Pontifícia Universidade Católica
do Rio de Janeiro

João Pedro Vieira

Curbing or Displacing Deforestation?
The Amazon "Blacklist" Policy

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Advisor: Juliano Assunção
Co-advisor: Clarissa Gandour

Economics Department

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Abstract

This paper studies spillovers impact from the Priority Municipalities policy to the Cerrado anthropization process. The policy subjected deforestation hotspots in the Brazilian Amazon to differential action with stricter monitoring and law enforcement. In the mid-2000s, the Brazilian government implemented several conservation efforts focused on curbing deforestation in the Amazon, while in Cerrado, a neighbor biome, these efforts arrived later and without the same intensity, creating a relevant institutional difference across biomes. I apply the differences-in-differences framework on a panel of Cerrado municipalities from 2004 through 2014 to estimate the cross-biome leakage, defining as the treatment group the municipalities within 200 kilometers of the closest Priority Municipality, and, also considering variations in the time of exposure. Results show an increase in the farming area and a decline in the forest area that supports the evidence of leakage effects. Disaggregated variables show that a rise in pasture and a reduction in the savanna drive the results. Impacts are more significant at intermediate distances, from 100 to 150 kilometers, and fade out after 150 kilometers or four years of exposure. Results are robust to the inclusion of controls and are not driven by pre-existing trend differences or the treatment cut-off definition. Counterfactual simulations estimate an increase in farming of 11,414 km^2 (a reduction in the forest of 15,150 km^2) from 2008 through 2014, representing an offset of 58% (77%) of the direct impact of the policy.

Keywords

Anthropization; Spillovers; Priority Municipalities; Amazon; Cerrado

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1 Introduction

Cerrado is the second-largest biome of South America, covering an area close to 2 million square kilometers (IBGE, 2004). Historically, almost 50% of the original area has suffered from anthropization (Strassburg et al., 2017), and, from 2006 to 2014, deforestation rates were the highest among Brazilian biomes (Assis et al., 2019). This scenario becomes very critical, given its vital role in providing ecosystem services and climate change mitigation. Regarding ecosystem services, Cerrado is considered the richest savanna of the world and a global biodiversity hotspot house to more than 11 thousand native species (Myers et al., 2000; Silva and Bates, 2002), it also contains 43% of Brazil's surface water outside the Amazon (Strassburg et al., 2017). Concerning its importance in climate change, the current pace of deforestation represents a contribution of 26% of total land-use change emissions, and this share is expected to increase (Rajão and Soares-Filho, 2015).

Since the 1980s, media attention and conservation efforts were focused on the Amazon, an adjacent biome (Little, 2019). In 2004, a novel integrated plan of action (PPCDAm) was implemented to curb tropical deforestation, mostly present in the Amazon biome. The main innovations were the adoption of a near-real-time detection system of tropical deforestation (DETER), targeting of law enforcement in deforestation hotspots, rural credit conditionalities, and strategic placement of protected areas. The sharp falls on amazon deforestation rates coincide with the policy turning points (Assunção, Gandour, and Rocha, 2015), and there is a vast literature documenting its effectiveness, which explains most of the 82% drop in deforestation rates from 2004 to 2014 (INPE, 2017). However, these institutional changes did not occur at the same time or with the same intensity in the Cerrado. The first plan of action (PPCerrado) was established only in 2010. The Brazilian Forest Code only requires 20% to 35% of a private's land area to be conserved (compared with 80% in the Amazon) (Brasil, 2012). In 2010, only 3,23% of the Cerrado area was under special protection [1] (compared with almost half of the Amazon) (Martins, 2016). Therefore,

[1] Considering indigenous lands, and conservation units (full protection and for sustainable use).

implemented policies curbed tropical deforestation in the Amazon but may have left other biomes and vegetation types relatively more vulnerable to anthropization.

In this paper, the main focus of the analysis is the Priority Municipalities (PMs) policy. This policy consisted of the publication of a “blacklist” of municipalities with recent high rates of deforestation that became subjected to differential law enforcement action. The first list was published in 2008, then updated in 2009, 2011, 2012, and 2017. To be removed from the “blacklist”, municipalities needed to reduce deforestation considerably. The goal of this paper is to explore if there were displacement effects to neighboring Cerrado municipalities. The rationale is that when a municipality enters the “backlist”, there is an exogenous rise in the cost of deforestation due to strict law enforcement (Assunção and Rocha, 2019) or other non-enforcement mechanisms (Cisneros et al., 2015), which results in less deforestation within the PMs but creates a risk of displacement to near municipalities. Additionally, many neighboring municipalities are in the Cerrado biome, due to the proximity of most PMs to the biome’s border. Finally, considering the focus of the policies, the Cerrado seems to be a more attractive region to displace compared to non-blacklisted Amazon municipalities due to weaker conservation requirements and law enforcement.

To tackle this question, I analyze a panel of 340 Cerrado municipalities from 2004 through 2014 using the differences-in-differences framework and considering both distance and time of exposure measures to define treatment. The control group is composed of all municipalities that are too distant[2] from any PM. The fundamental identifying assumption in this setup is that the control group trend is a valid counterfactual for the treatment group trend if they were not treated. The outcomes of interest are the changes in land use and land cover shares of the municipal area. They are obtained from the latest collection of Mapbiomas (2019), which is a multi-institutional initiative to generate annual land use and cover maps based on automatic classification processes applied to satellite images[3].

The model indicates an increase in the farming area (ranging from 0.8 to 1.7 percentage

[2]More than 200km in the benchmark model and more than 250km in the robustness check.
[3]The complete project description can be found at http://mapbiomas.org.

points) while the forest area declined (ranging from 1.4 to 1.9 percentage points), supporting the evidence of leakage effects. Exploring the disaggregated categories, one can see that for farming, what drives its increase is pasture, while crops have null results, and that is consistent with the Brazilian context of low pasture productivity. For forest, what drives its decrease is the savanna, while dense forest has mostly null results, and that is consistent with the fact that dense forest has a higher level of protection compared to the savanna vegetation due to DETER presence in the Legal Amazon. Impacts are more significant at intermediate distances, from 100 to 150 kilometers, and fade out after 150 kilometers or four years of exposure. Robustness checks show supporting evidence for the parallel trends assumption with no significant differences in trends in the period before the policy implementation (2008). Also, I verify that results are not driven by the arbitrary treatment cut-off using a more conservative threshold of 250 kilometers. Finally, the coefficients are stable to the inclusion of controls[4], minimizing omitted variable concerns.

Furthermore, counterfactual simulations, of scenarios in which the blacklist policy was not implemented, suggest an increase (reduction) in farming (forest) of 11,414 km^2 (15,150 km^2) from 2008 through 2014. Following the recommendation from Pfaff and Robalino (2017), I calculate the spillover impact as the percentage of the within-boundary impact. For the direct impact, I use the estimates from Assunção and Rocha (2019), and the indirect effects are obtained from the counterfactual simulation, resulting in an offset of 58% (77%) considering the increase (decrease) in farming (forest) as a proxy for deforestation.

The first and major contribution is to the growing but still scarce literature of spillovers from conservation policies. Spillovers matter for policy because when they are not considered cost-benefit analysis may be underestimated or super estimated, which could mislead policy-makers decisions and public investments. Also, climate change is a global negative externality (Stern, 2008; Nordhaus, 2019), and its main driver are greenhouse gas (GHG) emissions. Hence, it is crucial to identify if conservation policies are only displacing

[4] Weather, commodity prices, policies, available forest area, and farming area time-trends.

emissions to other activities or geographic areas because their net benefit can be null, even if direct impacts are substantial. As noticed in a recent review of this literature by Pfaff and Robalino (2017), there was an explosion in the impact evaluation of conservation programs, but spillover effects are often ignored. They also document that spillovers may or may not occur, can vary in magnitude, and even in direction. I contribute to this literature by documenting and quantifying the magnitude of a leakage effect from an important conservation program in the Brazilian Amazon. There are a few other studies that documented spillover effects from policies under the PPCDam "umbrella" (Cisneros et al., 2015; Andrade, 2016; Gandour, 2018; Amin et al., 2019; Assunção and Rocha, 2019; Assunção et al., 2019 a,c; Herrera et al., 2019) but none of them look at cross-biome spillover.

Secondly, it speaks to the crime literature strand that evaluates potential spatial spillovers from variations in the presence of law enforcement in a given region, as is the case with the PMs policy. Chalfin and McCrary (2017) define this type of reallocation of existing resources to places where crime is highly concentrated as hotspot policing. They also present the debate about the existence and direction of this type of spillover, which could either be deterring or displacing crime to surrounding areas. Gandour (2018) reviews this literature and finds mixed empirical results, because in some contexts there are no significant spillovers (Braga et al., 1999; Di Tella and Schargrodsky, 2004; Braga and Bond, 2008; Taylor et al., 2011; Draca et al., 2011), and in others, there is evidence of crime displacement (Gonzalez-Navarro, 2013; Dell, 2015; Blattman et al., 2019). I contribute to this debate by analyzing this question outside of an urban context. There are a few other studies that contributed to this debate in an environmental law enforcement context, as mentioned above.

Thirdly, within the PPCDAm effectiveness literature[5], some papers focus specifically on the Priority List policy. Regarding direct impacts, there is evidence of a significant reduction in deforestation for these areas (Arima et al., 2014; Cisneros et al., 2015, Assunção

[5]See Gandour (2018) for a recent and broad revision of the PPCDam effectiveness literature.

and Rocha, 2019; Assunção et al., 2019c; Koch et al., 2019). For the mechanism of impact, Assunção and Rocha (2019) argue that law enforcement fully explains the reduction, while Cisneros et al. (2015) estimate that non-enforcement mechanisms account for most of the impact. Abman (2014) and Koch et al. (2019) estimate impacts on other outcomes, showing evidence of electoral punishment for incumbent mayors running for reelection and no evidence of adverse effects on agricultural production and productivity, respectively.

Furthermore, looking at spatial spillover effects, Cisneros et al. (2015) find no evidence of either deterrence or displacement effects using a combination of matching and double-differences frameworks. On the other hand, Andrade (2016) uses a spatial differences-in-differences model and estimates a significant and economically relevant deterrence effect, showing a reduction in forest clearing for non-blacklisted municipalities with a PM as a neighbor. Assunção and Rocha (2019) do a similar exercise and find similar results. Moreover, Assunção et al. (2019c) use a changes-in-changes model to estimate flexible treatment effects and compute an ex-post optimal blacklist. To do that, they also account for spillover effects and find an indirect impact of 618 km^2 avoided deforestation in the 2009-2010 period. Note that the mentioned studies look only to tropical deforestation, which is present almost exclusively in the Amazon Biome. Hence, my main contribution is to be the first paper, to the best of my knowledge, that focuses on a cross-biome leakage effect from a PPCDAm policy to the Cerrado, using a novel dataset that allows me to look at fine land use and vegetation categories.

The rest of this paper is organized as follows: Section 2 gives more details about the Cerrado biome, discusses the Amazon and Cerrado antideforestation policies, and analyze its institutional differences; Section 3 describes variables construction and data sources; Section 4 explains the empirical strategy used to estimate the spatial spillover effect; Section 5 discusses the results of the paper; Section 6 provides robustness checks and caveats for the main model; Section 7 concludes by presenting its policy implications.

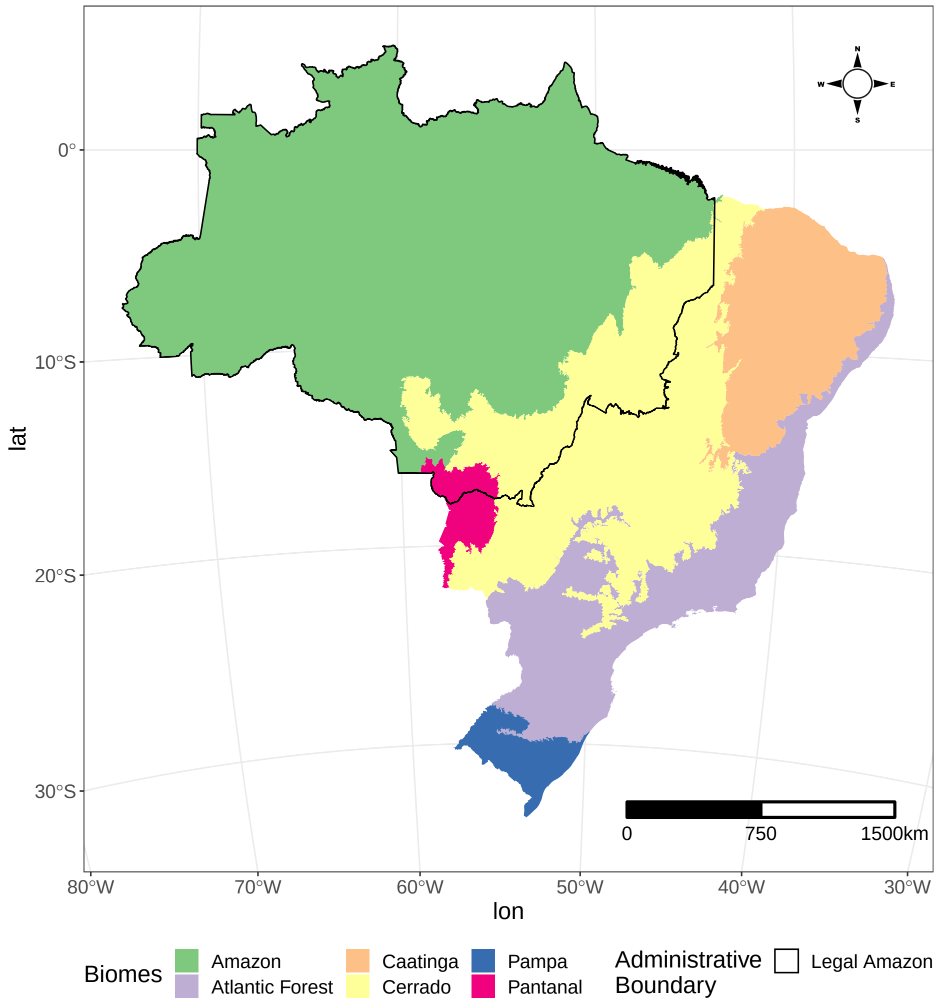
2 Institutional context

This section provides an overview of geographic and ecological characteristics of Cerrado biome, then describes the deforestation trends in the Amazon and the Cerrado, and, finally, compares their institutional setup presenting the central implemented policies to curb deforestation.

