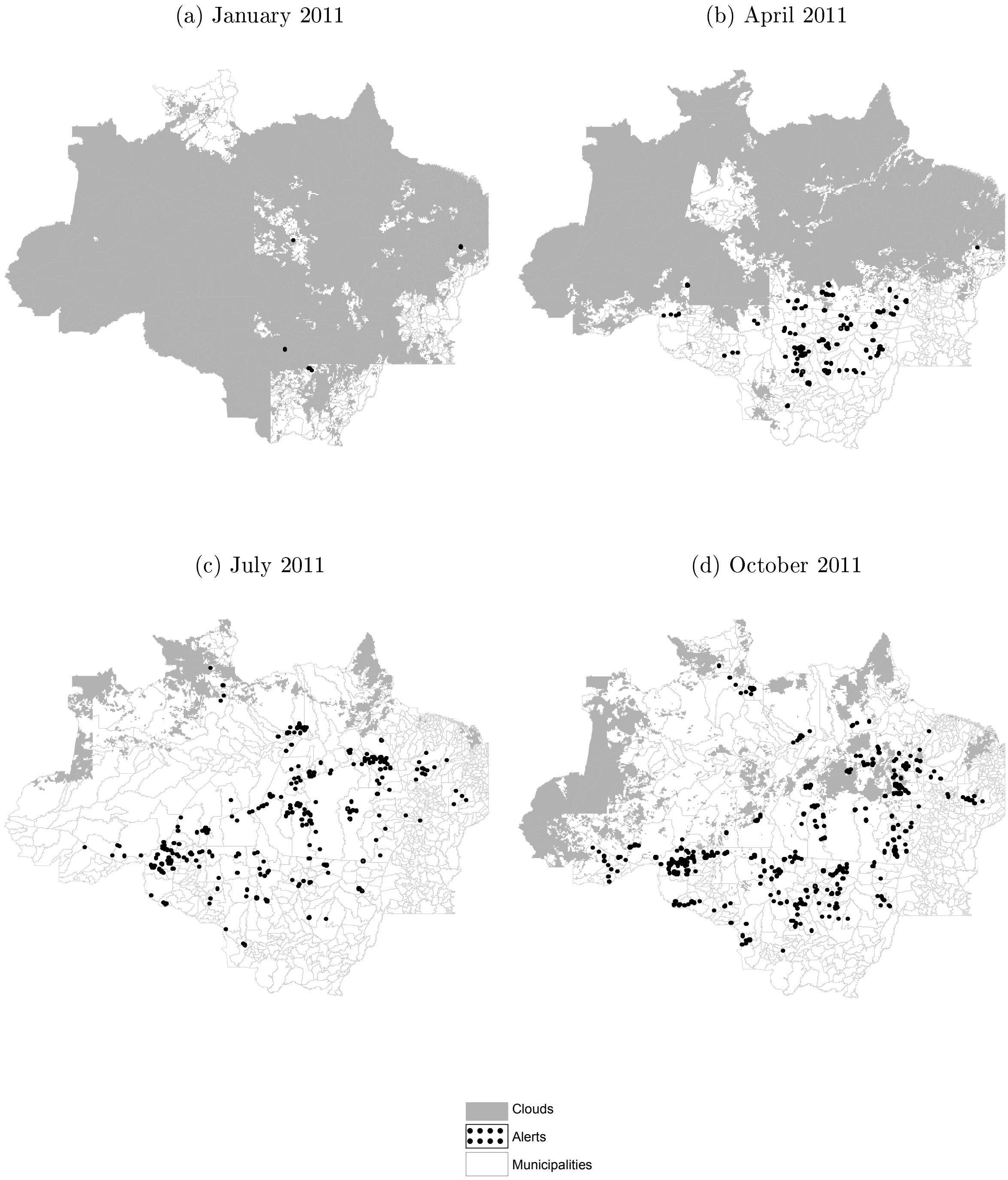
Figure 1
DETER: How is Deforestation Detected in Satellite Imagery?



Notes: Top and bottom panels show satellite images of the same location recorded at two different moments in time – the top panel is an earlier image and the bottom panel a later one. Green indicates forest areas and purple indicates deforested areas.

Source: Ibama.

