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DETERring Deforestation in the Amazon: Environmental Monitoring and Law Enforcement

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Abstract

This paper proposes a novel instrumental variable to estimate the causal impact of law enforcement on deforestation. DETER, a satellite-based system for mapping land cover, is the key tool in Amazon monitoring. It determines the location of recent forest clearings and is used to target enforcement. Because DETER cannot detect land cover patterns beneath clouds, it detects no clearings in covered areas. Results conrm that DETER cloud coverage is systematically correlated with nes, a proxy for the presence of law enforcers. The study explores this exogenous source of variation in the allocation of law enforcers as an instrument for the intensity of enforcement. Stricter law enforcement eectively deterred Amazon deforestation, helping avoid over 22,000 km^2 of cleared forest area per sample year. Leakage of criminal activity into neighboring areas does not appear to have occurred. Results are submitted to a series of robustness checks.

Keywords

law enforcement, crime, deforestation, conservation policies

JEL codes

K42, Q18, Q23, Q58

1. Introduction

The economics of law enforcement and crime have garnered much attention since the seminal work of Becker (1968). Understanding how offenders respond to law enforcement in practice is crucial for the design of more effective interventions to counter illegal behavior. Yet, because the relationship between law enforcement and crime is characterized by strong endogeneity, documenting its causal effect is a very challenging task (Cameron, 1988; Levitt, 1997; Tella and Schargrodsky, 2004; Draca et al., 2011). The matter is no less complex when it concerns environmental crimes. If anything, the importance of better understanding the effectiveness of law enforcement is heightened when dealing with illegal behavior that carries externalities at the global level — precisely the case of environmental infractions that increase greenhouse gas emissions, the main driving force behind climate change. Because emissions are not constrained by geopolitical borders, they will always imply in global externalities (Stern, 2008; Greenstone and Jack, 2015). The IPCC (2007) estimates that, in the mid-2000s, almost a fifth of global emissions originated from the forestry sector, mostly from tropical deforestation. Combating deforestation and conserving tropical forests have therefore become priorities in the global policy agenda (Burgess et al., 2012). The matter is aggravated by the fact that forest clearings in recent decades have largely been made under illegal circumstances, and often classify as criminal behavior. A wide range of environmental law enforcement instruments are currently available to protect the forest, but in-depth and evidence-based understanding of these instruments' efficacy is still scant.

This article proposes a novel instrumental variable approach that enables the estimation of the causal impact of environmental monitoring and law enforcement on tropical forest clearings in the Brazilian Amazon. Brazil is a central figure in the global tropical deforestation story. The country originally held two thirds of the Amazon, totaling over 4 million square kilometers of native Amazon vegetation — an area equivalent to almost half of continental Europe. Extensive forest clearings in the Brazilian Amazon were responsible for a substantial share of the observed loss of tropical vegetation worldwide through the beginning of the 21st century (Hansen and DeFries, 2004; Hansen et al., 2008). Yet, after peaking at 27,000 square kilometers per year in 2004, Brazilian Amazon clearing rates fell sharply in the second half of the decade to about 6,000 square kilometers in the early 2010s (INPE, 2013b). Our study assesses the contribution of policy-induced stricter environmental monitoring and law enforcement to this recent Brazilian Amazon deforestation slowdown.

In 2004, the Brazilian federal government launched an action plan to combat Amazon deforestation. One of the plan's key components was the introduction of new procedures for monitoring forest clearing activity, with the implementation of the Real-Time System for Detection of Deforestation (DETER) as its cornerstone. DETER is a satellite-based system that provides near real-time identification of deforestation hot spots throughout the full extent of the Brazilian Amazon. Hot spots map into alerts signaling areas in need of immediate attention, which then serve as the basis for targeting law enforcement efforts. Since the adoption of DETER, the allocation of environmental law enforcement personnel in the Brazilian Amazon has relied heavily on these alerts. The new remote sensing system thus enabled law enforcers to better identify, more closely monitor, and more quickly act upon areas being illegally deforested. This represented a substantial leap in environmental sanctioning capacity. Brazil's institutional setup is such that law enforcers can more easily punish offenders for illegal forest clearings when catching them red-handed, as offenders can thereby be held directly accountable for the crime. Although Brazilian environmental legislation allows for punishment of past deforestation, effective sanctioning of past clearings in the Amazon, where land and production property rights are unclear, is far less feasible.

Was more stringent environmental law enforcement effective in containing tropical forest clearings? To accurately answer this question, we must tackle the aforementioned law enforcement and crime endogeneity problem. In our context, the 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 potentially deterrent effect of environmental law enforcement and the crime-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 police and crime literature documents different efforts to identify and explore exogenous sources of variation in police presence and thereby isolate the causal effect of law enforcement. When data on the actual intensity of law enforcement is not available, indirect inference has been used to argue that specific terrorist attacks increased local patrolling and thereby reduced crime — see Tella and Schargrodsky (2004) for an assessment of attacks in Buenos Aires, Argentina, and Klick and Tabarrok (2005) for evidence based on terror alerts levels in Washington, D.C., US. In contexts where data on police deployment (or a proxy thereof) exist, the relationship of interest can be estimated upon availability of a plausible instrument. Using electoral cycles, which the author shows are correlated with police force staffing in the context of US elections, as one such instrument, Levitt (1997) provides evidence that increase police presence reduces crime.[1] Draca et al. (2011) explores regional increases in police deployment induced by terrorist attacks in London to uncover a reduction in crime rates during

[1] See McCrary (2002) for concerns regarding data and method validity in the well-known Levitt (1997) study, and Levitt (2002) for a response.

periods of more intense policing.

Our analysis draws on this literature, using an exogenous source of variation in the allocation of environmental law enforcers to capture the impact of monitoring and law enforcement on Amazon deforestation. We exploit a technical characteristic of the DETER monitoring system to derive an instrument for the local intensity of law enforcement. Our core argument is as follows. Because the satellite used in DETER is incapable of detecting land cover patterns in areas covered by clouds, no forest clearing activity is identified in these areas, such that no alerts pinpointing the location of recent deforestation activity are issued for the region covered by clouds. Thus, law enforcers have a lower probability of being allocated to these areas. We therefore propose using DETER cloud coverage as an instrument for the local intensity of law enforcement.

Based on a 2006 through 2011 panel of 526 municipalities in the Brazilian Amazon, we show that cloud coverage limiting satellite visibility in the DETER monitoring system does, in fact, systematically affect the intensity of law enforcement in the Brazilian Amazon — for a given municipality, greater average annual cloud coverage reduces the number of flora-related environmental fines issued in that municipality.[2] We control for municipality and year fixed effects and data on relevant observables, including rainfall and temperature, which are expected to be correlated with both deforestation and cloud coverage. In the second stage of our estimation, we find evidence that the presence of law enforcers effectively deters Amazon deforestation — an increase in the number of fines issued in a given year is found to significantly reduce forest clearings the following year.

Our inference is robust to weak instruments and passes a series of robustness tests. Results are shown to not have been driven by our choice of instrument, as they remain stable when using an alternative instrument that is arguably less vulnerable to potential correlation with our dependent variable. Coefficients are also robust to the inclusion of a variety of time trends that test for relevant potential baseline differences across municipalities that could set them on different forest clearing trends over time. These include varying stocks of deforested areas, different economic dynamics and deforestation pressures, and shifts in the distribution of law enforcement at baseline. Finally, the deterrent effect of law enforcement is also robust to sample composition changes, inclusion of relevant controls, and alternative data sets for climate variables.

Estimated effects are not only statistically significant, but also quantitatively relevant. In a counterfactual exercise, we estimate that, had it not been for monitoring and law enforcement efforts, total deforested area would have been more than 360% greater than

[2] Flora-related environmental fines issued at the municipality level serve as a proxy for the local intensity of law enforcement, since sanctions for illegal forest clearing are not restricted to, but usually include, fines.

was actually observed from 2007 through 2011. During this period, law enforcement helped avoid an average of over 22,000 square kilometers of Amazon forest clearings per year. We use these empirical findings to perform a back-of-the-envelope cost-benefit analysis, comparing a conservative (upward biased) estimate of the annual cost of Amazon monitoring and law enforcement with an also conservative (downward biased) estimate of the annual monetary benefits of preserving the forest and thereby avoiding carbon dioxide emissions. We calculate a break-even price of carbon in this conservative exercise to be 0.84 USD/tCO_2. Compared to the price of 5.00 USD/tCO_2 commonly used in current applications, these figures suggest that active monitoring and law enforcement in the Brazilian Amazon have the potential to yield significant net gains. To address another potential cost dimension of stricter monitoring, we investigate whether increased intensity of law enforcement had adverse effects on local agricultural production. We find no significant immediate impact on municipality-level agricultural GDP. Unfortunately, our empirical setup neither allows us to identify the mechanisms behind this result, nor does it capture long-term and informal production impacts of stricter law enforcement.

The analysis also explores potential leakage of deforestation into neighboring areas, but finds no evidence to support displacement of forest clearing activity from localities subject to stricter law enforcement into their immediate surroundings.[3] In fact, the impact of stricter law enforcement in a given municipality is even greater when deforestation in neighboring areas is taken into account. The absence of within-Amazon leakage is to be expected when one considers that the satellite-based monitoring system indiscriminately covers the full extent of the Brazilian Amazon — potential offenders are as exposed to the satellite in a given locality as they are in that locality's surroundings. We therefore argue that monitoring and law enforcement effectively contributed to contain total Amazon deforestation.

This paper speaks to different strands of the economic literature. First, as has been mentioned, it is closely related to existing efforts to establish the causal impact of law enforcement on illegal activity. Yet, unlike previous works (Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al., 2011), our empirical circumstances allow us to assess law enforcement efforts that cover the full extent of the area that is subject to the illegal activity. It is therefore not as context-specific, which ultimately allows us to draw conclusions about the effectiveness of law enforcement as a deterrent of crime within the full scope of interest without having to resort to additional assumptions or extrapolations.

Second, it contributes to a growing literature on the enforcement of environmental regulation in developing countries. Such regulation has long been assessed — both in

[3]Note that, due to data availability, we are only able to capture deforestation of tropical vegetation. Thus, we cannot test if increased Amazon monitoring contributed to displace forest clearing into non-tropical vegetation within Brazilian territory.

terms of policy effectiveness in meeting its goals and policy impacts on socioeconomic outcomes — but almost exclusively within the context of developed nations.[4] However, as argued by Greenstone and Hanna (2014), considering that developing countries typically exhibit a weaker institutional environment that poses obstacles to effective environmental law enforcement, one cannot usually extend empirical findings from developed countries to developing ones.[5] Yet, as the authors further argue, it is precisely developing countries that most urgently need to successfully enact and enforce environmental policies, since most of the increase in greenhouse gas emissions over the coming decades is projected to originate in such countries.[6] With the bulk of research on climate change and policy focused on developed economies, little is actually known about effects and workings of climate policy where it currently matters most (Burke et al., 2016). Our work directly assesses an environmental policy that was enacted in and is entirely enforced by a developing country with large potential to contribute to global greenhouse gas emissions reductions.