The Cerrado is known as the richest savanna in the world, house to more than 11.000 different species (Myers et al., 2000; Silva and Bates, 2002) with a high rate of endemism (45%) (Klink and Machado, 2005; Little, 2019). Its vegetation is very varied in form, ranging from dense grassland, usually with a sparse covering of shrubs and small trees, to an almost closed woodland with a canopy height of 12-15 meters. Moreover, the most widespread type consists of a community of trees and large shrubs, about 2-8 meters, with a grassy ground layer between (Ratter, Ribeiro and Bridgewater, 1997). It is also referred to as an "inverted forest" because the trees can house as much as 80% of their biomass in the roots, and its average estimated carbon stock is 265Mg/ha, which is higher than the Amazon average that ranges from 65 to 125 Mg/ha. It also provides critical ecosystem services, such as biodiversity conservation, water for human consumption, connectivity of vegetation areas, and fertile soils for agricultural production (Little, 2019).

It is essential to locate both Cerrado and Amazon Biomes geographically. As one can see in Figure 1 below, they share an extensive border, and together represent 74% of Brazil's total area (50% Amazon and 24% Cerrado) (IBGE, 2004). Another important boundary represented in Figure 1 is the Legal Amazon, which is an administrative division that includes all the Brazilian Amazon and part of Cerrado and Pantanal. It is often used as the unit of reference in the context of conservation policies.

Figure 1: Map Brazilian Biomes and Legal Amazon



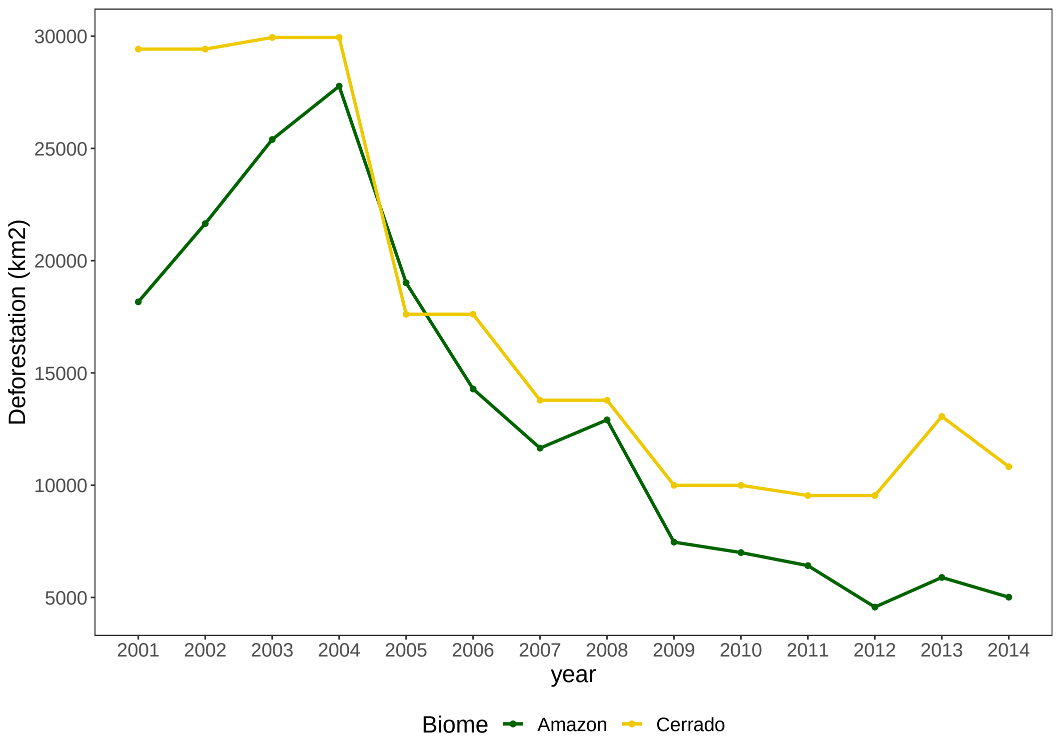
Note: Map of Brazil with all biomes and Legal Amazon boundary.
Data sources: IBGE, MapBiomas.

Historically, Cerrado has lost 46% of its native vegetation (Strassburg, 2017), while Amazon has lost 20%. Figure 2 shows recent annual trends from 2001 through 2014[6]. One can see that, from 2004 through 2009, deforestation rates in both biomes were similar in magnitude and trends, but after 2009 they diverged with Cerrado rates sticking at a higher level. Also, considering that the available area for anthropization in the Cerrado is much smaller than in the Amazon, the fact that in all represented years, except for 2005, deforestation rates were higher in Cerrado compared to the Amazon becomes even more worrisome. A critical characteristic of these clearings is that most of them are illegal. This

[6]Cerrado deforestation data is biannual from 2001 through 2012.

fact is more evident for the Amazon due to stricter conservation requirements, but it seems to be also true for the Cerrado considering estimates from Valdiones et al. (2018) that 98% of Cerrado deforestation in Mato Grosso, the third state with highest deforestation rates, was illegal. Finally, analyzing what happens to these areas after deforestation suggests what the main drivers of this phenomenon are. For the Cerrado, 68% of its territory is used as pasture, and 27% is used as cropland (MMA, 2015).

Figure 2: Deforestation Trends (2001 - 2014)



Notes: The graph plots deforestation trends in square kilometers for the Cerrado and the Amazon biomes from 2001 througl
Source: INPE

As a response to the international pressure due to the rise in deforestation from 2000 to 2004, the Brazilian government created an integrated plan of action (PPCDAm) to propose new approaches to curb deforestation in the Legal Amazon. The two main reformulations were the use of a satellite-based system to detect tropical clearings and the creation of a "blacklist" of the municipalities in need of special attention.

The first phase of PPCDAm started in 2004, and its main component was the strengthening of monitoring and law enforcement. Since 1989, Ibama[7] is responsible for addressing environmental violations acting as the national police authority, and, until 2004, their actions were mostly based on voluntarily anonymous accusations of illegal activities. After 2004, however, there was a massive advance in the identification process of clearings in the Amazon, due to the adoption of DETER[8], developed by INPE[9]. This system processes images in 15-day intervals, and issues alert with the location of the areas with forest loss. In practice, DETER allowed Ibama to act more quickly; therefore, as timing is fundamental, offenders could be caught red-handed and be punished more efficiently (Gandour, 2018). Beyond law enforcement advances, 25 million hectares of protected areas have been created for sustainable use, and full protection and 10 million hectares of indigenous lands were approved (Casa Civil, 2009).

In 2008, the second phase of PPCDAm was initiated, marked by significant legal changes. The most important one, which is also the focus of this research, is the Presidential Decree 6,321 (Brasil, 2007), signed in December 2007, that allowed the exposure of municipalities with intense deforestation in recent years. In practice, the "blacklist" subjected the selected municipalities to differential action, which included stricter monitoring and environmental law enforcement, potential land title revisions, political commitments, changes in the approval of subsidized credit, and less market access due to restriction from international suppliers (Abman, 2014; Andrade, 2016; Assunção and Rocha, 2019; Assunção et al., 2019c, Cisneros et al. 2015). The primary mechanism of action was the adoption of a hotspot policing strategy that focused the attention of law enforcement on areas with high crime rates, with a larger share of dedicated Ibama resources (Assunção and Rocha, 2019), and alerts issued in these areas being prioritized (Andrade, 2016). The selection criteria to be included in the "blacklist" were: (i) total deforested area; (ii) deforested area over the past three years; and (iii) increase in deforestation rates in at least three of the last five years

[7]Brazilian Institute for the Environment and Renewable Natural Resources.
[8]Real-Time Detection of Deforestation System.
[9]National Institute for Space Research.

(Brasil, 2007). The first list was released in 2008 with thirty-six PMs, then seven more were included in 2009 and also in 2011, and two more in 2012[10]. Municipalities needed to reduce deforestation rates below a certain threshold and include 80% of their area [11] into a geo-referenced rural environmental register (CAR) to get their names removed from the list (Brito et al., 2010). Eleven municipalities achieved the exit criteria from 2008 to 2014 (one in 2010, another one in 2011, four in 2012 and five in 2013).

There were other three relevant changes in 2008. First, the Presidential Decree 6,514 regulated the use of penalties like fines, embargoes, and seizure and destruction of equipment as a punishment of environmental crimes (Brasil, 2008a). Secondly, the Brazilian Central Bank published Resolution 3,545 (Brasil, 2008b), which made the concession of rural credit in the Amazon conditional to compliance with legal titling and conservation requirements (Assunção et al., 2019b). Finally, the Brazilian government started to actively support the monitoring and enforcement of the Soy Moratorium, which was first introduced in 2006 and consisted of a voluntary commitment by major soy traders to no longer buy soy from farms that contributed to the Amazon deforestation (Brown and Koeppe, 2013; Gibbs et al., 2015; Svahn and Brunner, 2018).

The Cerrado itself, more recently, received attention from policymakers with the implementation of some conservation policies. In 2010, a plan of action, analogous to the PPCDAm, was adopted for the Cerrado, called the Action Plan for the Prevention and Control of Deforestation and Forest Fires in the Cerrado (PPCerrado). The main goal of the plan is to reduce deforestation by 40% (using 2002-2008 average rate as the baseline) until 2020, to accomplish the voluntary target set at the 15th Conference of the Parties (COP-15). There are three main fronts to achieve the goal. The first is monitoring and control, the second is protected areas, and the third is sustainable production. In practice, efforts were made to develop satellite-based systems to measure natural vegetation loss, and

[10] There was another updated in 2017, but it is out of the scope of this paper analysis because the panel used is from 2004 through 2014.

[11] Excluding publicly-owned protected areas.

a list of PMs was created for the Cerrado as well. The Cerrado version of the "blacklist" included 53 municipalities, was published in 2012, and there were two entry criteria, (i) deforestation rates in 2009 and 2010 higher than 25 km^2, and (ii) native vegetation area superior to 20% or presence of protected areas.

To conclude this section, we can compare the recent advances in the conservation agenda between the Amazon and the Cerrado, and see that there is an apparent institutional discontinuity across the biomes borders. First, the forest code requires 80% of conservation in private properties in the Amazon Biome, while for the Cerrado, it requires only 35% when inside the Legal Amazon and 20% outside of it (Brasil, 2012). Secondly, the innovative monitoring system (DETER) only detects tropical clearings, thus excluding the majority area of the Cerrado that is composed of savanna-vegetation. Thirdly, a similar project like the PPCDAm aimed at the Cerrado was created six years later and without the same technologies as the alert system mentioned above. Fourthly, in 2010, only 3.23% of the Cerrado area was legally protected by conservation units or indigenous lands, while almost half of the Amazon was protected (Martins, 2016). Lastly, tropical deforestation data for the Amazon is annually available and covering the whole biome since 1988, while the same type of data for the Cerrado became available only after 2010.

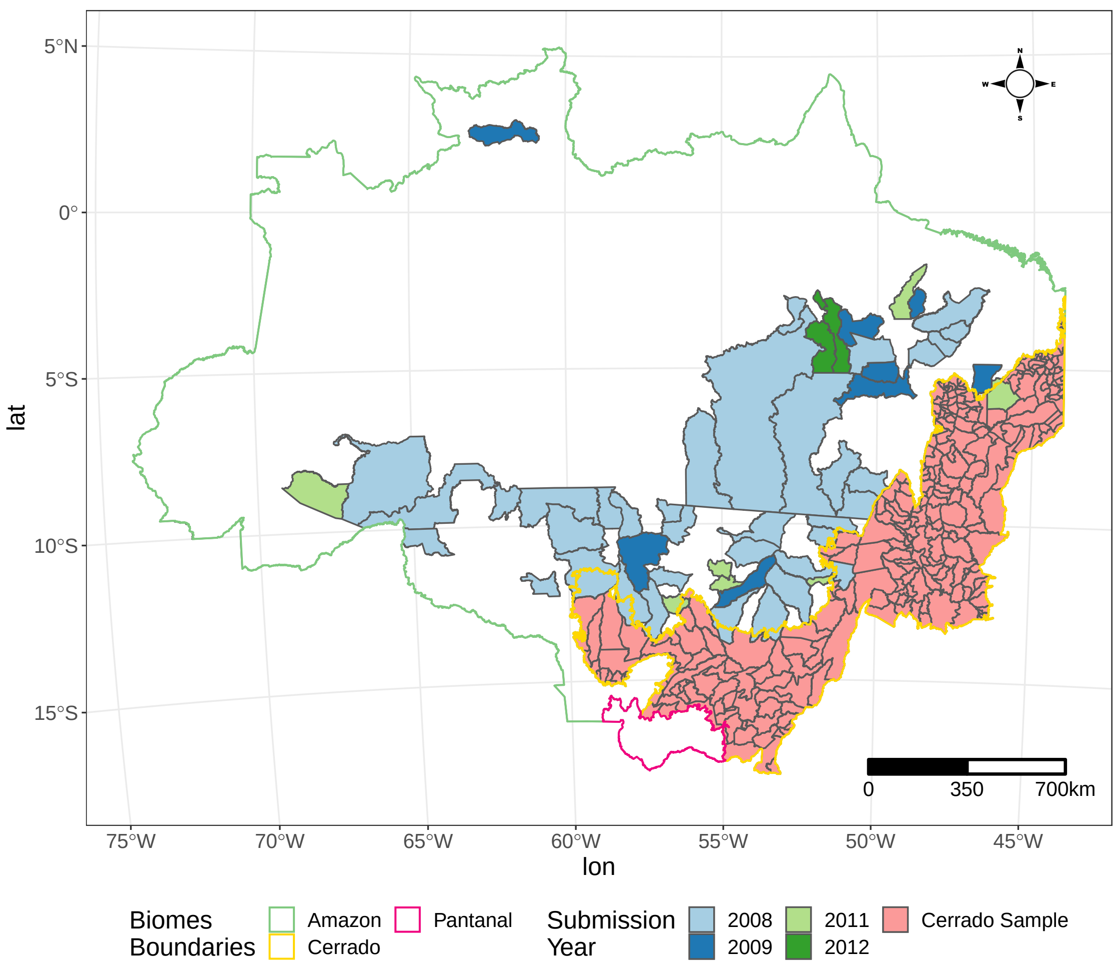
3 Data

The analysis is based on a municipality-by-year panel dataset from 2004 through 2014. I compile information from multiple publicly available data sources. The primary source that allowed this research to go beyond the Amazon biome is Mapbiomas, an initiative that automated land cover and land use classification for all Brazilian biomes from 1985 through 2018. The sample includes complete or partial municipalities[12] that are inside the Legal

[12]Municipal boundaries in the analysis refer to the 2015 administrative division from the Brazilian Institute for Geography and Statistics (IBGE).