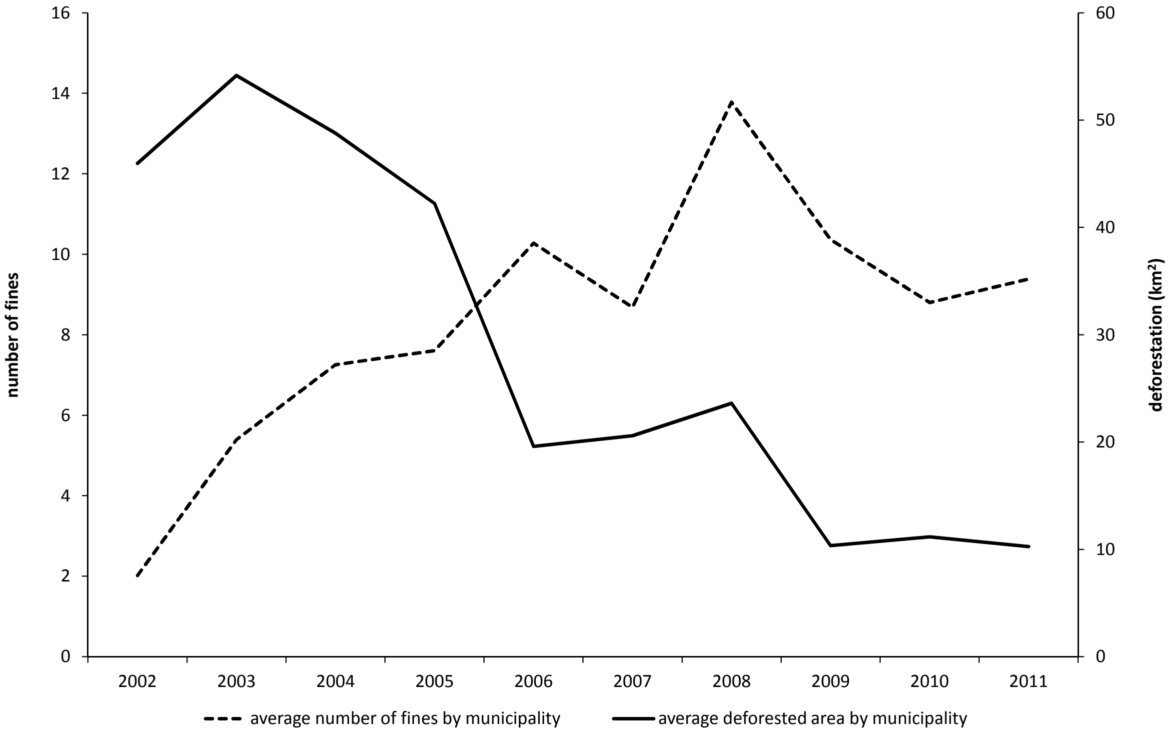
Figure 2
DETER Cloud Coverage and Deforestation Alerts



Notes: The figure illustrates the high degree of within-year variation in DETER cloud coverage and shows that, typically, no alerts are issued in areas covered by clouds.

Source: DETER/INPE.

Figure 3
Number of Environmental Fines and Deforestation in Sample Municipalities



Source: PRODES/INPE, Ibama.

