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Did the Soy Moratorium Reduce Deforestation in the Brazilian Amazon?

A Counterfactual Analysis of the Impact of the Soy Moratorium on Deforestation in the Amazon Biome

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Abstract

This paper investigates the impact of the Soy Moratorium (SoyM) on deforestation in the Brazilian Amazon biome. We study 39 municipalities in Mato Grosso that are divided by the natural biome border between the Amazon biome that was affected by the SoyM and the Cerrado biome, which was not affected by the SoyM during 2003-2013. To quantify the impact of the SoyM on deforestation, we perform a Difference in Difference analysis that we estimate with a fixed effects model. Using the Cerrado as the counterfactual, we are able to compare the difference between the actual change in deforestation in the Amazon to what the change in deforestation would have been without the implementation of the SoyM. The results from our DID analysis suggest that the SoyM had a significant impact on deforestation in the Amazon only after it was enforced with satellite monitoring from 2008. We find that deforestation in the Amazon decreased by an additional 24.6 percent compared to the Cerrado as a result of satellite monitoring, which his is equivalent to 430 km^2 of preserved forest cover and roughly 4.8 million tons of carbon were saved from being released in the atmosphere. However, from our graphical RD analysis we do not observe a discontinuity around the biome border, which does not support our findings from the DID analysis.

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1. Introduction

The Amazon is the largest tropical forest on earth and provides crucial ecosystem services such as the conservation of biodiversity and the sequestration of carbon (FAO, 2016; Hargrave & Kis-Katos, 2013). Consequently, the Amazon plays a key role in several of the United Nations Sustainable Development Goals (SDG), such as in improving the robustness of ecosystems and societies, regulating water flows and combating climate change (FAO, 2016).

Despite the great ecological value of the Amazon, it has experienced high levels of deforestation, largely driven by the conversion of forests to pasture and croplands (Alix-Garcia & Gibbs, 2017; FAO, 2016; Nepstad et al., 2009; Ometto et al., 2011; Pfaff et al., 2010). Especially Brazil, home to the largest part of the Amazon and among the world's primary producers of beef and soy (Statista, 2018; USDA, 2017), has long been the global leader in terms of forest loss and degradation (Assunção et al., 2015; FAO, 2006; Nepstad et al., 2014). Between the years 1996 and 2005, the Brazilian Amazon experienced average deforestation levels of 19,500 km² annually, which led to 0.7 to 1.4 billion tons of CO2 equivalents being released to the atmosphere each year (Nepstad et al., 2009). The high rates of deforestation and its consequences received increased attention both on a national and international level (Nepstad et al., 2014; The Economist, 2015), which resulted in the introduction of several policy reforms by the Brazilian government and a commitment to reduce deforestation by 80 percent compared to the average deforestation levels between 1996 and 2005.

In addition to the policy reforms, the civic society and international NGOs drove the implementation of supply chain interventions (Gibbs et al., 2015; Nepstad et al., 2014). One of these interventions that received great attention is the Soy Moratorium (hereafter SoyM). Introduced in 2006, the SoyM is a voluntary commitment by major soy traders in Brazil to no longer purchase soy that is grown on deforested lands in the Amazon biome (Brown & Koeppe, 2012; Gibbs et al, 2015) In 2008, the Brazilian government became involved as well by enforcing the SoyM on a large scale with satellite monitoring (Brown & Koeppe, 2012; Gibbs et al, 2015).

In the following years, deforestation levels decreased substantially in the Brazilian Amazon. From the all-time high of 27,000 km² in 2004, deforestation dropped to around 7,000 km² in 2009 (Assunção et al., 2015) and 5,800 km² in 2013, which represents a 70 percent reduction compared to the 10-year average of 19,500 km² (Nepstad et al., 2014).

