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DETERring Deforestation in the Amazon: Environmental Monitoring and Law Enforcement [1]

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Abstract

We study Brazil's recent use of satellite technology to overcome law enforcement shortcomings resulting from weak institutional environments. DETER is a system that processes satellite imagery and issues near-real-time deforestation alerts to target environmental enforcement in the Amazon. We propose a novel instrumental variable approach for estimating enforcement's impact on deforestation. Clouds limiting DETER's capacity to detect clearings serve as a source of exogenous variation for the presence of environmental authorities. Findings indicate that monitoring and enforcement effectively curbed deforestation. Results are not driven by the displacement of illegal activity into neighboring areas, and hold across several robustness checks.

Keywords: deforestation, conservation, monitoring and law enforcement, crime
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1. Introduction

Greenhouse gas (GHG) emissions, the key driver of anthropogenic climate change, imply global externalities (Stern, 2008; Nordhaus, 2019). Although most of the growth in emissions over the coming decades is expected to originate in developing countries, its impact will be felt worldwide (Wolfram et al., 2012; Greenstone and Jack, 2015). As the threat of climate change looms nearer, the world's well-being increasingly depends on developing countries' capacity to successfully enact and enforce environmental policies to reduce emissions (Greenstone and Hanna, 2014; Greenstone and Jack, 2015). Yet, weak institutions, which have long been barriers to policy implementation in developing countries, often limit effective enforcement (Banerjee et al., 2008; Duflo et al., 2013; Ashraf et al., 2016). With the bulk of research on climate change and associated policy focused on developed economies, little is actually known about the effects and workings of environmental policy enforcement where it currently matters most (Burke et al., 2016).

This paper assesses the effectiveness of an environmental policy that was enacted in and enforced by Brazil, a developing country with great potential to contribute to GHG emissions reductions. It explores a unique setting in which the innovative use of remote sensing technology was paramount in overcoming limitations imposed by the country's weak institutional environment. Specifically, we investigate if environmental law enforcement that was targeted using a pioneering satellite-based monitoring system effectively reduced Brazilian Amazon deforestation.

Brazil plays a prominent role in the global fight against climate change. Extending over an area nearly half the size of continental Europe, the Brazilian Amazon is a vital carbon sink. In the early 2000s, at a time when almost a fifth of global GHG emissions originated from the (mostly tropical) forestry sector, Brazil stood out as the country that cleared most tropical forest area in both absolute and relative terms (IPCC, 2007; Hansen and DeFries, 2004; Hansen et al., 2008). As the protection of tropical forests rose to the top of the global environmental policy agenda (Burgess et al., 2012), Brazil responded to rising international pressures by launching a conservation action plan aimed at combating Amazon deforestation. Within less than a decade, Amazon forest clearing rates fell by nearly 85% (INPE, 2017).

Strengthening command and control was central to the action plan's strategy, not least because the vast majority of Amazon clearings are illegal. The cornerstone of this strategy was the implementation of the Real-Time System for Detection of Deforestation (DETER), a satellite-based system that provides near-constant surveillance of deforestation activity throughout the full extent of the Brazilian Amazon. Upon detecting a change in tropical forest cover, DETER issues a georeferenced deforestation alert signaling areas in need of immediate attention, which then serves to target environmental law enforcement. In Brazil, the ability to provide a timely response is a crucial part of an effective strategy to inhibit deforestation, because the country's institutional setup is such that environmental law enforcers can apply more binding penalties when catching offenders red-handed. This is particularly relevant in a context of frail property rights, widespread illegality, and acute lawlessness, all of which characterize the Brazilian Amazon (Alston et al., 2000; Schmitt, 2015; Fetzer and Marden, 2017; Mueller, 2018). In this context, DETER was a major leap forward in Amazon enforcement capacity, allowing environmental authorities to better identify, more closely monitor, and more quickly act upon areas being illegally deforested.

Brazil's experience with satellite-based monitoring to combat Amazon deforestation therefore offers a unique opportunity for empirical assessment. It not only provides evidence on the effectiveness of enforcing environmental policy of great international salience in a developing country, but also sheds light on how technology can be used to leverage state capacity and tackle challenges inherent to weak institutional environments. Developing countries, in particular, stand to benefit from the technology's potential to bring oversight across regions often deemed too large, remote, or unsafe for the ground presence of law enforcement personnel.[2]

The relationship between law enforcement and criminal activity is characterized by strong endogeneity, so isolating a causal effect is an empirically challenging task (Levitt, 1997; Di Tella and Schargrodsky, 2004; Draca et al., 2011; Chalfin and McCrary, 2017). In this paper, we build on an empirical setting exclusive to the Brazilian Amazon to propose a novel instrumental variable for environmental law enforcement. Our core argument is as follows. Cloud coverage blocks visibility in satellite imagery and thereby limits DETER's capacity to detect changes in land cover patterns. Because the system issues no deforestation alerts for areas covered by clouds, enforcement personnel are less likely to be allocated to these areas. We argue — and provide supporting empirical evidence — that, controlling for relevant weather controls, DETER cloud coverage serves as a valid instrument for environmental law enforcement in the Brazilian Amazon.

We explore this exogenous source of variation in law enforcement using a 2006 through 2016 panel of Amazon municipalities to recover two-stage least squares (2SLS) estimates of the impact of enforcement on deforestation, conditional on a host of controls, as well as on municipality and year fixed effects. First-stage

[2]UNOSAT, a United Nations initiative, offers a collection of examples for the use of remote sensing technology in risk zones: damage assessment in the Gaza Strip, Iraq, Nepal, Syria, and Yemen; post-disaster monitoring in Haiti and Pakistan; and tracking of refugee camps in Syria to coordinate humanitarian support (UNITAR, 2016, 2019).

results corroborate that municipalities with greater DETER cloud coverage in a given year see a significantly reduced presence of law enforcement that year, as proxied by the total number of deforestation-related fines issued in that municipality by the environmental law enforcement authority. Fines are a good proxy for environmental law enforcement in this setting, in which most clearings are illegal, because fines are issued both as standalone penalties and alongside more severe penalties for environmental infractions. They therefore serve as a means of capturing that law enforcement was present in that specific locality. Second-stage results indicate that monitoring and law enforcement were effective in curbing Amazon deforestation. This finding holds across a series of robustness exercises accounting for potentially relevant differences at baseline, varying sample composition, and alternative controls. Results further suggest that the estimated impact was sizable: on average, reducing monitoring and law enforcement by half increases municipal deforestation by an estimated 44%. This is particularly timely considering that the 2020 budget originally presented by the Brazilian Federal Government proposes cutting back on financial support for environmental monitoring and law enforcement by up to 50%.

We discuss two possible explanations for this effect in light of the changes introduced by the new monitoring system. Improved targeting of law enforcement may have deterred deforestation by causing potential offenders to update their beliefs about their chance of getting caught and, thus, their expected costs from engaging in the illegal activity. Alternatively, enforcement action leading to the loss of capital goods used in forest clearing may have reduced potential offenders' ability to commit future offenses. The exercise does not, however, reveal the underlying mechanisms for the estimated impact.

The analysis also investigates whether the monitoring and law enforcement efforts that locally curbed deforestation had additional, albeit unintended, consequences. We find no evidence to support that local reductions in forest clearings were driven by leakage of tropical deforestation activity into neighboring areas, nor do we find evidence that local agricultural production was negatively affected by the presence of law enforcement. In fact, if anything, municipalities that saw a greater presence of environmental law enforcement in a given year exhibited improved agricultural outcomes the following year. We speculate that this might be driven by the increased presence of law enforcement contributing to an improved institutional and productive environment.

This paper speaks to different strands of the economic literature. First, it contributes to a burgeoning literature on the enforcement of environmental regulation in developing countries. Environmental regulation has long been assessed in terms of both policy effectiveness and impacts on socioeconomic outcomes, but almost exclusively within the context of developed nations

(Greenstone, 2002; Chay and Greenstone, 2005; Gray and Shimshack, 2011; Keiser and Shapiro, 2019). A smaller, but recently growing, number of studies address the topic in the context of developing countries, focusing mostly on regulation aimed at reducing air and water pollution (Greenstone and Hanna, 2014; Tanaka, 2015). Greenstone and Hanna (2014) stress the need for further research on the enforcement of environmental regulation in developing countries, since empirical findings from developed nations can seldom be extended to developing ones, which typically have very different institutional environments. This is, perhaps, where our paper makes its greatest contribution, as it provides insight into how a developing nation pioneered the use of technology to leverage its capacity to enforce environmental regulation with a potential for impact that extends far beyond its national borders. After all, although fighting tropical forest clearings might not be a policy priority in all developing nations, Amazon deforestation has global climate consequences, and Brazil is currently the only country that can address it at scale.

Second, the analysis relates to a broader literature on the determinants of tropical deforestation (Pfaff, 1999; Chomitz and Thomas, 2003; Burgess et al., 2012; Souza-Rodrigues, 2019), as well as to a narrower literature dedicated to the assessment of potential policy drivers of the 2000s Brazilian Amazon deforestation slowdown (Hargrave and Kis-Katos, 2013; Assunção et al., 2015, 2019a,b; Burgess et al., 2019). Although several works in the latter literature have documented that policies significantly contributed to reduce Amazon clearing rates, none have focused on estimating the impact of environmental monitoring and law enforcement efforts, despite their central role in the action plan.[3] To the best of our knowledge, this is the first empirical evaluation of environmental monitoring and law enforcement that adequately addresses known endogeneity between illegal deforestation and the presence of law enforcers in the Brazilian Amazon.

Finally, the paper also speaks to the police and crime literature, which has long sought to disentangle the causal impact of law enforcement on illegal activity (Chalfin and McCrary, 2017). Authors have explored several alternative sources of exogenous variation in police presence, ranging from electoral cycles (Levitt, 1997; McCrary, 2002; Levitt, 2002) to terrorist attacks (Di Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al., 2011), and have, more recently, even experimented with randomized deployment of hot-spot policing (Blattman et al., 2019). This analysis contributes to the field by assessing the impact of law enforcement on criminal activity within an empirical setting that is not context-specific, but rather encompasses the full extent of the geographical area

[3] Hargrave and Kis-Katos (2013) find a negative relationship between municipal fine density and deforestation in the Brazilian Amazon, but do not explicitly account for endogeneity between law enforcement and forest clearings.

subject to the illegal activity. Thus, no additional assumptions or extrapolations are needed to draw conclusions about the effectiveness of enforcement in this setting.

The rest of the paper is organized as follows. Section 2 describes the institutional context regarding Brazilian Amazon deforestation, as well as associated environmental monitoring and law enforcement. Section 3 details the empirical strategy used to estimate the effect of law enforcement on deforestation. Section 4 describes the data and provides descriptive statistics. Section 5 presents and discusses the main results, and explores potential leakage effects and policy costs. Section 6 provides a series of robustness checks. Section 7 concludes with policy implications.

2. Institutional Context

This section presents a contextual overview of Brazilian Amazon deforestation, focusing on the three elements that are most necessary to understand law enforcement's potential for impact in this setting. It starts with a characterization of deforestation activity since the early 2000s, which occurred primarily as a means of clearing the land for non-forest uses. Because this activity was mostly illegal, it was subject to law enforcement action. The section therefore follows with a description of how environmental law enforcement targeting deforestation evolved over recent decades, particularly after the introduction of satellite-based monitoring of Amazon forest cover. It closes with a discussion about the role the novel monitoring system played in enhancing enforcement capacity, largely because it allowed enforcement authorities to provide a more timely response to infractions. In being able to more quickly detect and thereby reach sites of recent deforestation activity, law enforcers had a greater chance of catching offenders red-handed and, thus, of applying more binding penalties.

2.1. Amazon Deforestation

At the beginning of the 21st century, Brazil stood out as the country that cleared most tropical forest, both in absolute area and relative to its year-2000 forest cover (Hansen et al., 2008). By 2004, deforested area totaled over 600 thousand km^2, nearly 15% of the country's original Amazon forest area (INPE, 2017). There are two aspects of Brazilian Amazon deforestation over the last two decades that are central to this paper: (i) it was largely an illegal practice; and (ii) its primary goal was to clear areas for non-forest land uses, and not to extract timber.

