DETER-ing Deforestation in the Amazon: Environmental Monitoring and Law Enforcement[†]

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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 curb deforestation. Results hold across several robustness checks. (JEL K32, K42, O13, Q23, Q28, Q54, Q58)

Greenhouse gas 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, Shelef, and Gertler 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, Duflo, and Glennerster 2008; Duflo et al. 2013; Ashraf, Glaeser, and Ponzetto 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 greenhouse gas emission reduction. 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 whether 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 one-fifth of global greenhouse gas emissions originated from the (mostly tropical) forestry sector, Brazil stood out as the country that cleared the most tropical forest area in both absolute and relative terms (Hansen and DeFries 2004; IPCC 2007; 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 pressure by launching a conservation action plan aimed at combating Amazon deforestation. Within less than a decade, Amazon forest-clearing rates fell by nearly 85 percent (INPE 2020c).

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, Libecap, and Mueller 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, monitor more closely, and act more quickly 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 provide oversight across regions often deemed too large, remote, or unsafe for the ground presence of law enforcement personnel.[1]

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, Machin, and Witt 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 2006–2016 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 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 stand-alone 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, increasing monitoring and law enforcement by half decreases municipal deforestation by an estimated 25 percent.

There are at least two possible explanations for this effect, considering 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. Our empirical strategy does not allow us to shed light on the underlying mechanisms driving the estimated impact.

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[1] 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; postdisaster monitoring in Haiti and Pakistan; and tracking of refugee camps in Syria to coordinate humanitarian support (UNITAR 2016; UNITAR 2019).

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 (Greenstone and Hanna 2014; Tanaka 2015). The impacts of environmental regulation have long been assessed but almost exclusively within the context of developed nations (Greenstone 2002; Chay and Greenstone 2005; Gray and Shimshack 2011; Keiser and Shapiro 2019). Greenstone and Hanna (2014) stress the need for further research 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 literature dedicated to the assessment of potential policy drivers of the 2000s Brazilian Amazon deforestation slowdown (Hargrave and Kis-Katos 2013; Assunção, Gandour, and Rocha 2015; Assunção et al. 2020, 2019; Burgess, Costa, and Olken 2019). Although several works 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. 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 enforcement 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 (Levitt 1997; McCrary 2002; Levitt 2002; Di Tella and Schargrodsky 2004; Klick and Tabarrok 2005; Draca, Machin, and Witt 2011) and, more recently, have 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 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 I describes the institutional context regarding Brazilian Amazon deforestation as well as associated environmental monitoring and law enforcement. Section II details the empirical strategy used to estimate the effect of law enforcement on deforestation. Section III describes the data. Section IV discusses the main results and explores policy costs. Section V provides a series of robustness checks. Section VI concludes with policy implications.

I. Institutional Context

This section presents a contextual overview of Brazilian Amazon deforestation, focusing on the three elements that are most necessary to understanding law enforcement's potential for impact in this setting: the nature of deforestation as an illegal activity aimed at clearing land for nonforest uses, the main features of environmental law enforcement for combating forest loss, and the role the novel monitoring system played in enhancing enforcement capacity and allowing for a more timely response to infractions.

A. *Amazon Deforestation*

At the beginning of the twenty-first century, Brazil stood out as the country that cleared the most tropical forest, both in absolute area and relative to its year-2000 forest cover (Hansen et al. 2008). By 2004, the deforested area totaled over 600,000 square kilometers, nearly 15 percent of the country's original Amazon forest area (INPE 2017a; IBGE 2004). There are two aspects of Brazilian Amazon deforestation over the last two decades that are central to this paper: first, it was largely an illegal practice, and second, its primary goal was to clear areas for nonforest 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.[2] 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 percent of total property area and further requiring landholders to preserve areas of permanent protection, such as riparian forests.[3] 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.[4]

The Brazilian Amazon covers an area of approximately 4.2 million square kilometers (IBGE 2004). Undesignated lands—where all clearings are illegal—extend over an estimated 700,000 square kilometers (Azevedo-Ramos and Moutinho 2018). An additional 2.2 million square kilometers are under protection as either indigenous lands or protected areas (Gandour 2018). Because clearing forest within protected

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

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

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

Amazon territory is either entirely forbidden or subject to stringent requirements, it is practically analogous to being illegal. The remaining 1.3 million square kilometers 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, Metzger, and Peres 2010; Godar, Tizado, and Pokorny 2012; Börner et al. 2014). Forest clearings in noncompliant 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 nonforest 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 percent and cropland 6 percent of cleared Amazon areas (INPE and Embrapa 2016).[5] The latter is a symptom of a long history of fragile property rights in the region, where public forest areas are often cleared as a means of illegally claiming ownership over the land (Alston, Libecap, and Mueller 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.[6]

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

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

[6]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; Chimeli and Soares 2017). This typically results in forest degradation (partial removal of forest biomass), not clear-cut deforestation.

what spatial permanence alone could not guarantee: the ability to catch offenders red-handed and hence impose binding penalties.