While decreasing commodity prices following the 2008 financial crisis might partly explain this substantial decline in deforestation, researchers have established that it can mainly be attributed to the policies and supply chain interventions (Arima et al., 2014). Especially the SoyM has been praised for having successfully contributed to the decline in deforestation (Kastens et al., 2017; Nepstad et al., 2014). However, to the best of our knowledge, no study has yet established a causal relationship between the SoyM and the decline in deforestation. While there is evidence that soy expansion into forests has declined substantially after the introduction of the SoyM, the amount of deforestation that was avoided by the SoyM has not been quantified to date (Gibbs et al., 2015). Therefore, we contribute to the existing literature by estimating the impact of the SoyM on deforestation in the Brazilian Amazon with a counterfactual analysis.

We study municipalities in Mato Grosso that are divided by the natural biome border between the Amazon biome that was affected by the SoyM and the Cerrado biome, which was not affected by the SoyM. To quantify the impact of the SoyM on deforestation, we perform a Difference in Difference analysis which we estimate with a fixed effects model. Using the Cerrado as the counterfactual, we are able to compare the difference between the actual change in deforestation in the Amazon to what the change in deforestation would have been without the implementation of the SoyM. Furthermore, we perform a graphical Regression Discontinuity (RD) analysis to investigate whether the levels of deforestation change significantly on either side of the biome border after the introduction of the SoyM.

The results from our analysis suggest that the SoyM had a significant impact on deforestation in the Amazon only after it was enforced with satellite monitoring from 2008. This is a novel finding that contrasts other studies related to SoyM, such as Kastens et al. (2017), but are in line with several studies that emphasize the effectiveness of command and control policies (Assunção, Gandour & Rocha, 2013; Burgess, Costa & Olken, 2012; Assunção & Rocha, 2014). We find that deforestation in the Amazon decreased by an additional 24.6 percent compared to the Cerrado as a result of satellite monitoring. This is equivalent to 430 km² of preserved forest cover, an area approximately the size of Bergen county (Bergen Byleksikon, 2018). Furthermore, roughly 4.8 million tons of carbon were saved from being released in the atmosphere.

The remainder of this paper is structured as follows. In section 2, we provide further background information on the SoyM and motivate our analysis. Furthermore, we elaborate on other policies that were implemented during our study period with the aim to reduce deforestation. Section 3 defines the study area of our analysis and section 4 describes the underlying data. Section 5 outlines the empirical strategy we follow in our analysis and potential threats to identification are addressed in section 6. Section 7 presents the results and the robustness of our model is tested in section 8. In section 9, we provide a discussion regarding the results obtained. We perform the graphical RD analysis of deforestation in section 10. Lastly, section 11 concludes the paper.

2. Background and Motivation of our Analysis

This section provides additional information regarding the background of the SoyM and subsequently motivates our analysis. Furthermore, we give an overview of other policies implemented to reduce deforestation in the Brazilian Amazon.

2.1 Background of the Soy Moratorium

The SoyM is a voluntary commitment by major soy traders in Brazil to eradicate soy that is associated with deforestation in the Amazon from their supply chains. It was drafted in cooperation with environmental groups and signed on 24 July 2006 by the Brazilian Association of Vegetable Oil Industries (Portuguese acronym ABIOVE) and the Association of Cereal Exporters in Brazil (Portuguese acronym ANEC) who pledged to refrain from purchasing soy that is grown on lands cleared in the Amazon biome after the SoyM's cut-off date. Together, the members of ABIOVE and ANEC purchase 90% of all soy produced in the Amazon (ABIOVE, 2008; Brown & Koeppe, 2012; Gibbs et al., 2015).

Soy producers that violate the SoyM lose market access as well as credit for seeds and fertilizers and consequently have strong incentives to comply (Brown & Koeppe, 2012; Gibbs et al. 2015). Since there are no benefits for complying with the SoyM, it functions as a policy of market exclusion (Brannstrom et al., 2012; Gibbs et al., 2015).