Amazon and Cerrado biome boundaries[13]. Some PMs have part of their territory inside the Cerrado biome, but I do not consider them as part of the sample because I am interested in what happens only in its neighborhood. Figure 3 illustrates the 340 sample municipalities and the PMs by submission year (2008, 2009, 2011, and 2012). The rest of this section describes the construction, the data sources, and descriptive statistics of each variable used in the analysis.

Figure 3: Map Sample and Priority Municipalities



Note: Map comprises Legal Amazon region, biomes boundaries, the cerrado sample (pink) and the Priority Municipalities coloured by submission year (blue and green). Data sources: IBGE, MMA, MapBiomas.

[13]Biomes boundaries refer to the one made available by MapBiomas, based on the Biomes Limits Map from IBGE and refined using the Territories Limits and the Phytophysiognomies Map.

3.1 Land Use and Land Cover

The outcomes of interest are extracted from a 30-meter resolution land use and land cover *raster* from Mapbiomas (2019) 4th Collection, available since August 2019. For all variables, I calculate the share of the municipal area destined for the category of interest that includes two main aggregated categories: farming, which is composed of pasture and agriculture, and forest, which is composed of dense forest and savanna. I also include the disaggregated categories separately.

Since 2015, MapBiomas uses machine learning algorithms to classify each 30-meter pixel using Landsat satellite images to generate annual land cover and land use maps of all Brazilian biomes. For each year of data, there are several processing steps. First of all, they create a mosaic with up to 105 layers of image information by pixel. Secondly, they apply the random forest technique to classify the pixel automatically with the algorithm trained with samples obtained by visual interpretation and other reference maps and runs on the Google Earth Engine. Thirdly, they use a spatial filter to reclassify inconsistent pixels (isolated or border) using neighborhood criteria. Fourthly, they apply a temporal filter to fix changes that are impossible or not allowed. Finally, they integrate all the maps into a single one, using prevalence rules and another spatial filtering step.

To generate the dependent variable of interest, I rasterized the sample using the same specifications of the Mapbiomas raster to guarantee a perfect spatial overlay. Then, for each municipality, I extracted all the 30 meters cells with its respective municipality code[14] and all Mapbiomas land use and land cover categories from 2004 through 2014. Next, I calculated the category share dividing the total number of cells destined to the class of interest by the total number of cells of the municipality.

[14] 7-digit code from IBGE.

3.2 Distance to Priority Muncipalities

The MMA first published the list of Priority Municipalities in 2008 and then updated three times (2009, 2011, and 2012) in the period of analysis, as explained in Section 2. I use these lists to construct the main regressors of interest that will define treatment and control groups. There are four main steps. First, I spatialize the PMs list at the municipal level using administrative boundaries data from the same source as the sample. Secondly, I calculate the distance[15] from each sample municipality to the PMs by submission year. Table 1 below shows summary statistics of these distance variables, from which can be inferred that the 2012 PMs are not relevant because they are too far away from the Cerrado border, more than both 200 and 250km cut-offs used to define treatment groups. Then, to include the time of exposure, I construct five variables that assume the value of the smallest distance from the PM created since e years, with e varying from 0 to 4 or more years. If in a year t there was not any PM created since e years, the value becomes 0. To capture spatial heterogeneity, I split these variables into multiple dummies based on 50 kilometers distance breaks (0-50, 50-100, 100-150, and 150-200), leaving as the control group the municipalities that are more than 200 kilometers away from the closest PM.

Table 1: Descriptive Distance Statistics

	Distance to Closest PM			
Submission Year	2008	2009	2011	2012
Min	0	0	0	297
1st Quartile	107	140	125	540
Median	194	263	219	714
Mean	202	282	235	757
3rd Quartile	282	410	327	961
Max	488	743	660	1428

Notes: The table displays summary statistics for the distances from all cerrado municipalities in the sample to the closest Priority Municipality grouped by submission year. All values are in kilometers. Source: MMA, IBGE.

[15] Distances are defined as the smallest distance from the borders of the polygons.

3.3 Agricultural Commodity Prices

The first set of controls accounts for agricultural commodity prices that are important determinants of deforestation (Hargrave and Kis-Katos, 2013; Assunção et al., 2015; Harding et al., 2019). As argued in Assunção et al. (2015), agricultural prices are endogenous to local agricultural production and a consequence of land-use decisions. As an alternative, the authors used the price series from the Agriculture and Supply Secretariat of the State of Paraná to capture exogenous variations in the demand for agricultural commodities produced locally. In this study, I follow an analogous strategy but using a series of commodities price index (USD, 2010 base year) from the World Bank Pink Sheet. Selected commodities are soybean, corn, rice, sugar (as a proxy to sugarcane), and beef cattle. To add variance across the municipalities, I weigh the prices by the commodity relevance in each municipality. For that, I use data from the Brazil Municipal Crop Production Survey (PAM/IBGE) for the crops and the Brazil Municipal Livestock Survey (PPM/IBGE) for the cattle. The following formula defines the controls:

$$PPA_{itc} = PP_{tc} * A_{ic,2000-2003}$$

where PPA_{itc} is the weighted real price of commodity c in municipality i and year t; PP_{tc} is the Pink Sheet real price of commodity c in year t' and $A_{ic,2000-2003}$ is the municipality specific weight. For crops, the weight is given by the share of the municipal area used as farmland for crop c in municipality i averaged over 2000 and 2003. To avoid endogeneity, I only consider the period before the sample for the analysis and policy implementation. For beef cattle, given that annual pasture specific for beef is unobservable, the weight is given by the ratio of heads of cattle to the municipal area in municipality i averaged over 2000 and 2003.

3.4 Weather Control

Based on the literature that forest loss can affect a region's microclimate, and that meteorological conditions can also affect land-use decisions (Nobre et al., 1991; Chomitz and Thomas, 2003; Negri et al., 2004; Aragão et al., 2008; Bagley et al., 2014), I add controls for annual average temperature and annual total precipitation.

The data source is a monthly gridded panel interpolated to a 0.5° by 0.5° resolution on precipitation and air temperature (Matsuura and Willmott, 2015). To construct annual measures for precipitation and temperature in each municipality I follow (Assunção et al., 2019a) with the following steps:

(i) for a municipality that intersects with at least one grid node, I calculate total precipitation and average temperature across nodes;

(ii) for a municipality that does not intersect with any grid nodes, I identify nodes that intersect with its 30km buffer and calculate average precipitation and average temperature across nodes;

(iii) for a municipality that neither intersects nor has its 30km buffer intersecting with any grid nodes, I identify nodes that intersect with its 60km buffer and calculate average precipitation and average temperature across nodes.[16]

Monthly values are then averaged to construct municipality-level annual measures for precipitation and temperature.

3.5 Policy control

Finally, I also use variables that capture the presence of other policies as the share of the protected area and a dummy for being a Priority Cerrado municipality. These policies

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

might be admittedly endogenous because they probably are affected by the treatment. Thus I only use them in Section 6.3 for robustness purposes.

For the Cerrado Priority Municipalities, I did the same spatializing process as the Amazon Priority Municipalities and then created an indicator variable equals to 1 if the municipality i in year t was in the list. For the protected areas, I gathered data from FUNAI on indigenous lands and MMA on strictly protected areas and protected areas for sustainable use and calculated the fraction of the municipal area that was legally protected in each sample year.

3.6 Summary Statistics

Tables 2 and 3 provide summary statistics for the main variables used in the paper. It shows a positive trend in the farming area, mainly after 2008 and a decrease in the forest area. The farming area is composed mostly by pasture representing roughly 80% while the crop area represents the remainings 20%. The forest area is roughly split into halves between dense forest and savanna. As argued in Section 2, the legally protected area in the Cerrado is scarce. In the sample, the average share varies from 5.52% to 5.76%. Finally, the Cerrado Priority municipalities represent only 8.53% of the total number of municipalities.

Table 2: Summary Statistics Table 2004-2008

	2004	2005	2006	2007	2008
Share Farming	0.242	0.253	0.250	0.254	0.255
	(0.193)	(0.193)	(0.194)	(0.193)	(0.195)
Share Forest	0.546	0.529	0.534	0.532	0.530
	(0.209)	(0.201)	(0.204)	(0.202)	(0.205)
Share Pasture	0.199	0.206	0.204	0.208	0.208
	(0.169)	(0.169)	(0.170)	(0.168)	(0.171)
Share Crop	0.0429	0.0473	0.0462	0.0463	0.0470
	(0.124)	(0.127)	(0.126)	(0.126)	(0.128)
Share Savanna	0.257	0.247	0.249	0.257	0.257
	(0.150)	(0.149)	(0.150)	(0.148)	(0.148)
Share Dense Forest	0.289	0.282	0.284	0.274	0.274
	(0.201)	(0.194)	(0.194)	(0.187)	(0.188)
Price, Corn	1.404	1.201	1.447	1.831	2.316
	(2.668)	(2.283)	(2.749)	(3.480)	(4.402)
Price, Sugarcane	0.323	0.433	0.631	0.405	0.478
	(1.804)	(2.413)	(3.519)	(2.260)	(2.664)
Price, Soybean	8.150	7.081	6.755	9.099	11.50
	(23.85)	(20.72)	(19.76)	(26.62)	(33.63)
Price, Rice	3.026	3.534	3.671	3.703	6.845
	(3.914)	(4.571)	(4.747)	(4.790)	(8.853)
Price, Cattle	923.2	932.2	884.9	852.1	953.3
	(786.6)	(794.2)	(754.0)	(726.0)	(812.2)
Rain	194.6	169.6	195.8	167.7	192.7
	(134.2)	(129.2)	(138.6)	(129.5)	(127.1)
Temperature	25.60	25.80	25.54	25.93	25.41
	(1.368)	(1.481)	(1.274)	(1.321)	(1.389)
Cerrado Priority Muni	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
Protected Area	0.0552	0.0560	0.0576	0.0576	0.0576
	(0.178)	(0.178)	(0.179)	(0.179)	(0.179)

Notes: The table reports annual averages and standard deviations (in parenthesis) at the municipal level for the variables used in the analysis from 2004 through 2008. Sources and units: Shares (share of the municipal area destined for the category, MapBiomas); Prices (year 2010 USD, World Bank, PAM/IBGE, and PPM/IBGE); Rain (annual average millimeters, Matsuura e Willmott (2015a)); Temperature (annual average Celsius degrees, Matsuura e Willmott (2015b)); Cerrado Priority Muni (dummy, MMA), Protected Area (share of the municipal area that is protected, MMA and FUNAI).

Table 3: Summary Statistics Table 2009-2014

	2009	2010	2011	2012	2013	2014
Share Farming	0.265	0.266	0.274	0.276	0.289	0.283
	(0.196)	(0.198)	(0.203)	(0.201)	(0.205)	(0.202)
Share Forest	0.527	0.521	0.522	0.522	0.509	0.512
	(0.193)	(0.198)	(0.193)	(0.190)	(0.188)	(0.188)
Share Pasture	0.218	0.217	0.225	0.226	0.237	0.226
	(0.176)	(0.178)	(0.184)	(0.183)	(0.191)	(0.183)
Share Crop	0.0469	0.0483	0.0489	0.0501	0.0522	0.0568
	(0.126)	(0.129)	(0.130)	(0.131)	(0.133)	(0.134)
Share Savanna	0.252	0.251	0.245	0.248	0.239	0.240
	(0.150)	(0.148)	(0.155)	(0.151)	(0.152)	(0.149)
Share Dense Forest	0.275	0.270	0.277	0.274	0.270	0.272
	(0.184)	(0.183)	(0.187)	(0.191)	(0.185)	(0.191)
Price, Corn	1.832	1.985	2.806	2.891	2.524	1.906
	(3.481)	(3.772)	(5.333)	(5.495)	(4.797)	(3.623)
Price, Sugarcane	0.722	0.817	0.899	0.750	0.619	0.604
	(4.027)	(4.557)	(5.015)	(4.185)	(3.452)	(3.371)
Price, Soybean	10.24	10.17	11.02	12.14	11.09	10.29
	(29.96)	(29.76)	(32.23)	(35.51)	(32.46)	(30.12)
Price, Rice	6.229	5.293	5.298	5.531	4.992	4.238
	(8.056)	(6.846)	(6.852)	(7.154)	(6.456)	(5.481)
Price, Cattle	853.9	1047.0	1137.8	1174.4	1159.8	1431.0
	(727.5)	(892.1)	(969.5)	(1000.6)	(988.2)	(1219.3)
Rain	211.8	173.1	212.8	178.0	193.2	196.7
	(136.5)	(133.7)	(158.0)	(146.0)	(138.4)	(148.8)
Temperature	25.37	26.23	25.45	25.56	25.54	25.47
	(1.286)	(1.526)	(1.348)	(1.509)	(1.615)	(1.354)
Cerrado Priority Muni	0	0	0	0	0.0853	0.0853
	(0)	(0)	(0)	(0)	(0.280)	(0.280)
Protected Area	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576
	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)

Notes: The table reports annual averages and standard deviations (in parenthesis) at the municipal level for the variables used in the analysis from 2009 through 2014. Sources and units: Shares (share of the municipal area destined for the category, MapBiomas); Prices (year 2010 USD, World Bank, PAM/IBGE, and PPM/IBGE); Rain (annual average millimeters, Matsuura e Willmott (2015a)); Temperature (annual average Celsius degrees, Matsuura e Willmott (2015b)); Cerrado Priority Muni (dummy, MMA), Protected Area (share of the municipal area that is protected, MMA and FUNAI).