In Brazil, removing native vegetation is only legal if the clearing of a specific area has been duly authorized by a government environmental authority. Authorizations can only be granted for areas within designated lands, which encompass private landholdings and public lands assigned either to protection or to agrarian reform settlements.[4] Private landholders must also comply with the Brazilian Forest Code, which sets legal guidelines for conversion and protection of native vegetation inside private properties. The Forest Code is particularly restrictive for properties in the Amazon, capping legal deforestation at no more than 20% of total property area, and further requiring landholders to preserve areas of permanent protection, such as riparian forests.[5] Clearing forest in undesignated lands (public areas that have not been assigned to a specific use) is always illegal. Currently available data on Amazon deforestation do not allow legal clearings to be distinguished from illegal ones. However, descriptive and anecdotal evidence, briefly summarized in what follows, corroborate the general consensus that forest clearing in the region is mostly illegal.[6]

The Brazilian Amazon covers an area of approximately 4.2 million km^2. Undesignated lands, where all clearings are illegal, extend over an estimated 700 thousand km^2 (Azevedo-Ramos and Moutinho, 2018). An additional 2.1 million km^2 are under protection, as either indigenous lands or protected areas (CNUC, 2018; FUNAI, 2018). Because clearing forest within protected Amazon territory is either entirely forbidden or subject to stringent requirements, it is practically analogous to being illegal. The remaining 1.4 million km^2 are either private landholdings or agrarian reform settlements, both of which must comply with conservation requirements established in the Brazilian Forest Code. While clearings inside properties can be legal, property-level assessments reveal very poor compliance with environmental regulation and the Forest Code in the Amazon (Michalski et al., 2010; Godar et al., 2012; Börner et al., 2014). Forest clearings in non-compliant properties are carried out in irregular circumstances and are therefore also illegal. In light of this, although the data on Amazon deforestation used in this paper may include legal clearings, it is safe to assume that this amounts to only a small fraction of total cleared area.

In addition to having been mostly illegal, Amazon deforestation since the early 2000s occurred primarily as a means to clear land for alternative non-forest uses. The two leading drivers of clear-cut deforestation (total removal of forest biomass) in the Brazilian Amazon are agricultural conversion and illegal land grabbing. The former is reflected in the pattern of land use within the stock of deforested areas: pasture occupies 63% and cropland 6% of cleared Amazon areas (INPE & Embrapa, 2016).[7] The latter is a symptom of a long history of fragile property rights in the

[4]Specific regulations determining requirements and procedures for legal deforestation vary across land tenure categories.

[5]See Chiavari and Lopes (2015) for an overview of the Brazilian Forest Code.

[6]Representatives of the Brazilian Ministry of the Environment and the federal environmental police authority have stated, in informal conversations, that over 90% of Amazon forest clearings within the past two decades were illegal.

[7]The remaining cleared area is covered by forest regrowth (23%), or a mix of other uses (8%), including urban and mining areas.

region, where public forest areas are often cleared as a means of illegally claiming ownership over the land (Alston et al., 2000; Alston and Mueller, 2010; Fetzer and Marden, 2017; Mueller, 2018; Azevedo-Ramos and Moutinho, 2018). Occupied areas are typically held for speculative purposes. The key implication of a pattern of forest clearing for agricultural conversion and land grabbing is spatial permanence. As land itself is the main input in both practices, it is unlikely that recently deforested areas in the Amazon are immediately abandoned.[8]

Combined, these two aspects of Amazon deforestation suggest there is room for law enforcement to affect forest clearing practices. Illegal activities are, by nature, the central target of law enforcement efforts. Moreover, because deforested areas in the Amazon are not quickly abandoned, enforcement officers have a non-negligible chance of identifying the offenders who are responsible for the illegal clearing. In this sense, spatial permanence contributes to enforcement's capacity to attribute responsibility for the environmental infraction. In the remainder of this section, we discuss how, in spite of this, law enforcement was regarded as having only a very limited capacity to impact Amazon deforestation. This was largely because the severity of penalties that can be applied as punishment for deforestation in Brazil depends on the timing of the enforcement response. It was not until the adoption of a novel satellite-based monitoring system that the Brazilian environmental law enforcement authority was able to provide a timely response. This system essentially introduced what spatial permanence alone could not guarantee: the ability to catch offenders red-handed and, hence, impose binding penalties.

2.2. Environmental Monitoring and Law Enforcement

During the 1980s and 1990s, administrative sanctions were regarded as having little capacity to inhibit environmental offenders (Schmitt, 2015). The enactment of the 1998 Law of Environmental Crimes (Brasil, 1998) brought regulatory stability to the investigation and prosecution of environmental violations by providing clearer definitions of infractions, as well as setting legal directives for the application of administrative and penal sanctions. In the Amazon, this law was enforced by the Brazilian Institute for the Environment and Renewable Natural Resources (Ibama), an executive branch of the Brazilian Ministry of the Environment. Ibama is responsible for environmental monitoring and law enforcement at the federal level, operating as the national police authority in the investigation of environmental infractions and application of administrative sanctions.

[8] In contrast, logging is an inherently mobile practice. Although logging has been associated with tropical forest loss, timber extraction in the Amazon is performed selectively to target high-value trees and avoid the high costs of clearing large areas covered with tropical vegetation (Angelsen and Kaimowitz, 1999; Hargrave and Kis-Katos, 2013; Chimelli and Soares, 2017). This typically results in forest degradation (partial removal of forest biomass), not clear-cut deforestation.

Although the participation of Amazon states in environmental management has grown since the 1990s, Ibama still holds a large and central role in carrying out command and control policy in the region. In addition to its headquarters in the Brazilian capital of Brasília, the institute holds several regional offices in the Amazon to support its field operations. Yet, given the sheer magnitude of the Brazilian Amazon, Ibama's enforcement capacity largely hinges on its ability to accurately detect and target environmental infractions. Through the very early 2000s, targeting was mostly based on strategic intelligence Ibama collected, and complemented by anonymous reports of forest clearing activity received via a hot line. In this setting, enforcement capacity would clearly benefit from remote monitoring technology capable of placing large forest areas under regular surveillance. At the time, however, the available technology was limited to air vehicles, such as helicopters, which offered only a relatively short range of action, and still put Ibama officers at great personal risk.

Conditions for environmental monitoring and law enforcement in the Amazon drastically changed with the enactment of Brazil's Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). Launched in 2004, the action plan inaugurated a novel approach towards combating tropical deforestation in Brazil. It integrated actions across different government institutions and proposed new procedures for monitoring, environmental control, and territorial management. Because Amazon deforestation was known to be mostly illegal, strengthening command and control policy was the action plan's tactical-operational priority, and adopting high-frequency remote monitoring of forest clearing activity was its pivotal endeavor. Developed by the Brazilian Institute for Space Research (INPE), DETER was a satellite-based system that regularly collected and processed georeferenced imagery on Amazon land cover to detect forest loss. DETER used optical imagery from the MODIS sensor on the Terra satellite, which had a spatial resolution of 250m and a daily revisit rate for the full extent of the Brazilian Amazon. Figure 1 portrays how DETER captured deforestation using this imagery. The system classified land cover seen on satellite-based pictures, distinguishing between areas that were covered by vegetation and those that were not. Images from two different points in time for the same location were compared to identify recent changes in forest cover, which were regarded as potential forest clearing hot spots. Once detected, each hot spot was associated with a georeferenced deforestation alert marking the area in need of immediate attention, as shown in Figure 2.

DETER was created specifically to support Ibama's law enforcement efforts.[9] Deforestation alerts served as the basis for targeting ground operations in which law enforcement officers visited alert sites and, upon finding evidence of illegal clearing activity, applied administrative sanction. Brazilian law allowed officers to apply several different penalties as punishment for the same infraction. In light of this, fines were the most commonly used administrative sanction — law enforcement officers would typically issue a fine for every environmental infraction they detected, whether or not they also applied other sanctions for the same infraction. Fines were not, however, the most severe form of punishment environmental offenders potentially faced. Some of the stricter penalties for illegal Amazon deforestation included the setting of economic embargoes (which obstruct access to rural credit) and the seizure/destruction of products and equipment associated with forest clearing. Combined, administrative sanctions imposed a high financial burden on offenders both directly (via fine payment, loss of product/equipment) and indirectly (via restricted access to credit, foregone production, legal fees). Offenders could also face civil and criminal charges, in addition to administrative ones. In this setting, although fines were not the most severe sanction available, they were the most common one, being applied both as standalone penalties and alongside other forms of punishment. This supports the use of fines as proxies for the presence of environmental law enforcement.

The remote monitoring system represented a major leap forward in Amazon monitoring capacity, but suffered from an important technical limitation: it could not detect land cover patterns beneath clouds. This is a common limitation of systems that use optical imagery — in the presence of clouds, images show the clouds themselves, not the land beneath them. This pattern is apparent in Figure 2, which illustrates how deforestation alerts were typically located in uncovered areas. The inability to detect clearings beneath clouds, which significantly limited monitoring capacity, serves as the basis for this paper's identification strategy (see Section 3).

2.3. The Importance of a Timely Response

From an environmental law enforcement perspective, DETER was groundbreaking. It not only allowed the enforcement authority to spot illegal activity throughout the entire Amazon, but it did so with unprecedented speed. This timing element was critical in boosting law enforcement's potential for impact. Prior to the activation of DETER, it was extremely difficult for law enforcement officers to locate and access new deforestation hot spots in a timely manner, since the identification of new clearings essentially relied on either

[9]Although the satellite used in DETER provided daily observations for every region of the Brazilian Amazon, the system aggregated data into biweekly alert maps through the early 2010s. In 2011, INPE started processing imagery on a daily basis, providing Ibama with near-real-time information on deforestation activity every weekday.

Ibama's capacity to accurately anticipate spatial deforestation patterns, or reports received via its hot line. By the time officers reached deforested areas, it was often too late to apply the more severe — and, thus, more binding — sanctions. Even if officers were able to correctly identify and locate the responsible parties, which is not a trivial task in a setting rife with insecure property rights (Alston et al., 2000; Schmitt, 2015; Mueller, 2018), their capacity to impose the most costly penalties ultimately depended on their capacity to catch offenders red-handed. Consider, as an example, the seizure and destruction of equipment used for clearing. If law enforcement officers find heavy machinery, like tractors, on-site in a deforestation hot spot, they can inflict an immediate and severe financial loss on the offender by seizing and destroying it. Expensive capital goods were not usually left unused in deforested areas once clearing was completed, so seizure/destruction could only be resorted to when officers interrupted offenders mid-clearing. DETER essentially increased the probability of such caught-in-the-act operations.

In light of this, the adoption of near-real-time satellite-based monitoring of forest loss was particularly salient. Since its implementation in 2004, DETER has served as the main targeting tool for Amazon law enforcement. By allowing Ibama to quickly locate and act upon areas afflicted by recent deforestation, it increased law enforcement's capacity to catch offenders red-handed, and thereby enhanced the potential for the application of binding sanctions.

3. Empirical Strategy

This paper's central empirical challenge is to adequately address the endogeneity that exists in the relationship between environmental law enforcement and illegal deforestation. In the context of the Brazilian Amazon, this endogeneity can be briefly stated as follows. On the one hand, the presence of law enforcement is intuitively expected to negatively impact illegal forest clearings by either inhibiting potential offenders or reducing their capacity to commit future offenses; on the other hand, law enforcers are knowingly allocated, at least in part, based on the actual occurrence of clearings. As we only observe an equilibrium situation, an estimator that does not adequately account for reverse causality will be biased. To address the possible upward bias in ordinary least squares (OLS) estimators, our estimation must tackle simultaneity in addition to the usual concerns regarding omitted variables. This section proposes an instrumental variable strategy to estimate the causal effect of law enforcement 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. Alerts serve as the basis for targeting Amazon law enforcement, so law enforcers are less likely to be allocated to areas that are blocked from view by clouds in the monitoring system, even if forest clearing is occurring in these areas. This suggests that, after the adoption of the satellite-based monitoring system, the presence of environmental law enforcement in the Brazilian Amazon should be at least partially determined by DETER cloud coverage. If this is, in fact, the case — and we will provide empirical evidence that supports this claim at the municipal level (see Section 5.1) — average annual DETER cloud coverage is arguably a source of exogenous variation in the presence of environmental law enforcement at the municipal level. Hence, we propose using DETER cloud coverage as an instrument for environmental law enforcement in the Brazilian Amazon.

The instrument's validity hinges on it being uncorrelated with the error term in the equation that regresses deforestation on law enforcement, conditional on observable variables. There are two scenarios in which this condition could be violated in our empirical setup: (i) if DETER cloud coverage correlates with other geographical characteristics that, in turn, correlate with forest clearings; and (ii) if DETER cloud coverage correlates with the outcome of interest, namely deforestation. The availability of relevant observable variables helps make the case for the instrument's validity.

We address the potential correlation between geographical characteristics and forest clearings using a combination of available data and fixed effects. Rainfall and temperature are an obvious source of concern here, as both are expected to correlate with clouds via weather phenomena. They may also correlate with deforestation, either as determinants of forest clearing decisions, or as ecological consequences of forest loss (Nobre et al., 1991; Negri et al., 2004; Aragão et al., 2008; Chomitz and Thomas, 2003; Bagley et al., 2014). Although delving into the specifics of this relationship is out of the scope of this paper, the empirical strategy accounts for it by using precipitation and temperature data to control for municipal weather. Another source of concern in validating the instrument's exclusion restriction is the potential correlation between average cloud coverage and soil type. Biophysical conditions that determine soil type could be correlated with local weather conditions, and soil quality, which affects agricultural outcomes, could influence forest clearing decisions in the Brazilian Amazon. The inclusion of location fixed effects helps mitigate this concern. All specifications therefore include municipal precipitation and temperature controls, as well as municipality fixed effects.