Third, there is a substantial stream of literature documenting both underlying and immediate causes of tropical deforestation, including agricultural commodity prices, infrastructure, transportation costs, population pressures, climate-related phenomena, and rent-extracting incentives at the local politician/bureaucrat level.[7] More recently, works have started to look specifically at the mid-2000s Amazon deforestation slowdown, seeking to identify its main drivers. Evidence suggests that novel conservation policies implemented within the scope of the mid-2000s Brazilian action plan to combat tropical forest clearings significantly contributed to curb deforestation in the Brazilian Amazon.[8] However, none have directly measured the impact of environmental monitoring and law enforcement, despite its central role in the action plan.[9] To the best of our knowledge, ours is the first assessment of environmental monitoring and law enforcement in the context of the Brazilian Amazon that adequately addresses known endogeneity between the illegal activity and the presence of

[4] A series of pieces on the U.S. Clean Air Act Amendments, for example, has documented impacts on air pollution levels, infant mortality, housing prices, and firm-level productivity and growth (Greenstone, 2002; Chay and Greenstone, 2003, 2005; Greenstone et al., 2012). See, also, Gray and Shimshack (2011) for a recent survey on empirical evidence concerning pollution monitoring and law enforcement in the U.S.

[5] Greenstone and Hanna (2014) provide one of the few assessments of environmental regulation in a developing country, finding evidence that, despite the weak regulatory environment, policies aimed at improving air and water quality in India achieved varying degrees of success.

[6] Broner et al. (2013) find evidence that countries with laxer environmental regulations actually provide a source of comparative advantage to polluting industries. This aggravates their own environmental quality, of course, but also exposes other nations to environmental degradation via externalities.

[7] See, among others: Angelsen and Kaimowitz (1999); Pfaff (1999); Chomitz and Thomas (2003); Burgess et al. (2012); Souza-Rodrigues (2015).

[8] See: Assunção and Rocha (2014); Assunção et al. (2015, 2016); Burgess et al. (2016).

[9] Hargrave and Kis-Katos (2013) find a negative relationship between fine intensity and deforestation in the Brazilian Amazon, but do not account for endogeneity issues.

law enforcers. It therefore contributes not only to the police and crime literature, but also serves as one of the few studies that performs policy effectiveness analysis in the context of the recent Brazilian Amazon deforestation slowdown.

The remainder of this paper is organized as follows. Section 2 describes the institutional context regarding Amazon monitoring and law enforcement in Brazil. Section 3 details the empirical strategy used to identify the causal effect of law enforcement on deforestation. Section 4 introduces the data and descriptive statistics. Section 5 presents and discusses results. Section 6 provides robustness checks. Section 7 explores potential costs and collateral effects of the policy. Section 8 concludes with policy implications.

2. Institutional Context

2.1. Deforestation as a Crime

In Brazil, unlicensed clearing of native vegetation is an illegal activity punishable by law. Although licenses for legal deforestation, including in the Amazon, can be obtained, the vast majority of clearings during our period of interest were performed under illegal circumstances.

Since its creation in 1989, the Brazilian Institute for the Environment and Renewable Natural Resources (Ibama) has been responsible for environmental monitoring and law enforcement in Brazil. Ibama is an executive branch of the Brazilian Ministry of the Environment. It executes environmental policy actions and operates as the national police authority in both the investigation and sanctioning of environmental infractions. As the country's leading force in environmental law enforcement, Ibama plays a large and central role in the control and prevention of Amazon deforestation.

2.2. Novel Conservation Policy and Satellite Monitoring

Launched in 2004, the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) inaugurated a novel approach towards combating tropical deforestation in Brazil. The plan inaugurated integrated actions across different government institutions and proposed new procedures for monitoring, environmental control, and territorial management. The strengthening of monitoring and law enforcement was a fundamental part of the PPCDAm's tactical-operational strategy. It was implemented via a combination of technological changes and legal actions.

From a technological standpoint, the cornerstone of PPCDAm law enforcement was the major leap forward in Amazon monitoring capacity brought about by the adoption of high-frequency remote sensing of forest clearing activity. Developed by the Brazilian Institute for Space Research (INPE), the Real-Time System for Detection of Deforestation (DETER) is a satellite-based system that processes georeferenced imagery on Brazilian

Amazon land cover on a regular basis to detect loss of forest area. Figure 1 shows how DETER captures deforestation. The system differentiates forested and deforested areas (shown in different colors in the figure), such that, for any given location, later satellite images are compared with earlier ones to identify changes in forest cover. The images are prepared and distributed in the form of georeferenced digital maps, pinpointing the location (geographical coordinates) of deforestation hot spots. Figure 2 provides examples of such maps. Each clearing hot spot triggers the issuing of a DETER deforestation alert, signaling areas in need of immediate attention.

[Figure 1 about here.]

However, the system suffers from an important technical limitation: DETER cannot detect land cover patterns beneath clouds. In fact, most satellite-based systems cannot — when clouds are present, satellite images are essentially pictures of the clouds themselves, not the land beneath them. So if an area is deforested but is covered by clouds, DETER can only capture the change in forest cover and, consequently, issue an associated deforestation alert once cloud coverage clears. The pattern is apparent in Figure 2, which shows that deforestation alerts are only located in uncovered areas. This characteristic poses a relevant limitation for monitoring capacity, but it is the basis upon which we build our empirical strategy (see Section 3 for details).

[Figure 2 about here.]

Since its implementation in the mid-2000s, DETER has served as the main tool for targeting Ibama's law enforcement efforts in the Amazon. Prior to the activation of the remote sensing system, identification of recent forest clearing activity depended on voluntary and anonymous reports of threatened areas. This made it extremely difficult for Ibama to locate and access deforestation hot spots in a timely manner. With the adoption of DETER, Ibama was given regular and high-frequency access to georeferenced data on forest clearing activity, and was thus able to better identify and more quickly act upon areas afflicted by illegal deforestation.[10]

From a legal standpoint, the PPCDAm also promoted institutional changes that enhanced law enforcement capabilities in the Amazon. Ibama sought to improve the qualification of its personnel through the establishment of stricter requirements in its recruitment process and more intensive training of law enforcers. Additionally, Ibama's

[10] More specifically, the satellite used in DETER provides daily observations for the full extent of the Brazilian Amazon. During our sample period, the best daily images (those with best visibility of land cover) for each area were aggregated into biweekly maps and sent to Ibama. Since 2011, INPE has processed daily images on a daily basis, such that Ibama receives updated information on recent deforestation activity every weekday.

law enforcement efforts gained greater legal support with the passing of Presidential Decree 6,514 in 2008, which reestablished directives for the investigation and sanctioning of environmental infractions. The decree determined the administrative processes for punishing offenders in more detail than had been previously incorporated in legislation, increasing both clarity and speed of such processes. It also regulated the use of both existing and new instruments for the punishment of environmental crimes, including fines, embargoes, and seizure and destruction of production goods, tools, and materials. 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.

Given Brazil's institutional setup, law enforcers have greater capacity to punish offenders for illegally clearing forest areas when caught red-handed. This is particularly relevant for a subset of sanctioning instruments — namely the establishment of embargoes and seizure of production goods, tools, and material — whose use essentially depends on law enforcers having access to seizable items and being able to identify and hold the offender accountable for the illegal activity. 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 considerably less feasible. The adoption of satellite-based monitoring and targeting of law enforcement significantly increased law enforcers' capacity to identify and reach forest clearings as the environmental crimes happen, thereby also increasing their ability to punish illegal deforestation. Thus, overall, policy efforts adopted starting in the mid-2000s improved, intensified, and more accurately targeted monitoring and law enforcement efforts in the Brazilian Amazon.

2.3. Other Relevant Policies

Several other policies to combat deforestation were implemented within the scope of the PPCDAm. Two such policies are relevant for consideration in our empirical strategy: the creation of priority municipalities and the expansion and strategic allocation of protected areas.

The signing of Presidential Decree 6,321 in late 2007 established the legal basis for singling out municipalities with intense deforestation activity and taking differentiated action towards them. These municipalities, selected based on their recent 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 law enforcement policy. Examples include harsher licensing and georeferencing requirements for private landholdings, revision of land titles, and economic sanctions applied by agents of the commodity industry. In light of this, the consequences of being added to the list of priority municipalities could therefore extend beyond that of stricter monitoring and law enforcement.

The PPCDAm also promoted the expansion of protected territory and introduced the strategic allocation of protected areas, such that new areas served as shields to advancing deforestation.[11] Thus, starting in the mid-2000s, newly protected territory was often in very close proximity to areas recently affected by deforestation.

3. Empirical Strategy

Our relationship of interest — how law enforcement affects illegal tropical forest clearing — suffers from known endogeneity. The presence of law enforcers is expected to have a deterrent effect on illegal deforestation, but law enforcement personnel are allocated, at least partly, based on the actual occurrence of environmental crimes. As we only observe an equilibrium situation — the sanction applied by Ibama once the environmental infraction has been committed — our estimation must tackle simultaneity in addition to the usual concerns regarding omitted variables. This section builds the case for and proposes an instrumental variable strategy to identify the causal effect of law enforcers' presence on Amazon deforestation.

Recall from Section 2 that, because DETER is unable to detect land cover patterns beneath clouds, it does not issue alerts for any given area when cloud coverage is limiting visibility in that area. Since these alerts serve as the basis for targeting Amazon law enforcement efforts, law enforcers are less likely to be allocated to areas that are covered by clouds during remote sensing, even if forest clearing activity is occurring in these areas. In this sense, the presence of environmental law enforcers will be at least partially determined by an area's cloud coverage. If this is, in fact, the case — and we will provide empirical evidence that supports it — average annual DETER cloud coverage at the municipality level is arguably a source of exogenous variation in the presence of law enforcers in Amazon municipalities. We therefore propose using DETER cloud coverage as an instrument for environmental law enforcement intensity.

Our instrument's validity depends on it being uncorrelated with the error term in the equation that regresses deforestation on law enforcement, conditional on all

[11] These areas are protected to the extent that illegal activities conducted within them are subject to stricter sanctions.

observable variables. There are two scenarios in which this condition could be violated in our empirical setup: (i) if there is correlation between cloud coverage and other geographical characteristics that, in turn, are correlated with deforestation; and (ii) if there is correlation between DETER cloud coverage and our measure of deforestation (dependent variable), which is also affected by cloud coverage. The availability of relevant observable variables and the use of fixed effects help make the case for the instrument's validity.