The SoyM was initiated by the Greenpeace campaign "Eating up the Amazon" that accused the multinational agro commodity giant Cargill and the world's largest fast-food chain McDonald's of facilitating deforestation in the Amazon by purchasing soy from illegally cleared lands (Greenpeace, 2006). The resulting public pressure led the soy industry in Brazil to sign the SoyM (Gibbs et al., 2015).

While the SoyM was initially limited to the period from 2006 until 2008, it has since been extended on an annual basis. (Gibbs et al., 2015). With the extension in 2014, the cut-off date of the SoyM was shifted to 2008, to be in line with changes in Brazilian law that granted amnesty for landowners that had engaged in illegal deforestation prior to 2008 (Gibbs et al., 2015; Nepstad et al., 2014). The latest extension of the SoyM in 2016 was indefinite (Greenpeace, 2016).

2.1.1 Monitoring of the SoyM

Since the SoyM was established without involvement of the Brazilian government, the Soybean Working Group (GTS) was created to facilitate the implementation of the SoyM. The GTS consists of three subgroups, responsible for educating soy producers and other local stakeholders to ensure compliance, establishing institutional relations, and developing a mapping and monitoring system as a basis for the enforcement of the SoyM (ABIOVE, 2008; Brown & Koeppe, 2012).

From June 2008, the Brazilian government supported the SoyM, with the Brazilian National Institute for Space Research (INPE) taking responsibility of monitoring the compliance with the SoyM using satellite images (Brown & Koeppe, 2012; Gibbs et al., 2015).

The GTS limits monitoring to municipalities with at least 5,000 hectares of soy in a respective crop year in the states of Mato Grosso, Pará and Rondônia. Furthermore, monitoring does not apply to protected areas. Despite these limitations, the GTS claims that 97% of all soy production in the Amazon biome is subject to monitoring (ABIOVE, 2008; Gibbs et al., 2015).

Monitoring occurs annually and is a three-step process. First, satellite images from Programme for the Estimation of Deforestation in the Brazilian Amazon (Portuguese acronym PRODES) are analysed to identify areas with more than 25 hectares of deforestation. Secondly, the subsequent land use of the deforested areas is determined using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images. Thirdly, areas with crops are further analysed with Landsat and Resourcesat satellite images as well as flyovers to verify whether the identified crops are soy.

Before the INPE took responsibility of monitoring the compliance with the SoyM in 2008, the identification of crops solely relied on flyovers which significantly limited the capacity for enforcement of the SoyM. With the introduction of satellite monitoring, the GTS added an additional step in the process of detecting whether soy was planted or not. As previously, PRODES would identify if deforestation had occurred in a given area. However, instead of having to fly over a deforested area to identify whether it was devoted to crops, this could be detected by the INPE satellite monitoring directly. Consequently, efficiency of the monitoring improved, as they could rule out areas for flyovers that had not been deforested for planting crops instantly by observing the satellite images from INPE (ABIOVE, 2008 & 2010; Gibbs et al., 2015; Rudorff et al., 2011 & 2012).

Finally, if soy is found on recently cleared lands on a property, it is added to a list with non-compliant properties which is maintained by the GTS. This list is made available to the soy traders to ensure that no soy is purchased from properties that violate the SoyM (Gibbs et al., 2015).

Consequently, the enforcement of the SoyM is dependent on the monitoring, as it is the only measure in place to identify properties that grow soy on lands deforested after the SoyM's cut-off date.

2.1.2 Previous Studies of the SoyM and Motivation for our Analysis

The GTS claims that the SoyM has been effective, since soy was only found in few newly deforested areas monitored for compliance with the SoyM. As such, the claimed effectiveness of the SoyM might be misleading, since it implies that the SoyM has successfully contributed to a reduction in deforestation in the Amazon. However, the scope of the SoyM is limited to reducing deforestation related to soy, not overall deforestation. In the following, we present findings by Gibbs et al. (2015) and Arima et al. (2011) which suggest that while compliance with the SoyM was high, it remains unclear whether the SoyM effectively reduced overall deforestation in the Amazon. We therefore aim to contribute to the existing research by estimating the impact of the SoyM on overall deforestation.