B. *Environmental Monitoring and Law Enforcement*

In the Amazon environmental law is 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. 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 with anonymous reports of forest-clearing activity received via a hotline. 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 that 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 toward 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 250 meters and a daily revisit rate for the full extent of the Brazilian Amazon. 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 1.

DETER was created specifically to support Ibama's law enforcement efforts.[7] Deforestation alerts served as the basis for targeting ground operations in which law enforcement officers visited alert sites and, upon finding evidence of illegal

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[7] 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.
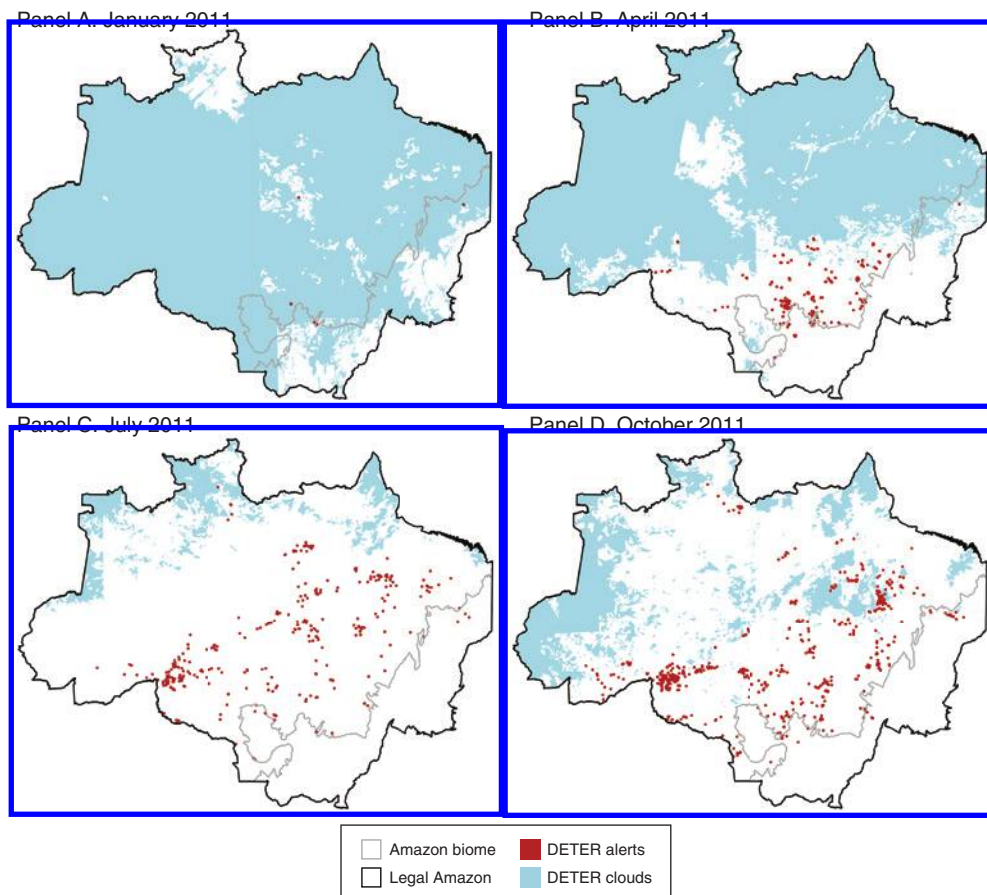
Figure 1. DETER Cloud Coverage and Deforestation Alerts

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: IBGE 2004; Ibama 2007; INPE 2017b, c

clearing activity, applied administrative sanctions. 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 and the seizure and destruction of products and equipment associated with forest clearing. Combined, administrative sanctions imposed a high financial burden on offenders both directly (via fine payment and loss of product and equipment) and indirectly (via forgone production and 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, applied both as stand-alone penalties and along-side 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 1, 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.

C. *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 Ibama's capacity to accurately anticipate spatial deforestation patterns or reports received via its hotline. 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, Libecap, and Mueller 2000; Schmitt 2015; Mueller 2018), their capacity to impose the costliest 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 and destruction could only be resorted to when officers interrupted offenders midclearing. 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.

II. 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 clearing by either inhibiting potential offenders or reducing their capacity to commit future offenses; on the other hand, law enforcement is 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.

As DETER is unable to detect land cover patterns beneath clouds (see Section I), 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 enforcement is 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—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, Sellers, and Shukla 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 beyond 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 map deforested areas annually. 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 to 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 nonobservable 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

$$(1) \qquad LawEnforcement_{i,t} \;=\; \beta DETERclouds_{i,t} + \sum_{k} \gamma_k \mathbf{X}_{i,t} + \alpha_i + \phi_t + \epsilon_{i,t},$$

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; $\mathbf{X}_{i,t}$ 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. Standard errors are estimated using municipality and microregion-year two-way clustering. Municipality-level clustering addresses serial correlation while microregion-year clustering mitigates concerns regarding potential correlation in cloud coverage across municipalities within the same microregion (Bertrand, Duflo, and Mullainathan 2004; Cameron, Gelbach, and Miller 2011). Brazil uses homogeneity criteria to group adjacent municipalities into microregions. The 521 municipalities in our sample comprise 85 microregions, so each microregion covers about 6 municipalities, on average.