Rainfall and temperature present themselves as obvious candidates in the first scenario. Both are expected to be correlated with clouds via weather phenomena. They may also be correlated with deforestation, be it as direct or indirect determinants of agents' forest clearing decisions, or through weather impacts of deforestation itself.[12] Although delving into the nature of this correlation is out of the scope of this paper, we account for it by using precipitation and temperature data compiled by Matsuura and Willmott (2015) to control for weather at the municipality level.[13] Another source of concern regarding our instrument's exclusion restriction is the potential relationship between average cloud coverage and soil type. The quality of soil in a given area could be correlated with deforestation through its impact on production outcomes, which affect agents' forest clearing decisions. However, because soil types change relatively slowly over time, this concern can be mitigated by the inclusion of location fixed effects in studies with relatively short time windows like our own (5 years). All our specifications therefore include municipality-level precipitation and temperature controls, as well as municipality fixed effects.

We also address the second scenario using available observable data. INPE's Project for Monitoring Deforestation in the Legal Amazon (PRODES) calculates annual forest clearing rates for the Brazilian Amazon based on interpretation of satellite imagery. It is similar to DETER in the sense that changes in forest cover are detected by comparing earlier images of a given area with later images of that same area, though it uses a different satellite that provides imagery at higher resolutions, but at far less frequent intervals. Although the systems use different satellites and span across different time frames (see Section 4 for details), both cover the same geographic area and both cannot detect land cover patterns beneath clouds. We therefore expect correlation between DETER and PRODES cloud coverages to be potentially relevant and control for PRODES cloud coverage in all specifications, such that coefficients are estimated considering only DETER cloud coverage that is orthogonal to that in PRODES.[14] In robustness checks, we further explore the fact that PRODES collects satellite imagery only within a restricted

[12] See Section 4 for a brief discussion on the matter.

[13] Section 6 discusses robustness checks that explore alternative datasets for climate variables.

[14] Shadows cast by clouds and smoke from forest fires have the same effect as clouds on PRODES imagery, obstructing land cover patterns from view. In PRODES data, such "non-observable areas"

window in a given year, while DETER collects daily satellite imagery all year round. We replace 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 municipality-level precipitation, temperature, PRODES cloud coverage and non-observable areas, and fixed effects, we argue that the only remaining channel through which DETER cloud coverage could be correlated with deforestation in the Brazilian Amazon is that of the allocation of environmental law enforcers. We start by exploring this potential relationship between law enforcement and DETER cloud coverage. Our OLS estimation equation is given by:

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

where $Fines_{it}$ is the number of flora-related environmental fines issued by Ibama in municipality i and year t, which serves as proxy for the presence of law enforcers; $DETERclouds_{it}$ is average annual DETER cloud coverage for municipality i and year t; X_{it} is a vector of municipality-level controls including precipitation, temperature, and PRODES cloud coverage and non-observable areas; α_i is the municipality fixed effect; ϕ_t is the year fixed effect; and ϵ_{it} is the idiosyncratic error.

In our instrumental variable estimation, we intend to capture the impact of law enforcement (instrumented by DETER cloud coverage) on Amazon deforestation. We follow the literature on monitoring and law enforcement assessment and, based on the expected timing of the criminal response, explore the impact of lagged law enforcement variables on current illegal activity (Magat and Viscusi, 1990; Levitt, 1997; Shimshack and Ward, 2005). A one-year response window seems plausible in the context of DETER-based monitoring and annual data. For a given area, increased deforestation in year t likely triggers the issuing of DETER deforestation alerts associated with that area, thereby increasing the presence of law enforcement personnel via targeted allocation in the same year t. If potential offenders perceive the observed greater intensity of law enforcement in year t as a higher probability of getting caught and sanctioned in year $t+1$, they may choose to not (re)engage in criminal activity the following year, consequently contributing to reduce forest clearings in $t+1$.

Hence, we estimate the effect of the number of flora-related fines issued in year $t-1$ (instrumented by DETER cloud coverage in year $t-1$) on deforestation in year t. 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 include

are distinguished from clouds; DETER makes no such distinction. We include both PRODES clouds and non-observable areas as controls.

one-year lags for precipitation and temperature controls, but not for any other variables. The second-stage estimation equation is given by:

$$Deforestation_{it} = \gamma_1 Fines_{it-1} + \sum_k \gamma_k X_{kit} + \psi_i + \lambda_t + \xi_{it} \tag{2}$$

where $Deforestation_{it}$ is the normalized deforestation increment in municipality i and year t; $Fines_{it-1}$ is the number of flora-related environmental fines issued by Ibama in municipality i and year $t-1$, and is instrumented by $DETERclouds_{it-1}$; X_{it} is a vector of municipality-level controls including lagged values for precipitation and temperature, as well as current PRODES cloud coverage and non-observable areas; ψ_i is the municipality fixed effect; λ_t is the year fixed effect; and ξ_{it} is the idiosyncratic error. Standard errors in all specifications are clustered at the municipality level, making them robust to heteroscedasticity and serial correlation (Bertrand et al., 2004).

In addition to variables added to support the validity of our exclusion restriction, X_{it} also includes other relevant controls to mitigate omitted variable bias. First, because agricultural commodity prices have been shown to be relevant drivers of tropical deforestation (Angelsen and Kaimowitz, 1999; Hargrave and Kis-Katos, 2013; Assunção et al., 2015), we control for crop and cattle prices. Drawing on Assunção et al. (2015), we include output prices for the first and second semesters of the previous year, as well as for the first semester of the current year. Second, there are important municipality and time characteristics that could determine both forest clearing activity and law enforcement efforts. We take advantage of our data set's panel structure to control for municipality and year fixed effects and thereby address such characteristics. Finally, we recognize that there were relevant conservation policy efforts — namely the creation of priority municipalities and the strategic allocation of newly protected territory — being implemented alongside improvements in monitoring and law enforcement. Although we expect these policies to have had an impact on Amazon deforestation, endogeneity concerns keep us from including available data on them in our preferred specification.[15] In robustness checks, we include controls for priority municipalities and percentage of municipal area under protection.

[15]Priority municipality status, which focused monitoring and law enforcement, was granted based on recent deforestation history. Also, within the scope of the PPCDAm, the allocation of newly created protected areas was partially based on recent deforestation occurrence and trends, since these areas were used as buffers against advancing deforestation. See Section 2 for details.

4. Data

Our empirical analysis is based on a 2006 through 2011 municipality-by-year panel data set entirely built from publicly available data.[16] There are 553 municipalities located partially or entirely within the Amazon Biome.[17] Missing data for 6 municipalities imposes a first sample restriction. It is further restricted to municipalities that portray variation in forest cover during the sample period to allow for the normalization of our main deforestation variable (see Section 4.1 for variable construction) and for the use of municipality fixed effects.[18] The final sample comprises 526 municipalities.

4.1. Deforestation

Since 1988, INPE annually processes satellite imagery to identify and map deforested land through its Project for Monitoring Deforestation in the Legal Amazon (PRODES). INPE uses images from Landsat class satellites with a spatial resolution of 20 to 30 meters, allowing it to detect contiguously cleared areas of at least 6.25 hectares throughout the full extent of the Brazilian Legal Amazon. It compares images of a given area in years $t-1$ and t to capture changes in forest cover. PRODES only identifies clear-cut deforestation, and therefore does not encompass forest degradation or selective logging. The system also only accounts for the clearing of tropical forest — it is not technically fit to compute the clearing of vegetation that falls into any other category.[19]

PRODES was created — and is still used — for the sole purpose of quantifying and spatially locating annual tropical deforestation increments, which then serve to calculate an Amazon-wide annual deforestation rate. When an area is identified as deforested in PRODES imagery, it is classified as part of that year's deforestation increment; as of the following year, it is classified as accumulated deforestation and is incorporated into what is known as the "PRODES deforestation mask". Once part of this mask, an area is never reclassified. Thus, by construction, PRODES can neither detect deforestation of areas covered by tropical regeneration, nor include this type of forest clearing in its calculation of the annual deforestation rate. The PRODES deforestation increment is

[16] Although DETER was implemented in 2004, it remained in an experimental stage through 2005. Although a few months of data are available for 2004 and 2005, consistent remote sensing data on DETER cloud coverage only starts in 2006.

[17] Note that Brazilian Amazon Biome and Brazilian Legal Amazon refer to two different regions. The Amazon Biome ia a biological and ecological concept, whereas the Legal Amazon is a geopolitical administrative subdivision. The Amazon Biome is entirely contained within the Legal Amazon. Although the PPCDAm covered the entire Legal Amazon, more than 90% of tropical area deforested over the past two decades was located inside the Amazon Biome.

[18] The 21 municipalities that portray no such variation exhibit very low municipal forest cover, averaging only 4 km^2.

[19] Although the Legal Amazon is mostly covered by tropical forest, some areas contain savanna-like native vegetation called *cerrado*. These are considered as "non-forest" areas in PRODES.

publicly released at an yearly basis both as an Amazon-wide georeferenced data set (starting in 2000), and as aggregated municipality-level areas.

Annual data generated via PRODES do not refer to a calendar year. For a given year t, PRODES measures deforestation that happened from August of the previous year $(t-1)$ through July of that year (t). Typically, images from the Amazon dry season (June through September) are used, due to lower cloud coverage. We henceforth refer to the August-through-July time frame as the "PRODES year".

In our empirical analysis, we take deforestation to be the annual municipality-level deforestation increment as defined by PRODES — total forest area cleared within a municipality over the twelve months leading up to August of a given year. Thus, for a given municipality, the annual deforestation increment of year t measures the area deforested between the 1st of August of $t-1$ and the 31st of July of t. 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 empirical analysis considers only relative variations in deforestation within municipalities. The normalized 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 1st of August of $t-1$ and the 31st 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.[20] We test whether results are driven by our choice of normalization technique by using the log of ADI_{it} as the dependent variable in alternative specifications.

