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# Getting Greener by Going Black: The Priority Municipalities in Brazil


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Juliano Assunção
Romero Rocha



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| Contact | Juliano Assunção  juliano@cpirio.org |


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# Getting Greener by Going Black: The Priority Municipalities in Brazil

Juliano Assunção[a,b,*], Romero Rocha[a]

[a] *Climate Policy Initiative Rio de Janeiro (CPI Rio) & Núcleo de Avaliação de Políticas Climáticas da PUC-Rio (NAPC/PUC-Rio)*

[b] *Department of Economics, PUC-Rio*

**Abstract**

In 2008, the Brazilian government blacklisted municipalities in the Amazon to better target the efforts to repress deforestation. Not only law enforcement and monitoring activities were intensified, but also economic sanctions and political pressures were imposed to those municipalities. We find that (i) the blacklisting has significantly reduced deforestation; and (ii) this effect was primarily driven by the monitoring and law enforcement channel – there is no effect on agricultural production or credit concessions. Together, these results illustrates that better protection of the Amazon forest does not necessarily constrain agricultural production.

*Keywords:* Deforestation, Priority Municipalities, Monitoring
JEL codes: Q23, Q24, Q28

*Presenter and Corresponding author. Phone number: +55 (21) 3527 2520. Address: Estrada da Gávea 50, 4º Andar, Gávea - Rio de Janeiro - RJ, 22451-263, Brazil.

*Email addresses:* `juliano@cpirio.org` (Juliano Assunção), `romero.rocha@cpirio.org` (Romero Rocha)

## 1. Introduction

The Amazon is the world's largest rainforest, stretching over an area of more than five million square kilometers. In Brazil, the forest originally occupied over 4 million square kilometers – an area equivalent to almost half of continental Europe. Today, around 80% of the Brazilian Amazon remains covered by native vegetation, making it an important carbon sink. Moreover, the Brazilian Amazon holds unique biodiversity and 20% of the planet's fresh water (MMA (2012)). Protecting the Amazon from illegal deforestation and enforcing environmental regulation in the region is a challenge as immense as the forest itself. Yet, the pace of forest clearings appears to have lost momentum in recent years. Amazon deforestation rates escalated in the early 2000s, but after peaking at over 27,000 square kilometers in 2004, decreased sharply to about 5,000 square kilometers in 2011 (INPE (2013)).

In 2008, the Brazilian Ministry of Environment blacklisted thirty-six municipalities to better target monitoring and law enforcement efforts, setting them as *Municípios Prioritários* (Priority Municipalities, or MPs). This group of municipalities accounted for 45% of the Amazonian deforestation in the previous year ? an astonishing figure considering Brazil has 547 municipalities that transect the Biome. Seven municipalities were added in 2009 and another seven ones were included in 2011. The MPs were intended to serve as targets for a more stringent system of deforestation monitoring and environmental law enforcement. The Brazilian Institute for the Environment and Renewable Natural Resources (Ibama), which operates as the national environmental police and law enforcement authority, focused law enforcement activities on MPs, issuing fines and embargoing farms. These command and control activities were complemented by a series of actions that were not explicit on the original decree launched by the government. These actions included political commitments led by local governments, changes in the approval of subsidized credit contracts, the refusal of meatpacking plants to buy cattle from embargoed farms and development of local plans for sustainable production (Brito et al. (2010), Maia et al. (2011), Arima et al. (2014)).

Was the MPs policy effective to curb deforestation? What is the relative importance of the monitoring and law enforcement activities in comparison to the other actions? Was agricultural production affected in those municipalities?

We address these questions in a panel of municipalities in the Brazilian Amazon from 2002 through 2011. Deforestation data is obtained from processed satellite imagery made publicly available by the National Institute for Space Research. Based on the decrees enacted by the government we create a dummy variable indicating which municipalities are blacklisted in each year. We run fixed-effect models using the blacklist dummy as the main variable of interest.

Our results indicate that the MPs policy significantly reduced deforestation. According to our estimates, the policy avoided the clearing of 11,218 km$^2$ of forest area from 2008 through 2011. In the absence of the policy, the deforestation would have been 54% higher than the 20,689 km$^2$ observed for the period. In a robustness exercise, we show that there is no pre-trend that systematically differentiated municipalities before they became blacklisted.

After identifying the overall impact of the MPs policy, we study the relative importance of the monitoring and law enforcement in comparison to other political and economic actions that came along. While we find that the number of fines increased in the blacklisted municipalities, there was no effect on agricultural GDP, crop production, or credit concessions (total, crops and livestock). This result suggests that command and control component was the primary driver of the deforestation slowdown determined by the policy. Moreover, it suggests that combating deforestation in the Brazilian Amazon does not necessarily create obstacles for agricultural production.

In order to further explore this issue, we come back to the impact of MPs on deforestation and check what happens when we control for the number of fines. The challenge in this exercise is that the number of fines is endogenously determined. We use an instrumental variable approach, based on Assunção et al. (2013), in which cloud cover is used as source of exogenous variation in the number of fines. The main idea is that, after 2004, the government uses satellite imagery to monitor and allocate law enforcers. But the technology does not identify deforestation hot spots under clouds, which generates exogenous variation in law enforcers and, therefore, on the number of fines. When adequately control for the number of fines, the effect of the MPs on deforestation disappears.