4 Empirical Strategy

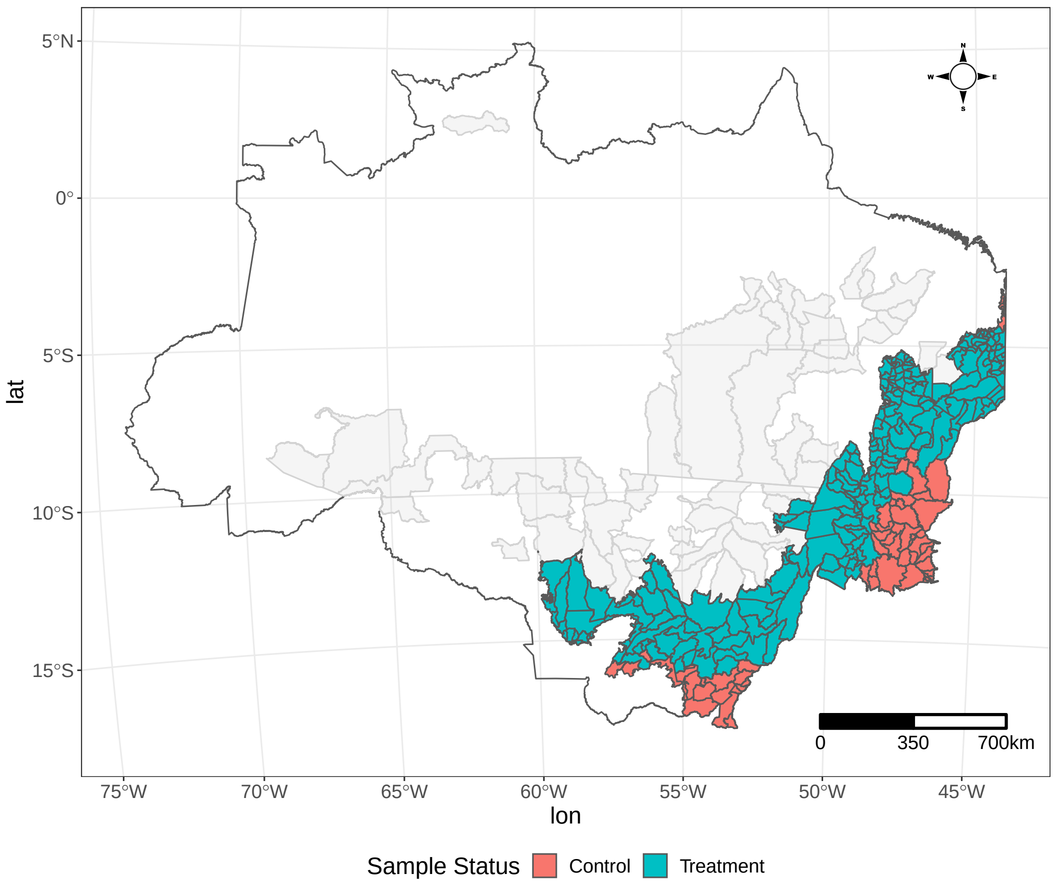
4.1 Main Model

The proposed empirical strategy aims at exploring how the implementation of the Amazon “blacklist” policy changed the land-use trends in near Cerrado municipalities, which may indicate the presence of leakage effects. The rationale is that when a municipality enters the “blacklist”, there is an exogenous rise in the cost of deforestation, which results in less deforestation within the PMs but creates a risk of displacement to neighboring municipalities. Additionally, many neighboring municipalities are in the Cerrado biome, due to the proximity of most PMs to the biome’s border. Finally, considering the focus of the policies presented in Section 2, the Cerrado seems to be a more attractive region to displace compared to non-blacklisted Amazon municipalities due to weaker conservation requirements and law enforcement. I draw on a differences-in-differences framework to infer causality with the following benchmark equation:

$$ShareLandUse_{i,t} = \sum_{e=0}^{4+}(\beta_e(Treatment\_YearsExposure_e)_{i,t}) + X'_{i,t} * \omega + \alpha_i + \theta_t + \varepsilon_{i,t} \quad (1)$$

where $ShareLandUse_{i,t}$ is the fraction of the municipality i area destined, in year t, for one of the following land use categories: farming, forest, pasture, crop, savanna or dense forest; $Treatment\_YearsExposure_e$ are treatment dummies equal to 1 if the distance from the municipality i to the closest PM created since e years is less than 200 kilometers; $X'_{i,t}$ is a vector of muni-level controls for weather, agricultural prices, and policies; α_i and θ_t are, respectively, municipality and time fixed effects; $\varepsilon_{i,t}$ is the muni-year idiosyncratic error. Estimates are robust to heteroskedasticity, and standard errors are clustered at the municipality level in all specifications, making them robust to intra-municipal serial correlation (Bertrand et al., 2004). β_e are the difference-in-differences estimators of the spillover effect for each additional year of exposure from 0 to 4 or more[17], totaling five estimates of interest. It is also relevant to notice that the control group is composed of all the municipalities more than 200 kilometers distant from the closest PM, which is represented in Figure 4.

Figure 4: Map Sample Status



Note: Map comprises Legal Amazon region, the cerrado sample divided into sample status categories (coloured) and the Priority Municipalities (gray). Treatment is defined as being less than 200km from the closest PM
Data sources: IBGE, MMA, MapBiomas.

The fundamental identifying assumption in the differences-in-differences framework is that the control group trend is a valid counterfactual for the treatment group trend in the absence of treatment. One can never directly test it since only one potential outcome is observed each year. However, to get confidence that this assumption holds, I inspect the

[17]Which includes 4, 5, and 6 years.

trends of the treatment and control groups using the leads and lags framework (Angrist and Pischke, 2008) in Section 6.1 as specified below:

$$
\begin{aligned}
ShareLandUse_{i,t} = & \sum_{e=-7}^{-1} (\Phi_e(Treatment\_YearsExposure_e)_{i,t}) + \\
& \sum_{e=1}^{4+} (\beta_e(Treatment\_YearsExposure_e)_{i,t}) \; + X'_{i,t} * \omega \; + \; \alpha_i \; + \; \theta_t \; + \; \varepsilon_{i,t} \quad (2)
\end{aligned}
$$

where all the variables are defined in the same way of Equation (1), the only difference is that I included negative years of exposure from -1 (one year before the closest PM submission year) to -7 (seven years before the nearest PM submission year), omitting the 0-year category. So, the leads coefficients are the β_e's, and the lags are the Φ_e's.

The parallel pre-trends is a good sign but certainly does not pin down the identification. One might still argue that the control group is also being affected by the policy, or that, after the policy, variables relevant to land-use decisions might have changed in ways that made the treatment and control group trends diverge for reasons not associated with the policy itself. For the former, I argue that 200 kilometers are a considerable amount of distance to avoid contamination, but it is still an arbitrary cut-off, thus, in Section 6.2, I check if the results hold using a more conservative cut-off of 250 kilometers. For the latter, I add not only municipality and time fixed effects, controlling for all time-invariant and unit-invariant covariates but also control for weather and agricultural prices that vary across time and municipalities to mitigate possible omitted variable bias. Additionally, in Section 6.3, I include controls for other policies implemented in the Cerrado and for baseline land-use trends.

4.2 Distance Breaks Model

The literature of hotspot policing, mentioned in Section 1, suggests that spatial spillovers can occur in any direction, if crime reduces in the neighborhood it is called difussion (deterrence) effect and if crime increases it is called displacement effect. Also, Short et al.

(2010) argue that displacement and diffusion effects are spatially heterogeneous varying with the distance. So, I explore this possible heterogeneity of the treatment effects to disentagle both effects and see which one predominates in each distance break, using the following model:

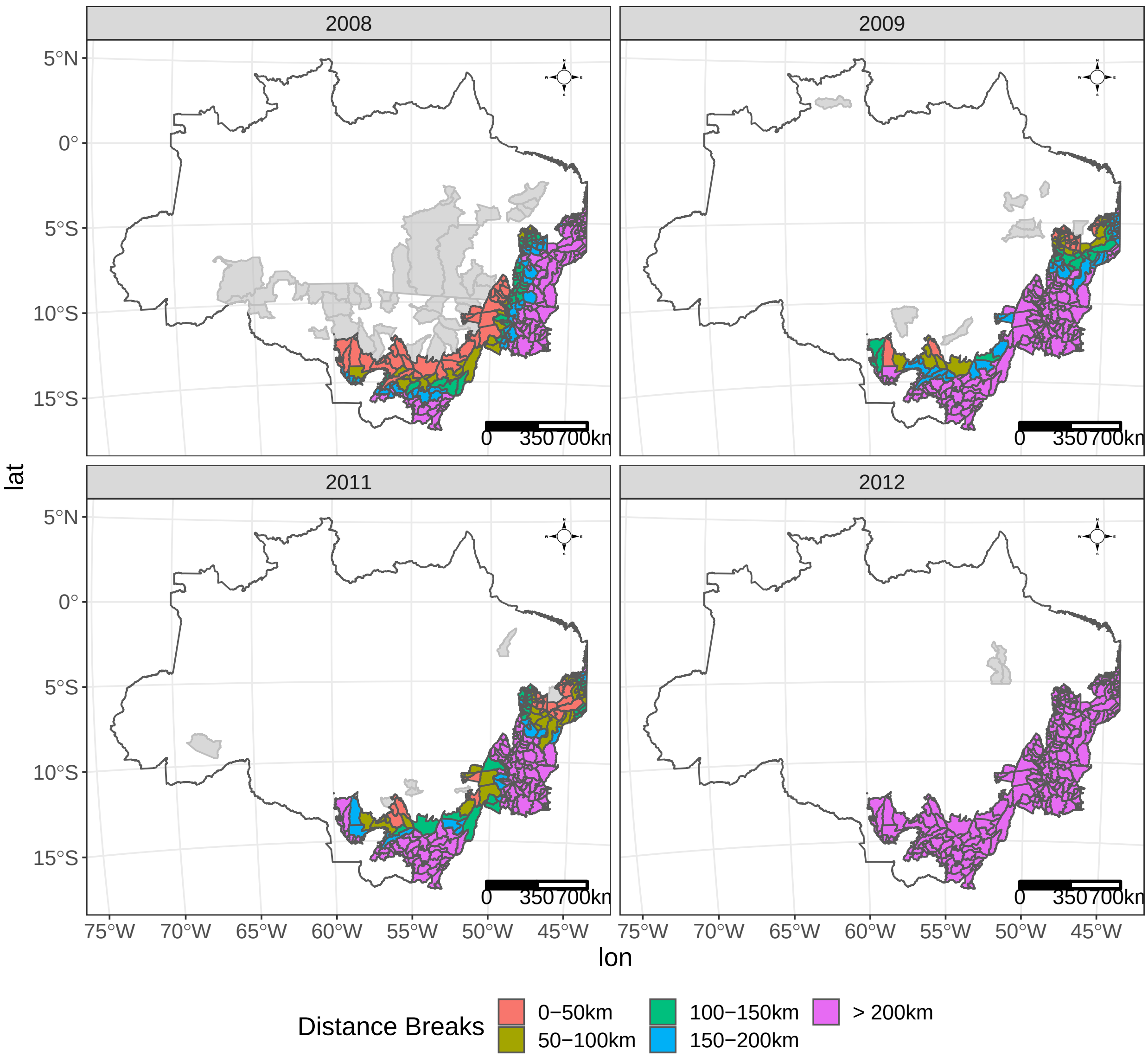
$$ShareLandUse_{i,t} = \sum_{d=0-50km}^{150-200km} \sum_{e=0}^{4+} (\beta_{d,e}(distanceBreak_d\_YearsExposure_e)_{i,t}) + X'_{i,t} * \omega \; + \; \alpha_i \; + \; \theta_t \; + \; \varepsilon_{i,t} \quad (3)$$

where all the variables are defined in the same way of Equation (1), the only difference is that the $Treatment\_YearsExposure_e$ variable was substituted by $distanceBreak_d\_YearsExposure_e$. The former allows for time of exposure heterogeneity but restricted to a single treatment group defined by the 200 kilometers cut-off while the latter keeps the exposure heterogeneity and additionally split the treatment group into smaller groups of 50 kilometers breaks (0-50km; 50-100km; 100-150km; 150-200km) to allow spatial heterogeneity. Now, there are 20 $\beta_{d,e}$ coefficients of interest instead of 5.

Here, an hypothetical example might be useful to explain how the dummies $distanceBreak_d\_YearsExposure_e$ are defined. Supose there is a municipality i that is 40km away from the closest 2008 PM, 70km from the closest 2009 PM and 120km from the closest 2011 PM. From 2004 through 2007 all treatment dummies would be 0. In 2008, $distanceBreak_{0-50km}\_YearsExposure_0$ would be 1 because the closest PM created since 0 ($e = 0$) years ago (2008 PM) is less than 50 kilometers away ($d = 0 - 50km$). In 2009, $distanceBreak_{50-100km}\_YearsExposure_0$ would be 1 because the closest PM created since 0 ($e = 0$) years ago (2009 PM) is between 50-100 kilometers away ($d = 50 - 100km$) and $distanceBreak_{0-50km}\_YearsExposure_1$ would also be 1 because the closest PM created since 1 ($e = 1$) years ago (2008 PM) is less than 50 kilometers away ($d = 0 - 50km$). For the following years treatment variables are defined using this same pattern.

Figure 5, below, illustrates the distance breaks variation considering each submission year of PM (2008, 2009, 2011, and 2012). For 2008 there is much variation because a lot of PMs are located near the biome's border. For 2009 and 2011, there are fewer PMs, but they create additional variation in the northeast region of the map because they are closer than the 2008 PMs in that region of the border. Finally, as mentioned in Section 3, the PMs from 2012 are not relevant because they do not create any variation since all the sample municipalities are more than 200 kilometers away.

Figure 5: Map Distance Breaks by PM submission year



Note: Map comprises Legal Amazon region, the cerrado sample divided into the distance breaks categories (coloured) and the Priority Municipalities (gray). Each panel refers to the submission years of Priority Municipalities
Data sources: IBGE, MMA, MapBiomas.

5 Results

5.1 Main Model Results

Tables 4 and 5 provide the estimated coefficients from Equation (1) for farming and forest as the dependent variable, respectively. Column 1 controls only for fixed effects; column 2 adds temperature and precipitation controls; column 3 adds weighted agricultural price controls.