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 stand-alone penalties and alongside other sanctions, if law enforcement finds evidence of illegal deforestation, they will almost certainly issue a fine. Moreover,

considering that the vast majority of forest clearings happening during the sample period were illegal and that the adoption of DETER enabled a more timely law enforcement response, law enforcement's presence in deforestation hot spots was 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

$$(2) \quad Deforestation_{i,t} = \delta LawEnforcement_{i,t-1} + \sum_k \theta_k \mathbf{X}_{i,t} + \psi_i + \lambda_t + \xi_{i,t},$$

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 $DETERclouds_{i,t-1}$, $\mathbf{X}_{i,t}$ 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 two-way clustered at municipality and microregion-year levels in all specifications, making them robust to both serial and regional correlation (Bertrand, Duflo, and Mullainathan, 2004; Cameron, Gelbach, and Miller 2011).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), $\mathbf{X}_{i,t}$ 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, Gandour, and Rocha 2015). Conservation policy efforts implemented alongside improvements in monitoring and law enforcement may also have

affected deforestation outcomes during the sample period. We include available policy controls in robustness exercises but refrain from adding them to benchmark specifications due to endogeneity concerns.

III. Data

This paper's empirical analysis uses a 2006–2016 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.[8] 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 percent average ratio of forest to municipal area (INPE 2017a). The nonmissing data for deforestation criteria eliminate 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.[9] Descriptive statistics for the analysis's main variables are presented in the online Appendix.

A. *Deforestation*

Since 1988 INPE has tracked the loss of tropical vegetation in the Brazilian Amazon annually 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 nontropical 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 and not calendar ones.

PRODES was created to map and measure tropical deforestation increments, which are used to calculate an Amazon-wide annual deforestation rate.[10] When an

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[8] The Legal Amazon refers to a geopolitical territorial division, whereas the Amazon biome refers to an ecological one. Figure 1 maps the two regions. Although DETER monitoring covers the full extent of the Legal Amazon, 95 percent of the area deforested in the Amazon since the adoption of the remote monitoring system occurred within the Amazon biome (INPE 2020a, 2020b). This is consistent with the fact that at the time DETER was launched, tropical forest covered less than 5 percent of nonbiome Legal Amazon territory (IBGE 2004, 2007; Ibama 2007; INPE 2017a).

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

[10] 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.

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 on an annual basis both as an Amazon-wide georeferenced dataset and as a panel containing municipal aggregates.

Municipality-level deforestation increments from PRODES serve as the basis for the construction of our main outcome of interest (INPE 2017a). These increments are normalized to account for the large variation in municipality size. (The sample standard deviation is 16,000 square kilometers.) The benchmark normalization procedure uses the inverse hyperbolic sine transformation. Some exercises explore alternative normalization procedures based on the natural log of deforestation, municipality size, and across-time average deforestation.[11]

B. *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. Fines are a good proxy for the presence of law enforcement in the Brazilian Amazon because they are issued both as stand-alone penalties and alongside more severe punishments. In a context in which the vast majority of forest clearings are illegal, 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.[12]

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 (Ibama 2016). Using this record, we build a panel containing the total count of deforestation-related fines issued in each municipality and each year. We also build an analogous monthly panel for use in exercises that explore within-year dynamics.

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[11] The log normalization is implemented as $\ln(deforest_{i,t} + 0.01)$, where $deforest_{i,t}$ is the deforestation increment in kilometers squared 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 square kilometers for all observations in the raw data.

[12] 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.

C. *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 (INPE 2017c). In these datasets areas that are covered by clouds were blocked from view throughout the entire month (see Figure 1).[13] 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. In the exercises that explore within-year dynamics, we use the monthly cloud coverage data.

Although the earliest monthly DETER data are from the 2004 calendar year, the DETER system remained in an experimental phase halfway through the 2005 calendar year. The benchmark sample therefore starts in 2006 (using data from August 2005 through July 2006) and continues through 2016, the latest year for which data were available at the time the dataset was built.

D. *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. 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 municipality-level annual control variables from monthly gridded data on total precipitation and average air temperature (Matsuura and Willmott 2018a, b). Monthly precipitation and temperature data are used in the exercises that explore within-year dynamics. A detailed account of the data construction procedure is provided in the online Appendix.

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 nonobservable areas, and the latter include both shadows cast by clouds and smoke from forest fires (INPE 2017a).[14] We include the two ratios of PRODES obstructed to municipal area in all regressions to control for measurement error as well as to address

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[13] 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.

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

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 to local deforestation activity, we follow Assunção, Gandour, and Rocha (2015) in constructing output price series that capture exogenous variations in the demand for agricultural commodities produced locally. The set of agricultural commodity price controls for year t includes real prices for the first and second semesters of calendar year $t - 1$ as well as real prices for the first semester of calendar year t for beef cattle, soybean, cassava, rice, corn, and sugarcane (IBGE 2014–2018; IBGE 2003–2017; FGV 2019; SEAB-PR 2019). Again, monthly prices are used in the exercises that explore within-year dynamics. A detailed account of the data construction procedure is provided in the online Appendix.