This paper contributes to the literature on the drivers of deforestation in the Amazon. The closest paper is Arima et al. (2014), which focus mainly on the impact of the blacklist on deforestation, without exploring the mechanisms. Although the authors follow an empirical strategy that requires a stronger set of assumptions[1] they find similar quantitative results. We show that policies also can interact with other structural determinants such as population, road density, and agroclimatic characteristics (Pfaff (1999), Chomitz and Thomas (2003), Reis and Guzmán (1994), Reis and Margulis (1991)). More recently, there is a literature on the immediate drivers of the recent Amazon deforestation slowdown. Assunção et al. (2012) show that, even when controlling for commodity prices and relevant fixed effects, conservation policies introduced in the second half of the 2000s helped avoid over 60,000 square kilometers of forest clearings. Hargrave and Kis-Katos (2013) and Assunção et al. (2013) find a negative relationship between the number of fines and deforestation in the Amazon. We contribute to this particular literature showing that targeting can further boost effective monitoring and law enforcement efforts.

The paper is also related to a broader literature on the evaluation of effectiveness of environmental monitoring and law enforcement. Gray and Shimshack (2011) provides a recent survey of this literature. Most studies refer to plant-level environmental performance, as captured by standard emissions or accidental discharges (see, for example, Epple and Visscher (1984), Magat and Viscusi (1990), Anderson and Talley (1995), Eckert (2004), Gray and Shadbegian (2005), Shimshack and Ward (2005), and Earnhart and Segerson (2012)). Our paper addresses a different dimension of environmental monitoring and law enforcement, focusing on the impact of a targeted law enforcement policy on deforestation.

The rest of this paper is organized as follows: Section 2 discusses the institutional context in the time of the implementation of priority municipalities; Section 3 provides a detailed description of the data used in the paper; Section 4 explains the empirical strategy used to calculate the impact of priority municipalities on deforestation; Section 5 discusses the results of the paper; and Section 6 addresses the conclusions and policy implications of our results.

## 2. Institutional Context

Brazilian conservation policies were reformulated twice throughout the 2000s. The first change was made in 2004, when satellite imagery and other efforts strengthened monitoring and law enforcement in the Amazon. The second change, began in 2008 and was comprised of better targeting of the protection policies through a blacklist of priority municipalities. These two turning points in the Brazilian conservation policies are analyzed in Assunção et al. (2012).

### *2.1. Phase I: strengthened monitoring and law enforcement*

The government launched, in 2004, a new approach towards combating deforestation in the Brazilian Amazon after a surge in the deforestation rates in early 2000s. The pivotal conservation policy effort was the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (Plano de Prevenção e Controle do Desmatamento na Amazônia Legal, PPCDAm). The PPCDAm integrated actions across different government institutions and proposed new procedures for monitoring, environmental control, and territorial management. PPCDAm also improved the qualification of the environmental authority personnel through intensive training and recruitment.

One of the key components of PPCDAm was the remote sensing-based Amazon monitoring capacity brought about by the implementation of the satellite-based Real-Time Detection of Deforestation System

[1]The exercises implemented in Arima et al. (2014) are substantially different from our specifications in a few dimensions. First, they consider deforestation in absolute terms, which creates an artificial correlation with the policy dummy due to the way the policy was designed. There are also problems with the pre-trends when we consider deforestation in absolute terms. Second, the paper focuses only on two statistical periods and therefore ignore that seven municipalities were included in the list in 2009 and not in 2008. Finally, the specification does not include fixed-effects or other observed variables.

(DETER) - the main tool for allocating law enforcement efforts in the Amazon. Developed by the National Institute for Space Research, DETER is a satellite-based system that captures and processes imagery on Brazilian Amazon forest cover in 15-day intervals, with precision of 25 hectares. The imagery is translated into digital maps, which are used to locate deforestation hot spots and issue alerts signaling areas in need of attention.

Before the DETER system, the Amazon monitoring was dependent on voluntary and anonymous reports of threatened areas. With the new system, the environmental authority was given rapid access to geo-located data on forest clearing activity, and was thus able to better identify and more quickly act against illegal deforestation.

There is a specific characteristic of the DETER system that we also explore in this paper, following Assunção et al. (2013). The system is not able to identify land cover patterns beneath clouds. Cloud coverage, which can be quite extent in the Amazon, limits the ability of the environmental authority to identify deforestation hot spots and, thus, is an exogenous source of variation in monitoring and law enforcement. Assunção et al. (2013) explore this characteristic to estimate the impact of monitoring and law enforcement on deforestation. This paper uses a similar method.

### *2.2. Phase II: better targeting*

The creation of a blacklist to better target efforts that combat illegal deforestation was the main component of the second phase of the PPCDAm. The signing of Presidential Decree 6,321 in December 2007 established the legal basis for singling out municipalities with intense deforestation activity and taking differentiated action towards them. These municipalities, classified based on their recent deforestation history, were marked as in need of priority action to prevent, monitor, and combat illegal deforestation. Any Legal Amazon municipality could be added to what became known as the list of *Municípios Prioritários* (MPs). Municipality-level selection criteria for this list were: (i) total deforested area; (ii) total deforested area over the past three years; and (iii) increase in the deforestation rate in at least three of the past five years. Exiting the list of priority municipalities was conditioned upon significantly reducing deforestation. Issued in January 2008, MMA Ordinance 28 listed the first thirty-six priority municipalities. Seven municipalities were added to the list in 2009, and another seven in 2011.

Differential action taken in priority municipalities largely consisted of more rigorous environmental monitoring and law enforcement. Ibama monitored the municipalities more closely and dedicated a larger share of its resources to them. Licensing and georeferencing requirements for rural establishments were harsher in MPs, and, in an effort to identify fraudulent documents and illegal occupations, private land titles were revised.

In addition to concentrating a large share of Ibama's attention and monitoring efforts, MPs also became subject to a series of other administrative measures that did not necessarily stem from command and control policy. Although not officially established through legislation, these measures imposed an additional cost to being blacklisted. These actions have included political commitments led by local governments, changes in the approval of subsidized credit contracts, the refusal of meatpacking plants to buy cattle from embargoed farms, and development of local plans for sustainable production (Brito et al. (2010), Maia et al. (2011), Arima et al. (2014)).