Table 4: Main Results - Farming

	(1)	(2)	(3)
	depvar: share farming		
Treatment (0 year)	0.009***	0.009***	0.008***
	(0.003)	(0.002)	(0.002)
Treatment (1 year)	0.013***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	0.015***	0.014***	0.012***
	(0.003)	(0.003)	(0.003)
Treatment (3 years)	0.017***	0.016***	0.012***
	(0.003)	(0.003)	(0.003)
Treatment (4+ years)	0.006	0.007*	0.008**
	(0.004)	(0.004)	(0.004)
R-squared	0.215	0.227	0.243
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Farming. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators $= 1\{Distance\,closest\,PM\,in\,the\,list\,since\,e\,years\ <\ 200km\}$. The control group is the omitted category $1\{Distance\,closest\,PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Main Results - Forest

	(1)	(2)	(3)
		depvar: share forest	
Treatment (0 year)	-0.015***	-0.015***	-0.014***
	(0.004)	(0.004)	(0.004)
Treatment (1 year)	-0.018***	-0.017***	-0.016***
	(0.003)	(0.003)	(0.003)
Treatment (2 years)	-0.019***	-0.018***	-0.015***
	(0.005)	(0.005)	(0.005)
Treatment (3 years)	-0.017**	-0.017**	-0.013
	(0.008)	(0.008)	(0.008)
Treatment (4+ years)	-0.001	-0.002	-0.003
	(0.007)	(0.006)	(0.006)
R-squared	0.060	0.065	0.071
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

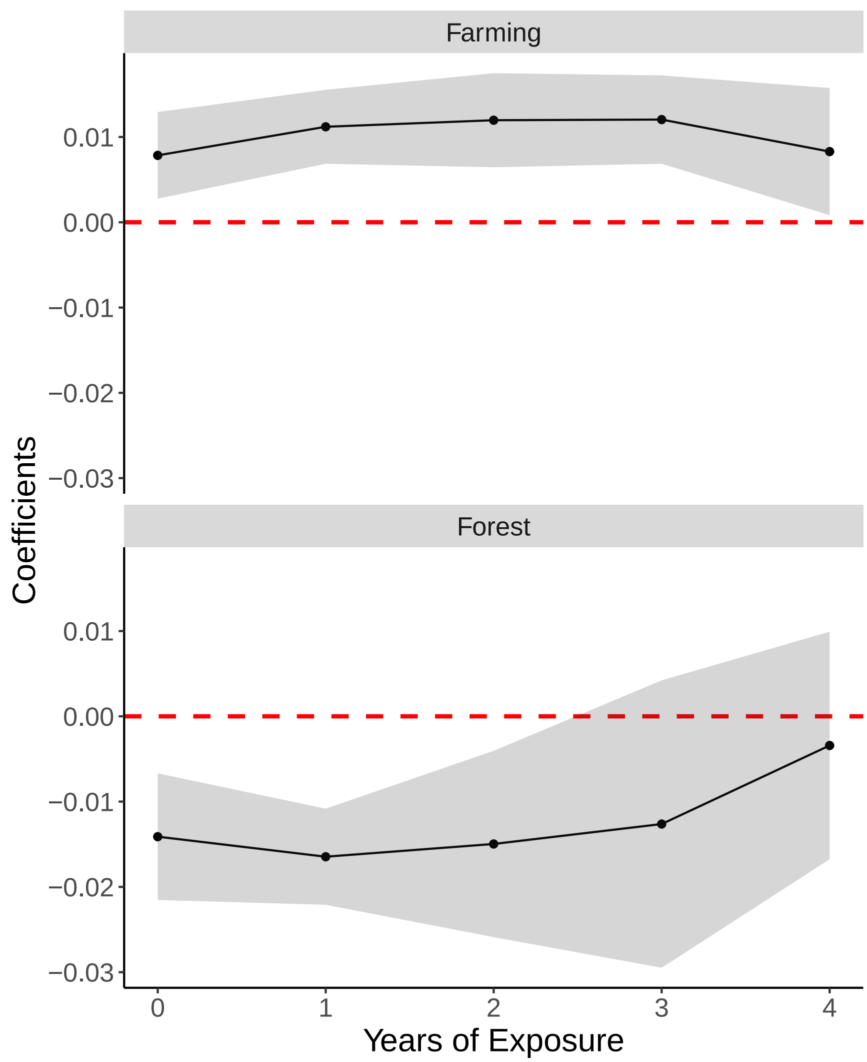
Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Forest. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

The preferred specification is column 3 because it uses all the sets of controls. Still, estimates from columns 1 and 2 are very similar, indicating that the treatment effects are stable to the inclusion of controls. These results show an increase in the anthropization process, with a positive impact on the farming share and a negative effect on the forest share, corroborating the hypothesis of displacement effects. For municipalities exposed to 1 year of treatment, the policy had a positive and significant impact, at the 99% confidence level, generating an increase of 1.1 percentage points in the fraction destined for farming, and a negative and significant impact, at the 99% confidence level, causing a decrease of 1.6

percentage points in the fraction destined for forest.

Figure 6, below, represents the coefficients from column 3 of Tables 4 and 5 graphically, showing how the impact of the policy varies with the time of exposure. The impact on farming is stable and significant across all years, but on the forest, the effect is only significant from 0 to 2 years of exposure.

Figure 6: Coefficients Main Model - Farming and Forest

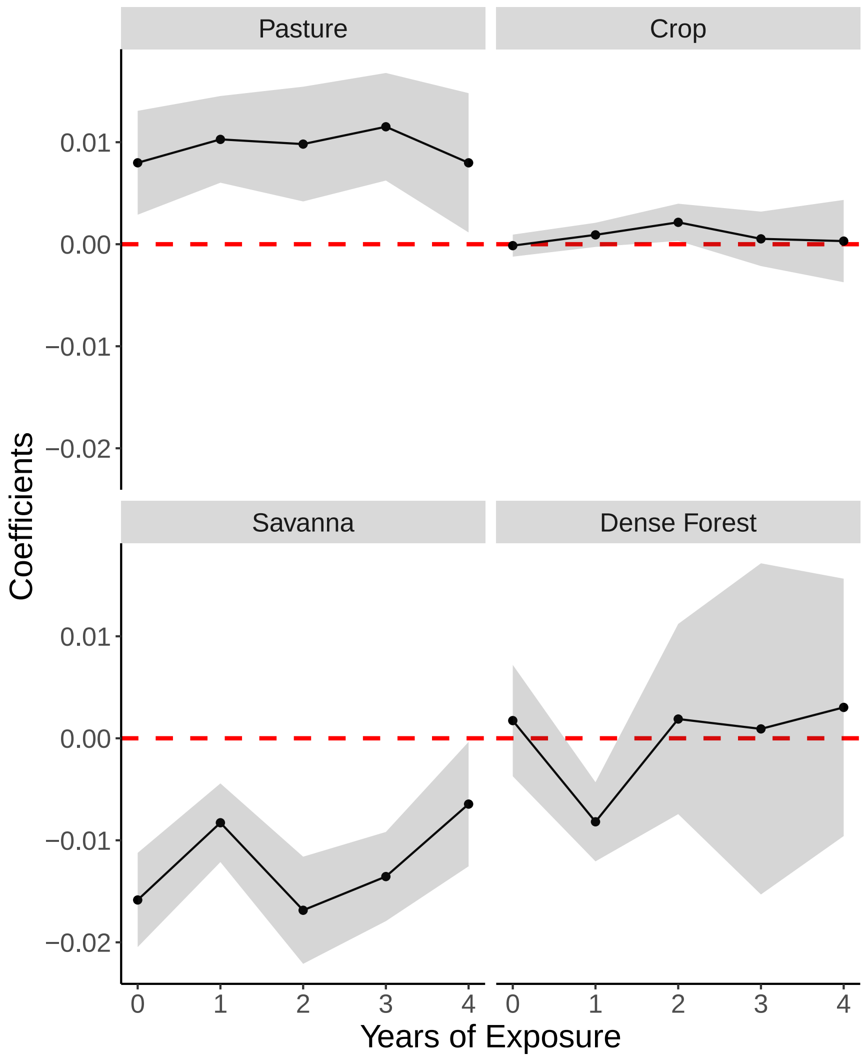


Notes: The graph plots the fixed effects coefficients on farming and forest for each year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices.
The shaded area is the 95% confidence interval.

To have a better understanding of how exactly land uses are changing, I look at the impacts on more disaggregated variables. Farming is split in pasture and crop, and forest is divided into savanna and dense forest. Figure 7, below, represents the treatment coefficients, graphically, for each year of exposure and outcome of interest[18]. Farming effects are mostly driven by pasture, while crop has null or small contributions, which are consistent with other findings showing that cattle ranching is more affected by policy changes (Assunção et al. 2019b). Decreases in savanna mostly drive forest decline while dense forest has null effects except for one year of exposure. That is consistent with DETER monitoring being capable of observing tropical forests, which are included in dense forest, but not savanna vegetation, making the latter more vulnerable to spillovers in the Legal Amazon.

[18] Complete regression tables equivalent to Tables 4 and 5 are in the Appendix (Section 9.1 - Tables 10-13).

Figure 7: Coefficients Main Model - Pasture, Crop, Savanna and Dense Forest



Notes: The graph plots the coefficients on pasture, crop, savanna and dense forest for each year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices.
The shaded area is the 95% confidence interval.

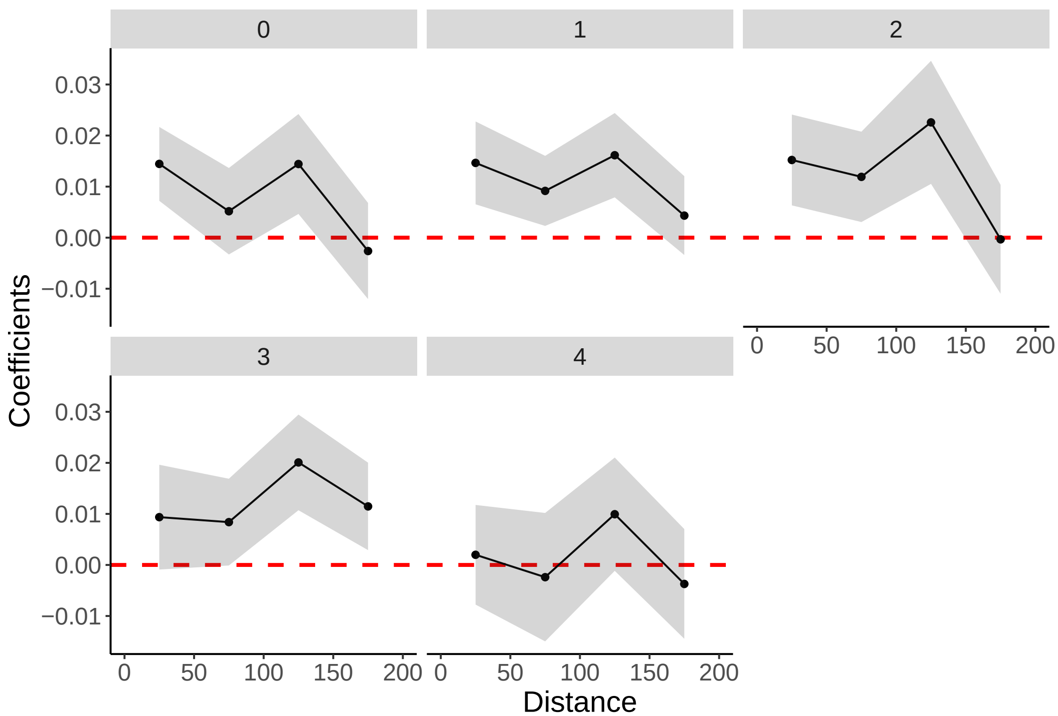
5.2 Distance Breaks Results

Figures 8 and 9 represent the estimated coefficients graphically from Equation (3), using fixed effects, weather, and price control, for farming and forest as the dependent variable, respectively[19]. The general picture is the same as Section 5.1. There is supporting evidence for displacement effects, with positive impacts on farming when significant and with negative

[19]Complete regression tables are in the Appendix (Section 9.2 - Tables 14-15).

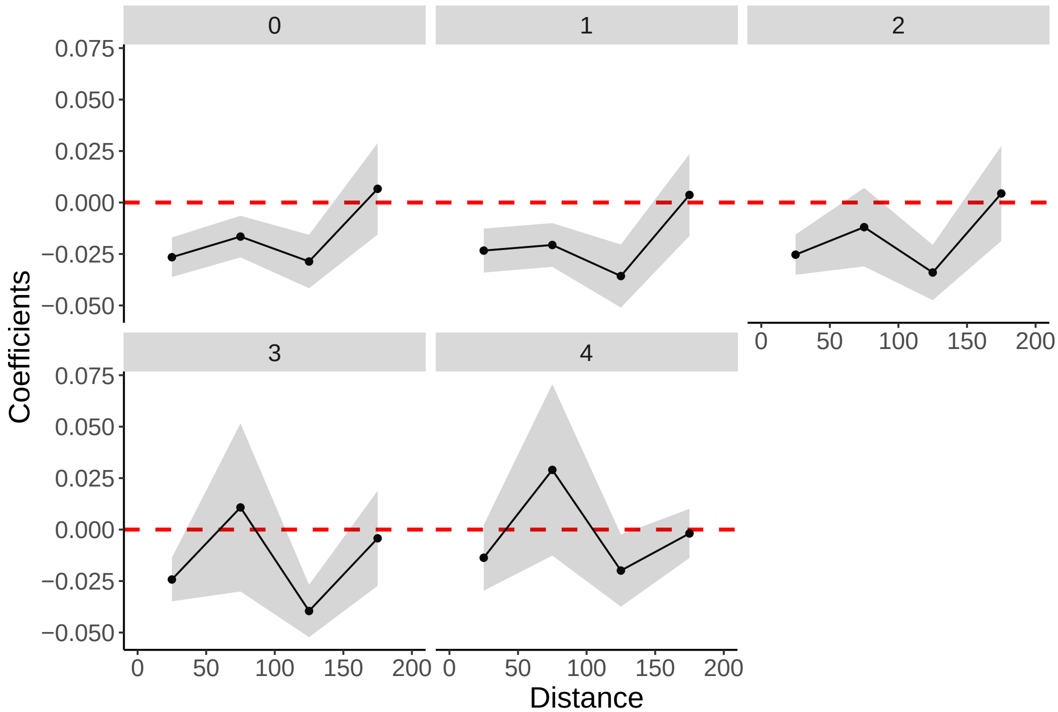
impacts on the forest when significant. Intermediate distances, from 100 to 150 kilometers, have the most significant coefficients for all years of exposure, which is consistent with Short et al. (2010) simulations. Smaller coefficients for closer distance breaks can be explained by the fact that when offenders are nearer to areas with hotspot policing, they might perceive an increase in the cost of illegal deforestation, thus reducing their activities and attenuating the displacement effect. Also, the 200 kilometers cut-off seems to be reasonable, considering that most results are null from 150 to 200 kilometers. Finally, after three years of exposure, an additional year seems not to be relevant.