IV. Results

This section presents the main results of the analysis. 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 looks into potential costs of enforcing environmental law in the Amazon.

A. *Cloud Coverage and Law Enforcement*

The relationship between DETER cloud coverage and law enforcement is central to this paper's empirical strategy. We therefore start by investigating whether visual obstructions in the satellite monitoring system affect the presence of environmental law enforcement, in specifications that mirror the first-stage regression of the instrumental variable (IV) strategy. We then explore how this effect varies across cloud coverage lags and leads. This exercise provides a better understanding of the dynamics of this relationship as well as an opportunity to run placebo tests regarding the validity of cloud coverage as an instrument for law enforcement. In doing so, it lays the foundation for the proposed empirical strategy. Finally, we take advantage of the availability of monthly data to repeat the lags and leads exercise and explore within-year dynamics.

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. Table 1 presents estimated fixed-effect coefficients for different combinations of cloud coverage lags and leads. Results indicate a negative and statistically significant association between contemporaneous cloud coverage and law enforcement (column 1). A 10 percentage point increase in cloud coverage reduces the average number of fines by 5.6 percent. This result supports the validity

TABLE 1—OLS REGRESSIONS: CLOUD COVERAGE AND LAW ENFORCEMENT, ANNUAL DATA

	Depvar: enforcement			
	(1)	(2)	(3)	(4)
DETER cloud coverage	−5.5320			−8.7485
	(2.5557)			(2.7926)
DETER cloud coverage, $t-1$		1.1939		0.3804
		(2.4460)		(2.5715)
DETER cloud coverage, $t+1$			−2.4560	0.7660
			(2.5075)	(2.4378)
R^2	0.6203	0.6199	0.6365	0.6384
FE: municipality and year	Yes	Yes	Yes	Yes
Controls: full	Yes	Yes	Yes	Yes
Observations	5,731	5,731	5,210	5,210
Municipalities	521	521	521	521

Notes: OLS coefficients are estimated based on equation (1) from Section II. 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 nonobservable areas (satellite visibility), and agricultural commodity prices. The dataset is a municipality-by-year panel covering the period 2006–2016. 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 in parentheses, clustered by municipality and microregion-year.

of the inclusion restriction imposed by the IV strategy. Moreover, it is consistent with the argument that greater DETER cloud coverage lowers law enforcement's capacity to detect and target deforestation. The remaining columns in Table 1 explore how clouds in year $t-1$ (column 2), year $t+1$ (column 3), and a combination of years $t-1$, t, and $t+1$ (column 4) are associated with law enforcement in year t. Specifications that include leads of cloud coverage serve as placebo tests. While the contemporaneous relationship between cloud coverage and law enforcement is statistically significant, coefficients for cloud coverage lags and leads remain insignificant across specifications.

To shed light on the within-year dynamics of this relationship, we rerun this exercise using monthly data in a municipality and year-month fixed effects model. The paper's main specifications use annual data because the outcome of interest, PRODES deforestation, is only available at annual frequency. DETER cloud coverage, law enforcement, and most control variables (precipitation, temperature, agricultural prices) are available at monthly frequency. Taking advantage of the more frequent data, monthly specifications include double lags and leads for cloud coverage. They also use municipality and microregion-month-year two-way clustering. Results presented in the event-study-like Figure 2 indicate that only lagged cloud coverage negatively affects law enforcement and only cloud coverage from two months ago $(t-2)$ does so with statistical significance. Although DETER alerts are issued in near real time, the law enforcement response and particularly the processing of the administrative penalty may happen over the course of a few weeks. It is again reassuring to see that the placebo exercise with leads yielded insignificant coefficients with point estimates also nearing zero.
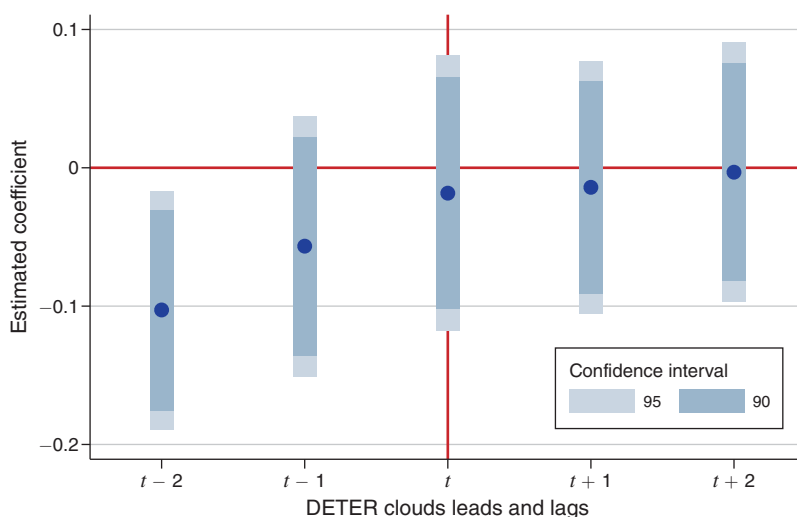
FIGURE 2. DETER CLOUD COVERAGE AND LAW ENFORCEMENT, MONTHLY DYNAMICS

Notes: The graph plots estimated coefficients for an OLS specification relating lagged, current, and future cloud coverage with current law enforcement based on a municipality-by-month panel. The total number of fines issued in each municipality and month serves as a proxy for law enforcement. Robust standard errors are clustered by municipality and microregion-month-year.