In light of this, the impact of being added to the list of priority municipalities could be broader than just that of being subject to stricter monitoring and law enforcement. Our empirical analysis takes this potentially broader impact into consideration.

A closer look at the example of the Paragominas, a municipality in the State of Pará, can provide a more concrete notion of what happened. Paragominas was founded in 1965 as part of the occupation process that followed the construction of the Belem-Brasilia road. Logging and extensive practices in agricultural and cattle ranching have resulted in a suppression of 45% of the original forested area.

Paragominas was in the MPs list published in 2008 and was the first municipality to be excluded from the list, after reducing deforestation dramatically, in 2013. Right after being included in the MPs list, Paragominas started a process to set up a plan to reduce deforestation, led by the local government. According to Brito et al. (2010), the mayor's office, local producers associations, and groups from the civil society signed a pact for zero deforestation. Under the new regime, the mayor's office started to support the monitoring and law enforcement implemented by the federal government, while the producers associations with support with NGOs organized a series of meetings and seminars to promote registry and titling, in order to improve property rights. As a consequence, the deforestation rates computed by the PRODES system was reduced from 64.1km$^2$ in 2007/2008 to 18.2km$^2$ in the 2011/2012.

## 3. Data

We compile data from different sources.

### *3.1. Deforestation*

Data on deforestation is built from satellite-based images that are processed at the municipality level and publicly released by PRODES/INPE. We define deforestation as the annual deforestation increment, that is, the area in square kilometers of forest cleared over the twelve months leading up to August of a given year.[2]

For any given municipality, cloud cover during the period of remote sensing may compromise the accuracy of satellite images, requiring images to be produced at a different time. As a result, image records for different years may span from less to more than twelve months. To control for measurement error, variables indicating unobservable areas are included in all regressions. This data is also publicly available at the municipality-by-year level from PRODES/INPE.

To smoothen the cross-sectional variation in deforestation that arises from municipality size heterogeneity, we use a normalized measure of the annual deforestation increment as in Assunção et al. (2012) and Assunção et al. (2013). The normalization ensures that our analysis considers relative variations in deforestation increments within municipalities. The variable is constructed according to the following expression:

$$Deforest_{it} = \frac{ADI_{it} - \overline{ADI}_{it}}{sd\left(ADI_{it}\right)} \tag{1}$$

where $Deforest_{it}$ is the normalized annual deforestation increment for municipality $i$ and year $t$; $ADI_{it}$ is the annual deforestation increment measured in municipality $i$ between the 1$^{st}$ of August of $t-1$ and the 31$^{st}$ of July of $t$; and $\overline{ADI}_{it}$ and $sd\left(ADI_{it}\right)$ are, respectively, the mean and the standard deviation of the annual deforestation increment calculated for each $i$ over the 2002 through 2011 period. The variable $ADI_{it}$ replaces $Deforest_{it}$ in robustness checks. Our sample does not include municipalities that showed no variation in deforestation throughout the sample years, as this variation is needed to calculate the normalized variable.

### *3.2. Municípios Prioritários - MPs*

Our main interest is to study the effect of blacklisting a municipality on different economic outcomes. Thus, we define a variable $MP_{it}$ that is set to 1 if municipality $i$ is in the list in year $t$ and 0 otherwise. Figure 1 shows where are the municipalities that were included in the lists of 2008, 2009 and 2011. We can see that, except for a few cases, they are concentrated in southern and eastern part of the Amazon, less than 300km from the Amazon biome border.

[Figure 1]

[2] More precisely, the annual deforestation increment of year $t$ measures the area in square kilometers deforested between the 1$^{st}$ of August of $t-1$ and the 31$^{st}$ of July of $t$.

### 3.3. *Number of fines*

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

It is worth highlighting that the knowingly low collection rates for environmental fines applied in Amazon municipalities do not interfere with our analysis (Hirakuri (2003), Brito and Barreto (2008), Brito (2009)). These fines are often accompanied by other sanctioning instruments that are more binding, such as seizure and destruction of production goods, tools and materials, and embargoes of production areas. Because panel data for the use of these instruments are not available, we use the number of fines as a proxy for command and control efforts as a whole. Essentially, we are interested in exploring fines as a means of capturing the effect of environmental police (Ibama) presence – not of the sanctioning instrument itself – on deforestation.

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

### 3.4. *Credit and Agricultural Production*

The credit data is constructed from a contract-level microdata set of rural credit loan contracts compiled by the Central Bank from Recor data from 2003 to 2011. This is an administrative microdata set encompassing all rural contract records negotiated by official banks - both public and private - and credit cooperatives in the Legal Amazon. It contains detailed information about each contract, such as the exact day on which it was signed, its value in BRL, the contracted interest rate and maturation date, its intended use by agricultural activity, and the category under which credit was loaned (short-term operating funds, investment, or commercialization). All contracts are linked to a code identifying the municipality in which the borrower's landholding is located. We add up the value of the contract loans across all days in each year and each municipality to convert the microdata panel into a municipality-by-year panel.

To smooth the large cross-sectional variation in values of credit contracts generated by different municipality sizes, we use a normalized measure of rural credit. This normalization ensures that our analysis captures relative variations in credit lending within municipalities. The variable is constructed according to the following expression:

$$Credit_{it} = \frac{C_{it} - \overline{C}_{it}}{sd\left(C_{it}\right)} \tag{2}$$

where $Credit_{it}$ is the normalized amount of rural credit loaned in municipality $i$ and year $t$; the term $C_{it}$ is the amount of rural credit loaned in municipality $i$ and year $t$ in BRL; and the terms $\overline{C}_{it}$ and $sd\left(C_{it}\right)$ are, respectively, the mean and the standard deviation of the amount of rural credit loaned in municipality $i$ over the 2003 through 2011 period.