Table 1
Descriptive Statistics

	(1)					
	2006	2007	2008	2009	2010	2011
Deforested Area	19.593	20.591	23.616	10.352	11.167	10.256
	(53.432)	(58.119)	(56.834)	(33.940)	(27.768)	(27.431)
GDP - Agriculture	17,537.479	19,794.515	22,939.198	21,877.435	.	.
	(19,449.504)	(27,497.535)	(34,985.537)	(30,407.689)	(.)	(.)
Crop Production	9,657.458	11,489.442	15,149.853	13,607.363	11,920.927	16,200.151
	(27,143.964)	(37,506.711)	(54,165.071)	(47,490.647)	(34,506.565)	(55,571.119)
Number of Fines	10.274	8.682	13.779	10.367	8.799	9.384
	(23.386)	(19.161)	(33.036)	(30.320)	(21.384)	(24.287)
Cloud Deter	0.381	0.708	0.604	0.677	0.611	0.538
	(0.072)	(0.172)	(0.203)	(0.216)	(0.222)	(0.199)
Rain	2,230.926	2,154.134	2,225.904	2,197.062	1,911.220	.
	(612.613)	(613.941)	(568.481)	(511.938)	(404.848)	(.)
Temperature	26.047	26.247	25.936	26.182	26.713	.
	(1.136)	(1.069)	(1.206)	(1.150)	(1.244)	(.)
Protected Areas	0.265	0.272	0.275	0.277	0.277	0.278
	(0.324)	(0.329)	(0.330)	(0.331)	(0.331)	(0.331)
Cloud Prodes	358.431	541.518	420.689	413.665	788.356	531.510
	(1,414.716)	(2,348.946)	(1,763.104)	(1,362.866)	(3,236.957)	(2,812.594)
Non-Observed Prodes	46.440	47.181	22.661	15.777	14.243	14.198
	(256.550)	(256.939)	(226.964)	(99.905)	(99.265)	(99.197)
Crop Prices 1st Semester	-0.572	-0.546	-0.520	-0.540	-0.549	-0.522
	(0.292)	(0.339)	(0.435)	(0.403)	(0.310)	(0.387)
Crop Prices in t-1	-0.551	-0.568	-0.537	-0.533	-0.543	-0.545
	(0.336)	(0.299)	(0.367)	(0.402)	(0.388)	(0.324)
Cattle Prices 1st Semester	21.164	23.536	29.237	28.335	27.735	31.821
	(24.880)	(27.668)	(34.369)	(33.310)	(32.604)	(37.408)
Cattle Prices in t-1	24.668	23.539	26.008	31.465	29.695	30.794
	(28.998)	(27.672)	(30.574)	(36.989)	(34.908)	(36.200)

Notes: The table reports annual means and standard deviations (in parentheses) for the variables used in the empirical analysis.

Source: DETER/INPE, Ibama, PRODES/INPE, SEAB-PR, Matsuura and Willmott (2012), and PAM/IBGE.

Table 2
First Stage Regressions: The Effect of DETER Cloud Coverage on the Number of Fines

VARIABLES	(1) Number of Fines	(2) Number of Fines	(3) Number of Fines	(4) Number of Fines	(5) Number of Fines
Cloud Deter	-12.584***	-14.437***	-8.791**	-11.706***	-9.926**
	(2.713)	(2.574)	(3.674)	(4.071)	(3.854)
Rain		0.000	-0.005***	-0.004***	-0.005***
		(0.001)	(0.001)	(0.001)	(0.001)
Temperature		0.665	-3.229**	-3.231**	-2.879**
		(0.756)	(1.320)	(1.329)	(1.326)
Cloud Prodes		0.000	0.000*	0.000*	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
Non-Observed Prodes		-0.001	0.001	0.001	0.001
		(0.002)	(0.001)	(0.001)	(0.001)
Crop Prices 1st Semester				2.098	2.390
				(5.213)	(5.244)
Cattle Prices 1st Semester				-0.189**	-0.156*
				(0.091)	(0.089)
Crop Prices in t-1				-4.997	-3.157
				(6.486)	(6.266)
Cattle Prices in t-1				0.023	0.039
				(0.089)	(0.091)
Priority Municipalities					8.089**
					(3.572)
Protected Areas					14.977**
					(7.408)
Observations	3,156	2,630	2,630	2,630	2,630
R-squared	0.011	0.012	0.028	0.030	0.037
Municipality and Year FE	No	No	Yes	Yes	Yes
Number of municipalities			526	526	526

Notes: Coefficients are estimated using a municipality-by-year panel data set covering the 2007 through 2011 period. The sample includes all Amazon Biome municipalities. Column 1 presents OLS coefficients for a specification with no controls; column 2 adds controls for rainfall, temperature, PRODES cloud coverage, and non-observable areas during period of PRODES remote sensing; column 3 adds municipality and time fixed effects; column 4 adds controls for current and lagged cattle prices, and current and lagged crop prices; column 5 adds controls for priority municipality status, and percentage of municipality area occupied by protected areas. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3

Second Stage Regressions: The Effect of Monitoring and Law Enforcement on Deforestation