Data availability also serves to address the potential correlation between DETER cloud coverage and the outcome of interest. Deforestation data come from INPE's Project for Monitoring Deforestation in the Legal Amazon (PRODES), which uses satellite-based optical imagery to annually map deforested areas (see Section 4.1 for a detailed description). Although both PRODES and DETER use satellite imagery to detect changes in Amazon land cover, PRODES' goal is to measure deforestation more accurately only once per year, not monitor it frequently. PRODES data are constructed using information collected from a different satellite that provides images at higher resolutions. While DETER uses daily imagery all year round, PRODES selects only the best images from the Amazon dry season to minimize cloud coverage and maximize visibility of land surfaces. PRODES is thus less likely to suffer from limited visibility, but if present in selected imagery, clouds will still block land cover from view. In light of this, a sound empirical strategy must ensure that the potential correlation between the proposed instrument, DETER cloud coverage, and the key dependent variable, PRODES deforestation, is adequately accounted for. Fortunately, PRODES data are released containing information on areas that were blocked from view, so all specifications include controls for these areas. Coefficients are therefore estimated considering only DETER cloud coverage that is orthogonal to PRODES non-observable areas.

Having controlled for municipal precipitation, temperature, and PRODES satellite visibility, as well as for municipality 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 environmental law enforcement allocation. The empirical analysis starts by testing the relationship between law enforcement and DETER cloud coverage. The OLS estimation equation is given by:

$$LawEnforcement_{i,t} = \beta DETERclouds_{i,t} + \sum_{k} \gamma_k \vec{X}_{i,t} + \alpha_i + \phi_t + \epsilon_{i,t} \tag{1}$$

where $LawEnforcement_{i,t}$ is proxied by the total number of deforestation-related fines issued in municipality i and year t; $DETERclouds_{i,t}$ is average DETER cloud coverage in municipality i and year t; $\vec{X}_{i,t}$ is a vector of k municipality-level controls that includes precipitation, temperature, and PRODES satellite visibility; α_i is the municipality fixed effect; ϕ_t is the year fixed effect; and $\epsilon_{i,t}$ is the idiosyncratic error. We stress that total fine count is used only as a proxy for law enforcement, not as a penalty of interest in and of itself. Because environmental fines can be issued both as standalone penalties and alongside other sanctions, if law enforcers find evidence of illegal deforestation, they will almost certainly issue a fine (see Section 2.2). Moreover, considering that the vast majority of forest clearings happening during the sample period were illegal (see Section 2.1), and that the adoption of DETER enabled a more timely law enforcement response (see Section 2.3), law enforcement's presence in deforestation hot spots were very likely accompanied by the issuing of fines. As fines may be issued for environmental infractions other than forest clearing, we restrict fine count to those that specifically refer to deforestation. For simplicity, we refer to deforestation-related fines simply as fines throughout the paper.

If the inclusion restriction represented in Equation (1) and the aforementioned exclusion restrictions hold, an instrumental variable setup can be used to capture the impact of law enforcement (instrumented by DETER cloud coverage) on Amazon deforestation. The 2SLS second-stage estimation equation is given by:

$$Deforestation_{i,t} = \delta LawEnforcement_{i,t-1} + \sum_{k} \theta_k \vec{X}_{i,t} + \psi_i + \lambda_t + \xi_{i,t} \qquad (2)$$

where $Deforestation_{i,t}$ is a normalized measure of total deforested area in municipality i and year t; $LawEnforcement_{i,t-1}$ is the total number of deforestation-related fines issued in municipality i and year $t-1$, and is instrumented by $DETERclouds_{i,t-1}$; $\vec{X}_{i,t}$ is the vector of k municipality-level controls; ψ_i is the municipality fixed effect; λ_t is the year fixed effect; and $\xi_{i,t}$ is the idiosyncratic error. Estimates are robust to heteroskedasticity, and standard errors are clustered at the municipality level in all specifications, making them robust to serial correlation (Bertrand et al., 2004).

The use of a one-year lag for the enforcement variable is based on the literature that documents a lagged response of illegal activity to enhanced enforcement (Levitt, 1997; Shimshack and Ward, 2005; Chalfin and McCrary, 2017). A one-year lag seems plausible in a setting with DETER-based monitoring and annual deforestation data. For a given area, increased forest clearing in year t likely triggers the concurrent issuing of DETER alerts associated with that area, thereby increasing the presence of law enforcement via targeted allocation that same year t. If potential offenders perceive the increased presence of law enforcement in year t as a higher probability of getting caught and sanctioned in year $t+1$, they may choose to not engage in the illegal activity the following year, consequently contributing to reduce deforestation in year $t+1$. We therefore test whether lagged environmental law enforcement affected current deforestation. To capture DETER cloud coverage that is correlated with the allocation of law enforcement, but uncorrelated with deforestation through all other channels, we include one-year lags for precipitation and temperature controls, but current measures for all other controls.

In all specifications, municipality fixed effects control for potentially relevant municipality-specific characteristics affecting both deforestation activity and law enforcement efforts, and year fixed effects account for aggregate shocks. In addition to the variables added to support the validity of the exclusion restriction (precipitation, temperature, and PRODES satellite visibility), $X_{i,t}$ in Equation (2) also includes agricultural commodity price controls, which have been shown to be relevant drivers of tropical deforestation (Angelsen and Kaimowitz, 1999; Hargrave and Kis-Katos, 2013; Assunção et al., 2015). Conservation policy efforts implemented alongside improvements in monitoring and law enforcement may have also affected deforestation outcomes during the sample period. We discuss these policies in more detail and include available policy controls in robustness exercises (see Section 6.3), but refrain from adding them to benchmark specifications due to endogeneity concerns.

4. Data

This paper's empirical analysis uses a 2006 through 2016 municipality-by-year panel dataset built entirely from publicly available data. The sample includes all municipalities that are either partially or entirely located in the Amazon biome, that exhibited variation in forest cover during this period, and for which deforestation data were available.[10] The variation in forest cover criteria enables the use of municipality fixed effects. This eliminates 25 municipalities that did not contain a significant amount of forest cover at baseline, as evidenced by a 2% average ratio of forest to municipal area (INPE, 2017). The non-missing data for deforestation criteria eliminates seven municipalities that lie only marginally within the far northeast region of the Legal Amazon, such that there is no relevant coverage of their respective territories in Amazon satellite systems. The final sample comprises 521 municipalities.[11]

4.1. Deforestation

Since 1988, INPE annually tracks the loss of tropical vegetation in the Brazilian Amazon via PRODES. The system uses optical images from Landsat class satellites, with a spatial resolution of 20 to 30 meters, to detect changes in tropical forest cover throughout the full extent of the Brazilian Amazon. PRODES only accounts for clear-cut deforestation, which it defines as the near-complete or complete loss of tropical vegetation. Deforested areas in PRODES therefore do not include the loss of degraded forests, or non-tropical vegetation. The system provides annual data, but because PRODES typically uses imagery from the Amazon dry season to minimize cloud coverage in imagery, these data do not refer to a calendar (January through December) year. Rather, they refer to what we call the "PRODES year": for a given year t, PRODES measures deforestation that happened from August of year $t-1$ through July of year t. Unless otherwise stated, years referenced throughout the analysis refer to PRODES years, not calendar ones.

PRODES was created to map and measure tropical deforestation increments,

[10] The Legal Amazon refers to a geopolitical territorial division, whereas the Amazon biome refers to an ecological one. Figure 2 maps the two regions. Although DETER monitoring covers the full extent of the Legal Amazon, 97% of the area deforested in the Amazon since the adoption of the remote monitoring system occurred within the Amazon biome (INPE, 2017). This is consistent with the fact that, at the time DETER was launched, tropical forest covered less than 5% of non-biome Legal Amazon territory (INPE, 2017).

[11] Municipal boundaries in the analysis refer to the 2007 administrative division from the Brazilian Institute for Geography and Statistics (IBGE).

which are used to calculate an Amazon-wide annual deforestation rate.[12] 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 publicly released at an annual basis both as an Amazon-wide georeferenced dataset and as panel containing municipal aggregates.

Municipality-level deforestation increments from PRODES serve as the basis for the construction of our main outcome of interest. These increments are normalized to account for the large variation in municipality size — the sample standard deviation is 16 thousand km^2. The two benchmark normalization procedures use the natural log and the inverse hyperbolic sine transformations.[13] Some exercises explore alternative normalization procedures, based on municipality size and across-time average deforestation (see Section 5.3).

4.2. Law Enforcement

Ideally, we would like to use deployment data to capture the presence of environmental law enforcement in the Brazilian Amazon. However, to the best of our knowledge, there is neither an existing dataset that contains this information, nor a means of accurately compiling the data from scratch. We therefore use the total number of deforestation-related fines issued by Ibama in each municipality and year as proxy for the presence of law enforcement at the municipal level. Our interest lies in the proxy for law enforcement, not in fines as penalties in and of themselves. They are a good proxy for the presence of law enforcement in the Brazilian Amazon, because they are issued both as standalone penalties and alongside more severe punishments (see Section 2.2). In a context in which the vast majority of forest clearings are illegal (see Section 2.1), fines serve as an indication that law enforcement was both present at the site of an environmental infraction and able to hold someone accountable for it.[14]

[12]Deforestation increments encompass all visible deforested areas; the deforestation rate is closely related to the increment, but it further accounts for cleared forest areas that were partially or entirely blocked from view during remote sensing. INPE (2013) provides a detailed account of PRODES methodology and rate estimation details.

[13]The log normalization is implemented as $ln(deforest_{i,t} + 0.01)$, where $deforest_{i,t}$ is the deforestation increment in km^2 for municipality i and year t, to allow for the occurrence of observations with null deforestation in the analysis. Note that non-null deforestation is greater than 0.01 km^2 for all observations in the raw data.

[14]The knowingly low collection rates for environmental fines in the Brazilian Amazon (Schmitt, 2015) do not invalidate their use as proxies for the presence of law enforcement in the Brazilian Amazon, which essentially depends on the issuing — not the payment — of fines.

Ibama holds a public electronic record of all environmental fines issued in the country, with fine-level information on the type of infraction (enabling the distinction between different types of environmental occurrences), as well as its issue date (day, month, and year) and location (municipality), among other administrative details. Using this record, we build a panel containing the total count of deforestation-related fines issued in each municipality and each year.

4.3. DETER Cloud Coverage

Although DETER provides law enforcement with high-frequency information on deforestation hot spots, the system's cloud coverage data are aggregated into monthly georeferenced datasets for public release. In these datasets, areas that are covered by clouds were blocked from view throughout the entire month (see Figure 2).[15] When visibility is at least partial, the monthly data show exactly which areas were covered by clouds. When visibility is too precarious throughout the entire month to derive any information about land cover, however, no data is produced for that month — we follow INPE's recommendation and assume DETER cloud coverage to be complete in this case. We use these spatial data to calculate the monthly ratio of cloud coverage to municipal area, and average these municipality-level ratios across each year to derive our instrument.

Although the earliest monthly DETER data are from the 2004 calendar year, the DETER system remained in experimental phase halfway through the 2005 calendar year. The benchmark sample therefore starts in 2006 (using data from August 2005 through July 2006) and follows through 2016, the latest year for which data were available at the time the dataset was built. We use DETER cloud coverage data from the early experimental phase in robustness exercises (see Section 6.2).

4.4. Controls

The benchmark set of controls contains variables that account for local weather, PRODES satellite visibility, and agricultural commodity prices. First, weather controls include measures of precipitation and temperature to address the potential correlation between deforestation and regional microclimate (see Section 3). This set of controls is critical to the validity of DETER cloud coverage as an instrument for law enforcement, as it mitigates concerns regarding the potential correlation between cloud coverage, local geographic characteristics, and deforestation. We build our control variables from monthly gridded data on total precipitation (Matsuura and Willmott, 2017b) and average air temperature (Matsuura and Willmott, 2017a) interpolated to a $0.5°$ by $0.5°$ grid resolution.

[15] There are a few months for which the raw data contains biweekly, as opposed to monthly, information on DETER cloud coverage. In these cases, we follow INPE's recommendation and intersect the biweekly spatial data to identify areas that were blocked from view throughout the entire month.