Like most satellite-based systems, PRODES cannot detect land cover patterns beneath clouds, which show up as visual obstructions in imagery. Shadows cast by clouds and smoke from forest fires have the same effect — these are referred to as “non-observable areas” in PRODES data. Full disclosure on cloud coverage and non-observable areas is available with every year of PRODES data as of 2000 — we include these variables in all regressions to control for measurement error. If a forest area that has been covered by clouds for any number of years shows up as deforested once clouds clear, INPE records

[20]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 estimate all specifications using the mean and standard deviation over the 2007 through 2011 period for the normalization of our dependent variable. Results are generally robust to this alternative normalization and are available from the authors upon request.

that area as part of that year's deforestation increment, but notes the length of time it remained unseen in satellite imagery. Calculation of the deforestation rate takes this time period into account, in an attempt to more closely reflect the actual speed at which the Amazon was cleared.[21]

4.2. Law Enforcement

We use the total annual number of flora-related fines issued in each municipality as a measure of the annual intensity of monitoring and law enforcement at the municipal level. These data are publicly available from Ibama upon request. For each fine, the data set provides information on the type of environmental infraction being sanctioned (allowing us to select flora-related occurrences), the location (municipality level only, not georeferenced), the amount to be paid, and the legal details of the sanction. To maintain consistency across our panel, we consider the PRODES year as the relevant unit of time in our sample. Thus, for each municipality, we calculate the total number of fines in a given year as the sum of all fines applied in that municipality in the twelve months leading up to August of that year.

Note that the knowingly low collection rates for flora-related fines applied in the Brazilian Amazon do not interfere with our analysis (Barreto et al., 2008, 2009; Schmitt, 2015). Fines are often accompanied by other sanctions that are more binding, such as seizure and destruction of goods, tools and materials, and embargoes of production areas. Because adequate panel data on the use of these other sanctions are not available, we use the number of flora-related fines as a proxy for monitoring and law enforcement efforts as a whole. Essentially, we are interested in exploring fines as a means of capturing the effect of law enforcers' presence on deforestation, and not that of the sanctioning instrument itself.

4.3. Cloud Coverage

INPE publicly releases maps containing georeferenced data on DETER cloud coverage for every month throughout the year.[22] We construct our instrument — average annual DETER cloud coverage at the municipal level — from these maps. Figure 2 provides examples for a sample year and illustrates the high degree of within-year variation in DETER cloud coverage. When visibility is at least partial, the maps show exactly which areas were covered by clouds. When visibility is too precarious to derive any information

[21] See INPE (2013a) for a detailed account of PRODES methodology.

[22] As discussed in Section 2, DETER actually provides law enforcers with higher-frequency data on deforestation hot spots. However, data is publicly released only at an aggregate level. Most data is released as monthly aggregates, although a few occurrences of two data points for a single month do occur in earlier years. In the latter case, we followed INPE's instruction to build a single month-based observation by only considering areas that were covered by clouds in both data points as blocked from satellite view in that month.

about land cover, however, no map is produced — we assume DETER cloud coverage to be complete in this case. We use monthly data to calculate, for each sample municipality and year, average DETER cloud coverage for that municipality and year as a share of total municipal area. Again, the relevant unit of time is the PRODES year to ensure consistency with deforestation data time frames.

4.4. Additional Controls

Our analysis includes two sets of control variables — measures of local climate and agricultural commodity prices — to address potential correlation with deforestation.

The first set of controls deals with potential correlation between deforestation and regional microclimate, in particular, rainfall and temperature. Although the literature is yet to reach a consensus, there is evidence that tropical forest clearings may affect a region's microclimate (Nobre et al., 1991; Chen et al., 2001; Negri et al., 2004; Aragão et al., 2008). Moreover, deforestation activity may itself be partially determined by meteorological conditions that make it easier to penetrate, cut, and burn the forest. Although understanding this relationship in detail is out of the scope of this paper, we include a municipal measure of total precipitation and average temperature to account for potential weather effects. In doing so, we also mitigate the concern regarding the validity of our instrument under correlation between cloud coverage and geographical characteristics that are, in turn, correlated with deforestation (see Section 3).

We construct our controls from monthly precipitation and temperature data compiled by Matsuura and Willmott (2015), who draw on worldwide climate data to calculate a regular georeferenced world grid of estimated precipitation and temperature over land. Their estimations are based on geographic extrapolations of rainfall and temperature data collected at weather stations. This database has been extensively used in the economic literature both to evaluate the impact of climate variables on economic outcomes and to provide relevant precipitation and temperature controls (Jones and Olken, 2010; Dell et al., 2012).

Using this monthly georeferenced grid, we calculate total annual precipitation and average annual temperature in each municipality according to the following rule: (i) for municipalities that overlap with only one grid node, we take that node's value as the municipal value; (ii) for municipalities that overlap with two or more grid nodes, we average across nodes; (iii) for municipalities that have no overlap with any grid nodes, we take the area of a 28-kilometer buffer around the municipality and average across nodes falling into this buffer; and (iv) for the few municipalities whose 28-kilometer buffer do not overlap with any grid nodes, we use the value for the nearest grid node.[23] Our annual

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

precipitation and temperature variables are constructed to fit the PRODES year time frame.

For the second set of controls, we consider agricultural commodity prices, which have been shown to be drivers of deforestation (Angelsen and Kaimowitz, 1999; Hargrave and Kis-Katos, 2013; Assunção et al., 2015). As commodity 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. (2015), 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 of the State of Paraná (SEAB-PR).The set of commodities includes beef cattle, soybean, cassava, rice, corn, and sugarcane.[24]

For each of the six commodities, we build an index of real prices for the first and second semester of each calendar year. We start by deflating monthly nominal prices to year 2000 Brazilian currency, and averaging the deflated monthly prices across semesters. To introduce cross-sectional variation in the commodity price series, we calculate a weighted real price for each commodity according to the following expression:

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

where PPA_{itc} is the weighted real price of commodity c in municipality i and semester/year t; PP_{tc} is the Paraná-based real price of commodity c in semester/year t; and $A_{ic,2004-2005}$ is the municipality-specific weight. For crops, the weight is given by the share of municipal area used as farmland for crop c in municipality i averaged over 2004 and 2005. This term captures the relative importance of crop c within municipality i's agricultural production in years immediately preceding our sample period. For beef cattle, as annual pasture is not observable, the weight is given by the ratio of heads of cattle to municipal area in municipality i averaged over 2004 and 2005.[25]

Our set of agricultural commodity price controls for year t includes prices for the first and second semesters of year $t-1$, as well as prices for the first semester of year t. Price variables refer to calendar years, not PRODES years.

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

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

4.5. *Trends and Descriptive Statistics*

The average number of flora-related fines at the municipal level was on the rise since the early 2000s (see Figure 3). While it grew nearly sevenfold from 2002 through 2008, average annual municipal deforestation declined by almost half during the same period. In the following years, the number of fines generally decreased alongside decreasing deforestation. Such trends, although suggestive, are not conclusive, because they suffer from endogeneity — an increase in law enforcement is expected to deter illegal forest clearings, and less deforestation implies a lesser need for fines. Our empirical analysis aims at isolating the causal effect of law enforcement on deforestation, thereby shedding light on the driving forces behind the trends shown.

[Figure 3 about here.]

Table 1 presents the means and standard deviations of the variables used in our empirical analysis. Despite rising agricultural commodity prices and rising agricultural production, both of which could have pushed for greater deforestation via incentives to convert forest areas into agricultural land, average deforestation at the municipality level decreased over the sample period. The table indicates that average DETER cloud coverage (as share of total municipal area) is typically over 50%, and that there is substantial variation in cloud coverage between municipalities.

[Table 1 about here.]

5. Main Results

5.1. *Distribution of Law Enforcement*

We start by looking at a set of descriptive regressions to shed light on how the implementation of DETER monitoring affected Amazon law enforcement. Table 2 shows coefficients estimated using univariate OLS in which the number of flora-related fines issued in year t are regressed on the number of flora-related fines issued in year $t-1$ over a period covering both pre- and post-DETER years. The table's main result is captured in the progression of the R-squared along the columns. The R-squared values for columns 1 and 2, as well as for columns 4 through 9 are relatively high, suggesting that there is a certain degree of persistence in law enforcement activity — a high incidence of fines in a given year tends to be correlated with a high incidence of fines the following year. This is an intuitive finding, because deforestation itself is a spatially persistent phenomenon, typically advancing into forested areas at the forest/non-forest frontier.

[Table 2 about here.]

Yet, both the R-squared and the estimated coefficient for column 3 are considerably lower than in all other columns. This indicates that the average municipal number of fines issued in 2005 were not as closely correlated with that of 2004. Recalling that the DETER system was adopted in 2004, and that our variables are constructed to fit the PRODES year, this can be interpreted as evidence of a DETER-induced shift in the distribution of flora-related fines across Amazon municipalities — the adoption of DETER changed the basis for targeting Amazon law enforcement, leading to a reallocation of law enforcers across municipalities from 2004 to 2005. The comparatively high values of R-squared for columns associated with post-DETER years capture the persistence of law enforcement that is reestablished after the shift. This is to be expected, considering that the new satellite-based targeting system directs law enforcers to areas affected by recent forest clearing activity, which itself exhibits persistence. Thus, in addition to an increase in the absolute number of flora-related fines observed after the implementation of DETER (see Figure 3), there appears to have been a shift in the distribution of these fines across Amazon municipalities.

5.2. Cloud Coverage and Law Enforcement

Bearing these results in mind, we now turn to the assessment of the impact of average annual DETER cloud coverage on the intensity of law enforcement, using the number of flora-related fines issued in each Amazon municipality as a proxy for the presence of law enforcers in that municipality. Table 3 presents OLS coefficients for specifications that gradually include controls as follows: column 1 reports results for the univariate regression; column 2 adds controls for rainfall, temperature, PRODES cloud coverage, and PRODES non-observable areas; column 3 adds municipality and year fixed effects; column 4 adds controls for agricultural commodity prices; and column 5 adds controls for priority municipality status and percentage of municipal area covered by protected areas. Note that the conservation policy controls in column 5 are known to suffer from endogeneity with deforestation (see discussion in Section 3) and are therefore only included as robustness checks.

[Table 3 about here.]

Results indicate that, for a given municipality and year, an increase in average annual DETER cloud coverage significantly reduces the number of flora-related fines issued in that municipality and year. Coefficients remain negative and significant at standard significance levels in all specifications. Taking column 4 as our main specification, we find that a 10 percentage point increase in DETER cloud coverage leads to a reduction of 1.18 in the number of fines at the municipality level. In relative terms, this is equivalent to a 17% increase in the sample average for annual DETER cloud coverage leading to a

11% decrease in the sample average for the number of flora-related fines during our period of interest. Estimated coefficients for PRODES cloud coverage and non-observable areas are not significant at 1% and 5% levels, which lends support to our instrument meeting exclusion restrictions.