VARIABLES	(1) Normalized Deforestation	(2) Normalized Deforestation	(3) Log Deforestation
Number of Fines in t-1	-0.0005	-0.0597**	-0.0976**
	(0.0007)	(0.0272)	(0.0454)
Rain in t-1	0.0000	-0.0002	-0.0002
	(0.0000)	(0.0001)	(0.0002)
Temperature in t-1	-0.0912**	-0.2738**	-0.0280
	(0.0453)	(0.1135)	(0.1845)
Cloud Prodes	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Non-Observed Prodes	0.0001	0.0002	0.0004*
	(0.0001)	(0.0001)	(0.0002)
Crop Prices 1st Semester	-0.0588	-0.0439	0.3748
	(0.0784)	(0.1826)	(0.5592)
Cattle Prices 1st Semester	-0.0047	0.0076	0.0168
	(0.0039)	(0.0084)	(0.0149)
Crop Prices in t-1	0.0165	0.1366	0.0154
	(0.1093)	(0.2554)	(0.4570)
Cattle Prices in t-1	-0.0017	-0.0138	-0.0513***
	(0.0036)	(0.0090)	(0.0172)
Observations	2,630	2,630	2,392
Number of municipalities	526	526	505
Municipality and Year FE	Yes	Yes	

Notes: Coefficients are estimated using a municipality-by-year panel data set covering the 2007 through 2011 period. The sample includes all Amazon Biome municipalities with available data and variation in forest cover during the sample period. The dependent variable used in columns 1 through 2 is the normalized annual deforestation increment; in column 3 it is replace by the log of the annual deforestation increment. Columns 1 through 3 includes controls for lagged rainfall, temperature, PRODES cloud coverage, non-observable areas during period of PRODES remote sensing, current and lagged cattle prices, and current and lagged crop prices. Column 1 presents OLS coefficients; columns 2 through 3 repeat specifications of previous columns and present 2SLS coefficients using DETER cloud coverage as an instrument for the number of fines. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4
Counterfactual Simulations

Year	Observed Deforestation (square kilometers)	Estimated Deforestation (Fines = Fines from 2003)	Difference Estimated - Observed (Fines = Fines from 2003)	Estimated Deforestation (Fines=0)	Difference Estimated - Observed (Fines=0)
2007	11263	20704	9441	34058	22794
2008	12918	23926	11008	37280	24362
2009	5663	21976	16313	35330	29667
2010	6109	21219	15110	34572	28464
2011	5610	16594	10984	29948	24338
Total	41563	104418	62856	171188	129626

Notes: Counterfactual simulations are conducted using the sample, specifications, and estimated coefficients from Table 3. "Observed Deforestation" presents total recorded deforestation in the sample; "Estimated Deforestation" presents total estimated deforestation in alternative counterfactual scenarios; "Difference" reports the difference between estimated and observed deforestation for each counterfactual scenario.

Table 5
Second Stage Regressions: Does the Effect of Monitoring and Law Enforcement on Deforestation Last?

VARIABLES	(1) Normalized Deforestation	(2) Normalized Deforestation
Number of Fines in t-2	-0.0387*	
	(0.0215)	
Rain in t-2	-5.20e-05	
	(0.000114)	
Temperature in t-2	-0.188*	
	(0.100)	
Cloud Prodes	-9.46e-06	1.01e-05
	(1.93e-05)	(1.31e-05)
Non-Observed Prodes	-3.85e-05	-0.00912
	(0.000236)	(0.00762)
Crop Prices 1st Semester	-0.273	0.224*
	(0.280)	(0.119)
Cattle Prices 1st Semester	0.00954	0.00507
	(0.00669)	(0.00528)
Crop Prices in t-1	0.150	-0.0654
	(0.287)	(0.135)
Cattle Prices in t-1	0.00824	0.0907***
	(0.00555)	(0.0126)
Number of Fines in t-3		-0.000572
		(0.00988)
Rain in t-3		0.000343**
		(0.000139)
Temperature in t-3		-0.0621
		(0.0549)
Observations	2,104	1,578
Number of municipalities	526	526
Municipality and Year FE	Yes	Yes

Notes: Coefficients shown are estimated using a municipality-by-year panel data set covering the 2007 through 2011 period. The sample includes all Amazon Biome municipalities with available data and variation in forest cover during the sample period. All specifications are estimated using 2SLS and the normalized annual deforestation increment as dependent variable. Column 1 presents coefficients for specifications using the two period-lagged total number of fines, which is instrumented by two period-lagged DETER cloud coverage; Column 2 repeats the specification of previous column using the three period-lagged total number of fines, which is instrumented by three period-lagged DETER cloud coverage. All specifications include controls for lagged rainfall (double and triple lagged, accordingly), PRODES cloud coverage, non-observable areas during period of PRODES remote sensing, current and lagged cattle prices, and current and lagged crop prices. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6
Second Stage Regressions: The Effect of Monitoring and Law Enforcement on Agricultural Production