Combined, results from Table 1 and Figure 2 corroborate the proposed empirical strategy. They show that DETER cloud coverage is negatively and significantly associated with environmental law enforcement and that the timing of this association is consistent with the use of DETER monitoring as a means of detecting deforestation and thereby targeting the administrative enforcement response. Results from the placebo specifications indicate that the hypothesized relationship between cloud coverage and law enforcement is not spurious; thus, visual obstructions in the DETER monitoring system systematically affect the environmental law enforcement response in the Amazon.

B. *Law Enforcement and Deforestation*

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 2 presents estimated coefficients using both OLS and 2SLS estimators for the benchmark inverse hyperbolic sine normalization as well as 2SLS coefficients for three alternative normalizations of the dependent variable. 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 second-stage 2SLS coefficients, which isolate the effect of law enforcement on deforestation. The OLS coefficient is reported for comparative purposes only. It is statistically insignificant and the point estimate is virtually zero, suggesting that law enforcement does not significantly affect deforestation. This conclusion, however, does not hold, since

Table 2—IV Regressions: Law Enforcement and Deforestation

Panel A. 2SLS, second-stage results and OLS

Depvar:	IHS(deforest) 2SLS (1)	ln(deforest) 2SLS (2)	deforest/muni area 2SLS (3)	deforest/mean 2SLS (4)	IHS(deforest) OLS (5)
Enforcement, $t-1$	−0.0503 (0.0235)	−0.0743 (0.0399)	−0.0244 (0.0123)	−0.0452 (0.0243)	0.0002 (0.0006)
FE: municipality and year	Yes	Yes	Yes	Yes	Yes
Controls: full	Yes	Yes	Yes	Yes	Yes
Observations	5,210	5,210	5,210	5,210	5,210
Municipalities	521	521	521	521	521

Panel B. 2SLS, first-stage results

	Depvar: enforcement 2SLS
DETER cloud coverage	−9.6628 (3.0394)
Precipitation	−0.0004 (0.0003)
Temperature	−0.5530 (1.5160)
PRODES cloud coverage	0.0002 (0.0001)
PRODES nonobservable	0.0029 (0.0026)
First-stage F-statistic	10.11
FE: municipality and year	Yes
Controls: agricultural prices	Yes
Observations	5,210
Municipalities	521

Notes: OLS and 2SLS coefficients are estimated based on equation (2) from Section II. Panel A presents second-stage 2SLS and OLS results; panel B presents first-stage 2SLS results. In panel A the normalization procedures for the dependent variables are inverse hyperbolic sine transformation (columns 1 and 5), natural log transformation (column 2), division by municipal area (column 3), and division by the mean deforested area for 2002–2016 (column 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 nonobservable areas (satellite visibility), and agricultural commodity prices. The dataset is a municipality-by-year panel covering the period 2006–2016. 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 in parentheses, clustered by municipality and microregion-year.

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 coefficient reported in Table 2 suggests 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 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 the inverse hyperbolic sine transformation and refer to column 1 as the benchmark specification. This specification provides a sense of the magnitude of the effect. On average, increasing monitoring and law enforcement by half decreases municipal deforestation by an estimated 25 percent.[15] First-stage 2SLS results 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 percent of the sample mean. These findings validate the inclusion restriction. Finally, with a first-stage F-statistic greater than ten, instrument strength is not a source of concern (Stock, Wright, and Yogo 2002).

Results from Table 2 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. 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 costs and benefits 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 locate recent clearings more quickly, law enforcement officers could also reach the clearing sites faster. This increased the chance that equipment used for deforestation was still on-site and could be apprehended. The loss of such capital goods, which are 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.

C. Policy Costs

Monitoring and law enforcement appear to have been effective at curbing deforestation in the Brazilian Amazon, but were they a cost-effective way of protecting the forest? We perform a back-of-the-envelope cost-benefit calculation to arrive at a simplified answer. Combined, total budgets for Ibama and INPE amounted to

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[15] This magnitude derives from an elasticity of deforestation with respect to law enforcement calculated at 53 percent for the mean municipality (mean values for deforestation and lagged law enforcement for the period 2007–2016 are 13.3 and 10.5, respectively). Calculations are based on elasticities for specifications using the inverse hyperbolic sine (arcsinh) transformation in dependent or explanatory variables derived by Bellemare and Wichman (2020). The authors show that for arcsinh-linear specifications with a continuous independent variable, the elasticity is given by $\hat{\xi}_{yx} = \hat{\beta}\cosh\left(\text{arcsinh}(y)\right) \cdot \frac{x}{y}$.