5.3. Law Enforcement and Deforestation

Table 4 provides estimated coefficients for the impact of law enforcement on deforestation. Were we to use OLS estimation (Panel A, column 1), we would find that an increase in the municipality-level number of flora-related fines in a given year does not significantly affect deforestation the following year — not only is the point-estimate zero, but it is also statistically insignificant. This finding is, however, incorrect. The magnitude and significance of coefficients estimated using 2SLS (Panel A, columns 2 and 3) indicate that OLS results are biased. By contrast, 2SLS results show that a greater number of flora-related fines in a given year will significantly reduce deforestation the following year. This provides causal empirical evidence that increased intensity of monitoring and law enforcement effectively curbs tropical deforestation. The result is consistent in both magnitude and significance across instrumental variable specifications, indicating that the main findings are not driven by our choice of normalization for the dependent variable.

[Table 4 about here.]

Note, however, that F-statistics for first-stage estimations in Table 4 raise concerns about our instrument's strength, with $F < 10$ suggesting a weak instrument (Stock et al., 2002). To address this, Table 4 also reports statistics for Anderson and Rubin (1949) and Stock and Wright (2000) tests, both of which provide weak instrument-robust inference for testing the significance of the endogenous regressor. AR and SW statistics indicate that the coefficient of the endogenous law enforcement variable is significantly different from zero in spite of the weak instrument. This corroborates our finding that increased intensity of law enforcement in a given year has a significant deterrent effect on Amazon deforestation the following year.

5.4. Counterfactual Simulation

To better understand the magnitude of this effect, we conduct a counterfactual simulation to estimate total sample deforestation in a hypothetical scenario in which Amazon monitoring and law enforcement has been entirely shut down. To do this, we assume that no fines were applied in all municipalities from 2006 through 2011 — law enforcers were entirely absent from the Amazon. Table 5 presents both observed and counterfactual annual deforestation figures. We estimate that, without environmental monitoring and law enforcement, over 152,500 square kilometers of tropical forest would have been cleared between 2007 and 2011 — more than three and a half times total observed sample deforestation during this period. Results indicate that monitoring and law enforcement efforts helped avoid the cutting down of an average 22,000 square kilometers of forest per year.

[Table 5 about here.]

5.5. Persistence of Deterrent Effect

Thus far, findings attests to the strong deterrent effect of law enforcement on Amazon deforestation. To further characterize this effect, we test for its persistence. Table 6 presents estimated coefficients from regressions that reproduce our preferred specification (Table 4, Panel A, column 2) with additional double and triple lags for the number of flora-related fines. Results indicate that the deterrent effect of law enforcement dissipates over time — greater intensity of law enforcement today will have a strong deterrent effect on deforestation one year from now, a smaller deterrent effect on deforestation two years from now, and no significant effect on deforestation three years from now. This pattern reinforces the need to sustain continuous monitoring and law enforcement efforts in the Amazon to effectively combat tropical forest clearings.

[Table 6 about here.]

5.6. Leakage Effects

Results indicate that law enforcement was effective at curbing Amazon in the second half of the 2000s. Yet, our strategy does not ensure that deforestation reduction was a widespread phenomenon — within-municipality clearings may have been contained in light of stricter law enforcement, but potential leakage may have redistributed forest clearings into municipalities where law enforcers were not as present. We use descriptive, anecdotal, and regression-based evidence to argue that monitoring and law enforcement effectively contributed to contain aggregate Amazon deforestation.

First, recall Figure 3, which shows that total deforestation in the Amazon Biome fell sharply from 2003 through 2011. Indeed, during this period, the Amazon-wide deforestation rate peaked at over 27,000 square kilometers and subsequently dropped to around 6,000 square kilometers (INPE, 2013b). This illustrates how aggregate forest clearings slowed down in the Brazilian Amazon starting in the mid-2000s, which coincides with the timing of adoption of the DETER system.

Second, the very nature of the DETER system inhibits leakage of deforestation. As the monitoring satellite covers the full extent of the Amazon at all times, potential forest clearing agents cannot easily identify an area that is subject to more or less monitoring at any given time. One could argue that, because details regarding DETER's limitation to detect land cover beneath clouds are public, offenders could try to concentrate clearing activity in areas more prone to cloud coverage. We find this to be an unlikely story. After all, once clouds clear and deforestation is detected by DETER, an alert would be issued and the area would likely be targeted by law enforcers. Considering that clearing tropical forest and converting the land to productive agricultural use is usually a time-consuming process, basing one's decision of where to deforest on the location of clouds would probably not allow sufficient time for offenders to collect the benefits from deforestation before law enforcers reach them. In addition, recall from Figure 2 that there is considerable spatial variation in cloud coverage within the year.[26] Thus, it is unlikely that a substantial area of the Amazon will be constantly covered by clouds.

Finally, we explore the effect of law enforcement on forest clearings using a more aggregate unit of analysis — a municipality's neighborhood. We test three alternative definitions for neighborhood: (i) a municipality plus all municipalities with which it shares a border; (ii) a municipality plus its three closest neighbors; and (iii) a municipality plus all municipalities located within its 200-kilometer buffer.[27] We estimate the impact of an increase in the number of environmental fines in a given municipality on total deforestation occurring within its neighborhood. The estimation equation is given by:

$$Deforestation_{\partial i,t} = \beta_1 Fines_{it-1} + \sum_k \beta_k X_{kit} + \alpha_i + \phi_t + \epsilon_{it} \tag{5}$$

where all variables are defined as before, $Fines_{it-1}$ are again instrumented by $DETERclouds_{it-1}$, and the ∂i subscript denotes a variable at the neighborhood level.

Table 7 presents estimated coefficients for each of the alternative definitions of neighborhood. Results show that, in all specifications, the number of environmental fines in municipality i had a significant negative impact on deforestation in its neighborhood. These empirical findings, combined with the observed decrease in aggregate Amazon deforestation rates and the nature of the DETER monitoring system, suggest that increased law enforcement in a given municipality did not lead to leakage of forest clearing activity into neighboring areas.

[Table 7 about here.]

[26] Although Figure 2 illustrates select data for 2011, other sample years exhibit similar patterns in terms of within-year variation in cloud coverage.

[27] In definition (ii), distance is measured from municipalities' centroids. In definition (iii), deforestation in each neighbor is weighted by a factor of $exp(-\tau * distance)$, where τ is chosen such that a neighbor that is 50 kilometers away from a given municipality receives a weight of 1/2.

6. Robustness Checks

Although our results are consistent with the relevant Brazilian institutional context, we subject them to a series of robustness tests.

6.1. Instrument Definition

We start by testing whether coefficients capture a spurious effect due to the potential correlation between PRODES cloud coverage and DETER cloud coverage.[28] Although the satellites used in the two remote sensing systems are different, both cannot detect land cover patterns beneath clouds. Yet, while DETER is an year-round system, PRODES uses imagery only from the Amazon's dry season to optimize visibility (see details in Section 4.1). We explore this feature to create an alternative instrument for law enforcement that is, by construction, better insulated against cloud correlation — we recalculate average DETER cloud coverage for each municipality excluding the period of PRODES remote sensing. Table 8 presents second-stage coefficients estimated using the alternative instrument. Results remain robust throughout, suggesting our main findings are not being driven by a mechanical correlation between DETER cloud coverage and PRODES cloud coverage and non-observable areas.

[Table 8 about here.]

6.2. Time Trends

Our identification strategy relies on the fact that municipalities are comparable after controlling for observable characteristics and municipality and year fixed effects. However, one could argue that our results may have been driven by baseline differences across municipalities that cause them to follow different deforestation trends, and that are not adequately mitigated by the inclusion of municipality and year fixed effects. We raise three scenarios in which this concern might hold, and propose empirical means of testing for them individually by adding scenario-specific controls to our preferred 2SLS specification (Table 4, Panel A, column 2).

First, remaining forest cover prior to the implementation of DETER varies significantly across Amazon municipalities. This variation could affect municipal deforestation trends, since the area in which forest clearings can still take place within a municipality decreases with decreasing forest cover.[29] We therefore control for a trend

[28] Correlation coefficients are 0,21 for DETER cloud coverage and PRODES cloud coverage, and 0,08 for DETER cloud coverage and PRODES non-observable areas.

[29] In addition to being correlated with current deforestation increments, the stock of deforestation might also be correlated with local microclimate, as discussed briefly in Section 4.4. Thus, in addressing this case, we are also addressing one of the concerns regarding the validity of our instrument's exclusion restriction.

determined by the pre-DETER share of cleared forest area in each municipality — an interaction between a linear year trend and total deforested area in 2003 as share of municipal area. Second, the deforestation increment in pre-sample years could itself be associated with municipal forest clearing patterns in our sample. If higher municipality deforestation is indicative of a more dynamic local economy, a baseline difference in deforestation increment could result in different clearing trends over time, as economically more dynamic municipalities may be subject to greater deforestation pressures. While the first scenario looks at a stock dimension of municipal deforestation, this scenario looks at a flow dimension of it. We run a similar test as in the previous case, but instead of using the pre-DETER share of deforested territory, we control for a trend determined by municipal deforestation increments observed in 2003 — an interaction between a linear year trend and the 2003 deforestation increment.[30] Third, the pre-DETER distribution of law enforcement could have affected municipalities' post-DETER deforestation trends. The deterrent effect of monitoring may have pushed municipalities subject to more intense law enforcement in the early 2000s into different deforestation trajectories as compared to those that were relatively less targeted by law enforcers during the same period. We address this by controlling for a trend determined by the 2002 through 2004 fines average — an interaction between a linear year trend and the average number of flora-related fines issued in each municipality between 2002 and 2004.

[Table 9 about here.]

Should our results have been driven by the natural convergence in forest clearing activity between municipalities with varying stocks of deforested areas, different economic dynamics and deforestation pressures, or shifts in the distribution of law enforcement, tests involving the proposed time trends should yield insignificant coefficients for our law enforcement variable. Results, shown in Table 9, Panel A, attest to the robustness of our estimated effects.

6.3. Sample and Variable Selection

As an additional set of robustness checks, we test whether alternative definitions for sample and controls affect our results. Table 9, Panel B, shows estimated coefficients. We again address the concern regarding the municipal stock of remaining forest area by restricting our sample to municipalities that had over 50% of forest cover in 2003. Results show that the coefficient for law enforcement is negative and significant in the restricted sample. Finally, we consider other conservation policies that, although relevant,

[30] Note that this test captures potential effects from differences in infrastructure across municipalities, such as road networks.

are not included in our preferred specification due to endogeneity concerns (see Section 3). As seen in Column 2, the inclusion of controls for priority municipalities and share of municipal area under protection reduces the significance of our coefficient of interest, which remains significant at a level of 10%, but does not affect its sign. Note that the positive point-estimate for the protected areas variable confirms our endogeneity concerns. Protected areas created in the second half of the 2000s as a means to block the advance of deforestation were typically located near areas of intense forest clearing activity. The estimated positive coefficient captures this activity, as municipalities where deforestation was highest tended to concentrate the creation of new protected areas, and therefore had a higher share of protected territory.