Gibbs et al. (2015) analyse whether municipalities located the monitored states Pará, Rondônia and Mato Grosso, and that have at least 1,000 hectares of soy planted in the Amazon biome, were in compliance with the SoyM. Similar to the GTS and INPE, Gibbs et al. (2015) rely on satellite images from PRODES and MODIS to identify deforestation and soy expansion between 2001 and 2014. They find that in the two years prior to the introduction of the SoyM, roughly 30 percent of newly planted soy occurred on deforested lands and that this share decreased significantly to about 1 percent by 2014. Therefore, Gibbs et al. (2015) conclude that compliance with the SoyM is high and that it effectively reduced deforestation directly related to soy expansion. However, they neither establish a causal relationship between the SoyM and the observed decline in overall deforestation during their study period, nor do they quantify the amount of deforestation that was avoided by the SoyM.

Despite of the high compliance with the SoyM, Gibbs et al. (2015) find evidence that suggest that the SoyM was not effective in reducing deforestation overall. For example, roughly 17 percent of the deforested areas in Mato Grosso between 2007 and 2014 were smaller than 25 hectares and therefore not included in the monitoring of the SoyM. Furthermore, a great number of properties in Mato Grosso engaged in deforestation that was illegal under Brazilian law despite being in compliance with the SoyM. Since the SoyM only sanctions direct deforestation for soy, it could cause leakage of deforestation within properties.

Gibbs et al. (2015) further study soy expansion in the Cerrado biome during the same period and find that between 11 and 23 percent of newly planted soy occurred in areas of native vegetation, which points to potential leakage from the SoyM to other biomes.

In addition to potential leakage of deforestation within properties or to the Cerrado, the SoyM could cause additional deforestation through Indirect Land Use Change (ILUC) (Arima et al., 2011, Gibbs et al., 2015). ILUC describes the phenomenon of converting existing pastures to cropland and which leads to the emergence of new pastures in other areas, potentially the Amazon. While the effect of ILUC on deforestation is difficult to measure, Arima et al. (2011) estimate that if the soy expansion into existing pasture areas between 2003 and 2008 had been 10 percent lower, it would have avoided roughly 25,000 km² of deforestation.

Consequently, while the SoyM appears to be effective in reducing deforestation directly related to soy, it is unclear whether it has a significant effect on deforestation overall, due to limited monitoring, potential leakage and ILUC. As mentioned previously, we therefore aim to add to the existing research by analysing whether there is a causal relationship between the SoyM and overall deforestation in the Amazon.

Additionally, we aim to investigate the role of the monitoring in the enforcement of the SoyM, especially after the Brazilian government supported the GTS in monitoring compliance. Furthermore, since the scale of the monitoring was substantially smaller prior to the Brazilian government's involvement in the SoyM, we reason that the SoyM likely did not have a significant impact on deforestation before the Brazilian government and the INPE supported the GTS with satellite monitoring. We therefore formulate the following hypothesis that we will test in our analysis.

The SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring from 2008.

Before we define our study area and introduce our approach, we provide an overview of other policies that affected deforestation in the Brazilian Amazon in the following subsection.

2.2 Other Policies that affected Deforestation

2.2.1 Forest Code

The Forest Code (FC) was introduced in 1965 and is the most important environmental legislation with regards to land use and property management on private lands, since it determines how land owners are allowed to treat their forests. That is, it regulates private properties to conserve a certain portion of their lands as natural vegetation, known as the Legal Reserve (LR). Therefore, the FC in itself is not a policy but serves as the fundament for many of the implemented policies. (Nepstad et al., 2009; Nepstad et al., 2014; Soares-Filho et al., 2014).