Figure 8: Coefficients Distance Breaks Model - Farming



Notes: The graph plots the fixed effects coefficients on farming for each distance break and year of exposure(4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

Figure 9: Coefficients Distance Breaks Model - Forest



Notes: The graph plots the fixed effects coefficients on forest for each distance break and year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

I use the distance breaks model on the disaggregated variables, too, but the interpretation of the results is similar to the one presented in this section and Section 5.1, so the coefficients graphics are shown in the Appendix (Section 9.2 - Figures 12-15).

5.3 Counterfactual Simulation and Economic Impact

To assess the economic impact, I propose a counterfactual exercise to simulate a scenario with no implementation of the "blacklist" policy. First, I calculated the predicted share of farming and forest areas using Equation (1) and observed data. Then I convert it to the total area in square kilometers multiplying the share by the municipality area (observed column). Secondly, I set all treatment variables to 0 in all years to simulate the no PM policy scenario and followed the same steps to calculate the total area in square kilometers (counterfactual column). Finally, I calculated the difference between observed and hypothetical scenarios, which represents the magnitude of impact. Tables 6 and 7 show the results by year for farming and forest, respectively.

Table 6: Counterfactual - Farming

	farming (km2)		
year	observed	counterfactual	difference
2008	163,592	162,334	1,258
2009	170,665	169,245	1,420
2010	172,876	171,268	1,608
2011	176,895	175,079	1,816
2012	177,638	175,518	2,120
2013	187,020	185,202	1,818
2014	183,931	182,557	1,374
total	1,232,617	1,221,203	11,414

Notes: The table displays counterfactual simulation results using estimated coefficients from the preferred specification (Table 4, column 3). The hypothetical scenario sets the treatment interaction terms as zero to capture the complete absence of the "blacklist" policy. Observed shows predicted farming area by year using observed data; counterfactual shows predicted farming area by year using the hypothetical scenario; Difference reports the difference between observed and counterfactual totals. All values are in square kilometers.

Table 7: Counterfactual - Forest

	forest (km2)		
year	observed	counterfactual	difference
2008	386,819	389,017	-2,198
2009	384,329	386,720	-2,391
2010	378,853	381,142	-2,289
2011	380,521	383,010	-2,489
2012	382,259	384,654	-2,395
2013	373,480	375,543	-2,063
2014	373,679	375,004	-1,325
total	2,659,940	2,675,090	-15,150

Notes: The table displays counterfactual simulation results using estimated coefficients from the preferred specification (Table 5, column 3). The hypothetical scenario sets the treatment interaction terms as zero to capture the complete absence of the "blacklist" policy. Observed shows predicted forest area by year using observed data; counterfactual shows predicted forest area by year using the hypothetical scenario; Difference reports the difference between observed and counterfactual totals. All values are in square kilometers.

Comparing these two annual results (difference column), one can see that the PM policy generated an increase of 11,414 km^2 of farming and a decrease of 15,150 km^2 of forest, from 2009 through 2014. Then one can compare it to the direct impact, estimated by Assunção and Rocha (2019)[20], of 11,218 km^2 of avoided clearings due to the same policy. To make an equivalent comparison between the studies, I use the average annual leakage: 1,631 km^2 considering farming and 2,164 km^2 considering the forest, and the average yearly direct impact: 2,805 km^2. Using these numbers, I calculate that the cross-biome leakage generated an offset of 58%, considering farming, and 77%, considering the forest, in the policy impact.

6 Robustness Checks

6.1 Parallel Trends Test

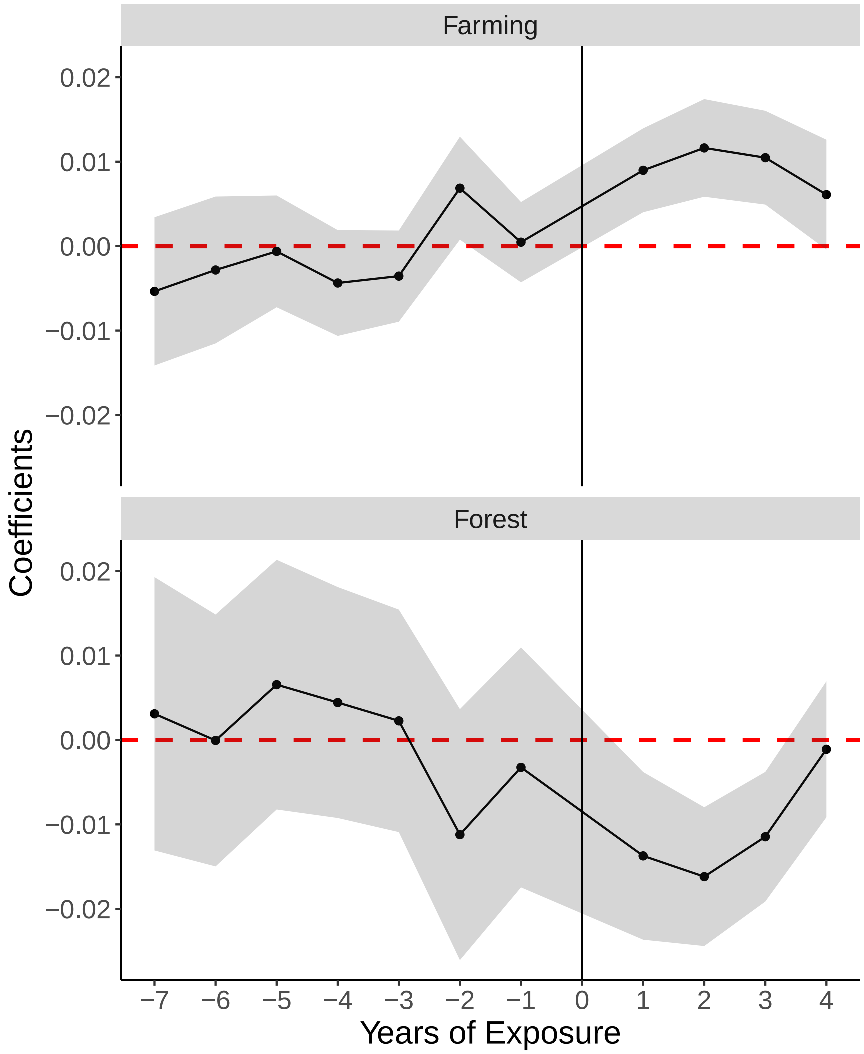
As discussed in Section 4.1, the parallel trends assumption is vital to differences-in-differences identification. Although one cannot test it directly, it is possible to gain confidence in it by analyzing the pre-trends. To formally test the assumption, I use the leads and lags regression (Angrist and Pischke, 2008). In this model, the leads (post-treatment effects) should be significant, and the lags (anticipatory effects) should be null.

Figure 10, below, represents the coefficients of interest graphically from Equation (2)[21]. There is supporting evidence for the parallel trend assumption because, for forest results, all leads are not statistically different from 0, at the 95% confidence level, and 3 out of 4 lags are significant. For farming results, 6 out of 7 leads are not statistically different from 0, at the 95% confidence level, and all lags are significant. In summary, the evidence supports the claim that pre-existing differences in trends are not driving the treatment effects.

[20] I chose Assunção and Rocha (2019) as reference because of the similar time period analyzed but other estimates for the average annual direct impact were made: Harding et al. (2019) find 1,126 km^2 for the 2008-2013 period; Arima et al. (2014) find 3,551 km^2 for the 2009-2011 period; and Assunção et al. (2019c) find 2,705 km^2 for the 2009-2010 period.

[21] Complete regression tables are in the Appendix (Section 9.3 - Tables 16-17).

Figure 10: Coefficients Leads and Lags Model



Notes: The graph plots the leads and lags coefficients on farming and forest for each year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices.
The shaded area is the 95% confidence interval.

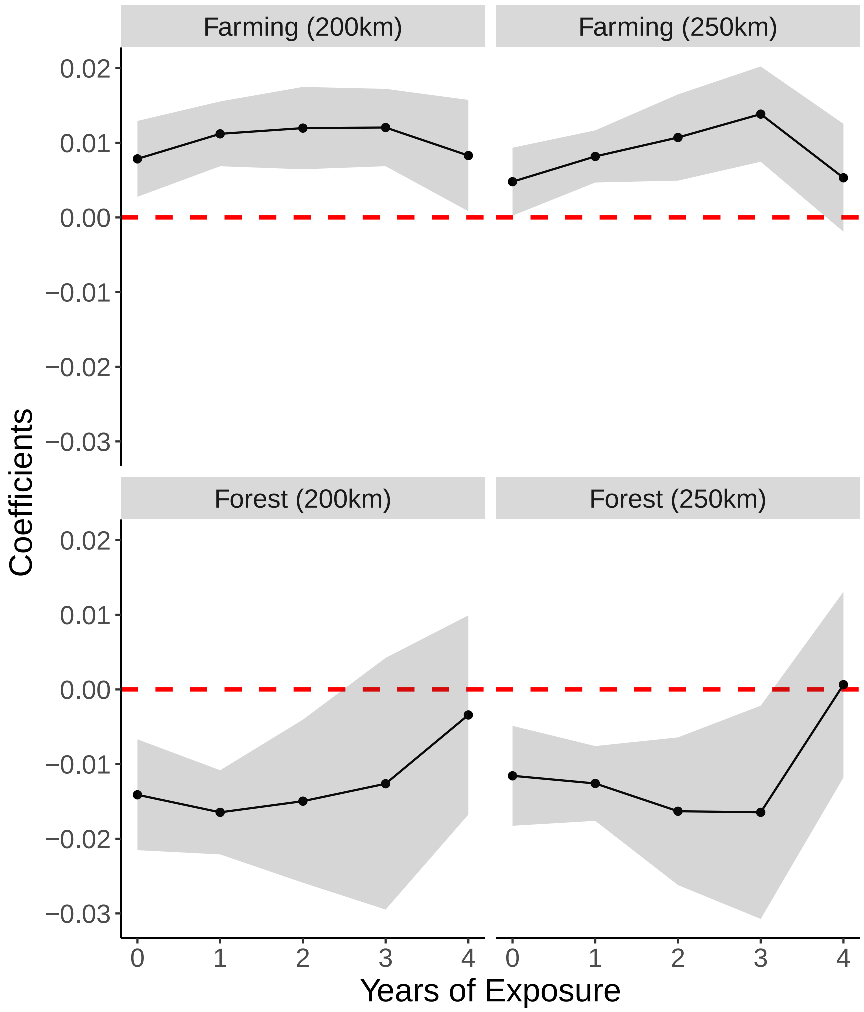
6.2 Treatment Cut-off Robustness Check

As discussed in Section 5.2, it is necessary to check if an arbitrary choice of treatment cut-off is driving the results and also verify that the control group is not being affected by the policy. To address both concerns, I use the same model as in Equation (1), though changing the threshold from 200 to 250 kilometers[22]. Looking at Figure 11, below, one can

[22]Figure 16 in the Appendix represents the new treatment and control groups.

conclude that the overall results did not change much.[23] Therefore, they seem to be robust to the cut-off definition.

Figure 11: Coefficients Robustness 250km cut-off



Notes: The graph plots the fixed effects coefficients on farming and forest for each year of exposure (4 refers to 4, 5 or 6 years).
Baseline coefficients (left) use the 200km cut−off and robustness coefficients (right) use 250km.
Controls: weather and agricultural prices.
The shaded area is the 95% confidence interval.

6.3 Policy and Baseline Trend Controls

Finally, I test if the results are robust to the inclusion of policy controls, 2003 forest share trends, and 2003 farming share trends. The policy controls include the share of the protected

[23]Complete regression tables are in the Appendix (Section 9.4 - Tables 18-19).

area and a dummy indicating if the Cerrado municipality was in the Cerrado PMs list. These variables might be endogenous because, as shown in Section 2, they were strategically implemented to slow down the anthropization process. So, I do not include them in the main model, but as they are observed and might be relevant, I include them here to see if treatment coefficients remain stable. Forest and farming baseline share trends are necessary controls because municipalities with a lot of forested areas can be more attractive to displacement due to its potential of conversion or less attractive due to unobserved characteristics that make them more preserved. Also, municipalities with a lot of farming area can be less attractive due to the lack of natural areas to be converted or more attractive due to unobserved infrastructure that makes it cheaper to displace. I use Equation (1) with all controls as the benchmark and add each new control separately. Tables 8 and 9 present the results. In summary, coefficients are stable to the inclusion of all covariates, attenuating omitted variables concerns.