We also have data from national accounts (IBGE) on agricultural GDP (which includes crop and livestock production) from 2002 to 2009. Besides that, we have data from the Monthly Crop Survey (PAM/IBGE) on crop production from 2002 to 2011.

### 3.5. *Cloud Coverage*

Georeferenced data on deforestation activity produced by the satellite-based Real-Time Detection of Deforestation (DETER) system are used to identify deforestation hot spots and issue alerts that serve to target law enforcement activity. Figure 2 shows examples of maps containing both cloud coverage and alerts captured by DETER. In addition to portraying the high degree of within-year variation in DETER cloud coverage, the figure also clearly illustrates DETER's inability to detect land cover patterns in areas covered by clouds – typically, no deforestation activity is captured and no deforestation alerts are issued in these areas. This supports the perception that the allocation of Ibama personnel is directly affected by

DETER cloud coverage, such that law enforcers are less likely to be present in areas that are systematically under greater cloud coverage.

[Figure 2]

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

### *3.6. Agricultural Output Prices*

Agricultural prices are endogenous to local agricultural production. Thus, to control for fluctuations pressuring deforestation at the municipality level, we must construct output price series that capture exogenous variations in the demand for agricultural commodities produced locally. As argued in Assunção et al. (2012), agricultural commodity prices recorded in the southern Brazilian state of Paraná are highly correlated with average local crop prices calculated for the Legal Amazon sample municipalities. Hence, we use the Paraná agricultural commodity price series as exogenous indicators of local market conditions within our empirical context. Prices for beef cattle, soybean, cassava, rice, corn, and sugarcane were collected at the Agriculture and Supply Secretariat of the State of Paraná (*Secretaria de Agricultura e do Abastecimento do Estado do Paraná*, SEAB-PR). Soybean, cassava, rice, and corn are predominant crops in the Legal Amazon in terms of harvested area. Although not a predominant crop in the region, sugarcane is also included to take into consideration the recent expansion of Brazilian ethanol biofuel production. Together, the five crops account for approximately 70% of total harvested area averaged across sample years.

The Paraná price series are used to build two variables of interest. The first of these variables, an annual index of crop prices, is constructed in three steps. First, we calculate nominal monthly price series for each calendar year-month and culture. Annual prices are deflated to year 2011 BRL and are expressed as an index with base year 2011.

Second, we calculate a weighted real price for each of the crops according to the following expression:

$$PPA_{itc} = PP_{tc} * A_{ic,2000-2001} \tag{3}$$

where $PPA_{itc}$ is the weighted real price of crop $c$ in municipality $i$ and year $t$; $PP_{tc}$ is the Paraná-based real price of crop $c$ in year $t$ expressed as an index with base year 2000; and $A_{ic,2000-2001}$ is the share of municipal area used as farmland for production of crop $c$ in municipality $i$ averaged over the 2000 through 2001 period.[3] This latter term captures the relative importance of crop $c$ within municipality $i$'s agricultural production in the years immediately preceding the sample periods. It thus serves as a municipality-specific weight that introduces cross-sectional variation in the commodity price series.

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

[3]Variables on annual municipality crop production (harvested area, *quantum*, or value in current prices) are based on data originally from the Municipal Crop Survey of the Brazilian Institute for Geography and Statistics (*Pesquisa Agrícola Municipal do Instituto Brasileiro de Geografia e Estatística*, PAM/IBGE).

themselves. Moreover, by using the index of crop prices, which absorbs both cross-sectional and time-specific trends at the municipality level plausibly correlated with credit demand, we overcome an important empirical limitation.

The second variable of interest is an annual index of cattle prices, which is derived analogously to $PPA_{itc}$. However, as land pasture is not observable, in this case $A_{ci,2000-2001}$ is the ratio of heads of cattle to municipal area in municipality $i$ averaged over the 2000 through 2001 period.

*3.7. Other Data Sets*

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

We include a measure of total precipitation in each sample municipality to account for the effect of rainfall on forest clearing activities. We do so by using annual precipitation data compiled by Matsuura and Willmott (2012), who draw on worldwide climate data to calculate a regular georeferenced world grid of estimated precipitation over land.

Finally, we include controls for other relevant conservation policies implemented during the sample period. In particular, we account for total protected area in each municipality, including both conservation units and indigenous lands.

## 4. Empirical Strategy

This section describes the empirical strategy used to identify the causal effect of blacklisting policy on Amazon deforestation and other variables. We also control for year fixed-effects, for agricultural commodity prices, rainfall, and other relevant conservation policies.

Figure 1 suggests that municipalities that were blacklisted are spatially concentrated. If we restrict the sample to municipalities with distance below 300km from the Amazon biome border, we encompass most of the MPs. We consider this sample in our baseline exercises. In robustness exercises, we consider other choices for our sample.

*4.1. Direct impact of blacklisting on deforestation and other outcomes*

The main specification is:

$$Outcome_{it} = \gamma_1 MP_{it} + \sum_k \gamma_k X_{itk} + \psi_i + \lambda_t + \epsilon_{it} \tag{4}$$

where $Outcome_{it}$ is one of our outcome variables (deforestation, number of fines, agricultural production or credit); $MP_{it}$ is a dummy indicating if municipality $i$ is blacklisted on year $t$; $X_{itk}$ is a vector of controls; $\psi_i$ is the municipality fixed effect; $\lambda_t$ is the year fixed effect; and $\epsilon_{it}$ is the idiosyncratic error.