An initial attempt to subdue the deforestation rates occurred in 1996 when the Brazilian government updated the FC (Nepstad et al., 2009; Nepstad et al., 2014; Soares-Filho et al., 2014). Prior to 1996, properties in the Amazon biome were required to conserve 50 percent of natural vegetation, which meant that the other half of forest could legally be cleared. In 1996, the FC conservation requirement for the LR increased to include 80 percent of the property area in the Amazon biome and 20 percent in other. This requirement was unachievable for many farmers, especially for the ones in the Amazon biome (Nepstad et. al, 2009; Nepstad et al., 2014; Soares-Filho et al., 2014). They all explain that these high requirements undermined the FC and reduced its credibility significantly. In Mato Grosso alone, the new requirements resulted in huge opportunity costs for landowners, which in turn substantially increased the non-compliance level to 83 percent (Nepstad et al., 2014). Furthermore, enforcement of the new requirements was hindered by the lack of proper data on the rural properties registered. In 2012, the FC was revised and granted amnesty to landowners that had illegally deforested their lands prior to 2008 (an area of roughly 290,000 km^2).

There is no evidence that the FC itself contributed in the reduction of deforestation rates in the Amazon (Nepstad et. al, 2009; Nepstad et al., 2014; Soares-Filho et al., 2014). Conversely, with the amendment of the FC in 1996, compliance level with the legislation even declined.

2.2.2 Critical Counties Program (Blacklist)

The Critical Counties Program (also referred to as the Blacklist) was introduced in 2008, with the novel approach aimed to combat deforestation on the municipal level. Previously, policy implementation on property and farm level had been common practice (Nepstad et al., 2014). As such, it stimulated collaboration among the properties within the blacklisted municipalities to reduce deforestation rates and be removed from the list (Nepstad et al., 2014).

The Blacklist is the result of the collaboration between the Brazilian Central Bank and the Ministry of the Environment that enabled various actions, such as credit restriction and intensified monitoring, towards individual municipalities with high deforestation rates (Assunção et al., 2015; Nepstad et al., 2014). Three criteria determine whether municipalities are placed on the blacklist: the total area deforested, the total deforested area in the three previous years and the increase in deforestation of minimum three out of the past five years. The criteria were reinforced in 2010 (Cisneros et al., 2015).

The farms and ranches within the municipalities placed on the Blacklist lost access to credit lines and were subject to increased monitoring (Cisneros et al., 2015; Nepstad et al., 2014). At the start of the program in 2008, 36 municipalities, responsible for half of all Amazon deforestation in 2007, were put on the list. That number increased to 43 by 2009 and seven more were added in 2011 (Cisneros et al., 2015). From 2009, municipalities could be removed from the list given that the following criteria were satisfied. At least 80 percent of suitable land must be registered under the CAR and that annual deforestation could not exceed 40 km^2 (Cisneros et al., 2015).

Several studies agree that the Blacklist was one of the most significant and efficient policies implemented to combat deforestation in the Amazon (Arima et al., 2014; Assunção et al., 2015; Assunção & Rocha, 2014; Cisneros et al., 2015; Nepstad et al., 2014).

For example, Cisneros et al. (2015) find that the Blacklist was highly effective in decreasing deforestation and resulted in roughly 4,800 km^2 of forest cover conserved after implementation in 2008. Assunção & Rocha (2014) also suggests that the blacklisting was efficient in reducing deforestation. In their study, they isolate the component of intensified activity in law enforcement and monitoring from the component of restriction of credit. They find that the main contributor in reducing deforestation was the enforcement and monitoring component of the blacklist policy, not the restriction of credit.

The Blacklist policy is active from year 2008 and implementation coincides with the introduction of satellite monitoring of the SoyM. Out of the 39 municipalities we study in our sample, 11 of them are placed on the blacklist at some point during our observed study period.

Due to the acknowledged effectiveness of the policy and the fact that almost one third of the municipalities we study are at some point on the Blacklist, we expect that the effect of the Blacklist could bias our results. We account for this by including municipality-year fixed effects in our estimation which we outline in section 8.