Using this grid, we construct monthly measures for precipitation and temperature in each municipality as follows: (i) for a municipality that intersects with at least one grid node, we calculate total precipitation and average temperature across nodes; (ii) for a municipality that does not intersect with any grid nodes, we identify nodes that intersect with its 30km buffer and calculate average precipitation and average temperature across nodes; and (iii) for a municipality that neither intersects nor has its 30km buffer intersect with any grid nodes, we identify nodes that intersect with its 60km buffer and calculate average precipitation and average temperature across nodes.[16] Monthly values are then added (precipitation) or averaged (temperature) to construct municipality-level annual measures.

Second, satellite visibility controls account for areas that are blocked from view in satellite imagery. Clouds, shadows cast by clouds, and smoke from forest fires can all affect PRODES visibility. INPE publicly discloses annual municipality-level information on these obstructions, classifying them as "cloud coverage" or "non-observable areas" (the latter includes both shadows cast by clouds and smoke from forest fires).[17] We include the two ratios of PRODES obstructed to municipal area in all regressions to control for measurement error, as well as to address potential correlation between PRODES deforestation and the DETER cloud coverage instrument.

Finally, the last set of controls account for agricultural commodity prices. As these prices are endogenous to local agricultural production and thereby also to local deforestation activity, we follow Assunção et al. (2015) to construct output price series that capture exogenous variations in the demand for agricultural commodities produced locally. The authors show that commodity prices recorded by the Agriculture and Supply Secretariat of the State of Paraná (SEAB-PR) closely correlates with average local agricultural prices for Amazon municipalities.[18] Select commodity prices cover beef cattle, as well as soybean, cassava, rice, corn, and sugarcane to capture incentives for both cattle ranching and crop farming activities.[19] For each of the six commodities, we build an index of real prices for the first and second semester of each calendar year.[20] We start by deflating monthly nominal prices to year 2000 Brazilian currency, and averaging

[16]Buffer distance is based on the grid size, with 30km being approximately equivalent to half the distance between grid nodes.

[17]In DETER raw data, all visual obstructions are recorded as cloud coverage.

[18]Paraná is a non-Amazon state located in the far south of Brazil.

[19]Soybean, cassava, rice, and corn systematically account for more than 84% of the planted area in sample municipalities during the sample period. Although not present in the Amazon, sugarcane is also included to address concerns regarding the expansion of sugarcane-based ethanol biofuel production in Brazil over the past decades.

[20]We use January through July of year t as the first semester of year t to more closely match the breaks in PRODES years, which end in July. August through December of year t make up the second semester of year t.

the deflated monthly prices across semesters. To introduce cross-sectional variation in the commodity price series, we weight the prices using a measure of that commodity's relevance in each municipality in years immediately preceding the sample period. The weighted real price for each commodity is therefore given by:

$$PW_{c,i,st} = P_{c,st} * W_{i,c} \tag{3}$$

where $PW_{c,i,st}$ is the weighted real price of commodity c in municipality i and semester/year st; $PP_{c,st}$ is the real price of commodity c in semester/year t; and $W_{i,c}$ is the municipality/commodity-specific weight. For crops, the weight is given by the 2004 through 2005 average ratio of farmland to municipal area for crop c in municipality i, using annual data from Brazil's Municipal Crop Production Survey (PAM/IBGE). For beef cattle, the weight is given by the 2004 through 2005 average ratio of heads of cattle to municipal area in municipality i, using data from Brazil's Municipal Livestock Survey (PPM/IBGE). The set of agricultural commodity price controls for year t includes prices for the first and second semesters of calendar year $t-1$, as well as prices for the first semester of calendar year t.

4.5. Descriptive Statistics

Table 1 provides descriptive statistics for the analysis' main variables. It shows that deforestation, law enforcement, and DETER cloud coverage exhibit substantial variation both across and within sample years. The downward trend in mean deforestation over time is consistent with a context in which forest clearing was slowing down in the Brazilian Amazon as a whole. Figure 3 portrays the deforestation slowdown alongside the trajectory for total annual fine count, offering some insight into the endogeneity that exists among the two. While the sharp increase in the number of fines issued through 2008 could be expected to have contributed to the observed reduction in deforestation, lower forest clearing rates imply a lower incidence of illegal clearings and, thus, lower fine counts over time. The proposed IV strategy aims at disentangling these effects to isolate the impact of law enforcement on Amazon deforestation.

5. Results

This section presents the analysis' main results. It starts by providing empirical evidence that DETER cloud coverage significantly influenced environmental law enforcement in the Brazilian Amazon. Drawing on this evidence as support for using cloud coverage as an instrument for enforcement in this specific setting, it then follows with the benchmark results, which indicate that environmental law enforcement effectively curbed tropical deforestation. The section also explores regional impacts of local enforcement, and looks into potential costs of enforcing environmental law in the Amazon.

5.1. Law Enforcement and Deforestation

To be a valid instrument for environmental law enforcement in the Brazilian Amazon, DETER cloud coverage must systematically affect enforcement outcomes. We test whether this condition holds using the specification from Equation (1), in which the total number of fines issued in each municipality and year serves as a proxy for law enforcement. This exercise mirrors the first-stage regression of the proposed instrumental variable (IV) strategy, but allows for the gradual inclusion of relevant controls. Table 2 presents estimated OLS coefficients. Column 1 starts with the univariate regression; column 2 adds weather controls (precipitation and temperature); column 3 adds satellite visibility controls (PRODES cloud coverage and other non-observable areas); and column 4 adds municipality and year fixed effects, as well as the set of agricultural commodity prices. The coefficient of interest — the effect of DETER cloud coverage on law enforcement — remains negative and statistically significant across specifications. Thus, for any given Amazon municipality, years with greater DETER cloud coverage also saw laxer environmental law enforcement, as proxied by a smaller number of fines. These results support the validity of the inclusion restriction imposed by the proposed IV strategy.

Having provided empirical evidence that DETER cloud coverage systematically affects environmental law enforcement targeting deforestation in the Brazilian Amazon, we now explore this relationship in the IV specification from Equation (2). Table 3 presents estimated coefficients using both OLS and 2SLS estimators, as well as two alternative normalizations for the dependent variable (two additional normalizations are discussed in Section 5.3). All specifications use the full set of fixed effects (municipality, year) and controls (weather, satellite visibility, agricultural commodity prices). Our main interest lies in the 2SLS coefficients (Panel A, even columns), which isolate the effect of law enforcement on deforestation. OLS coefficients (Panel A, odd columns) are reported for comparative purposes only. They are all statistically insignificant and point-estimates are virtually zero, suggesting that law enforcement does not significantly affect deforestation. This conclusion, however, does not hold, since OLS yields biased estimators in the presence of reverse causality. In this setting, because the OLS estimator is expected to be upward biased, the null coefficients reported in Table 3 suggest that estimation strategies that adequately tackle endogeneity should yield smaller (negative) point estimates.

The proposed IV strategy was designed to address reverse causality between law enforcement and deforestation. Second-stage 2SLS coefficients (Table 3, Panel A) are all negative and statistically significant, indicating that the presence of law enforcement in any given Amazon municipality and year led to a reduction in total forest area cleared in that municipality the following year. This pattern holds across normalizations for the dependent variable, so findings do not appear to be driven by the choice of normalization procedure. We report second-stage results for the remaining exercises using both log and inverse hyperbolic sine transformations, and refer back to columns 2 and 4 as their respective benchmark specifications. The log-level specification provides a sense of the magnitude of the effect. On average, reducing monitoring and law enforcement by half increases municipal deforestation by an estimated 44% ($= 1 - e^{(9.87/2)\times 0.0743}$). First-stage 2SLS results (Table 3, Panel B) support the use of DETER cloud coverage as an instrument for law enforcement. In years with greater cloud coverage, municipalities systematically saw a significantly smaller number of fines. Estimated coefficients show that, on average, an increase of one sample standard deviation in DETER cloud coverage reduced the presence of law enforcement at the municipal level by nearly 25% of the sample mean. These findings validate the inclusion restriction. Finally, with a first-stage F-statistic greater than 10, instrument strength is not a source of concern (Stock et al., 2002).

Results from Table 3 capture the paper's main finding: IV estimation provides empirical evidence that environmental law enforcement effectively curbed tropical deforestation in the Brazilian Amazon from 2006 through 2016. The adoption of the near-real-time monitoring system allowed law enforcement to more quickly detect and react to illegal forest clearings, notably increasing enforcers' capacity to catch offenders red-handed (see Sections 2.2 and 2.3). As enforcement became more salient to offenders, who then faced a higher chance of getting caught and punished, they updated their beliefs about the expected costs of engaging in the illegal activity. The change in the perceived cost/benefit of deforestation is the driving force behind a deterrence mechanism — in light of higher expected costs, potential offenders rationally choose to refrain from engaging in the illegal activity. Additionally, in being able to more quickly locate recent clearings, law enforcement officers could also reach the clearing sites faster. This increased the chance that equipment used for deforestation were still on-site and could be apprehended. The loss of such capital goods, which were typically expensive and hard to replace, limited offenders' capacity to deforest in the near future. Our empirical strategy does not reveal which of these underlying mechanisms drove the estimated impact of law enforcement of deforestation, but DETER enhanced the potential for both. Hence, although we are not able to disentangle the two channels in the analysis, both operate in the same direction and likely contribute to our empirical results.

5.2. Spillovers

Thus far, the finding that monitoring and law enforcement were effective at curbing Amazon forest clearing refers solely to the direct policy impact, estimated based on the effect of local (municipal) enforcement on local deforestation. Yet, local interventions may also have had regional impacts. On the one hand, if law enforcement officers were more present in a given municipality, clearings might have fallen locally due to a redistribution of deforestation activity towards municipalities where enforcement was not as salient. In this scenario, enforcement would displace illegal clearings, but not actually contain them at the aggregate level. On the other hand, the presence of enforcement officers in a given municipality might have led potential offenders in the whole region to update their beliefs about the probability of being caught. In this case, local enforcement's impact on deforestation might not have been restricted to the local level, having had a more widespread regional effect.

To investigate whether leakage or contagion occurred, we assess the effect of municipal law enforcement on deforestation outcomes within the broader region of a municipality's neighborhood. The 2SLS second-stage estimation equation builds on Equation (2), but is now given by:

$$\begin{aligned} Deforestation_{\partial i,t} = \delta LawEnforcement_{i,t-1} + \sum_{m} \upsilon_m \vec{X}_{i,t} + \\ + \sum_{n} \mu_n \vec{W}_{\partial i,t} + \psi_i + \lambda_t + \xi_{i,t} \end{aligned} \tag{4}$$

where ∂i denotes a variable defined at the neighborhood level, such that $Deforestation_{\partial i,t}$ is a normalized measure of total deforested area in municipality i's neighborhood and year t; $\vec{X}_{i,t}$ is a vector of m municipality-level controls covering precipitation and temperature; and $\vec{W}_{\partial i,t}$ is a vector of n neighborhood-level controls covering average precipitation, average temperature, total PRODES clouds and other non-observable areas, average agricultural commodity prices, and average DETER cloud coverage.[21] All other terms are defined as in Equation (2). Deforestation outcomes for the central municipality are not included in this specification's outcome of interest.

Table 4 presents estimated coefficients using the following three alternative definitions for a municipality's neighborhood: (i) all municipalities that share a border (are contiguous) with the central municipality (columns 1 and 4); (ii) the three municipalities that are nearest to the central municipality, where proximity is based on the linear distance between municipalities' centroids (columns 2 and 5); and (iii) all municipalities whose centroid lies within a 100km buffer from the central municipality (columns 3 and 6).[22] Although the benchmark sample was

[21] Average neighborhood DETER cloud coverage is included to account for potential correlation between cloud coverage in the central municipality and cloud coverage in its neighborhood, which could affect enforcement outcomes in both the central municipality and its neighborhood.

[22] To account for spatial decay across larger distances, the construction of deforestation outcomes for the buffer-based definition weighs deforested area in each neighboring municipality by a factor of $e^{distance \times (\frac{-ln2}{50})}$, such that deforestation in a neighbor that is 50km away receives a weight of 0.5.

preserved to ensure comparability across neighborhood and benchmark results, some observations were lost due to limitations in data availability.[23]

The evidence appears to support that contagion, not leakage, occurred. Estimated coefficients are systematically negative and statistically significant, suggesting that the presence of law enforcers in a given municipality helped contain forest clearings not only locally (within that municipality), but also regionally (within its neighborhood). These results further indicate that the benchmark estimated local impact of law enforcement on deforestation was not driven by leakage of forest clearing activity into surrounding areas. Amazon monitoring and law enforcement may therefore have had positive regional spillovers, but further investigation is needed to attest to its magnitude and spatial characteristics.