There are some econometric issues that we must account for to ensure validity of our main assumption that priority municipalities are comparable to non-priority ones. They refer to the criteria used for blacklisting: (i) the total deforested area within a municipality since its creation; (ii) the total deforested area over the past three years; and, (iii) the increase in the municipality-level deforestation area in at least three of the past five years. The way the municipalities are chosen, however, also give us an opportunity. The criteria of total deforested area over the last three years take into account the whole deforested area. However, the size of the territory within municipality is not taken into account. Therefore, we have to check whether after normalized the deforestation variable is comparable between groups or not.

We address these issues as follows. First, we include fixed effects, such that we only consider variations in deforested area and account for past deforestation. We also conduct an exercise in which we restrict our sample to municipalities having at least half of their territory covered by native vegetation in the initial sample year.

Second, we consider a normalized version of the deforestation variable, as described in 3.1, such that the scale of the variation is the same for all municipalities. Because total deforested area over the last three years is directly influenced by the absolute size of the municipality, the normalized variable should be comparable between groups in our specifications.

Third, we check if there are differences in pre-trends between treatment and control groups when using the normalized deforestation variable. We address this question in two ways. First, we build dummy variables signaling whether each municipality was attributed priority status in each year. We do it by fixing the year before the municipality have received priority status as year zero. Then, the dummy indicating one year before the year zero is labeled as "1 year before the program" and so on. The same logic is used for the dummies after the program. The pre-treatment dummies are expected to have no significant effect if the pre-trends are alike, and the post-treatment dummies are expected to be negative and significant if the policy had a significant effect. To ensure we are not capturing some pre-trend pattern, we also run the main specification controlling for municipality-specific time trends.

### *4.2. Testing the monitoring and law enforcement channel*

In another exercise, we investigate how the MPs coefficient changes when we control for the number of fines, which is our proxy for monitoring and law enforcement. The challenge of this exercise is that the number of fines is endogenous. Not only do fines have a deterring effect on deforestation, but also the environmental authority allocates more efforts in areas under higher deforestation pressure.

To disentangle these two effects, we follow the approach of Assunção et al. (2013). The authors use the DETER cloud coverage, that affects the identification of hot spots of deforestation, as a source of exogenous variation for the number of fines. Thus, we use a two-stage procedure in which the first-stage is a regression of the number of fines on DETER cloud coverage while the second-stage specifies equation 4 augmented by the number of fines as another explanatory variable.

Thus, the goal is to check whether, after adequately controlling for law enforcement activity, blacklisting still have an impact on deforestation. If the effect is still present, this would suggest that the other political and economic sanctions applied in MPs (political pressure, downstream stricter requirements or credit limitations) are relevant elements of the policy. On the other hand, if the effect is no longer present after controlling for the number of fines, this is suggestive that priority status only affects deforestation through improved monitoring and targeting of law enforcement.

## 5. Results

### *5.1. Direct impact of blacklisting on deforestation*

Table 1 shows the effect of the priority municipalities policy on Amazon deforestation. All specifications include municipality and time fixed effects along with controls for rain, image quality (clouds Prodes and Non-observed Prodes), price, and existence of protected areas.

[Table 1]

Column 1 presents coefficients for our main specification, as described in Section 4. Column 2 uses a restricted sample of municipalities with more than half of their territory covered by native vegetation in the first sample year. Column 3 uses the share of municipality area deforested instead of normalized deforestation as the dependent variable. Column 4 restricts the sample to the years after 2006, and uses the whole Amazon Biome in the sample to allow for comparison with the regressions we later run using the number of fines and DETER cloud coverage (as data on DETER cloud coverage is only available starting in 2006 and cloud coverage is a strong instrument for fines only when using all municipalities of Amazon Biome).

Priority municipalities appears to have a negative and significant impact on deforestation. Results are robust to all specifications. Quantitatively, counterfactual analysis shows that the policy avoided the clearing of 11,396 km$^2$ of Amazon forest area in our sample from 2008 through 2011. Total deforestation observed in the sample in the same period was 20,689 km$^2$, 35.1% smaller than in the absence of the policy.

[Table 2]

Table 2 suggests that our results are not coming from differences in pre-policy trends. In Column 1, we see that only the dummies indicating post-policy priority status have a significant effect on deforestation. The pre-treatment dummies are not statistically significant, indicating that different pre-policy trends are likely not a concern for our specifications. Even so, in Column 2, we run the main specification controlling for municipality- specific time trends. The priority municipalities policy still appears to have a significant negative effect on deforestation. Thus, it seems that we are really capturing the policy effect on deforestation, and not that of unobservables or pre-policy trends.

*5.2. Direct impact of blacklisting on fines, production and credit*

Finally, we investigate the mechanism through which the policy was most effective. To do this, we first calculate the impact of the policy on the number of fines applied by IBAMA and on other economic variables (credit concessions and agricultural production). Table 3 shows the impact of the policy on these variables. Results indicate that the policy had effect only on the number of fines, with no effect on credit concessions and agricultural production. It seems that the mechanism through which the policy had effect on deforestation was the increase on monitoring intensity and quality, since it had no effects on economic variables.

[Table 3]

*5.3. Testing the monitoring and law enforcement channel*

We also run similar regressions as in the Table 1, but controlling for the number of fines applied by Ibama, as instrumented by DETER cloud coverage. Table 4 shows the results. Column 1 use the main specification of Table 1. In Column 2, we use a restricted sample of municipalities with more than half of their territory covered by native vegetation in the first sample year. In Column 3, we use the share of municipality area deforested instead of normalized deforestation as the dependent variable. In Column 4, we control for municipalities specific time trends. The results of all columns show that, when adequately controlling for law enforcement, the priority municipalities policy has no significant impact on deforestation.