2.2.3 PPCDAm: DETER Satellite Monitoring and Conservation Zones (CZs)

The Action Plan for the Prevention and control of Deforestation in the Legal Amazon (PPCDAm) was introduced in 2004 as a response to the high rates of deforestation from previous years (Assunção et al., 2015; Nepstad et al., 2014). The PPCDAm encouraged collaborative measures between the federal, state and municipal governments, which enhanced their ability (e.g. improved monitoring) to hinder illegal deforestation, logging and resource grabbing (Nepstad et al., 2014; Assunção et al., 2015). Over the course of seven years (2004-2011), over 600 operations against these illegal activities took place, imprisoning roughly 600 people and issuing substantial fines to perpetrators (Nepstad et al., 2014).

A part of the PPCDAm framework was the introduction of the Detecting Deforestation in Real Time (DETER) satellite-based system that locates deforestation hotspots in real time, which increased the capacity of law enforcement (Assunção et al., 2015; Assunção, Gandour & Rocha, 2013; Nepstad et al., 2014). Before the introduction of DETER, IBAMA (the national environmental police) were solely dependent on voluntary reports on areas exposed to deforestation, which hindered them to find and access deforestation hot spots on time (Assunção, Gandour & Rocha, 2013).

Another part of the PPCDAm framework was related to territorial management, in which the area devoted to protected areas increased. Protected lands, or Conservation Zones (CZs), are areas under strict regulation, which means that deforestation is prohibited within these zones. Simultaneously as the DETER system was rolled out, CZs saw a significant increase in the Brazilian Amazon (Anderson et al., 2016; Assunção. 2015; Nepstad et al., 2009). These CZs and indigenous areas grew by 68 percent over an eight-year period and by 2012 included 47 percent of the entire Brazilian Amazon region (Nepstad et al., 2014).

The PPCDAm framework policies' impact on deforestation have been studied and identified as significant drivers in the reduction of deforestation in the Legal Amazon (Assunção et al., 2015; Burgess, Costa & Olken, 2012; Nepstad et al., 2014) However, as the effects of each policy within the PPCDAm framework are not isolated, it is difficult to determine what policies are most efficient. Assunção, Gandour & Rocha (2013) and Anderson et al. (2016) have studied the DETER satellite monitoring and the expansion of CZs on deforestation in isolation, respectively. While Anderson et al. (2016) find evidence that CZs had no impact in reducing deforestation, Assunção, Gandour & Rocha (2013) conclude that the DETER satellite monitoring had a significant impact on deforestation rates.

2.2.4 CAR Environmental Property Registration

The CAR Rural Environmental Registry is a program that requires property owners and landholders to register the boundaries of their property to the state environmental agency and outline how they aim to meet the LR requirement under the FC (Nepstad et al., 2014). According to Gibbs et al. (2015), it provides a transparent way to assess compliance with various regulation, and in particular the Forest Code (FC). It links the land owner to land use on a certain property and for which he is held accountable for. All rural properties are to register in the CAR by 2016 and 93% of all properties in Mato Grosso have done so (Alix-Garcia et al., 2017). It was first introduced in 2008 to include all rural properties in the state of Pará and in 2009, Mato Grosso introduced it on a voluntary basis (Alix-Garcia et al., 2017).

The CAR had an impact on deforestation according to Alix-Garcia et al. (2017) but they state, together with Gibbs et al. (2015), that other CAR- related policies had more influence in reducing deforestation rates.

2.2.5 Cattle Moratorium

During the years 1990-2005, roughly 80 percent of deforestation in the Amazon was attributed to the expansion of cattle pasture (FAO, 2016). Furthermore, the expansion of the cattle herd was tremendous from 1993 to 2013. During this period, the herd in the Amazon biome grew by 200 percent to a head count of 60 million cattle (IBGE, 2018; NWF 2015) and forest lands equivalent to the size of Italy were cleared in the Brazilian Amazon (Gibbs et al., 2015). Instigated by another Greenpeace campaign, the cattle moratorium was introduced in October 2009, where the major beef processing companies in Brazil pledged to no longer buy beef from properties that deforested illegally (Nepstad et, al, 2009; Alix-Garcia & Gibbs, 2017).