$6.85 billion for the whole sample period.[16] 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 refer to the specification that uses municipal areas to normalize the annual deforestation increments (Table 2, column 3).[17] We simulate what would have happened in two hypothetical scenarios: one in which Amazon monitoring and law enforcement have been entirely shut down, and 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 municipality to zero or pre-DETER (2002–2004 average fine count) levels, respectively, and simulating municipal deforestation outcomes under these conditions.

Results provided in the online Appendix indicate that both scenarios yield systematically larger estimated deforestation than was observed during the sample period. In the first scenario, if monitoring and law enforcement had been entirely shut down, the Amazon would have seen 338,000 square kilometers of cleared areas—almost five times greater than what was actually observed. 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 279,000 square kilometers. Combined, these exercises point toward 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 and considering that observed deforestation from 2007 through 2016 totaled 69,500 square kilometers, monitoring and law enforcement efforts avoided the clearing of almost 270,000 square kilometers of tropical forest during the sample period. This is equivalent to avoiding the emission of nearly ten billion metric tons of carbon dioxide (tCO_2) over ten years.[18] 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 costs ($6.85 billion) and benefits (10 billion tCO_2), we arrive at a break-even price of $0.69/$tCO_2$. Carbon prices are currently rising, with about half of emissions now covered by carbon-pricing initiatives priced at over $10/$tCO_2$e (World Bank, Ecofys, and Vivid Economics 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.

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[16] 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.

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

[18] Conversion is 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).

Overall, this exercise suggests that monitoring and law enforcement were a cost-effective way of curbing Amazon deforestation.

V. Robustness Checks

Results thus far indicate that the monitoring and law enforcement strategy for combating Amazon deforestation effectively curbed tropical clearings. Table 3 presents estimated coefficients for a series of tests that check the robustness of this finding.

We start by verifying whether our results are driven by differences at baseline (before the introduction of DETER monitoring) that could affect deforestation trends. We focus on three such differences: first, forest cover, since the forest area available for clearing within a municipality mechanically decreases as deforestation advances; second, deforestation increments, because 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.[19] Whereas the first case looks at the stock of deforested areas, this second case considers the flow of deforestation at baseline. Third, we focus on how 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. To implement the tests we separately control for an interaction between a linear year trend and the following baseline municipal characteristics: accumulated deforested area in 2003 as a share of municipal area (column 1), 2003 deforestation increment (column 2), and 2002–2004 average municipal fine count (column 3). 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 instrument strength.

Next we address sample composition. The benchmark sample contains a high degree of variability in municipal forest cover, including municipalities with a relatively small share of forest at baseline. More intense clearing activity in any place and time, which could be associated with a greater presence of law enforcement, mechanically implies that less forest is available for clearing in that same place in the future. To mitigate concerns about mechanical reductions in cleared areas due to a lower availability of forests, we run the benchmark specification using a restricted sample of municipalities containing an above-median ratio of forest to municipal area at baseline (column 4). The result is robust to the sample restriction, with the estimated coefficient remaining negative and statistically significant.

We also test whether results are sensitive to changes in benchmark controls. First, we consider conservation policies that were implemented alongside monitoring and law enforcement—namely, the extent of protected territory (the annual ratio of protected to municipal area) and priority municipality status (CNUC 2016; FUNAI

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[19] This test also captures potential effects from baseline differences in infrastructure across municipalities, such as road networks, that might determine future local forest-clearing dynamics.

TABLE 3—IV REGRESSIONS: ROBUSTNESS CHECKS

Panel A. 2SLS, second-stage results

	Depvar: IHS(deforest)						
	Trends: deforest. stock (1)	Trends: deforest. flow (2)	Trends: enforcement distribution (3)	2003 forest > median sample (4)	Additional policy controls (5)	Alternative weather variables (6)	Two-way cluster state-year (7)
Enforcement, $t-1$	−0.0665 (0.0271)	−0.0533 (0.0256)	−0.0458 (0.0206)	−0.0493 (0.0217)	−0.0535 (0.0259)	−0.0498 (0.0250)	−0.0503 (0.0288)
Priority municipality					0.2853 (0.3222)		
Protected territory					2.4940 (0.8780)		
FE: muni. and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: full	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,210	5,210	5,210	2,600	5,210	5,198	5,210
Municipalities	521	521	521	260	521	521	521

Panel B. 2SLS, first-stage results

	Depvar: enforcement						
	Trends: deforest. stock	Trends: deforest. flow	Trends: enforcement distribution	2003 forest > median sample	Additional policy controls	Alternative weather variables	Two-way cluster state-year
DETER cloud coverage	−9.8723 (3.0775)	−9.0611 (3.0006)	−10.5289 (2.9715)	−17.0926 (5.5638)	−8.9976 (3.0071)	−8.9377 (2.9258)	−9.6628 (3.1521)
Priority municipality					8.6511 (3.7334)		
Protected territory					22.8088 (11.7934)		
First-stage *F*-statistic	10.29	9.119	12.55	9.438	8.953	9.331	9.397
FE: muni. and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: full	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,210	5,210	5,210	2,600	5,210	5,198	5,210
Municipalities	521	521	521	260	521	521	521