Finally, our last set of robustness exercise tests the quality of our precipitation variable. Our instrument's exclusion restriction hinges on, conditional on controls, DETER cloud coverage being uncorrelated with deforestation through all channels other than law enforcement. The inclusion of rainfall as a control is therefore central to our instrument's validity. Although climate data have been extensively used in the economic literature, the applicability of certain datasets can be questioned in specific cases. In particular, data sets compiled from ground weather station data in areas with low station density — as is the case with the Brazilian Amazon — can carry significant inaccuracies. Climate scientists have developed several gridded data products using a variety of interpolation techniques to construct grid node-level data for these areas using information collected in ground stations. Because the constructed data associated with each grid node may vary according to the method chosen for interpolation, different techniques might yield considerably different datasets for the same region. Thus, results for evaluations that use climate data like our own might ultimately depend on the data that have been used.

Common practice to mitigate this concern in the economic literature determines that empirical results be subjected to robustness tests using alternative data sets for climate variables (Dell et al., 2014). If results prove robust to the change, they are more likely to be independent from the specific interpolation technique used in climate data construction. We therefore provide a last set of robustness checks, running regressions with our preferred specification, but using two alternative sources of data for the precipitation variable.The Global Precipitation Climatology Center (GPCC) is a gridded dataset built from interpolated ground station data (as is our main dataset), while the ERA Project data set uses climate model inference to calculate total precipitation.Table 10 presents OLS and 2SLS coefficients for both alternative sources. Columns 1 and 2 refer, respectively, to first- and second-stage regressions using GPCC data, while columns 3 and 4 refer to first- and second-stage regressions using ERA Project data. Results are generally consistent with those obtained using the Matsuura and Willmott (2015) data, which suggests that our findings are robust to alternative precipitation data sets.

[Table 10 about here.]

Overall, the robustness of our results supports the specifications chosen for our preferred regressions, as well as the interpretation of our findings.

7. Costs and Collateral Effects of the Policy

Overall, our findings suggest that stricter monitoring and law enforcement efforts were effective at curbing deforestation in the Brazilian Amazon — but at what cost? From a financial standpoint, were they a cost-effective way of protecting the forest? From a production standpoint, did they have any adverse effects on agricultural production? In this section, we address each of these concerns in turn.

7.1. Cost-benefit Analysis

We make a first attempt at answering whether more stringent Amazon monitoring and law enforcement was a cost-effective policy by performing a back-of-the-envelope calculation of its costs and benefits. 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. We use figures from our counterfactual simulation to account for the Amazon-wide deterrent effect of monitoring and law enforcement.

According to our simulation, monitoring and law enforcement efforts preserved an average of 22,200 km^2 of tropical forest area per year between 2007 and 2011. This is equivalent to approximately 815 million tCO_2 per year.[31] 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 0.84 USD/tCO_2 would more than compensate the cost of environmental monitoring and law enforcement in the Brazilian Amazon. Compared to the price of 5.00 USD/tCO_2 commonly used in current applications, these figures suggest that active Amazon monitoring and law enforcement have the potential to yield significant net monetary gains.

Note that our estimates only capture a lower bound for this potential gain. The assumption that Ibama and INPE are exclusively dedicated to Amazon monitoring and law enforcement leads to an overestimation of the cost of protecting the forest — in reality,

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

only a share of their budgets is used for this. In addition, we only consider the emissions-saving dimension of protecting tropical forest. There may well be other benefits of doing so, such as the preservation of biodiversity and protection of watersheds, implying that our calculations underestimate the benefits of protecting the forest (Stern, 2008; Burgess et al., 2012). Thus, in being a conservative estimate, our cost-benefit comparison becomes even more striking.

7.2. Agricultural Impact

There is an ongoing debate among both academics and policymakers regarding potential tensions between economic growth and conservation of natural resources. The concepts are not mutually exclusive by definition — in fact, there is anecdotal and limited causal evidence that some countries have experienced improvements in environmental quality alongside economic development.[32] Yet, the very nature of agricultural production, which essentially depends on the availability of land, implies it is closely related to practices that make such land available. Indeed, deforested land in the Amazon has largely been destined for use in cattle ranching — since the mid-2000s, more than two thirds of cleared areas had been converted into pasture (INPE, 2013c). In light of this, it would be reasonable to expect agricultural production to be affected by an increase in law enforcement stringency that slows down forest clearings.

The topic is of particular relevance to the Brazilian Amazon, which has a long history of insecure land property rights. As a historical account of the occupation of the Amazon and its consequences for land tenure in the region are out of the scope of this paper[33], it suffices to say that the Brazilian institutional framework does not favor the protection of landholders' rights, with land reform policies standing as a particular threat to title holders who risk losing their land to agrarian reform (Araujo et al., 2009). To this day, violent conflict over land is not uncommon in the Amazon, and squatters, which have been known to occupy both public and private lands, are still active in the region (Alston et al., 2000; Araujo et al., 2009). Combined, these factors serve as a disincentive to the formality of land tenure and agricultural production.

Bearing this in mind, we investigate whether the greater intensity of law enforcement had an adverse impact on local agricultural production. We use two different measures of municipality-level production: (i) agricultural GDP from Brazilian national accounts,

[32]See Arrow et al. (1995) for an early, but concise and targeted, criticism of the idea behind improvements in environmental quality following economic growth, and Stern (2004) for a brief review of the empirical literature that seeks to assess the phenomenon. Foster and Rosenzweig (2003) provide one of the few insights into the causes of an observed increase in forest area during a period of economic expansion in India. The authors explore an empirical setting that enables the distinction between an increase in demand for forest amenities (such as clean air) and an increase in demand for forest products (such as wood for fuel). They find support for the latter mechanism.

[33]See Mueller et al. (1994) for an overview.

and (ii) crop revenues from PAM/IBGE. Table 11 presents coefficients estimated in 2SLS using both our preferred specification (Table 4, Panel A, column 2) and a version of it that does not include agricultural commodity prices. Because agricultural GDP is a measure of value, controlling for prices allows us to capture the potential impact of law enforcement on agricultural quantum.

[Table 11 about here.]

Results, which are consistent across specifications, cannot statistically conclude that there is trade-off between conservation and agricultural production. This suggests that it would be possible to contain forest clearings without significantly compromising local agricultural production. Although informative, this exercise is not entirely conclusive. The effect may have resulted from agricultural producers responding to stricter law enforcement by shifting from a low-productivity setup to a more productive one.In this sense, production that was lost at the extensive margin may have been compensated for at the intensive one. Moreover, not having an immediate adverse effect on agriculture does not mean that law enforcement had no effect at all. If farmers adjust production over time, our sample period might not be sufficient to capture this effect. Future investigations of this topic, once data become available, could shed light on the matter.

Our results also fail to capture potential impacts on informal production, since agricultural GDP and crop revenue only measure production within the formal sector. This is an important caveat considering the Amazon's history of insecure property rights. In light of this, it is to be expected, though difficult to measure, that informality accounts for a relevant share of agricultural production in the Amazon. An analysis capable of looking at the informal sector, subsistence agriculture, or individual-level production, might yield different results to those presented in Table 11 — to the best of our knowledge, no data is currently available for this analysis.

8. Final Comments

Combined, our results show that monitoring and law enforcement played a crucial role in curbing Amazon deforestation, and thereby containing greenhouse gas emissions. Moreover, it appears that the policy was relatively cost-effective, both in financial and (immediate) agricultural production terms.

Our findings yield important policy implications. The sheer magnitude of estimated forest area spared from deforestation in counterfactual exercises suggests that monitoring and law enforcement is a cornerstone of Brazilian conservation policy. This does not in any way imply that other policies should not be used to combat tropical deforestation. Rather, it indicates that such policies are complementary to monitoring and law enforcement efforts, effectively deterring forest clearings at the margin, while monitoring and law enforcement contain the bulk of deforestation.

Additionally, our results strongly speak for the strategic use of advanced technology for combating deforestation. Indeed, they show there is substantial value in further improving remote sensing-based monitoring. In particular, overcoming DETER's incapacity to see through clouds and obtaining higher-resolution land cover imagery at high frequency are two examples of technological advances that could improve law enforcement targeting capability and add significant value to Brazil's conservation efforts. Some enhancements to Amazon monitoring capability are already in place: Ibama has used radar technology, capable of detecting land cover patterns beneath cloud coverage, to monitor forest clearing activity in select areas of the Amazon, and INPE is developing the DETER-B and DETER-C systems to provide information on deforestation hot spots at higher resolutions (though lower frequencies) than the one currently available in DETER. Our findings reinforce the need of continuing and amplifying the use of such technologies.

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 monitoring and law enforcement efforts, and for continuing to improve technology that supports these efforts.

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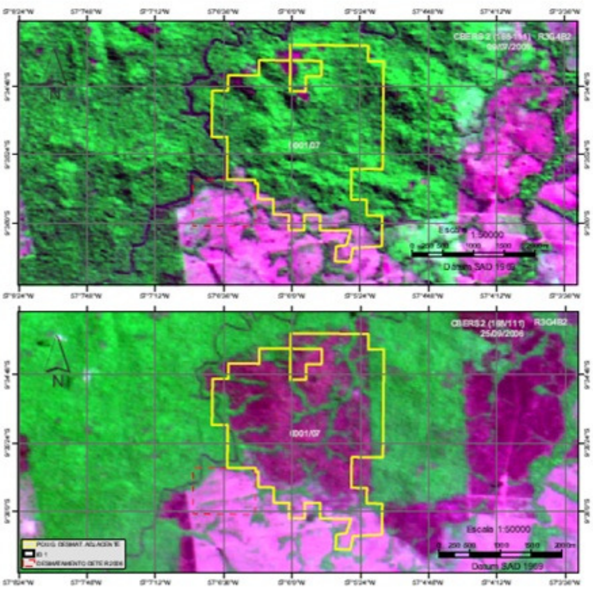
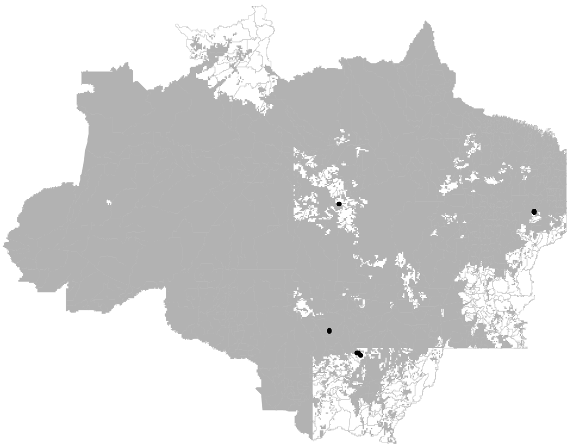
Figure 1: How is Deforestation Detected in DETER Satellite Imagery?