[Table 4]

Taken together, these results suggest that the impact of the priority municipalities policy stems from increased monitoring and improved law enforcement in these municipalities. Other potential consequences of being classified as a priority municipalities, such as economic sanctions, appear to have had no significant effect on Amazon deforestation. Of course, part of the effect on better monitoring these municipalities would be attributed to increasing political pressure, but the lack of effect on economic variables withdraw the possibility of economic forces driving the deforestation reduction in priority municipalities.

## 6. Conclusion

We show that the blacklist created by the Brazilian government in 2008 was an effective tool to combat deforestation. In principle, this policy could work by improving the instruments of monitoring and law enforcement or serve as the basis for additional political and economic pressures, as suggested in some studies. Our results suggest that the monitoring and law enforcement channel prevails over the other efforts.

This yields two main policy implications. First, maintaining targeted monitoring and law enforcement activities in the Brazilian Amazon is important to continue reducing deforestation. The MPs has successful targeted the law enforcement activities, thereby reducing deforestation in municipalities which were responsible for an important part of deforestation in the Amazon Biome before the policy implementation. Additionally, our findings show that the policy change had no effect on agricultural production. This finding reinforces the case for relying on monitoring and law enforcement to protect the Amazon. Moreover, it indicates that, in the Amazon region, both preservation and economic growth can happen simultaneously, contrary to any perceived dichotomy between these two goals.

Second, blacklisting does not change economic behavior. Our findings show that the policy change had no effect on agricultural production. This finding reinforces the case for relying on monitoring and law enforcement to protect the Amazon. Moreover, it indicates that, if the government wants to change economic behavior, they should promote actions that directly affect the economic variables, as the blacklist policy alone is not effective in changing these variables.

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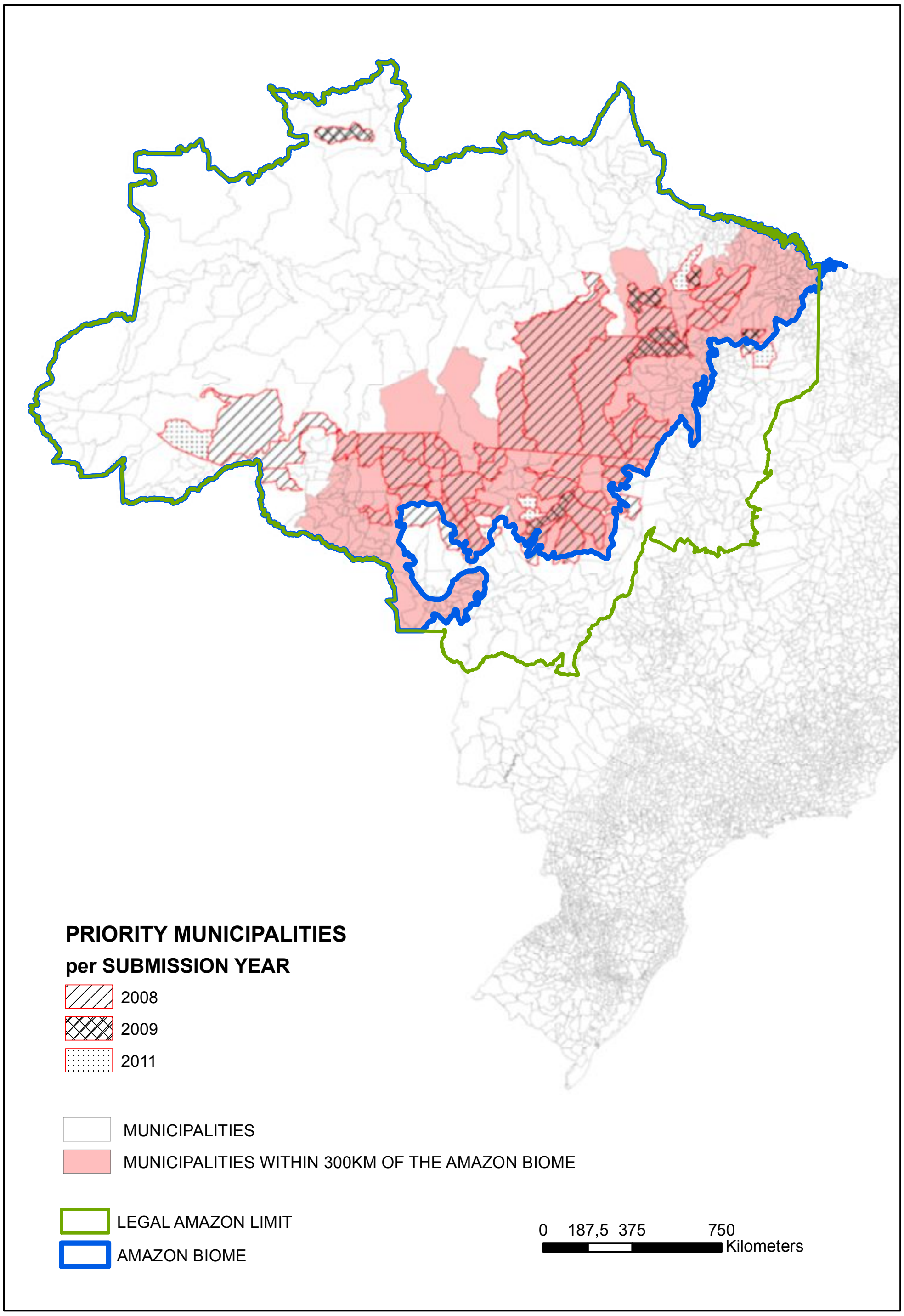
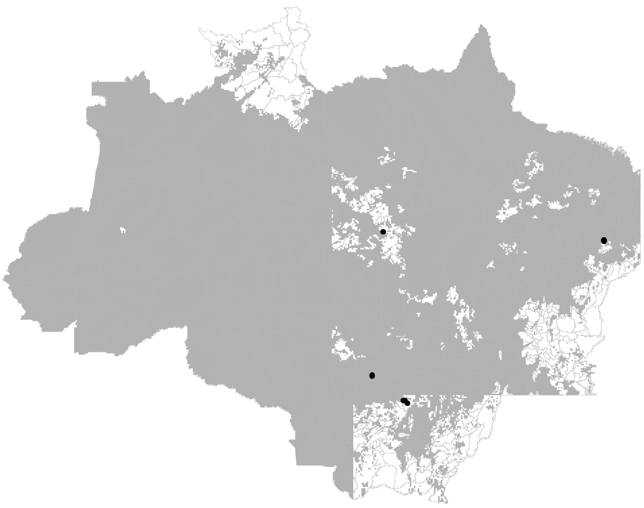
Figure 1: Blacklisted municipalities