Notes: 2SLS coefficients are estimated based on an adaptation of equation (2) from Section II. Panel A presents second-stage results; Panel B presents first-stage results. In panel A the normalization procedure for the dependent variable is inverse hyperbolic sine transformation (columns 1 through 7). The total number of fines issued in each municipality and year serves as a proxy for law enforcement. The trends are interactions between a linear year trend and accumulated deforested area in 2003 (as a share of municipal area) (column 1), the 2003 deforestation increment (column 2), or the 2002–2004 average municipal fine count (column 3). The dataset is a municipality-by-year panel covering the period 2006–2016. The sample includes all Amazon biome municipalities that exhibited variation in forest cover during the sample period and for which deforestation data were available; column 4 refers to a restricted sample consisting of municipalities containing an above-median ratio of forest to municipal area at baseline. The set of control variables contains precipitation and temperature (weather), PRODES cloud coverage and other nonobservable areas (satellite visibility), and agricultural commodity prices; column 5 includes additional conservation policy controls; and column 6 uses weather variables from an alternative dataset (CPC from NOAA's Climate Prediction Center). Robust standard errors are in parentheses, clustered by municipality and microregion-year; column 7 presents robust standard errors in parentheses, clustered by municipality and state-year.

2016a, b; ISA 2016; MMA 2017).[20] Table 3, column 5 presents estimated 2SLS coefficients for the benchmark specification adding conservation policy controls. The positive and significant coefficient for protection likely reflects the practice of

[20] Protected territories include protected areas and indigenous lands; priority municipalities were selected based on their recent deforestation history and were classified as in need of priority action to combat illegal forest clearings.

allocating protected areas in places heavily affected by forest clearings (Gandour 2018). 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.

Second, we test whether the paper's main results hold when using alternative weather controls. Precipitation and temperature are especially relevant in this empirical setting because they play a key role in ensuring the instrument meets the necessary exclusion restriction.[21] The benchmark controls are constructed using monthly average air temperature and total precipitation interpolated to a 0.5-degree by 0.5-degree grid resolution (Matsuura and Willmott 2018a, b). These datasets have been used extensively 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, Jones, and Olken 2012). The alternative datasets are provided by the National Oceanic and Atmospheric Administration (NOAA) from the U.S. Department of Commerce.[22] Table 3, column 6 presents estimated 2SLS coefficients for the benchmark specification using alternative datasets for precipitation and temperature variables. The result shows that the paper's main finding was not driven by our choice of benchmark weather datasets, with the estimated coefficient remaining robust in terms of both magnitude and statistical significance. Additional tests using a reanalysis-based dataset on precipitation as well as different combinations of weather controls are presented in the online Appendix.

We also test whether law enforcement's impact on deforestation is robust to using different units for two-way clustering. Table 3 reports coefficients estimated using municipality and state-year two-way clustering (column 7). In this specification the coefficient of interest is only significant at a level of 8 percent. Note, however, that the Brazilian Amazon comprises only nine states, some of which cover vast territories. The state-year cluster might therefore consider as part of the same group municipalities that are in practice quite far from one another. In using the microregion-year as the benchmark cluster, we aim to address the concerns regarding spatial correlation within a more homogeneous group of municipalities that are in fact close to each other.

Finally, we run two placebo exercises to test our claim that conditional on controls, law enforcement is the only channel through which cloud coverage and deforestation are correlated in the Brazilian Amazon. In the first placebo exercise, we

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[21] 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 geographic 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 also 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, Jones, and Olken 2014).

[22] The Climate Prediction Center (CPC) dataset contains daily information on precipitation and minimum and maximum temperatures registered by ground stations and interpolated to a 0.5-degree by 0.5-degree grid resolution (NOAA-CPC 2018a–c). Alternative weather controls are constructed in the likeness of benchmark controls.

Table 4—Reduced-Form Specifications and Placebo Checks: Cloud Coverage and Deforestation

	Depvar: IHS(deforest)			
	(1)	(2)	(3)	(4)
DETER cloud coverage, $t - 1$	0.4863			0.5313
	(0.1729)			(0.1891)
DETER cloud coverage, t		−0.1783		−0.0181
		(0.1696)		(0.1824)
DETER cloud coverage, $t + 1$			−0.2111	−0.2291
			(0.1944)	(0.1878)
FE: muni. and year	Yes	Yes	Yes	Yes
Controls: full	Yes	Yes	Yes	Yes
R^2	0.8702	0.8699	0.8676	0.8703
Observations	5,210	5,210	4,689	4,689
Municipalities	521	521	521	521