Gibbs et al. (2015) and Alix-Garcia & Gibbs (2017) study the effect of the cattle moratorium on deforestation and find that the policy had no significant effect in reducing deforestation rates around the affected slaughterhouses.

The above policies were implemented at some point during our observed study period (2003-2013). As such, these policies could have an impact on deforestation in the Amazon and bias our results. As mentioned, we outline how we account for the Blacklist policy in section 8. In section 9.2, we address the remaining policies that we are unable to control for in our estimation. The following section defines the area we study in our analysis.

3. Definition of the Study Area

This section defines the area we study and explains key concepts important for the understanding of our analysis.

For our analysis, it is important to distinguish between the Brazilian Legal Amazon, the Amazon biome and the Cerrado biome.

The Legal Amazon is a socio-geographic area in Brazil that contains nine states and 775 municipalities and encompasses more than five million square kilometres. It covers the entire Brazilian Amazon biome, 37 percent of the Cerrado biome and 40 percent of the Pantanal biome (ISA, 2009). As such, the Legal Amazon is as an administrative area, with no regards to geo-ecological borders. The data on deforestation we use in our study covers the entire Brazilian Legal Amazon.

Figure 1 shows the Brazilian Legal Amazon with the respective biomes.

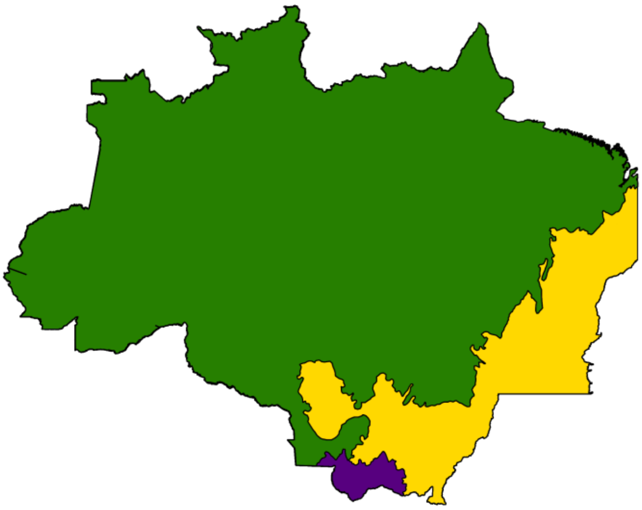

Figure 1: Map of the Brazilian Legal Amazon

Amazon biome highlighted in green, Cerrado biome highlighted in yellow, Pantanal biome highlighted in purple. (Source: own, created with QGIS).

As mentioned previously, the SoyM only applies to the Amazon biome, not the entire Legal Amazon. This allows us to study the effect of the SoyM on deforestation by comparing the development of deforestation in the Amazon biome with the development in the Cerrado biome.

Although the Amazon and the Cerrado biomes differ in some of their geo-ecological characteristics, they both have forested areas. While the Amazon biome predominantly consists of tropical rainforest (ISA, 2009) the Cerrado is a tropical-woody savanna where the landscape varies from grasslands, scrubland and canopy forests (CEA, 2016). Although the trees in the Cerrado biome are less dense than the Amazon biome, they still have substantial thicket (Koeppe, 2005). We exclude the Pantanal biome from our analysis, as it consists mostly of wetlands (WWF, 2018).

To mitigate the most prevalent differences in geo-ecological characteristics between the Amazon and Cerrado biome, we limit our analysis to an area close to the biome border, where we expect these differences to be least pronounced. Furthermore, we study deforestation at the municipal level, to minimise potential differences in institutional and economic factors between the Amazon and Cerrado biomes that could affect deforestation. Consequently, we focus on the biome portions of municipalities that are divided by the biome border between the Amazon and the Cerrado.