Table 8: Robustness Additional Controls - Farming

	(1)	(2)	(3)	(4)
		depvar: farming		
Treatment (0 year)	0.008***	0.008***	0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (1 year)	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (2 years)	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment (3 years)	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.002)	(0.003)
Treatment (4+ years)	0.008**	0.008**	0.008**	0.007**
	(0.004)	(0.004)	(0.004)	(0.004)
Priority Cerrado		-0.001		
		(0.008)		
Protected Area		0.073		
		(0.148)		
Forest 2003 Trend			0.005***	
			(0.002)	
Farming 2003 Trend				0.003
				(0.002)
R-squared	0.243	0.243	0.252	0.245
FE: muni & year	yes	yes	yes	yes
controls: weather	yes	yes	yes	yes
controls: agricultural prices	yes	yes	yes	yes
controls: policy	no	yes	no	no
controls: forest 2003 trend	no	no	yes	no
controls: farming 2003 trend	no	no	no	yes
observations	3,740	3,740	3,740	3,740
municipalities	340	340	340	340

Notes: The table reports fixed effects coefficients for Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Farming. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators = $1\{Distance\,closest\,PM\,in\,the\,list\,since\,e\,years\,<\,200km\}$. The control group is the omitted category $1\{Distance\,closest\,PM\,>\,200km\}$. Policy and time trend controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects, agricultural prices, weather; (ii) policy: share of protected area and Cerrado Priority Municipality dummy; (iii) share of 2003 forest area linear trend; and (iv) share of 2003 farming area linear trend. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Robustness Additional Controls - Forest

	(1)	(2)	(3)	(4)
		depvar: forest		
Treatment (0 year)	-0.014***	-0.014***	-0.013***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Treatment (1 year)	-0.016***	-0.016***	-0.015***	-0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment (2 years)	-0.015***	-0.015***	-0.013**	-0.015***
	(0.005)	(0.005)	(0.005)	(0.005)
Treatment (3 years)	-0.013	-0.013	-0.011	-0.012
	(0.008)	(0.008)	(0.008)	(0.009)
Treatment (4+ years)	-0.003	-0.003	-0.001	-0.001
	(0.006)	(0.006)	(0.007)	(0.008)
Priority Cerrado		0.003		
		(0.006)		
Protected Area		0.041		
		(0.058)		
Forest 2003 Trend			-0.022***	
			(0.007)	
Farming 2003 Trend				-0.009
				(0.006)
R-squared	0.071	0.071	0.145	0.079
FE: muni & year	yes	yes	yes	yes
controls: weather	yes	yes	yes	yes
controls: agricultural prices	yes	yes	yes	yes
controls: policy	no	yes	no	no
controls: forest 2003 trend	no	no	yes	no
controls: farming 2003 trend	no	no	no	yes
observations	3,740	3,740	3,740	3,740
municipalities	340	340	340	340

Notes: The table reports fixed effects coefficients for Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Forest. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Policy and time trend controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects, agricultural prices, weather; (ii) policy: share of protected area and Cerrado Priority Municipality dummy; (iii) share of 2003 forest area linear trend; and (iv) share of 2003 farming area linear trend. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

6.4 Caveats of the model

Although this model seems to identify a causal spatial spillover impact of the policy, with supporting evidence for the parallel trends, robust to treatment definition, and inclusion of relevant controls, it can still suffer from omitted variable bias and possible biases caused by spatial autocorrelation in the dependent variable. For example, if unobserved policies were implemented after 2008 in the control group and not in treatment, it might overestimate the impact. Still, since I am restricting the sample to the same administrative region, Legal Amazon, this potential bias is minimized.

Another important caveat is that the "blacklist" policy was implemented in the same year when the rural credit conditionality changed, and when the Brazilian government started to monitor the Soy Moratorium actively. Even though the model uses variation from the inclusion of new PM in 2009 and 2011 and defines treatment variables based on distances to the closest PM, these two policies can still be confounding some of the results considering that they are discontinuous at the biomes border's and most of the PMs are close to the border.

Finally, in contrast to the extensive literature measuring the effectiveness of conservation policies in the Amazon, the same type of literature is still scarce for the Cerrado. In Sections 1 and 2, I presented evidence that explains the recent Amazon deforestation trajectory (shown in Figure 2). However, for the Cerrado, to the best of my knowledge, the same type of evidence still does not exist. Although some evidence, like the impact of commodity prices, can be extrapolated, others like specific conservation policies may not. Therefore, more research is needed to understand the determinants of the recent deforestation trend in the Cerrado and, consequently, to improve the empirical strategy of this paper.

7 Final Considerations

This research provides important policy implications. Results indicate the presence of cross-biome leakages in the anthropization process from the Amazon to the Cerrado due to relevant institutional differences on conservation requirements, monitoring, and law enforcement. The magnitude of the leakage and findings from previous works (Gonzalez-Navarro, 2013; Dell, 2015; Andrade, 2016; Pfaff and Robalino, 2017; Gandour, 2018; Assunção et al., 2019 a,c; Assunção and Rocha, 2019; Blattman et al., 2019; Herrera et al., 2019) show that spillover effects are relevant, so they always need to be considered in policy impact evaluations. Moreover, emissions are a global negative externality (Stern, 2008; Nordhaus, 2019), thus identify conservation policies that are only displacing emissions to other activities or geographic areas becomes vital because their net benefit can be null even if direct impacts are substantial.

In light of these results, I argue that it is necessary to extend existing policies, like DETER, to be able to detect clearings in other vegetations and allow the government to issue more alerts in the Cerrado. However, law enforcement may not be enough in the Cerrado context because even with actual high levels of illegality in deforestation, the Forest Code conservation requirements and the scarcity of protected areas leave much room for legal deforestation. An alternative outside the legal framework is to focus on productivity gains and activities that demand fewer areas to reduce the need for expanding the agricultural frontier without sacrificing production gains. Some of these efforts are already being made under the umbrella of PPCerrado, but more action is needed to close the institutional gap in conservation protection between the Cerrado and the Amazon.

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9 Appendix

9.1 Main Model Results

Table 10: Main Results - Pasture

	(1)	(2)	(3)
		depvar: share pasture	
Treatment (0 year)	0.009***	0.009***	0.008***
	(0.003)	(0.002)	(0.002)
Treatment (1 year)	0.012***	0.011***	0.010***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	0.014***	0.013***	0.010***
	(0.003)	(0.003)	(0.003)
Treatment (3 years)	0.017***	0.016***	0.012***
	(0.003)	(0.003)	(0.003)
Treatment (4+ years)	0.006*	0.006*	0.008**
	(0.003)	(0.003)	(0.003)
R-squared	0.157	0.175	0.196
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Pasture. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 11: Main Results - Crop

	(1)	(2)	(3)
	depvar: share crop		
Treatment (0 year)	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)
Treatment (1 year)	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Treatment (2 years)	0.001	0.002*	0.002**
	(0.001)	(0.001)	(0.001)
Treatment (3 years)	-0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)
Treatment (4+ years)	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)
R-squared	0.100	0.120	0.123
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Crop. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 12: Main Results - Savanna

	(1)	(2)	(3)
	depvar: share savanna		
Treatment (0 year)	-0.015***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.002)
Treatment (1 year)	-0.007***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	-0.016***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)
Treatment (3 years)	-0.014***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.002)
Treatment (4+ years)	-0.008**	-0.006**	-0.006**
	(0.003)	(0.003)	(0.003)
R-squared	0.087	0.123	0.124
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Savanna. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 13: Main Results - Dense Forest

	(1)	(2)	(3)
	depvar: share dense forest		
Treatment (0 year)	-0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)
Treatment (1 year)	-0.011***	-0.009***	-0.008***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	-0.003	-0.001	0.002
	(0.005)	(0.004)	(0.005)
Treatment (3 years)	-0.004	-0.003	0.001
	(0.008)	(0.008)	(0.008)
Treatment (4+ years)	0.006	0.004	0.003
	(0.007)	(0.006)	(0.006)
R-squared	0.023	0.051	0.058
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1). The dependent variable is the share of the municipal area destined for Dense Forest. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators = $1\{Distance\,closest\,PM\,in\,the\,list\,since\,e\,years < 200km\}$. The control group is the omitted category $1\{Distance\,closest\,PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

9.2 Distance Breaks Results

Table 14: Distance Breaks Results - Farming

	(1)	(2)	(3)
	depvar: share farming		
Treatment (0-50km) (0 year)	0.013***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)
Treatment (50-100km) (0 year)	0.008*	0.007*	0.005
	(0.004)	(0.004)	(0.004)
Treatment (100-150km) (0 year)	0.016***	0.015***	0.014***
	(0.005)	(0.005)	(0.005)
Treatment (150-200km) (0 year)	-0.002	-0.002	-0.003
	(0.005)	(0.005)	(0.005)
Treatment (0-50km) (1 year)	0.014***	0.014***	0.015***
	(0.004)	(0.004)	(0.004)
Treatment (50-100km) (1 year)	0.012***	0.011***	0.009***
	(0.003)	(0.003)	(0.003)
Treatment (100-150km) (1 year)	0.019***	0.017***	0.016***
	(0.004)	(0.004)	(0.004)
Treatment (150-200km) (1 year)	0.006	0.005	0.004
	(0.004)	(0.004)	(0.004)
Treatment (0-50km) (2 year)	0.017***	0.016***	0.015***
	(0.005)	(0.004)	(0.004)
Treatment (50-100km) (2 year)	0.016***	0.015***	0.012***
	(0.004)	(0.004)	(0.004)
Treatment (100-150km) (2 year)	0.028***	0.026***	0.023***
	(0.006)	(0.006)	(0.006)
Treatment (150-200km) (2 year)	0.002	0.001	-0.000
	(0.005)	(0.005)	(0.005)
Treatment (0-50km) (3 year)	0.013**	0.013***	0.009*
	(0.005)	(0.005)	(0.005)
Treatment (50-100km) (3 year)	0.013***	0.013***	0.008**
	(0.004)	(0.004)	(0.004)
Treatment (100-150km) (3 year)	0.025***	0.025***	0.020***
	(0.005)	(0.005)	(0.005)
Treatment (150-200km) (3 year)	0.015***	0.014***	0.011***
	(0.005)	(0.004)	(0.004)
Treatment (0-50km) (4+ year)	-0.002	-0.000	0.002
	(0.005)	(0.005)	(0.005)
Treatment (50-100km) (4+ year)	-0.003	-0.002	-0.002
	(0.006)	(0.006)	(0.006)
Treatment (100-150km) (4+ year)	0.010*	0.010*	0.010*
	(0.006)	(0.005)	(0.005)
Treatment (150-200km) (4+ year)	-0.004	-0.004	-0.004
	(0.006)	(0.005)	(0.005)
R-squared	0.230	0.240	0.254
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

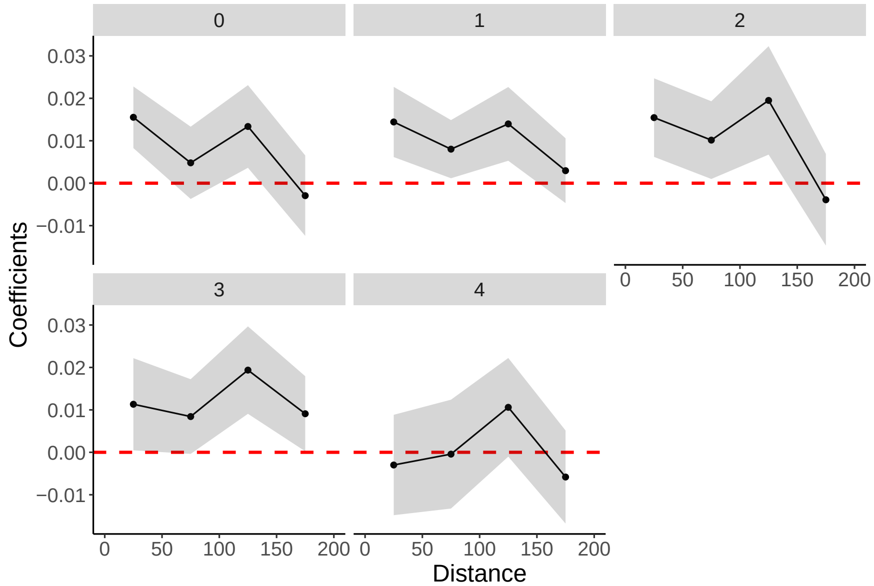
Notes: The table reports fixed effects coefficients from Equation 3 (Section 4.2). The dependent variable is the share of the municipal area destined for Farming. Reported independent variables are the spatial diff-in-diff estimators. Treatment ($distanceBreak$) (e year) are treatment indicators = $1\{Distance\,closest\,PM\,in\,the\,list\,since\,e\,years \subset distanceBreak\}$. The control group is the omitted category $1\{Distance\,closest\,PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 15: Distance Breaks Results - Forest

	(1)	(2)	(3)
	depvar: share forest		
Treatment (0-50km) (0 year)	-0.025***	-0.027***	-0.027***
	(0.005)	(0.005)	(0.005)
Treatment (50-100km) (0 year)	-0.019***	-0.019***	-0.017***
	(0.005)	(0.005)	(0.005)
Treatment (100-150km) (0 year)	-0.031***	-0.030***	-0.029***
	(0.006)	(0.006)	(0.006)
Treatment (150-200km) (0 year)	0.005	0.006	0.007
	(0.011)	(0.011)	(0.011)
Treatment (0-50km) (1 year)	-0.022***	-0.023***	-0.023***
	(0.005)	(0.005)	(0.005)
Treatment (50-100km) (1 year)	-0.023***	-0.022***	-0.021***
	(0.005)	(0.005)	(0.005)
Treatment (100-150km) (1 year)	-0.039***	-0.037***	-0.036***
	(0.007)	(0.008)	(0.007)
Treatment (150-200km) (1 year)	0.002	0.003	0.004
	(0.010)	(0.010)	(0.010)
Treatment (0-50km) (2 year)	-0.027***	-0.027***	-0.025***
	(0.005)	(0.005)	(0.005)
Treatment (50-100km) (2 year)	-0.017*	-0.015*	-0.012
	(0.010)	(0.009)	(0.009)
Treatment (100-150km) (2 year)	-0.040***	-0.038***	-0.034***
	(0.007)	(0.007)	(0.007)
Treatment (150-200km) (2 year)	0.002	0.003	0.004
	(0.011)	(0.011)	(0.011)
Treatment (0-50km) (3 year)	-0.028***	-0.028***	-0.024***
	(0.006)	(0.005)	(0.005)
Treatment (50-100km) (3 year)	0.005	0.006	0.011
	(0.020)	(0.020)	(0.020)
Treatment (100-150km) (3 year)	-0.045***	-0.044***	-0.040***
	(0.006)	(0.006)	(0.006)
Treatment (150-200km) (3 year)	-0.008	-0.007	-0.004
	(0.011)	(0.011)	(0.011)
Treatment (0-50km) (4+ year)	-0.010	-0.012	-0.014*
	(0.008)	(0.008)	(0.008)
Treatment (50-100km) (4+ year)	0.029	0.028	0.029
	(0.021)	(0.020)	(0.020)
Treatment (100-150km) (4+ year)	-0.020**	-0.020**	-0.020**
	(0.008)	(0.009)	(0.009)
Treatment (150-200km) (4+ year)	-0.003	-0.002	-0.002
	(0.006)	(0.006)	(0.006)
R-squared	0.104	0.108	0.114
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