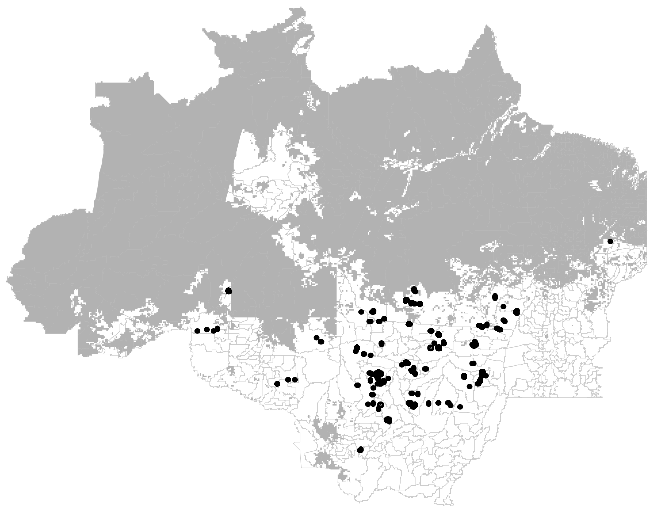

Source: IBGE and Ministry of Environment.

Figure 2: DETER Cloud Coverage and Deforestation Alerts

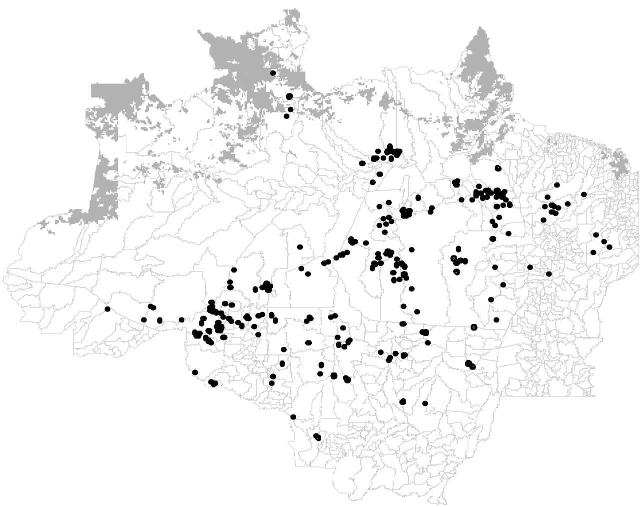
(a) January 2011



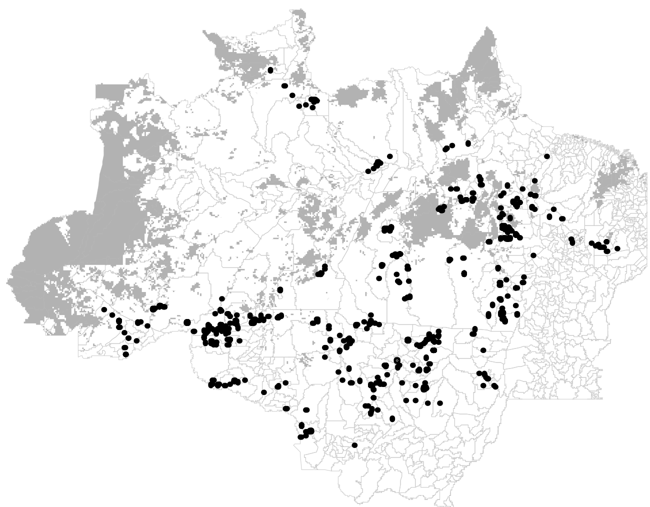
(b) April 2011

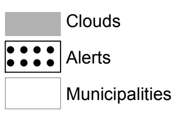


(c) July 2011



(d) October 2011






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

Source: DETER/INPE.