Finding that leakage did not occur at a regional level is consistent with the institutional context of Amazon monitoring and law enforcement (see Section 2). Indeed, the very nature of the DETER system inhibits displacement of deforestation activity. Continuous universal surveillance means that no area is subject to less monitoring at any given time. As such, potential offenders cannot reasonably attribute a smaller chance of getting caught to any one area. Still, because DETER's inability to detect land cover patterns beneath clouds is public information, one might posit that offenders could concentrate clearing activity in areas more prone to cloud coverage. We argue this is an unlikely story. Amazon cloud coverage is an inherently variable phenomenon, as evidenced by the descriptive statistics in Table 1 and illustrated in Figure 2. High within-year variation in cloud coverage means that clearings in most of the Amazon region are not systematically hidden from view in the high-frequency monitoring system. If an offender were to base his clearing decision on clouds, once they clear and deforestation is detected by DETER, his activity could be targeted by law enforcement. This is particularly relevant in a setting in which most deforestation occurs to clear land for non-forest uses. Moreover, considering that clearing tropical forest is both time-consuming and expensive, offenders do not typically leave recently cleared areas in the very short term — they need time to use the land to collect the benefits from deforestation.

That being said, although short-term variation in cloud coverage would not suffice to evade monitoring, it significantly affected the presence of law enforcement. To reconcile these apparently contradictory notions, it is important to recall two key points from the institutional context for Amazon monitoring and law enforcement (see Section 2). First, the new monitoring system shed light on

[23] For the shared borders and proximity-based neighborhoods, one municipality is dropped from the sample because deforestation data are missing for all of its neighbors. For the buffer-based neighborhood, forty-six municipalities are dropped from the sample because their 100km buffers do not intersect with any municipality centroids.

forest clearing activity that had remained hitherto unknown to law enforcement authorities. As such, it had the capacity to reveal several new deforestation hot spots and, over time, allow targeting of these areas. Second, cloud coverage played a key role in determining how quickly law enforcement could reach new clearing sites. This influenced enforcers' capacity to apply more or less binding punishments, which, in turn, fed into offenders' updated beliefs about the costs of engaging in illegal clearings. Combined, these arguments point towards DETER cloud coverage being sufficiently variable to be a poor long-term cover for illegal forest clearings, but also sufficiently salient to significantly impact the on-the-ground presence of law enforcement.

5.3. Policy Costs

Monitoring and law enforcement appear to have been effective at curbing deforestation in the Brazilian Amazon — but at what price? We explore two potential dimensions: a direct cost, and an opportunity cost.

We start with an investigation of whether monitoring and law enforcement efforts were a cost-effective way of protecting the Amazon. We perform a back-of-the-envelope cost-benefit calculation to arrive at a simplified answer. Annual budgets for Ibama (USD 560 million) and INPE (USD 125 million) provide an estimate for the total cost of both running the monitoring system and implementing law enforcement.[24] This is certainly an overestimate of the actual cost of Amazon monitoring and law enforcement efforts, because Ibama and INPE were not exclusively dedicated to this endeavor.

To quantify the benefits of preserving the forest, we revisit our benchmark specification using a linear transformation to normalize deforestation.[25] Table 5 presents estimated 2SLS coefficients for two alternative linear normalizations: the annual municipal deforestation increment as a share of municipal area (column 1); and the annual municipal deforestation increment as a share of the 2002 through 2016 mean municipal deforestation increment (column 2). Coefficients are consistent with those from Table 3, reinforcing that our benchmark results are not being driven by the choice of normalization procedure. These coefficients provide a measure of the average effect on deforestation of increasing the presence of law enforcement in any given municipality. We use these estimates to simulate what would have happened in two hypothetical scenarios: (i) one in which Amazon monitoring and law enforcement have been entirely shut down, and (ii) another one in which the novel satellite-based monitoring system was never adopted. We build these scenarios empirically by setting the total number of fines in each

[24]Information on annual budgets is not available for every sample year, so we resort to the actual budgets in 2011 for both institutes as an approximation.

[25]Linearity is needed to enable the derivation of the expected value for deforestation in the proposed simulation (see Appendix A).

municipality to zero or pre-DETER (2002 through 2004 average fine count) levels, respectively, and simulating municipal deforestation outcomes under these conditions. Figure 4 depicts total sample observed and simulated deforested areas, showing that both scenarios yield systematically larger deforestation.[26] From the first scenario, if monitoring and law enforcement had been entirely shut down, the Amazon would have seen 338 thousand km^2 of cleared areas — almost five times what was actually observed during the sample period. The second hypothetical scenario sheds light on the relative contribution of DETER. If the new satellite-based monitoring system had never been developed and law enforcement had sustained its pre-DETER pattern, total sample deforestation would have amounted to 279 thousand km^2. Combined, these exercises point towards the importance of correctly allocating — and not just intensifying — enforcement efforts. Accurate targeting of illegal activity was a crucial part of effective law enforcement in the Brazilian Amazon.

Based on results from the first hypothetical scenario, monitoring and law enforcement efforts avoided the clearing of an average of 27 thousand km^2 of tropical forest per year. This is equivalent to avoiding the emission of nearly 1 billion tCO_2 per year.[27] Again, this is certainly an underestimate of the true value of protecting the forest, as it focuses strictly on avoided emissions, and doesn't account for several other environmental services the forest provides, such as protection of biodiversity and hydrological resources (Stern, 2008; Watson et al., 2018). Comparing the estimated annual costs (USD 685 million) and benefits (1 billion tCO_2), we arrive at a break-even price of USD $0.69/tCO_2$. Carbon prices are currently rising, with about half of emissions now covered by carbon pricing initiatives priced at over USD $10/tCO_2e$ (World Bank et al., 2017) — well above the break-even price calculated in our setting. Hence, the benefits of protecting the forest more than compensate the costs of implementing Amazon monitoring and law enforcement efforts. This is particularly striking considering that our estimates only capture a lower bound for this potential gain, as costs are overestimated and benefits are underestimated. Overall, this exercise suggests that monitoring and law enforcement were a cost-effective way of curbing Amazon deforestation.

Despite being financially viable, the Amazon monitoring and law enforcement strategy might still have had relevant opportunity costs. There is an ongoing debate among academics and policymakers regarding potential tensions between economic growth and the conservation of natural resources. These concepts, however, need not be mutually exclusive. Indeed, there is both anecdotal and causal evidence of cases

[26]Reported simulation outcomes are based on the municipal area normalization, but results are analogous for the mean-based normalization and are available from the authors upon request.

[27]Conversion based on a factor of 10,000 tC/km^2 (36,700 tCO_2/km^2), as determined by the Brazilian Ministry of the Environment (MMA, 2011).

in which environmental quality improved in tandem with economic development (Arrow et al., 1995; Stern, 2004; Foster and Rosenzweig, 2003). Still, considering that agricultural land covers a large share of deforested areas in the Amazon (see Section 2.1), interventions that affect forest clearing practices might also influence agricultural production.

In light of this, we explore the proposed IV strategy to investigate whether law enforcement affected local agricultural production. Table 6 reports estimated coefficients for two different measures of production: (i) municipal gross domestic product (GDP) for the agricultural sector (Panel A, columns 1 and 2), which includes both livestock- and crop-based activities; and (ii) municipal value of crop production (Panel A, columns 3 and 4).[28] Due to missing raw data on municipal value of crop production for select municipalities and years, specifications that use crop value as the dependent variable (columns 3 and 4) are estimated using an unbalanced panel. Specifications that do not include agricultural price controls capture the impact of law enforcement on value outcomes (columns 1 and 3), whereas those that do include agricultural price controls capture the impact on quantum outcomes (columns 2 and 4).

Results indicate that monitoring and law enforcement did not harm agricultural production. If anything, they had a significant positive impact on production, with both value and quantum outcomes systematically improving in municipalities with greater presence of law enforcement. Combined with our benchmark results, this finding indicates that monitoring and law enforcement effectively contained Amazon deforestation without jeopardizing local agricultural production. Looking at a broader historical and economic context for the Brazilian Amazon can be insightful when interpreting these results. The region's long history of insecure property rights has been associated with severe land tenure uncertainty, particularly regarding the illegal squatting of both public and private lands, and violent rural conflict (Alston et al., 2000; Araujo et al., 2009; Chiavari et al., 2016; Fetzer and Marden, 2017; Mueller, 2018). This contributes to widespread informality in production. We speculate that, in this setting, the increased presence of law enforcement may have helped boost production by improving the local institutional environment. Alternatively, stricter monitoring and law enforcement may have created an incentive for producers to increase productivity, as opposed to expanding production along extensive margins.

Although this exercise sheds light on a currently salient debate about conservation policy and economic development, an important caveat is in place. By construction, the analysis' dependent variables only measure formal

[28] The municipal GDP series is available from IBGE; the municipal value of crop production series is available in PAM/IBGE. Although IBGE also conducts an annual survey on livestock, it provides no information on value of production for beef cattle.

agricultural production, so results fail to capture potential impacts on informal production. On the one hand, informal producers may have responded to law enforcement by shifting from a low-productivity setup to a more productive one, essentially compensating production that was lost at the extensive margin for that gained at the intensive margin. On the other hand, they may have ceased to produce entirely, with relevant consequences for individual or regional well-being. An analysis capable of assessing these impacts — on the informal sector, subsistence agriculture, and individual-level production — might yield different conclusions to those drawn from Table 6. To the best of our knowledge, no data is currently available for conducting such analysis at scale.

6. Robustness Checks

The set of results presented in Section 5 indicate that the monitoring and law enforcement strategy for combating Amazon deforestation effectively curbed tropical clearings. In addition to its effectiveness, the policy does not appear to have had negative collateral effects, neither displacing clearings to neighboring regions within the Amazon, nor imposing unfavorable policy costs. We now subject this main finding to a series of robustness checks

6.1. Baseline Differences

The paper's identification strategy partly depends on valid comparability across municipalities after controlling for relevant observable characteristics and municipality and year fixed effects. This comparability might not hold if included controls and fixed effects do not adequately account for baseline differences that set municipalities on different deforestation paths. We consider three scenarios where this might be a source of concern, and test whether results are robust to the inclusion of scenario-specific linear time trends.

First, when the new monitoring system was implemented, remaining forest cover varied significantly across Amazon municipalities. Such variation could affect deforestation trends, since the forest area available for clearing within a municipality mechanically decreases with decreasing forest cover.[29] To control for a trend determined by baseline accumulated deforestation, the saturated robustness specification builds on the benchmark specification from Equation (2), but also includes an interaction between a linear year trend and accumulated deforested area in 2003 (pre-DETER) as a share of municipal area. Second, deforestation levels at baseline could be associated with forest clearing patterns during the

[29]In addition to being correlated with future deforestation increments, accumulated deforested area might also correlate with local micro-climate (see Section 3). Thus, the robustness specification that controls for baseline accumulated deforested area also addresses concerns about the validity of the exclusion restriction.

sample period. If more dynamic municipalities in the Amazon have more intense clearing activity and are thereby subject to greater deforestation pressures, differences in current deforestation could determine different clearing trends over time. Whereas the first scenario looks at the stock of deforested areas, this second scenario considers the flow of deforestation at baseline. Its robustness specification is analogous to that of the first scenario, but includes an interaction between a linear year trend and the 2003 (pre-DETER) deforestation increment.[30] Third, the baseline distribution of law enforcement could impact local deforestation trends, particularly in a setting in which enforcement has been shown to effectively contain forest clearings. The last robustness specification in this exercise is, again, analogous to the two previous ones, but includes an interaction between a linear year trend and the 2002 through 2004 average municipal fine count.

Table 7 presents estimated 2SLS coefficients for the three specifications, and also replicates benchmark results for comparison. If the paper's main findings had been driven by the convergence in deforestation activity between municipalities with either varying stocks of deforested areas, different economic dynamics and deforestation pressures, or shifts in the distribution of law enforcement, adding the linear time trends to the benchmark specification should have returned insignificant estimated coefficients for law enforcement. Instead, second-stage coefficients remain negative and statistically significant across specifications, and first-stage results hold in terms of coefficient sign and significance, as well as of instrument strength. Table 7 therefore attests to the robustness of monitoring and law enforcement's capacity to have effectively curbed Amazon deforestation.

6.2. Sample Composition

Spatially, construction of the benchmark sample entails virtually no selection other than deforestation data availability and time-series variation (see Section 4). Moreover, it includes all Amazon biome municipalities meeting this selection criteria, so it has universal coverage of the relevant geographical region. The benchmark sample contains a high degree of variability in municipal forest cover, including municipalities with a relatively small share of forest at baseline. Deforestation dynamics specific to regions with little remaining forest cover could be driving the paper's main findings, and thereby contributing to a misinterpretation of results. More intense clearing activity in any place and time mechanically implies that less forest is available for clearing in that same place in the future. Thus, if increased clearing is also associated with greater presence of law enforcement in a given municipality, the estimated impact of lagged enforcement on current deforestation could have been driven, at least in part, by

[30] The test for the second scenario also captures potential effects from baseline differences in infrastructure across municipalities, such as road networks, that might determine future local forest clearing dynamics.

this mechanical reduction in the availability of forest areas. To mitigate concerns about mechanical reductions in cleared areas, this exercise assesses the impact of law enforcement on deforestation strictly in municipalities that contained a relatively large amount of forest cover at baseline. Table 8 presents estimated 2SLS coefficients for the benchmark specification using a restricted sample of municipalities containing an above-median ratio of forest to municipal area at baseline. Results are robust to the sample restriction, with estimated coefficients remaining negative and statistically significant across specifications.