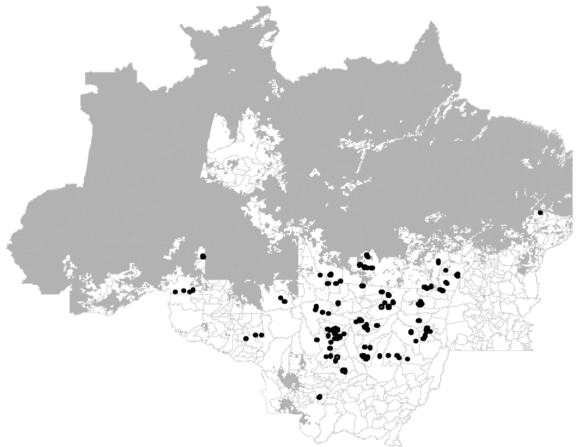
Notes: top and bottom panels show satellite images of the same location recorded at two different moments in time — the top panel is an earlier image and the bottom panel a later one. Green indicates forest areas and purple indicates deforested areas. The area outlined in yellow, which shows signs of changes in land cover, would trigger the issuing of a deforestation alert in DETER. Source (image): Ibama.

Figure 2: DETER Cloud Coverage and Deforestation Alerts

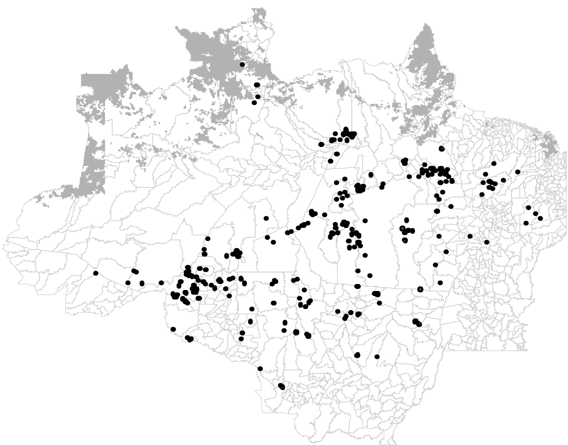
(a) January 2011



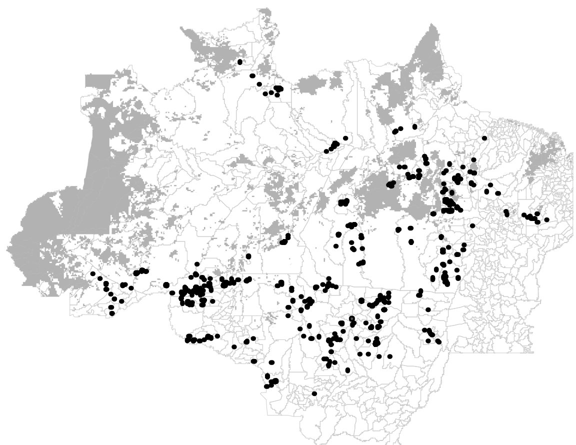
(b) April 2011

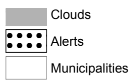


(c) July 2011



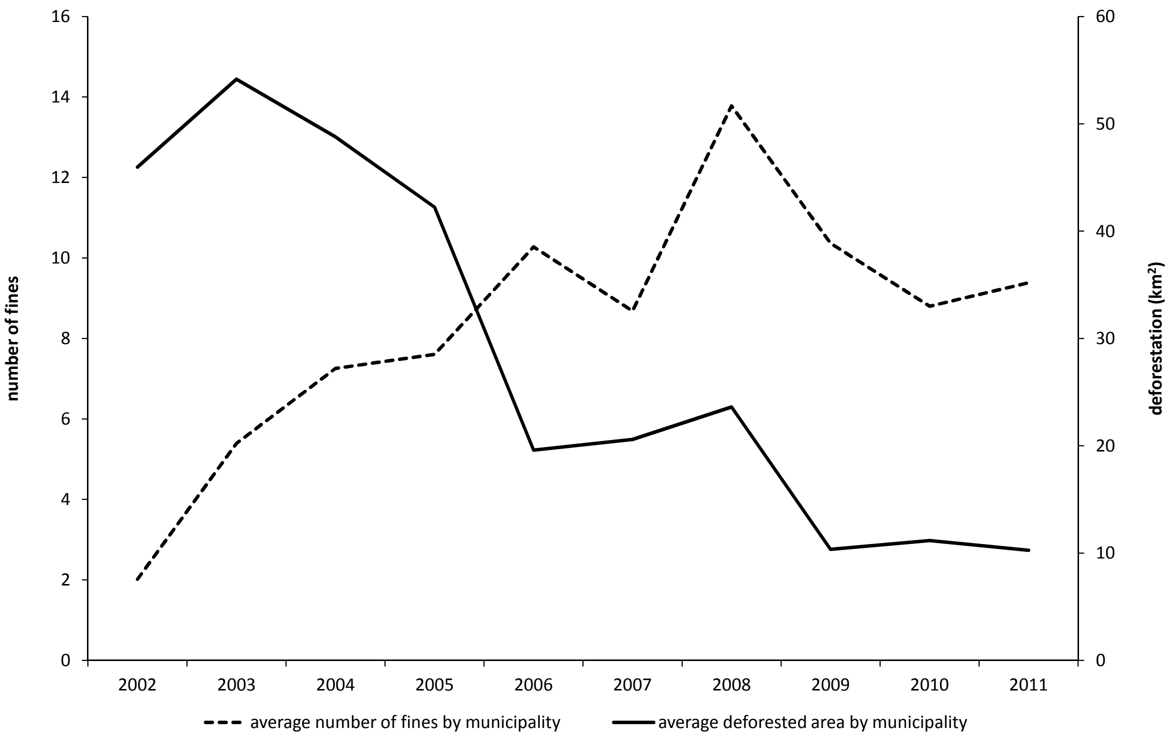
(d) October 2011





Notes: maps portray DETER cloud coverage and deforestation alerts for four sample months in 2011. The figure shows that no alerts are issued in areas covered by clouds. It also illustrates the typically high degree of within-year variation in DETER cloud coverage for any given area in the Brazilian Amazon. Source: authors' elaboration based on data from DETER/INPE.

Figure 3: Number of Flora-Related Fines and Deforestation



Notes: the figure shows the municipality-level average number of flora-related fines and average deforestation increment. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. Source: authors' elaboration based on data from Ibama (fines) and PRODES/INPE (deforestation).

Table 1: Descriptive Statistics

	2006	2007	2008	2009	2010	2011
Deforestation	20.38	21.41	24.56	10.77	11.61	10.67
	(54.34)	(59.12)	(57.76)	(34.55)	(28.23)	(27.90)
Number of fines	10.65	8.99	14.29	10.71	9.10	9.74
	(23.77)	(19.47)	(33.58)	(30.86)	(21.74)	(24.70)
DETER cloud	0.38	0.70	0.60	0.67	0.60	0.54
	(0.07)	(0.17)	(0.21)	(0.22)	(0.22)	(0.20)
PRODES cloud	372.73	563.13	437.46	430.15	819.80	552.70
	(1,440.88)	(2,392.92)	(1,795.98)	(1,387.30)	(3,297.15)	(2,866.25)
PRODES non-observable	48.29	49.06	23.56	16.41	14.81	14.76
	(261.46)	(261.85)	(231.41)	(101.83)	(101.19)	(101.12)
Rainfall	2,243.13	2,169.45	2,233.80	2,205.30	1,930.27	.
	(616.45)	(615.68)	(574.07)	(518.35)	(399.03)	(.)
Temperature	26.03	26.23	25.91	26.17	26.70	.
	(1.15)	(1.09)	(1.22)	(1.17)	(1.27)	(.)
Agricultural GDP	17,927.22	20,252.44	23,408.18	22,442.18	.	.
	(19,711.73)	(27,926.51)	(35,564.35)	(30,861.94)	(.)	(.)
Crop production	9,988.08	11,888.89	15,644.88	14,096.38	12,349.22	16,679.24
	(27,641.19)	(38,200.96)	(55,204.72)	(48,380.42)	(35,139.75)	(56,404.34)
Price, beef cattle	65.04	71.86	86.94	82.05	85.09	91.84
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price, soybean	74.73	86.80	103.59	106.54	83.67	89.70
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price, cassava	54.18	79.72	83.04	79.34	122.18	99.50
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price, rice	92.42	97.23	119.17	110.49	102.54	73.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price, corn	58.92	77.43	74.58	62.61	56.77	75.75
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price, sugarcane	108.81	93.09	74.49	80.11	88.34	107.86
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: the table reports municipality-level annual means and standard deviations (in parentheses) for the variables used in the empirical analysis. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. Sources and units: deforestation (square kilometers, PRODES/INPE); flora-related fines (total number, Ibama); DETER cloud coverage (share of municipal area, DETER/INPE); PRODES cloud coverage (square kilometers, PRODES/INPE); PRODES non-observable area (square kilometers, PRODES/INPE); rainfall (millimeters, Matsuura and Willmott (2015)); temperature (degrees Celsius, Matsuura and Willmott (2015)); agricultural GDP (BRL, IBGE); crop production as revenue (BRL, PAM/IBGE); crop price indices (year 2000 BRL, SEAB-PR and PAM/IBGE); cattle price index (year 2000 BRL, SEAB-PR and PPM/IBGE).