Table 1: The Effect of Blacklisting on Deforestation in the Amazon Biome

| VARIABLES | (1) Normalized Deforestation | (2) Normalized Deforestation | (3) Deforestation Share | (4) Normalized Deforestation |
|---|---|---|---|---|
| Priority Municipalities | -0.545** | -0.558** | -0.00736** | -0.447** |
| | (0.0629) | (0.0700) | (0.000857) | (0.0777) |
| Rain in t-1 | -0.00388 | 0.0104 | -3.83e-05 | 0.00512 |
| | (0.00759) | (0.0107) | (7.65e-05) | (0.00485) |
| Cloud Prodes | -0.00678 | -0.00509 | 7.36e-06 | -0.000140 |
| | (0.00395) | (0.00356) | (2.82e-05) | (0.00154) |
| Non-Observed Prodes | 0.0176 | 0.0216** | 0.000106 | 0.00878 |
| | (0.0151) | (0.00625) | (0.000158) | (0.00928) |
| Protected Areas | -0.371 | -0.135 | 0.0141** | 0.764 |
| | (0.598) | (0.671) | (0.00346) | (0.627) |
| Crops Price Index (Lagged) | 0.240* | 0.434** | 0.00148 | 0.00746 |
| | (0.114) | (0.126) | (0.00196) | (0.110) |
| Crops Price Index 1st Semester | 0.469** | 0.244* | 0.00325* | -0.0639 |
| | (0.142) | (0.0990) | (0.00147) | (0.0794) |
| Prices Cattle in t-1 | 0.0266** | 0.0485** | 3.36e-06 | -0.00200 |
| | (0.00506) | (0.0156) | (5.45e-05) | (0.00362) |
| Cattle Price Index (1st sem) | -0.0291** | -0.0549** | -9.22e-05* | -0.00530 |
| | (0.00394) | (0.0127) | (3.59e-05) | (0.00391) |
| Observations | 2,853 | 1,368 | 2,853 | 2,630 |
| Number of municipalities | 317 | 152 | 317 | 526 |
| Municipality and Year FE | Yes | Yes | Yes | Yes |

Notes: Significance: ** p<0.01, * p<0.05.

Table 2: Pre-Trend Regressions

| VARIABLES | (1)<br>Normalized Deforestation | (2)<br>Normalized Deforestation |
|---|---|---|
| 1 Year Before the Program | -0.180 | |
| | (0.0965) | |
| 2 Year Before the Program | 0.130 | |
| | (0.141) | |
| 3 Year Before the Program | 0.320 | |
| | (0.168) | |
| 4 Year Before the Program | -0.0284 | |
| | (0.151) | |
| 5 Year Before the Program | -0.331 | |
| | (0.294) | |
| 6 Year Before the Program | 0.606 | |
| | (0.544) | |
| 7 Year Before the Program | 0.342 | |
| | (0.630) | |
| 1 Year After the Program | -0.471** | |
| | (0.124) | |
| 2 Year After the Program | -0.435** | |
| | (0.118) | |
| 3 Year After the Program | -0.586** | |
| | (0.0995) | |
| 4 Year After the Program | -0.550** | |
| | (0.107) | |
| Priority Municipalities | | -0.285* |
| | | (0.130) |
| Observations | 2,853 | 2,853 |
| Number of municipalities | 317 | 317 |
| Municipality and Year FE | Yes | Yes |
| Municipality Time Trend | No | Yes |

Notes: Significance: ** p<0.01, * p<0.05.

Table 3: The Effect of Blacklisting on Fines, Agricultural Production and Credit Concessions

| VARIABLES | (1)<br>Fines | (2)<br>Agricultural<br>GDP | (3)<br>Crop<br>Production | (4)<br>Total<br>Credit | (5)<br>Credit for<br>Crop Production | (6)<br>Credit for<br>Livestock |
|---|---|---|---|---|---|---|
| Priority Municipalities | 0.451** | 0.0646 | 0.00149 | -0.0758 | -0.167 | 0.257 |
| | (0.120) | (0.0564) | (0.0699) | (0.158) | (0.157) | (0.137) |
| Observations | 2,871 | 2,359 | 2,798 | 2,996 | 2,996 | 2,988 |
| Number of municipalities | 319 | 337 | 324 | 337 | 337 | 336 |
| Municipality and Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Significance: ** $p<0.01$, * $p<0.05$.

Table 4: The Effect of Blacklisting on Deforestation in the Amazon Biome

| VARIABLES | (1) Normalized Deforestation | (2) Normalized Deforestation | (3) Deforestation Share | (4) Normalized Deforestation |
|---|---|---|---|---|
| Priority Municipalities | 0.146 | 0.550 | 0.000659 | 2.462 |
| | (0.374) | (0.591) | (0.00288) | (4.065) |
| Number of Fines in t-1 | -0.0621 | -0.0912 | -0.000476 | -0.185 |
| | (0.0350) | (0.0474) | (0.000264) | (0.269) |
| Rain in t-1 | -0.0222 | -0.0412 | -0.000153 | -0.173 |
| | (0.0161) | (0.0280) | (0.000120) | (0.283) |
| Cloud Prodes | 0.00169 | 0.00234 | 1.24e-05 | 0.00553 |
| | (0.00253) | (0.00339) | (1.60e-05) | (0.0126) |
| Non-Observed Prodes | 0.0251 | 0.0372* | 0.000129 | 0.0853 |
| | (0.0135) | (0.0190) | (0.000109) | (0.148) |
| Protected Areas | 2.852 | 3.727 | 0.0213 | 7.785 |
| | (1.473) | (2.133) | (0.0112) | (11.42) |
| Crops Price Index (Lagged) | 0.291 | 0.0714 | 0.00316 | 0.111 |
| | (0.321) | (0.327) | (0.00255) | (0.966) |
| Crops Price Index 1st Semester | -0.0711 | -0.260 | 8.37e-05 | 0.431 |
| | (0.190) | (0.281) | (0.00160) | (0.766) |
| Prices Cattle in t-1 | -0.0136 | 0.0165 | -0.000111 | -0.0466 |
| | (0.00975) | (0.0575) | (6.66e-05) | (0.107) |
| Cattle Price Index (1st sem) | 0.00966 | -0.0290 | 6.26e-05 | 0.0499 |
| | (0.0104) | (0.0422) | (7.17e-05) | (0.0666) |
| Observations | 2,630 | 1,655 | 2,630 | 2,630 |
| Number of municipalities | 526 | 331 | 526 | 526 |
| Municipality and Year FE | Yes | Yes | Yes | Yes |
| Municipality Time Trend | No | No | No | Yes |

Notes: Significance: ** p<0.01, * p<0.05.