Notes: The table shows OLS coefficients for reduced-form specifications with different combinations of DETER cloud coverage and deforestation years: lagged clouds and current deforestation (column 1), concurrent clouds and deforestation (column 2), future clouds and current deforestation (column 3), and all clouds and current deforestation (column 4). The normalization procedure for the dependent variable is the inverse hyperbolic sine transformation. The set of control variables contains precipitation and temperature (weather), PRODES cloud coverage and other nonobservable areas (satellite visibility), and agricultural commodity prices. The dataset is a municipality-by-year panel covering the period 2006–2016. 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 in parentheses, clustered by municipality and microregion-year.

test the correlation between current deforestation and DETER cloud coverage leads in reduced form. Table 4 presents estimated coefficients for reduced-form specifications with different combinations of DETER cloud coverage and deforestation years. We start by showing that results capture a positive and significant relationship between lagged clouds and current deforestation (column 1). This is consistent with the interpretation of our benchmark results: increased cloud cover in a given municipality and year decreases the presence of law enforcement in that municipality and year, which in turn increases the deforested area measured the following year. If this story holds, cloud cover in future years should not affect current deforestation. It is therefore reassuring to find that the specifications relating concurrent DETER cloud cover and deforestation (column 2) as well as that relating future DETER cloud cover and current deforestation (column 3) both yield insignificant coefficients. Results also hold when all DETER cloud cover variables are simultaneously included (column 4). Estimated coefficients for past cloud coverage remain positive and statistically significant while coefficients for current and future cloud coverage remain insignificant.

In the second placebo exercise, we investigate whether cloud cover and deforestation are correlated prior to the adoption of the DETER system. We obtain pre-DETER data on cloud coverage from NASA's Earth Data Giovanni platform, which provides globally georeferenced monthly cloud coverage for the period 2000–2016
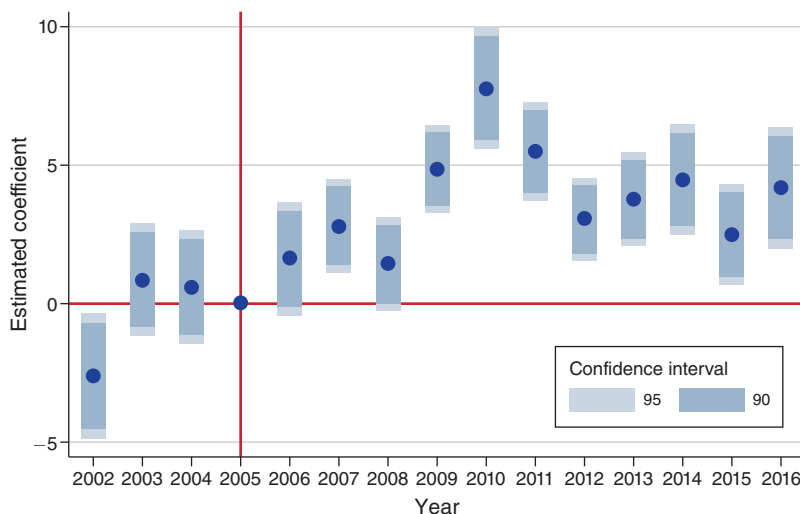
FIGURE 3. PLACEBO CHECK: CLOUD COVERAGE AND DEFORESTATION BEFORE AND AFTER REMOTE MONITORING

Notes: The graph plots estimated coefficients for a reduced-form specification relating cloud coverage in year $t - 1$ and deforestation in year t analogous to that of Table 4, column 1 but including interactions between cloud coverage and year dummies. DETER satellite monitoring was introduced in 2005, so 2002 through 2004 are pre-DETER years. The different shades for the box plot indicate different confidence intervals. Robust standard errors are clustered by municipality and microregion-year.

in calendar years (Platnick, King, and Hubanks 2017).[23] The correlation between DETER and NASA measures for cloud coverage is 0.603. The empirical test is a reduced-form specification relating cloud coverage in year $t - 1$ and deforestation in year t analogous to that of Table 4, column 1 but including interactions between NASA cloud coverage and year dummies. Figure 3 presents the results. Starting in 2006, following the introduction of DETER monitoring, current cloud cover had a significant and positive impact on next year's deforestation. This is to be expected, as NASA cloud coverage correlates with DETER cloud coverage, which affects deforestation via its impact on law enforcement. Yet in the pre-DETER period, current cloud coverage largely appears to have no effect on deforestation the following year. Although the estimated coefficient for 2002 is significant, it carries the opposite sign from what is observed for the post-DETER period. These findings lend support to our identification strategy, as they document a mostly insignificant effect of cloud cover on deforestation before the introduction of DETER-based monitoring and a consistently significant and positive effect thereafter.

VI. Final Comments

The analysis yields important policy implications. Results indicate that monitoring and law enforcement efforts were effective in curbing Amazon deforestation,

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[23] Because cloud and deforestation variables in our analysis are built according to PRODES years, the availability of the NASA cloud data determines 2001 as the first PRODES year in our expanded dataset.

helping to protect a substantial amount of tropical forest. The magnitude of the estimated impact combined with the favorable cost-benefit assessment reinforces 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.

APPENDIX: EXPECTED VALUE FOR DEFORESTATION

Rewrite the benchmark specification (equation (2), Section II) as

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

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

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

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

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

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

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

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