Table 2: Descriptive Regressions: Correlation Between Municipality-Level Number of Flora-Related Fines in Consecutive Years

	(1) Fines 2003	(2) Fines 2004	(3) Fines 2005	(4) Fines 2006	(5) Fines 2007	(6) Fines 2008	(7) Fines 2009	(8) Fines 2010	(9) Fines 2011
Fines 2002	2.340***								
	(0.099)								
Fines 2003		1.292***							
		(0.041)							
Fines 2004			0.356***						
			(0.027)						
Fines 2005				0.909***					
				(0.042)					
Fines 2006					0.584***				
					(0.025)				
Fines 2007						1.310***			
						(0.049)			
Fines 2008							0.696***		
							(0.026)		
Fines 2009								0.552***	
								(0.019)	
Fines 2010									0.827***
									(0.034)
Observations	526	526	526	526	526	526	526	526	526
R-squared	0.518	0.653	0.244	0.478	0.509	0.576	0.573	0.615	0.530

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2002 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. Each column presents the coefficient estimated using univariate OLS in which the number of flora-related fines issued in year t are regressed on the number of flora-related fines issued in year $t-1$ at the municipal level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: OLS Regressions: Effect of DETER Cloud Coverage on Number of Flora-Related Fines

	(1) Fines	(2) Fines	(3) Fines	(4) Fines	(5) Fines
DETER cloud	-12.584***	-14.437***	-6.385*	-11.807**	-10.243**
	(2.713)	(2.574)	(3.565)	(4.623)	(4.428)
Rainfall		0.007		-0.462***	-0.470***
		(0.103)		(0.155)	(0.156)
Temperature		0.665		-3.398**	-2.972**
		(0.756)		(1.395)	(1.392)
PRODES cloud		0.023		0.027*	0.026*
		(0.022)		(0.016)	(0.015)
PRODES non-observable		-0.058		0.074	0.061
		(0.193)		(0.062)	(0.056)
Priority municipalities					7.928**
					(3.598)
Protected areas					15.304**
					(7.584)
Observations	3,156	2,630	3,156	2,630	2,630
R-squared	0.011	0.012	0.020	0.034	0.040
Municipality and year FE	No	No	Yes	Yes	Yes
Prices	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 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. The dependent variable is the number of fines issued as sanction for flora-related infractions at the municipal level. Column 1 presents OLS coefficients for a specification with no controls; column 2 adds controls for rainfall, temperature, PRODES cloud coverage, and PRODES non-observable areas; column 3 adds municipality and year fixed effects; column 4 adds controls for agricultural commodity prices; column 5 adds controls for priority municipality status and percentage of municipal area under protection (note that these variables are known to be endogenous and are only added as robustness checks — see discussion in Section 3). Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: IV Regressions: Effect of Law Enforcement on Deforestation

Panel A: second-stage Results

	(1) OLS: normalized deforestation	(2) IV: normalized deforestation	(3) IV: log deforestation
Number of fines, t-1	-0.0006	-0.0564**	-0.0738**
	(0.0008)	(0.0267)	(0.0319)
Municipality and year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	2,630	2,630	2,630
Number of municipalities	526	526	526
F-statistic from first stage		6.336	6.336
AR - Chi2		13.50	24.60
Prob > AR		0.000239	7.04e-07
SW - S - stat		17.42	27.53
Prob > SW		2.99e-05	1.54e-07

Panel B: first-stage Results

	Fines
DETER cloud	-11.4735**
	(4.5583)
Rainfall, t-1	-0.4874***
	(0.1605)
Temperature, t-1	-2.9600**
	(1.3712)
PRODES cloud	0.0304
	(0.0289)
PRODES non-observable	0.2434
	(0.2059)
Municipality and year FE	Yes
Prices	Yes
Observations	2,630
Number of municipalities	526

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. Panel A reports second-stage results; column 1 presents OLS coefficients; columns 2 and 3 present 2SLS coefficients using DETER cloud coverage as an instrument for the number of flora-related fines. The dependent variable used in columns 1 and 2 is the normalized annual municipal deforestation increment; in column 3, it is replace by the log of the annual municipal deforestation increment. The specification used for all regressions in Panel A is that of equation (2), such that all columns include controls for lagged rainfall, lagged temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Panel B reports first-stage results. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Counterfactual Simulation: Shut Down of Amazon Law Enforcement

Year	Observed deforestation	Estimated deforestation	Difference estimated–observed
2007	11,263	30,941	19,678
2008	12,918	33,218	20,300
2009	5,663	31,203	25,541
2010	6,109	31,013	24,904
2011	5,610	26,173	20,563
Total 2007–2011	41,563	152,549	110,986

Notes: all figures are in square kilometers. The counterfactual simulation is conducted using estimated coefficients from our preferred specification (Table 4, Panel A, column 2). The hypothetical scenario sets the annual number of flora-related fines in each municipality from 2006 through 2011 as zero to capture the complete absence of law enforcers in the Amazon. "Observed deforestation" shows total recorded sample deforestation; "Estimated deforestation" shows total estimated sample deforestation in hypothetical scenario in which no flora-related fines are issued in any municipality throughout the sample period; "Difference" reports the difference between estimated and observed totals.

Table 6: Persistence of Law Enforcement Deterrent Effect

	(1) IV: normalized deforestation	(2) IV: normalized deforestation
Fines, t–2	-0.0324*	
	(0.0169)	
Fines, t–3		-0.0111
		(0.0118)
Observations	2,104	1,578
Number of municipalities	526	526
Municipality and year FE	Yes	Yes
Controls	Yes	Yes

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. All regressions are based on our preferred specification (Table 4, Panel A, column 2). 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 flora-related 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 flora-related fines, which is instrumented by three-period-lagged DETER cloud coverage. All specifications include controls for rainfall, temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7: Deforestation Leakage Effects

	(1) All border neighbors	(2) Three nearest neighbors	(3) 200km buffer
Fines in t–1	-0.107*	-0.089*	-0.116**
	(0.062)	(0.049)	(0.058)
Number of municipalities	545	540	545
Municipality and year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. All regressions are based on our preferred specification (Table 4, Panel A, column 2), but are adapted to capture leakage effects following equation (5). All specifications are estimated using 2SLS, the normalized annual municipal deforestation increment as dependent variable, and DETER cloud coverage as an instrument for the number of flora-related fines. A municipality's neighborhood is alternatively defined as: (i) a municipality plus all municipalities with which it shares a border (column 1); (ii) a municipality plus its three closest neighbors (column 2); and (iii) a municipality plus all municipalities located within its 200-kilometer buffer (column 3). All specifications include controls for rainfall, temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Robustness Checks: Effect of Law Enforcement on Deforestation Using Alternative Instrument

VARIABLES	(1) OLS: normalized deforestation	(2) IV: normalized deforestation	(3) IV: log deforestation
Number of fines, t-1	-0.0006	-0.0442**	-0.0555**
	(0.0008)	(0.0220)	(0.0250)
Observations	2,630	2,630	2,630
Number of municipalities	526	526	526
Municipality and year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
F-statistic from first-stage		6.598	6.598
AR - Chi2		9.503	14.69
Prob > AR		0.00205	0.000127
SW - S - stat		9.377	14.20
Prob > SW		0.00220	0.000165

Notes: average annual DETER cloud coverage is calculated excluding PRODES remote sensing months. Coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. Column 1 presents OLS coefficients; columns 2 and 3 present 2SLS coefficients using DETER cloud coverage as an instrument for the number of flora-related fines. The dependent variable used in columns 1 and 2 is the normalized annual municipal deforestation increment; in column 3, it is replace by the log of the annual municipal deforestation increment. The specification used for all regressions is the same as that of Table 4, Panel A, column 2, such that all columns include controls for lagged rainfall, lagged temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Robustness Checks: Effect of Law Enforcement on Deforestation

Panel A: time trends

	(1)	(2)	(3)
Fines, t–1	-0.0711**	-0.0547**	-0.0531**
	(0.0330)	(0.0276)	(0.0246)
Trend * 2003 share of deforested area	Yes		
Trend * 2003 deforestation increment		Yes	
Trend * 2002–2004 average of fines			Yes
Observations	2,630	2,630	2,630

Panel B: alternative sample and additional controls

	(1) restricted sample	(2) endogenous controls
Fines, t–1	-0.0680**	-0.0598*
	(0.0326)	(0.0357)
Priority municipalities		0.0821
		(0.414)
Protected areas		2.479*
		(1.500)
Observations	1,655	2,630

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. All regressions are based on our preferred specification (Table 4, Panel A, column 2). All specifications are estimated using 2SLS, the normalized annual deforestation increment as dependent variable, and average annual DETER cloud coverage as an instrument for the number of fines. All specifications include controls for lagged rainfall, lagged temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Panel A presents results for three different time trend tests: column 1 controls for an interaction between a linear year trend and total deforested area in 2003 as share of municipal area; column 2 controls for an interaction between a linear year trend and the 2003 deforestation increment; and column 3 controls for an interaction between a linear year trend and the average number of fines applied in each municipality between 2002 and 2004. Panel B presents results for non-trend tests: column 1 uses a restricted sample of municipalities that had over 50% of forest cover in 2003; and column 3 adds controls for priority municipality status and percentage of municipal area covered by protected areas. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Robustness Checks: Effect of Law Enforcement on Deforestation Using Alternative Precipitation Data

	(1) OLS using GPCC dataset	(2) 2SLS using GPCC dataset	(3) OLS using ERA Project dataset	(4) 2SLS using ERA Project dataset
Fines, t–1	-0.0005	-0.0622*	-0.0006	-0.0623**
	(0.0008)	(0.0328)	(0.0008)	(0.0312)
Observations	2,610	2,610	2,630	2,630
Number of municipalities	522	522	526	526
Municipality and year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
F-statistic from first-stage		5.110		5.518
AR - Chi2		11.39		13.01
Prob > AR		0.000740		0.000310
SW - S - stat		11.10		12.65
Prob > SW		0.000865		0.000376

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. All regressions are based on our preferred specification (Table 4, Panel A, column 2). All specifications are estimated using 2SLS, the normalized annual municipal deforestation increment as dependent variable, and DETER cloud coverage as an instrument for the number of flora-related fines. All specifications include controls for lagged rainfall, lagged temperature, PRODES cloud coverage, PRODES non-observable areas, agricultural commodity prices, and municipality and year fixed effects. Columns 1 and 2 refer, respectively, to first- and second-stage regressions using GPCC precipitation data, while columns 3 and 4 refer to first- and second-stage regressions using ERA Project precipitation data. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 11: The Effect of Monitoring and Law Enforcement on Agricultural Production

	(1) Agricultural GDP	(2) Crop production	(3) Agricultural GDP	(4) Crop production
Fines, t–1	0.00421	-0.0134	0.00228	-0.00372
	(0.00566)	(0.0127)	(0.00504)	(0.00954)
Observations	1,578	2,453	1,578	2,453
Number of municipalities	526	499	526	499
Municipality and year FE	Yes	Yes	Yes	Yes
Non-price controls	Yes	Yes	Yes	Yes
Price controls	No	No	Yes	Yes

Notes: coefficients are estimated using a municipality-by-year panel data set covering the 2006 through 2011 period. The sample includes all Amazon Biome municipalities that exhibited variation in forest cover during the sample period and for which data were available. All regressions are based on our preferred specification (Table 4, Panel A, column 2). All specifications are estimated using 2SLS and DETER cloud coverage as an instrument for the number of flora-related fines. The dependent variable in column 1 is agricultural GDP; in column (2) it is replaced by crop revenues. The lagged number of fines is instrumented by lagged DETER cloud coverage in all specifications. All specifications include controls for rainfall, temperature, PRODES cloud coverage, PRODES non-observable areas, and municipality and year fixed effects, but only columns 3 and 4 include controls for agricultural commodity prices. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.