Temporally, construction of the benchmark sample also entails little selection. Although the earliest DETER data refer to 2005, the DETER system remained in testing phase until 2006, when it became fully operational (see Section 4.3). The benchmark sample therefore starts in 2006 and follows through 2016, the latest year for which data were available at the time of dataset construction. As a second test of robustness to sample composition, Table 8 presents estimated 2SLS coefficients for the benchmark specification using an extended sample that covers the 2005 through 2016 period. Despite noisier DETER data for 2005, results indicate that the impact of law enforcement on deforestation remains robust to the inclusion of information from DETER's test phase.

6.3. Control Variables

The last set of robustness checks tests whether the paper's main results are sensitive to changes in the benchmark control variables. First, we consider the inclusion of additional controls for Amazon conservation policies that were implemented alongside monitoring and law enforcement. Two such policies stand out due to their close relationship with observed levels of deforestation: the expansion and targeted allocation of protected areas, and the listing of priority municipalities. As part of the novel action plan to tackle Amazon deforestation, Brazil introduced a new siting strategy for protected territory. In addition to maintaining ecological and biological criteria, siting was henceforth also determined based on regional deforestation pressures. New protected areas were meant to serve as shields to advancing deforestation, so protection tended to increase in regions where forest clearing was particularly intense (Gandour, 2018).[31] Furthermore, as of 2008, Brazil annually published a list of Amazon municipalities with a recent history of intense forest clearing activity. Listed municipalities were classified as in need of priority action to combat illegal deforestation, and could only be unlisted upon demonstrating significant reductions in forest clearing. Priority municipalities could be subjected to

[31]Protection has been shown to be an effective way of locally holding back deforestation in the Amazon, but there is still an ongoing debate about the magnitude of this effect at more aggregate levels, particularly considering the scope for spatial leakage (Nolte et al., 2013; Pfaff et al., 2014; Gandour, 2018; Herrera et al., 2019; Amin et al., 2019).

differentiated monitoring and law enforcement strategies, as well as to stricter administrative measures like harsher licensing requirements for private landholdings and economic sanctions from players in commodity supply-chains.[32] Both protected territory and priority municipalities policies might have affected deforestation outcomes in sample municipalities.

Protected territory controls are built from georeferenced data on protected areas provided by the Brazilian National Registry for Conservation Units (CNUC, 2018), as well as from georeferenced data on indigenous lands provided by the Brazilian National Native Foundation and the Socio-Environmental Institute (ISA, 2016; FUNAI, 2018). These datasets contain information on the date each territory was granted protection, enabling the construction of a spatial panel. Priority municipality controls are built from information contained in each of the Ministry of the Environment's annual listings of municipalities that were attributed priority status or removed from the blacklist. Table 9 presents estimated 2SLS coefficients for the benchmark specification adding controls for protected territory (annual ratio of protected to municipal area) and priority municipalities (annual indicator of priority status). The positive and significant coefficient for protection likely reflects the practice of allocating protected areas in places heavily affected by forest clearings. The coefficient for priority municipalities is statistically insignificant, suggesting that the effect of priority status on deforestation operates via a law enforcement mechanism, as found by Assunção and Rocha (2019). The impact of law enforcement on deforestation remains robust, and is even slightly larger after the inclusion of the conservation policy controls.

Finally, in the last robustness exercise, we test whether the paper's main results hold when using alternative weather controls. Precipitation and temperature are specially relevant in this empirical setting, because they play a key role in ensuring the instrument meets the necessary exclusion restriction (see Section 3). Weather datasets compiled from information collected at ground stations can carry inaccurate measures of actual weather, particularly in areas with low station density like the Brazilian Amazon. Climate scientists have attempted to mitigate this by using a variety of geographical interpolations to construct grid node-level data from ground stations. Still, if these gridded datasets are sensitive to the specific interpolation technique adopted in their construction, empirical results derived using these datasets might, too, vary with the choice of weather data. The economic literature typically addresses this concern by subjecting results to robustness tests using alternative datasets for weather variables (Dell et al., 2014).

[32] A number of studies document that the policy contributed to reduce deforestation in listed municipalities, but the literature is yet to reach a consensus about the mechanism through which it operated (Arima et al., 2014; Cisneros et al., 2015; Assunção et al., 2019b; Assunção and Rocha, 2019).

Table 10 presents estimated 2SLS coefficients for the benchmark specification using different combinations of benchmark and alternative datasets for precipitation and temperature variables. The benchmark controls are constructed using monthly average air temperature and total precipitation interpolated to a 0.5° by 0.5° grid resolution (Matsuura and Willmott, 2017b,a). These datasets have been extensively used in the economic literature both to evaluate the impact of weather variables on economic outcomes, and to provide relevant precipitation and temperature controls (Jones and Olken, 2010; Dell et al., 2012). The alternative datasets are both provided by the National Oceanic and Atmospheric Administration (NOAA) from the U.S. Department of Commerce. The Climate Prediction Center (CPC) dataset contains daily information on precipitation and maximum/minimum temperature registered by ground stations and interpolated to a 0.5° by 0.5° grid resolution (NOAA-CPC, 2018a; 2018b). The National Centers for Environmental Prediction (NCEP) dataset contains monthly information on average precipitation derived from reanalysis and recorded at a 2.5° by 2.5° grid resolution (NOAA-NCEP, 2019). Alternative weather controls are constructed in the likeness of benchmark controls (see Section 4.4). The table shows that the paper's main results were not driven by our choice our benchmark weather datasets, with estimated coefficients remaining robust in terms of both magnitude and statistical significance.

7. Final Comments

The analysis yields important policy implications. Results indicate that monitoring and law enforcement efforts were effective in curbing Amazon deforestation, helping protect a substantial amount of tropical forest. The magnitude of the estimated impact, combined with the favorable cost-benefit assessment, reinforce the case for maintaining and strengthening command and control strategies to protect vegetation in settings with pervasive illegal deforestation. Yet, the results also tell a broader story — one that is not restricted to the monitoring of tropical forest clearings. This is a story of how a developing country devised a new way of using technology in its favor, and thereby significantly leveraged its capacity to enforce environmental regulation in spite of its weak institutional environment. At a time when the world's future well-being largely hinges on developing countries' ability to enact and enforce effective environmental regulation to tackle the threats associated with climate change (Greenstone and Jack, 2015), Brazil's experience with satellite monitoring of tropical forests serves as an encouraging example of how innovation can enhance policy.

A. Expected Value for Deforestation

Rewrite the benchmark specification (Equation 2, Section 3) as:

$$y_{i,t} = \delta LawEnforcement_{i,t-1} + \sum_k \theta_k \vec{X}_{i,t} + \psi_i + \lambda_t + \xi_{i,t}, \tag{5}$$

where $y_{i,t}$ is normalized deforestation. In a counterfactual scenario where law enforcement is different to that which was observed, the expected difference between simulated (abbreviated as *sim*) and observed normalized deforestation is given by:

$$\begin{aligned} E[y_{i,t}|_{sim} - y_{i,t}] = \quad & \hat{\delta} LawEnforcement_{i,t-1}|_{sim} + \textstyle\sum_k \hat{\theta}_k \vec{X}_{i,t} + \psi_i + \lambda_t + \\ & -(\hat{\delta} LawEnforcement_{i,t-1} + \textstyle\sum_k \hat{\theta}_k \vec{X}_{i,t} + \psi_i + \lambda_t) \\ = \quad & \hat{\delta}(LawEnforcement_{i,t-1}|_{sim} - LawEnforcement_{i,t-1}). \end{aligned}$$

For the linear transformation in which annual municipal deforestation ($def_{i,t}$) is divided by a municipality-specific constant (μ_i), this difference is given by:

$$E\Big[\frac{def_{i,t}}{\mu_i}\Big|_{sim} - \frac{def_{i,t}}{\mu_i}\Big] = \quad \hat{\delta}(LawEnforcement_{i,t-1}|_{sim} - LawEnforcement_{i,t-1})$$

$$E\Big[\frac{def_{i,t}|_{sim} - def_{i,t}}{\mu_i}\Big] = \quad \hat{\delta}(LawEnforcement_{i,t-1}|_{sim} - LawEnforcement_{i,t-1})$$

$$E[def_{i,t}|_{sim} - def_{i,t}] = \quad \mu_i \times \hat{\delta}(LawEnforcement_{i,t-1}|_{sim} - LawEnforcement_{i,t-1}).$$

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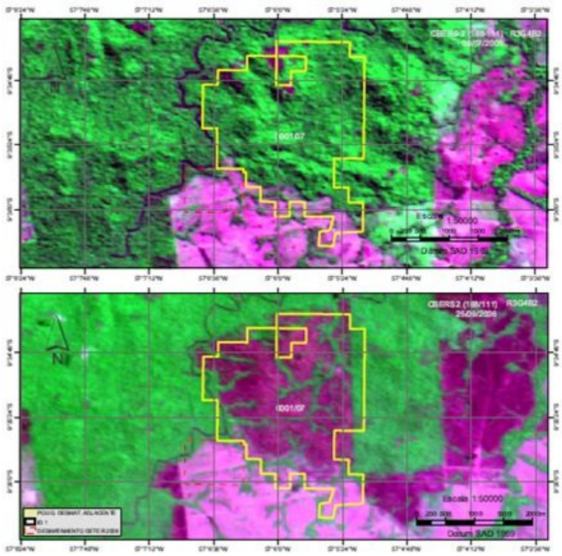
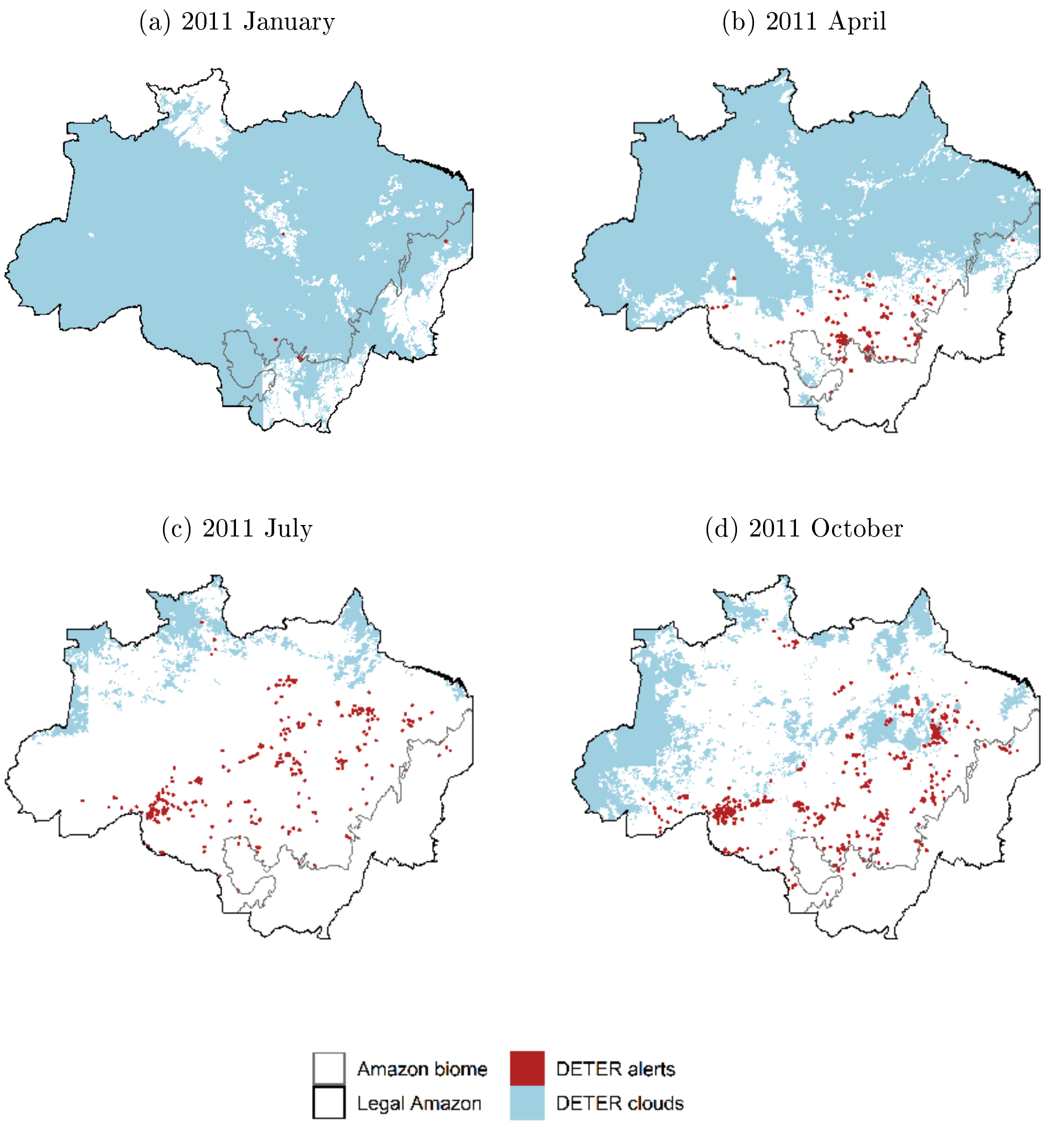
Figures and Tables