VARIABLES	(1) Agriculture GDP	(2) Crop Production
Number of Fines in t-1	0.00197	0.00492
	(0.00514)	(0.00941)
Rain in t-1	-0.000139**	4.54e-05
	(6.78e-05)	(5.52e-05)
Temperature in t-1	-0.140***	-0.0474
	(0.0356)	(0.0517)
Cloud Prodes	1.25e-05*	-3.88e-06
	(7.26e-06)	(1.45e-05)
Non-Observed Prodes	9.06e-05*	7.95e-05
	(5.33e-05)	(6.58e-05)
Crop Prices 1st Semester	0.919***	0.502***
	(0.233)	(0.118)
Cattle Prices 1st Semester	4.13e-06	-0.00910***
	(0.00197)	(0.00334)
Crop Prices in t-1	-0.537***	-0.0215
	(0.155)	(0.0906)
Cattle Prices in t-1	-0.000972	-0.00241
	(0.00157)	(0.00301)
Observations	1,578	2,453
Number of municipalities	526	499
Municipality and Year FE	Yes	Yes

Notes: Coefficients shown are estimated using a municipality-by-year panel data set covering the 2007 through 2011 period. The sample includes all Amazon Biome municipalities with available data and variation in forest cover during the sample period. All specifications are estimated using 2SLS regressions. The dependent variable in column 1 is agricultural GDP; in column (2) it is replaced by crop revenues. All specifications include controls for lagged rainfall, PRODES cloud coverage, non-observable areas during period of PRODES remote sensing, current and lagged cattle prices, current and lagged crop prices. The lagged number of fines is instrumented by lagged DETER cloud coverage in all specifications. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7

Robustness Checks: Second Stage Regressions for the Effect of Monitoring and Law Enforcement on Deforestation

VARIABLES	(1) Normalized Deforestation	(2) Normalized Deforestation	(3) Normalized Deforestation	(4) Normalized Deforestation	(5) Normalized Deforestation
Number of Fines in t-1	-0.0398**	-0.0809**	-0.0822**	-0.0588**	-0.0651*
	(0.0189)	(0.0347)	(0.0363)	(0.0287)	(0.0368)
Rain in t-1	-0.0001	-0.0003	-0.0003**	-0.0002	-0.000218
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.000160)
Temperature in t-1	-0.2124**	-0.2810**	-0.3559**	-0.2724**	-0.286**
	(0.0890)	(0.1379)	(0.1538)	(0.1142)	(0.133)
Cloud Prodes	0.0000	0.0000	0.0000	0.0000	1.86e-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(2.59e-05)
Non-Observed Prodes	0.0001	0.0003*	0.0002	0.0002	0.000189
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.000127)
Priority Municipalities					0.157
					(0.432)
Protected Areas					2.906*
					(1.539)
Observations	2,630	1,655	2,630	2,630	2,630
Number of municipalities	526	331	526	526	526
Municipality and Year FE	Yes	Yes	Yes	Yes	Yes
Time trend * initial deforestation rate				Yes	
Time trend * initial forest share			Yes		

Notes: Coefficients are estimated using a municipality-by-year panel data set covering the 2007 through 2011 period. The sample includes all Amazon Biome municipalities with available data and variation in forest cover during the sample period. All specifications are estimated using 2SLS regressions and normalized annual deforestation increment as dependent variable. Column 1 substitutes average DETER cloud coverage by average DETER cloud coverage using strictly the period for which there is no PRODES remote sensing. Column 2 presents results for a restricted sample of municipalities that had over 50% of forest cover at the beginning of our period of interest. Column 3 controls for a trend determined by the initial share of deforested area in each municipality (an interaction between a linear trend and initial deforested area). Column 4 controls for a trend determined by the initial value of deforestation increments (an interaction between a linear trend and initial deforestation increment). Column 5 adds controls for priority municipality status, and percentage of municipality area occupied by protected areas. All specifications include controls for lagged rainfall, PRODES cloud coverage, non-observable areas during period of PRODES remote sensing, current and lagged cattle prices, and current and lagged crop prices. The lagged number of fines is instrumented by lagged DETER cloud coverage in all specifications. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.