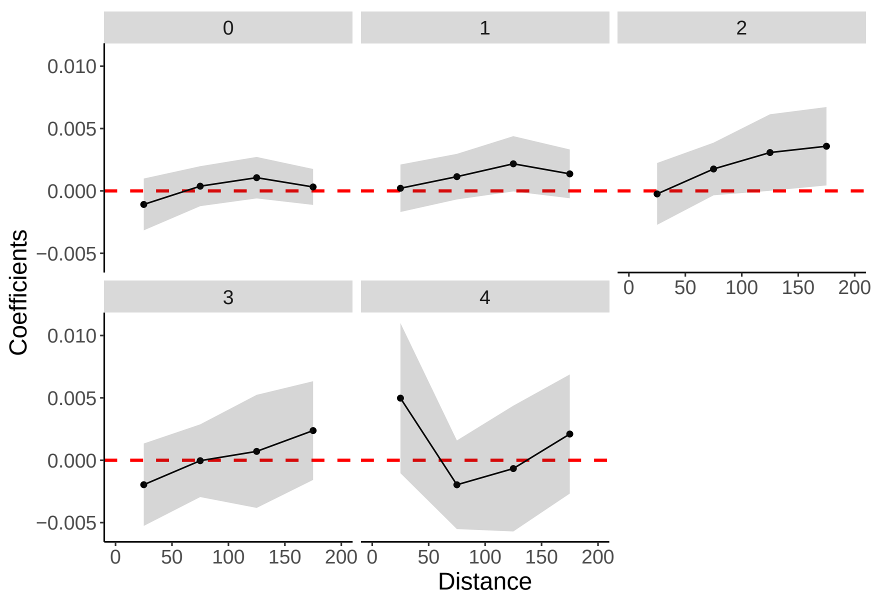
Notes: The table reports fixed effects coefficients from Equation 3 (Section 4.2). The dependent variable is the share of the municipal area destined for Farming. Reported independent variables are the spatial diff-in-diff estimators. Treatment ($distanceBreak$) (e year) are treatment indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years \subset distanceBreak\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Figure 12: Coefficients Distance Breaks Model - Pasture



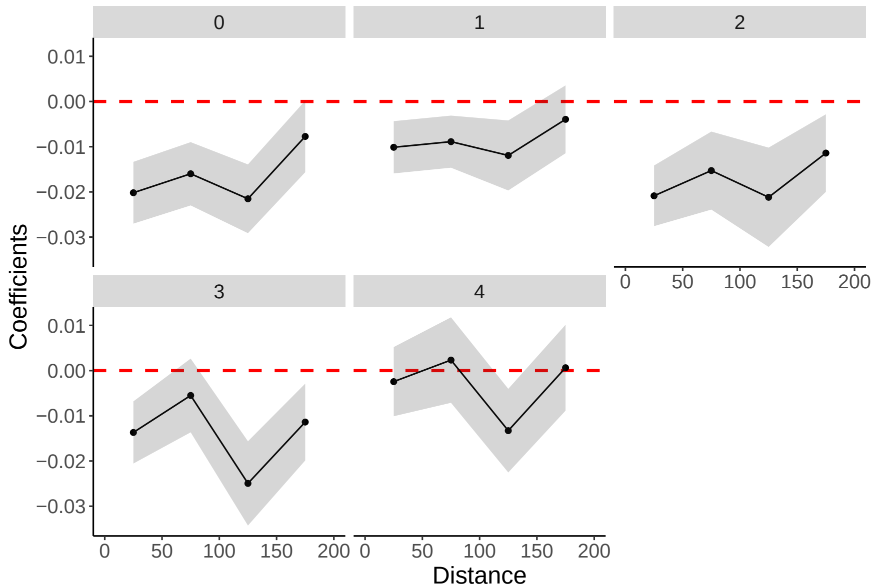
Notes: The graph plots the fixed effects coefficients on pasture for each distance break
and year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

Figure 13: Coefficients Distance Breaks Model - Crop



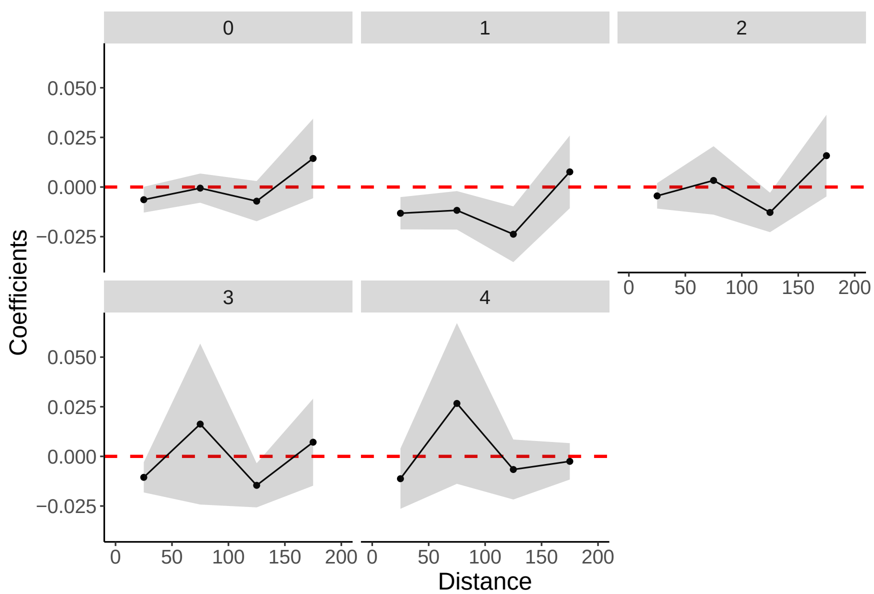
Notes: The graph plots the fixed effects coefficients on crop for each distance break
and year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

Figure 14: Coefficients Distance Breaks Model - Savanna



Notes: The graph plots the fixed effects coefficients on savanna for each distance break and year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

Figure 15: Coefficients Distance Breaks Model - Dense Forest



Notes: The graph plots the fixed effects coefficients on dense forest for each distance break and year of exposure (4 refers to 4, 5 or 6 years).
Controls: weather and agricultural prices. The shaded area is the 95% confidence interval.

9.3 Parallel Trends Test

Table 16: Leads and Lags Results - Farming

	(1)	(2)	(3)
	depvar: share farming		
Treatment (-7 years)	-0.006	-0.006	-0.005
	(0.004)	(0.004)	(0.004)
Treatment (-6 years)	-0.006	-0.004	-0.003
	(0.004)	(0.004)	(0.004)
Treatment (-5 years)	-0.007**	-0.004	-0.001
	(0.003)	(0.003)	(0.003)
Treatment (-4 years)	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
Treatment (-3 years)	-0.003	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)
Treatment (-2 years)	0.005*	0.005	0.007**
	(0.003)	(0.003)	(0.003)
Treatment (-1 year)	-0.000	-0.001	0.000
	(0.002)	(0.002)	(0.002)
Treatment (1 year)	0.009***	0.008***	0.009***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	0.013***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)
Treatment (3 years)	0.014***	0.013***	0.010***
	(0.003)	(0.003)	(0.003)
Treatment (4+ years)	0.002	0.003	0.006*
	(0.003)	(0.003)	(0.003)
R-squared	0.218	0.228	0.245
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: Notes: The table reports leads and lags coefficients from Equation 2 (Section 4.1). The dependent variable is the share of the municipal area destined for Farming. The lags are the Treatment (e year) indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 200km\}$. The leads are the Treatment (-e year) indicators = $1\{Distance\, closest\, PM\, in\, the\, list\, before\, e\, years < 200km\}$ The control group is the omitted category $1\{Distance\, closest\, PM > 200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 17: Leads and Lags Results - Forest

	(1)	(2)	(3)
	depvar: share forest		
Treatment (-7 years)	0.004	0.004	0.003
	(0.008)	(0.008)	(0.008)
Treatment (-6 years)	0.003	0.001	-0.000
	(0.007)	(0.007)	(0.007)
Treatment (-5 years)	0.011	0.010	0.007
	(0.007)	(0.007)	(0.007)
Treatment (-4 years)	0.005	0.005	0.004
	(0.006)	(0.006)	(0.007)
Treatment (-3 years)	0.003	0.004	0.002
	(0.006)	(0.006)	(0.006)
Treatment (-2 years)	-0.010	-0.009	-0.011
	(0.007)	(0.007)	(0.007)
Treatment (-1 year)	-0.002	-0.002	-0.003
	(0.007)	(0.007)	(0.007)
Treatment (1 year)	-0.014***	-0.013***	-0.014***
	(0.005)	(0.005)	(0.005)
Treatment (2 years)	-0.018***	-0.017***	-0.016***
	(0.004)	(0.004)	(0.004)
Treatment (3 years)	-0.015***	-0.014***	-0.011***
	(0.004)	(0.004)	(0.004)
Treatment (4+ years)	0.002	0.002	-0.001
	(0.004)	(0.004)	(0.004)
R-squared	0.061	0.065	0.072
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: Notes: The table reports leads and lags coefficients from Equation 2 (Section 4.1). The dependent variable is the share of the municipal area destined for Forest. The lags are the Treatment (e year) indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years\, < \,200km\}$. The leads are the Treatment (-e year) indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, before\, e\, years\, < \,200km\}$ The control group is the omitted category $1\{Distance\, closest\, PM\, > \,200km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

9.4 Treatment Cut-off Robustness Check

Table 18: Cut-off 250km Results - Farming

	(1)	(2)	(3)
	depvar: share farming		
Treatment (0 year)	0.006***	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
Treatment (1 year)	0.010***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	0.015***	0.013***	0.011***
	(0.003)	(0.003)	(0.003)
Treatment (3 years)	0.019***	0.018***	0.014***
	(0.003)	(0.003)	(0.003)
Treatment (4+ years)	0.003	0.004	0.006
	(0.004)	(0.004)	(0.004)
R-squared	0.212	0.223	0.240
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

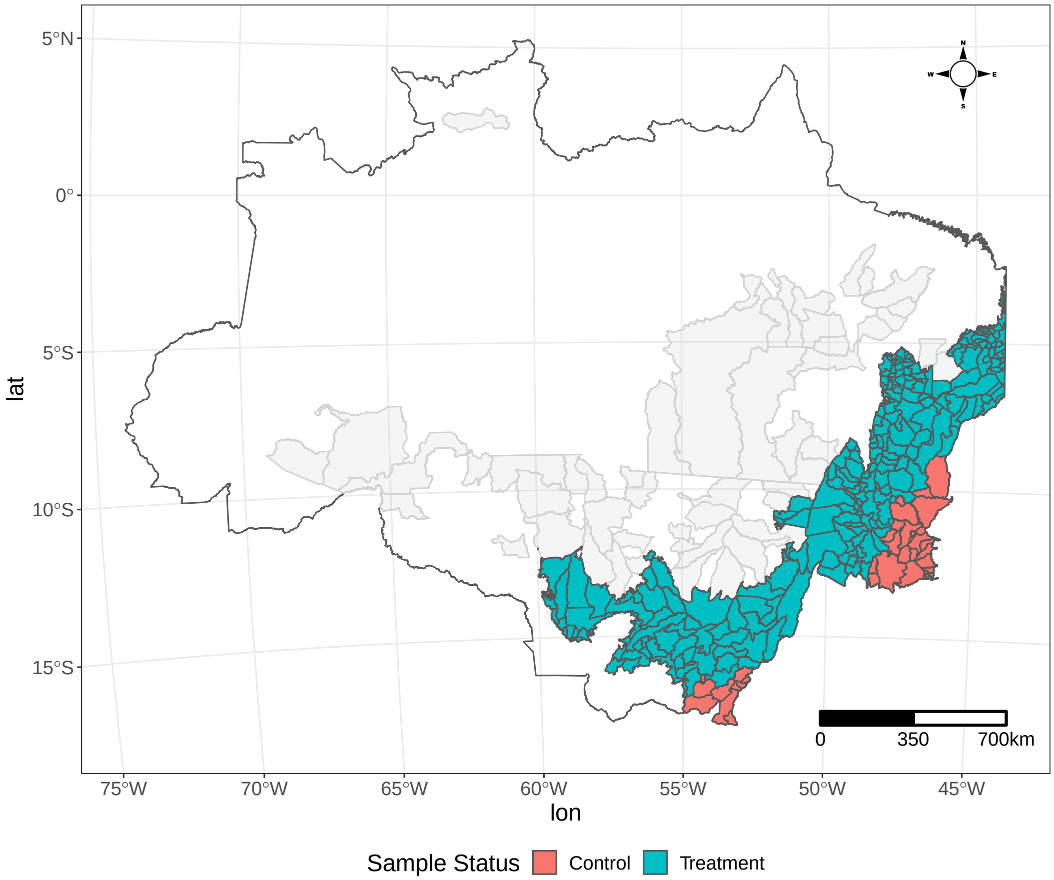
Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1), but changing the treatment cut-off from 200km to 250km. The dependent variable is the share of the municipal area destined for Farming. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years < 250km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 250km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 19: Cut-off 250km Results - Forest

	(1)	(2)	(3)
		depvar: share forest	
Treatment (0 year)	-0.014***	-0.014***	-0.013***
	(0.003)	(0.003)	(0.003)
Treatment (1 year)	-0.015***	-0.014***	-0.013***
	(0.002)	(0.002)	(0.002)
Treatment (2 years)	-0.020***	-0.019***	-0.016***
	(0.005)	(0.005)	(0.005)
Treatment (3 years)	-0.021***	-0.020***	-0.016**
	(0.007)	(0.007)	(0.007)
Treatment (4+ years)	-0.006	-0.006	-0.008
	(0.006)	(0.006)	(0.006)
R-squared	0.060	0.065	0.071
FE: muni & year	yes	yes	yes
controls: agricultural prices	no	yes	yes
controls: weather	no	no	yes
observations	3,740	3,740	3,740
municipalities	340	340	340

Notes: The table reports fixed effects coefficients from Equation 1 (Section 4.1), but changing the treatment cut-off from 200km to 250km. The dependent variable is the share of the municipal area destined for Forest. Reported independent variables are the diff-in-diff estimators. Treatment (e year) are treatment indicators $= 1\{Distance\, closest\, PM\, in\, the\, list\, since\, e\, years\ <\ 250km\}$. The control group is the omitted category $1\{Distance\, closest\, PM > 250km\}$. Controls are added gradually to the specification. The no/yes markers in bottom rows indicate the inclusion of the following sets of muni-level controls: (i) muni and year fixed effects; (ii) weighted agricultural prices: cattle, corn, soybean, rice, and sugarcane; and (iii) weather: precipitation and temperature. The muni-by-year panel includes 340 municipalities located in the Cerrado biome within the Legal Amazon from 2004 through 2014. Standard errors are robust and clustered at the municipality level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Figure 16: Map Sample Status 250km cut-off



Note: Map comprises Legal Amazon region, the cerrado sample divided into sample status categories (coloured) and the Priority Municipalities (gray). Treatment is defined as being less than 250km from the closest PM
Data sources: IBGE, MMA, MapBiomas.