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



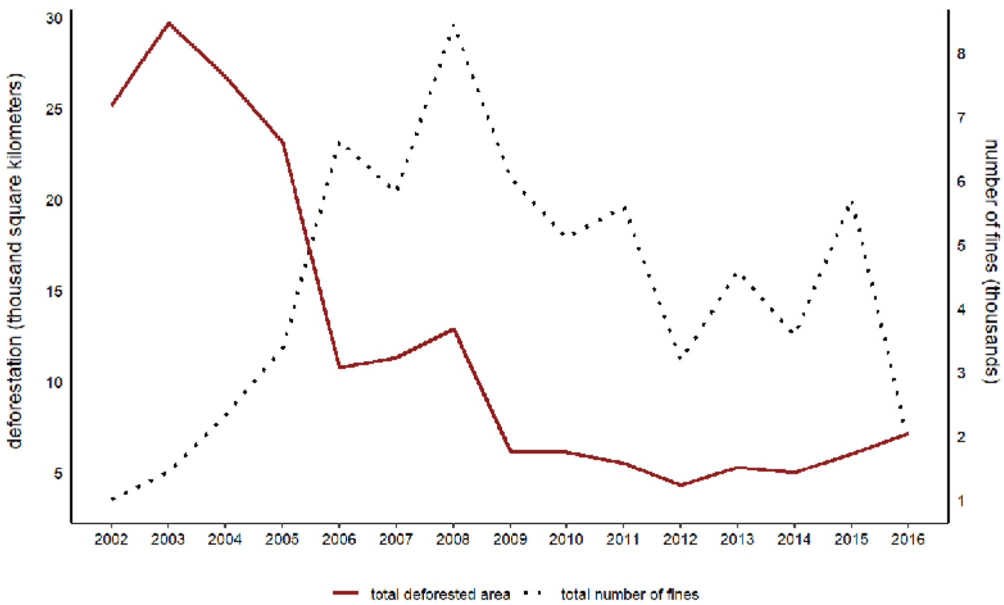
Notes: The top and bottom images show satellite pictures of the same location recorded at two different moments in time – an earlier image (top) and a later one (bottom). Green regions are covered by vegetation, while purple regions are not; the yellow outline marks changes in land cover. The deforestation alert associated with this area carries the spatial information that geographically locates it. Source: image from the Brazilian Institute for the Environment and Renewable Natural Resources (Ibama).

Figure 2: DETER Cloud Coverage and Deforestation Alerts



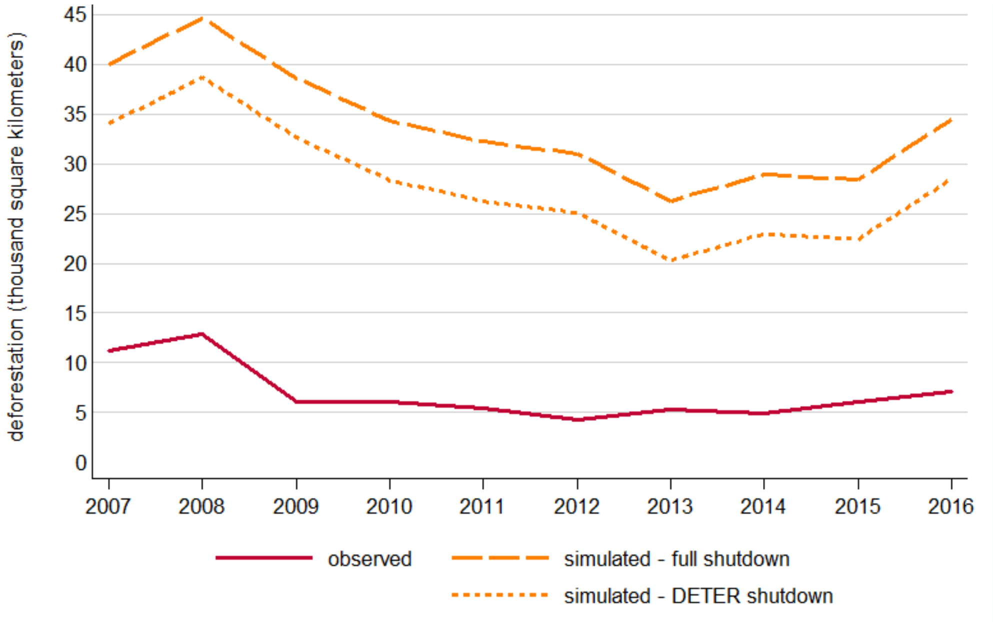
Notes: The maps display DETER cloud coverage and deforestation alerts for four sample months. The Legal Amazon is a geopolitical administrative concept, and the Amazon biome is an ecological one. Sources: DETER clouds and alerts from the Brazilian Institute for Space Research (INPE); territorial divisions from the Brazilian Institute for Geography and Statistics (IBGE).

Figure 3: Descriptive Statistics: Amazon Deforestation and Fine Count



Notes: The graph displays total annual deforested area and total annual deforestation-related fine count for all sample municipalities. Sources: deforestation from the Brazilian Institute for Space Research (INPE); fine count from the Brazilian Institute for the Environment and Renewable Natural Resources (Ibama).

Figure 4: Simulation: Full Shutdown of Amazon Monitoring and Law Enforcement



Notes: The graph displays observed and simulated annual values for total sample deforestation. The simulated trajectories refer to two hypothetical scenarios: (i) Amazon monitoring and law enforcement were entirely shut down, and (ii) DETER was never adopted. The simulations use estimated coefficients from the specification in Table 3 column 6, and set the total number of fines as: (i) zero in all municipalities and years; or (ii) the 2002 through 2004 (pre-DETER) average fine count for each municipality and year. Source: observed deforestation from the Brazilian Institute for Space Research (INPE).

Table 1: Descriptive Statistics

	full sample	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
deforestation												
mean	14	20.55	21.63	24.76	11.76	11.71	10.54	8.21	10.08	9.54	11.54	13.68
sd	39.64	54.58	59.37	57.94	35.64	28.20	26.60	20.68	28.60	24.13	31.61	39.28
enforcement												
mean	9.87	12.72	11.15	16.25	11.61	9.81	10.72	6.11	8.80	6.86	10.96	3.63
sd	28.25	26.85	23.85	37.27	32.74	23.25	26.73	16.19	30.91	24.36	41.01	13.15
DETER cloud coverage												
mean	0.46	0.37	0.65	0.49	0.58	0.49	0.50	0.35	0.37	0.45	0.48	0.39
sd	0.23	0.06	0.16	0.23	0.23	0.25	0.20	0.20	0.21	0.27	0.24	0.27
PRODES cloud coverage												
mean	664.3	376.33	568.60	441.75	434.12	827.65	557.99	585.36	1,237.18	783.31	487.27	1,007.75
sd	2,810.21	1,447.32	2,403.74	1,804.06	1,393.36	3,311.98	2,879.49	2,125.07	4,737.32	3,023.03	1,886.78	3,782.06
PRODES non-observable												
mean	15.2	46.64	47.45	21.71	9.27	7.66	7.62	7.13	7.26	6.97	0.00	5.48
sd	135.5	261.91	262.33	231.46	37.93	36.02	35.82	34.19	33.90	34.03	0.00	33.05
precipitation												
mean	6,962	7,493	7,057	7,414	7,393	6,524	7,084	6,911	7,034	7,164	6,678	5,825
sd	12,514	13,490	12,330	13,203	13,541	11,698	12,458	12,469	12,666	12,487	12,447	10,617
temperature												
mean	26.2	26.03	26.23	25.81	26.00	26.52	26.21	26.12	26.20	25.96	26.21	26.91
sd	1.29	1.22	1.13	1.28	1.21	1.32	1.21	1.28	1.30	1.38	1.26	1.24
agricultural GDP												
mean	55,189	23,078	26,833	34,213	35,401	40,197	54,310	63,100	76,261	76,308	81,703	95,676
sd	90,516	28,109	38,700	54,999	55,231	47,552	77,672	96,993	114,574	107,900	112,769	143,293
crop value												
mean	46,307	17,020	21,611	30,906	30,062	28,583	40,721	48,576	56,797	64,510	78,419	92,232
sd	157,375	47,386	68,907	107,769	101,576	79,036	135,107	157,266	170,334	190,417	224,658	270,509

Notes: The table reports municipality-level means and standard deviations. Variable labels, units, and sources are as follows. Deforestation: km^2, Project for Monitoring Deforestation in the Legal Amazon (PRODES) from the Brazilian Institute for Space Research (INPE); enforcement: number of fines, Brazilian Institute for the Environment and Renewable Natural Resources (Ibama); DETER cloud coverage: ratio of cloud to municipal area, Real-Time System for Detection of Deforestation (DETER) from the Brazilian Institute for Space Research (INPE); PRODES cloud coverage: km^2, PRODES/INPE; PRODES non-observable: km^2, PRODES/INPE; precipitation: mm, Matsuura and Willmott (2017b); temperature: °C, Matsuura and Willmott (2017a); agricultural GDP: BRL1,000, Brazilian Institute for Geography and Statistics (IBGE); crop value: BRL1,000, Municipal Crop Production (PAM) from IBGE. See Section 4 for details on variable construction.

Table 2: OLS Regressions: DETER Cloud Coverage and Law Enforcement

	(1)	(2)	(3)	(4)
		depvar: enforcement		
DETER cloud coverage	-8.1475***	-10.8186***	-8.5958***	-5.5320***
	(2.2383)	(2.5210)	(2.1566)	(2.0579)
precipitation		0.0005***	0.0007***	0.0001
		(0.0002)	(0.0002)	(0.0003)
temperature		-0.0056	0.1019	-1.9367*
		(0.5296)	(0.5178)	(1.0289)
PRODES cloud coverage			-0.0004	0.0011
			(0.0023)	(0.0013)
PRODES non-observable			-0.0018***	0.0003*
			(0.0005)	(0.0002)
R-squared	0.0046	0.0476	0.0688	0.0389
FE: muni & year	no	no	no	yes
controls: agricultural prices	no	no	no	yes
observations	5,731	5,731	5,731	5,731
municipalities	521	521	521	521

Notes: OLS coefficients are estimated based on Equation (1) from Section 3. The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: IV Regressions: Law Enforcement and Deforestation

	(1)	(2)	(3)	(4)
Panel A: OLS and 2SLS, second-stage results				
	depvar: ln(deforest)		*depvar: IHS(deforest)*	
	OLS	2SLS	OLS	2SLS
enforcement, t-1	-0.0003	-0.0743**	0.0002	-0.0503***
	(0.0006)	(0.0290)	(0.0006)	(0.0177)
FE: muni & year	yes	yes	yes	yes
controls: full	yes	yes	yes	yes
observations	5,210	5,210	5,210	5,210
municipalities	521	521	521	521

Panel B: 2SLS, first-stage results	
	depvar: enforcement
	2SLS
DETER cloud coverage	-9.6628***
	(2.5184)
precipitation	-0.0004
	(0.0003)
temperature	-0.5530
	(1.3285)
PRODES cloud coverage	0.0029
	(0.0027)
PRODES non-observable	0.0002
	(0.0001)
first-stage F-statistic	14.72
FE: muni & year	yes
controls: agricultural prices	yes
observations	5,210
municipalities	521

Notes: OLS and 2SLS coefficients are estimated based on Equation (2) from Section 3. Panel A presents OLS and second-stage 2SLS results; Panel B presents first-stage 2SLS results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 and 2); and inverse hyperbolic sine transformation (columns 3 and 4). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: IV Regressions: Law Enforcement and Deforestation Leakage

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS, second-stage results						
	depvar: ln(deforest)			*depvar: IHS(deforest)*		
	border	nearest	buffer	border	nearest	buffer
enforcement, t-1	-0.0695***	-0.0775***	-0.0954***	-0.0687***	-0.0783***	-0.0915***
	(0.0263)	(0.0295)	(0.0300)	(0.0241)	(0.0245)	(0.0284)
FE: muni & year	yes	yes	yes	yes	yes	yes
controls: weather	yes	yes	yes	yes	yes	yes
neigh. controls: full	yes	yes	yes	yes	yes	yes
observations	5,200	5,200	4,750	5,200	5,200	4,750
municipalities	520	520	475	520	520	475
Panel B: 2SLS, first-stage results						
	depvar: enforcement					
	border	nearest	buffer			
DETER cloud coverage	-8.4043***	-8.7812***	-8.9344***			
	(2.5992)	(2.3795)	(2.5920)			
first-stage F-statistic	10.45	13.62	11.88			
FE: muni & year	yes	yes	yes			
controls: weather	yes	yes	yes			
neigh. controls: full	yes	yes	yes			
observations	5,200	5,200	4,750			
municipalities	520	520	475			

Notes: 2SLS coefficients are estimated based on Equation (4) from Section 5.2. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 through 3); and inverse hyperbolic sine transformation (columns 4 through 6). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. A central municipality's neighborhood is defined in one of three ways: (i) all municipalities that share a border (are contiguous) with the central municipality (columns 1 and 4); (ii) the three municipalities that are nearest to the central municipality, where proximity is based on the linear distance between municipalities' centroids (columns 2 and 5); and (iii) all municipalities whose centroid lies within a 100km buffer from the central municipality (columns 3 and 6). The set of central municipality control variables contains: precipitation and temperature (weather). The set of neighborhood control variables contains: average precipitation and temperature (weather), total PRODES clouds and other non-observable areas (satellite visibility), average agricultural commodity prices, and average DETER cloud coverage. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available (see Section 5.2 for details on varying numbers of observations across specifications). Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 5: IV Regressions: Law Enforcement and Deforestation, Linear Normalizations for Counterfactual Simulation

	(1)	(2)
Panel A: 2SLS, second-stage results		
	depvar: deforest/muni area	*depvar: deforest/mean*
	2SLS	2SLS
enforcement, t-1	-0.0244***	-0.0452**
	(0.0093)	(0.0176)
FE: muni & year	yes	yes
controls: full	yes	yes
observations	5,210	5,210
municipalities	521	521
Panel B: 2SLS, first-stage results		
	2SLS	
DETER cloud coverage	-9.6628***	
	(2.5184)	
first-stage F-statistic	14.72	
FE: muni & year	yes	
controls: agricultural prices	yes	
observations	5,210	
municipalities	521	

Notes: 2SLS coefficients are estimated based on Equation (2) from Section 3. Panel A presents second-stage 2SLS results; Panel B presents first-stage 2SLS results. In Panel A, the normalization procedures for the dependent variables are: division by municipal area (column 1); and division by the mean deforested area for 2002 through 2016 (column 2). The second-stage 2SLS coefficient in column 1 should be interpreted as percentage points. The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6: IV Regressions: Law Enforcement and Agricultural Production

	(1)	(2)	(3)	(4)
Panel A: 2SLS, second-stage results				
	depvar: ln(ag GDP)		*depvar: ln(crop value)*	
	value	quantum	value	quantum
enforcement, t-1	0.0306***	0.0205***	0.0468**	0.0413***
	(0.0114)	(0.0073)	(0.0187)	(0.0142)
FE: muni & year	yes	yes	yes	yes
controls: weather	yes	yes	yes	yes
controls: satellite visibility	yes	yes	yes	yes
controls: agricultural prices	no	yes	no	yes
observations	5,210	5,210	5,176	5,176
municipalities	521	521	520	520
Panel B: 2SLS, first-stage results				
	depvar: enforcement			
	value	quantum	value	quantum
DETER cloud coverage	-7.3473***	-9.6628***	-7.4746***	-9.8006***
	(2.2322)	(2.5184)	(2.2335)	(2.5264)
first-stage F-statistic	10.83	14.72	11.20	15.05
FE: muni & year	yes	yes	yes	yes
controls: weather	yes	yes	yes	yes
controls: satellite visibility	yes	yes	yes	yes
controls: agricultural prices	no	yes	no	yes
observations	5,210	5,210	5,176	5,176
municipalties	521	521	520	520

Notes: 2SLS coefficients are estimated based on an adaptation of Equation (2) from Section 3, in which agricultural outcomes replace deforestation as the dependent variable. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedure for the dependent variables is the natural log transformation. The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. Specifications that do not include agricultural price controls capture value outcomes (columns 1 and 3), whereas those that do include agricultural price controls capture quantum outcomes (columns 2 and 4). The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Due to missing raw data on municipal value of crop production for select municipalities and years, specifications that use crop value as the dependent variable (columns 3 and 4) are estimated using an unbalanced panel. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Robustness Checks, IV Regressions: Baseline Municipal Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS, second-stage results								
	depvar: ln(deforest)				*depvar: IHS(deforest)*			
	benchmark				benchmark			
enforcement, t-1	-0.0743**	-0.1048***	-0.0805**	-0.0690***	-0.0503***	-0.0665***	-0.0533***	-0.0458***
	(0.0290)	(0.0348)	(0.0319)	(0.0254)	(0.0177)	(0.0212)	(0.0194)	(0.0152)
FE: muni & year	yes	yes	yes	yes	yes	yes	yes	yes
controls: full	yes	yes	yes	yes	yes	yes	yes	yes
trends:								
pre-DETER deforest accum.	no	yes	no	no	no	yes	no	no
pre-DETER deforest increm.	no	no	yes	no	no	no	yes	no
pre-DETER law enforcement	no	no	no	yes	no	no	no	yes
observations	5,210	5,210	5,210	5,210	5,210	5,210	5,210	5,210
municipalities	521	521	521	521	521	521	521	521

	(1)	(2)	(3)	(4)
Panel B: 2SLS, first-stage results				
	depvar: enforcement			
	benchmark			
DETER cloud coverage	-9.6628***	-9.8723***	-9.0611***	-10.5289***
	(2.5184)	(2.5775)	(2.4796)	(2.4305)
first-stage F-statistic	14.72	14.67	13.35	18.77
FE: muni & year	yes	yes	yes	yes
controls: full	yes	yes	yes	yes
trends:				
pre-DETER deforest accum.	no	yes	no	no
pre-DETER deforest increm.	no	no	yes	no
pre-DETER law enforcement	no	no	no	yes
observations	5,210	5,210	5,210	5,210
municipalities	521	521	521	521

Notes: 2SLS coefficients are estimated based on an adaptation of Equation (2) from Section 3, in which linear time trends are included as additional controls. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 through 4); and inverse hyperbolic sine transformation (columns 5 through 8). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. The trends are interactions between a linear year trend and accumulated deforested area in 2003 (as a share of municipal area), the 2003 deforestation increment, or the 2002 through 2004 average municipal fine count. Columns 1 and 5 replicate benchmark results. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Robustness Checks, IV Regressions: Sample Composition

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS, second-stage results						
	depvar: ln(deforest)			*depvar: IHS(deforest)*		
	benchmark			benchmark		
enforcement, t-1	-0.0743**	-0.0538***	-0.0532**	-0.0503***	-0.0493***	-0.0446**
	(0.0290)	(0.0201)	(0.0255)	(0.0177)	(0.0179)	(0.0176)
FE: muni & year	yes	yes	yes	yes	yes	yes
controls: full	yes	yes	yes	yes	yes	yes
pre-DETER forest	all	> median	all	all	> median	all
sample period	2006 – 2016	2006 – 2016	2005 – 2016	2006 – 2016	2006 – 2016	2005 – 2016
observations	5,210	2,600	5,731	5,210	2,600	5,731
municipalities	521	260	521	521	260	521
Panel B: 2SLS, first-stage results						
	depvar: enforcement					
	benchmark					
DETER cloud coverage	-9.6628***	-17.0926***	-8.7604***			
	(2.5184)	(4.8435)	(2.3508)			
first-stage F-statistic	14.72	12.45	13.89			
FE: muni & year	yes	yes	yes			
controls: full	yes	yes	yes			
pre-DETER forest	all	> median	all			
sample period	2006 – 2016	2006 – 2016	2005 – 2016			
observations	5,210	2,600	5,731			
municipalities	521	260	521			

Notes: 2SLS coefficients are estimated based on Equation (2) from Section 3. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 through 3); and inverse hyperbolic sine transformation (columns 4 through 6). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. Columns 1 and 4 replicate benchmark results. The benchmark dataset is a municipality-by-year panel covering the 2006 through 2016 period; columns 3 and 6 refer to an extended sample period covering the 2005 through 2016 period. The benchmark sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available; columns 2 and 4 refer to a restricted sample consisting of municipalities containing an above-median ratio of forest to municipal area at baseline. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Robustness Checks, IV Regressions: Inclusion of Conservation Policy Controls

	(1)	(2)	(3)	(4)
Panel A: 2SLS, second-stage results				
	depvar: ln(deforest)		*depvar: IHS(deforest)*	
	benchmark		benchmark	
enforcement, t-1	-0.0743**	-0.0804**	-0.0503***	-0.0535***
	(0.0290)	(0.0320)	(0.0177)	(0.0195)
priority municipality		0.6272		0.2846
		(0.4099)		(0.2749)
protected territory		3.9807***		2.4942***
		(1.2213)		(0.7888)
FE: muni & year	yes	yes	yes	yes
controls: full	yes	yes	yes	yes
observations	5,210	5,210	5,210	5,210
municipalities	521	521	521	521
Panel B: 2SLS, first-stage results				
	depvar: enforcement			
	benchmark			
DETER cloud coverage	-9.6628***	-8.9976***		
	(2.5184)	(2.4823)		
priority municipality		8.6511**		
		(3.7980)		
protected territory		22.8088*		
		(11.7749)		
first-stage F-statistic	14.72	13.14		
FE: muni & year	yes	yes		
controls: full	yes	yes		
observations	5,210	5,210		
municipalities	521	521		

Notes: 2SLS coefficients are estimated based on an adaptation of Equation (2) from Section 3, in which additional conservation policy variables are included as controls. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 and 2); and inverse hyperbolic sine transformation (columns 3 and 4). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. Columns 1 and 3 replicate benchmark results. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 10: Robustness Checks, IV Regressions: Alternative Weather Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: 2SLS, second-stage results										
	depvar: ln(deforest)					*depvar: IHS(deforest)*				
	benchmark					benchmark				
enforcement, t-1	-0.0743**	-0.0767**	-0.0707**	-0.0735**	-0.0726**	-0.0503***	-0.0519***	-0.0480***	-0.0498***	-0.0492***
	(0.0290)	(0.0303)	(0.0291)	(0.0308)	(0.0286)	(0.0177)	(0.0184)	(0.0177)	(0.0187)	(0.0174)
FE: muni & year	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
controls: full	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
precipitation dataset	MW	MW	CPC	CPC	NCEP	MW	MW	CPC	CPC	NCEP
temperature dataset	MW	CPC	MW	CPC	MW	MW	CPC	MW	CPC	MW
observations	5,210	5,198	5,210	5,198	5,210	5,210	5,198	5,210	5,198	5,210
municipalities	521	521	521	521	521	521	521	521	521	521

	(1)	(2)	(3)	(4)	(5)
Panel B: 2SLS, first-stage results					
	depvar: enforcement				
	benchmark				
DETER cloud coverage	-9.6628***	-9.3122***	-9.3844***	-8.9377***	-9.7835***
	(2.5184)	(2.4655)	(2.4880)	(2.4204)	(2.5486)
first-stage F-statistic	14.72	14.27	14.23	13.64	14.74
FE: muni & year	yes	yes	yes	yes	yes
controls: full	yes	yes	yes	yes	yes
precipitation dataset	MW	MW	CPC	CPC	NCEP
temperature dataset	MW	CPC	MW	CPC	MW
observations	5,210	5,198	5,210	5,198	5,210
municipalities	521	521	521	521	521

Notes: 2SLS coefficients are estimated based on an adaptation of Equation (2) from Section 3, in which weather variables from alternative datasets are included as controls. Panel A presents second-stage results; Panel B presents first-stage results. In Panel A, the normalization procedures for the dependent variables are: natural log transformation (columns 1 through 5); and inverse hyperbolic sine transformation (columns 6 through 10). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The set of control variables contains: precipitation and temperature (weather); PRODES cloud coverage and other non-observable areas (satellite visibility); and agricultural commodity prices. The table references the weather datasets as follows (see Section 6.3 for dataset details): MW for benchmark; CPC for NOAA's Climate Prediction Center; and NCEP for NOAA's National Centers for Environmental Prediction. Columns 1 and 6 replicate benchmark results. The dataset is a municipality-by-year panel covering the 2006 through 2016 period. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available. Robust standard errors are clustered at the municipality level. Significance: *** p<0.01, ** p<0.05, * p<0.10.