As mentioned previously, while the SoyM applies to the entire Amazon biome, its enforcement is dependent on satellite monitoring, which is limited to the states Pará, Rondônia and Mato Grosso.

To test our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring we therefore focus on municipalities in the three monitored states. Furthermore, since only four out of 43 municipalities that are divided by the biome border and are subject to satellite monitoring lie in Pará and Rondônia, we choose to limit our analysis to the remaining municipalities in Mato Grosso. In doing so, we also eliminate state-specific factors that could affect deforestation from our analysis. Furthermore, since the agricultural frontier in Mato Grosso is considered to be one of the most active ones globally, we expect the potential effect of the SoyM to be most pronounced in the municipalities that lie in this state (Kastens et al. 2017; Macedo et al., 2012).

The municipalities that we study are highlighted in Figure 2. We clearly see that the biome-border divides the municipalities into an Amazon biome-portion (hereafter Amazon) and a Cerrado biome-portion (hereafter Cerrado).

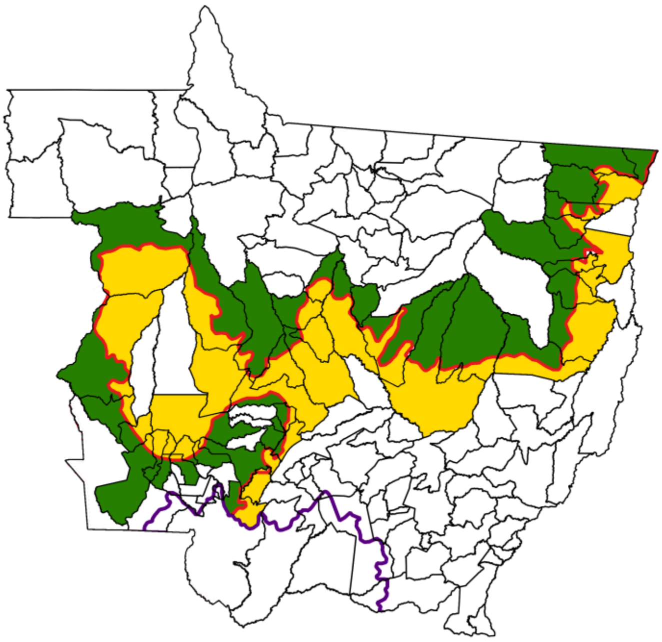

Figure 2: Map of Mato Grosso

The red line shows the biome border between Amazon and Cerrado. The purple line shows the biome border to the Pantanal. Amazon portions are highlighted in green and Cerrado portions are highlighted in yellow. (Source: own, created with QGIS).

Having defined our study area, we proceed with the description of the data that our analysis is based on in the next section.

4. Description of the Data

This section describes the underlying data we use to study the impact of the SoyM on deforestation in the Amazon. Furthermore, we explain how we aggregate the data for our DID and RD graphical analysis.

The dataset we use for our analysis builds on the dataset by Anderson et al. (2016), which comprises of deforestation data from the Brazilian Legal Amazon during the period 2002 to 2013. Deforestation is recorded from September *t-1* to August *t* for each year (Anderson et al., 2016). The deforestation data originates from high-resolution NASA satellite images that were processed at the Brazilian National Institute for Space Research (INPE) as part of the Programme for the Estimation of Deforestation in the Brazilian Amazon (PRODES). Anderson et al. (2016) aggregate the high-resolution data to grid cells of 1 km^2 and calculate the annual deforestation as well as the remaining forest cover for each cell. Since the coordinates of the centroids of the grid cells are known, further information can be assigned to each cell, such as the municipality code or the share of non-forest.

We extend the dataset of Anderson et al. (2016) by including information on the biome that each cell lies in (i.e. Amazon, Pantanal or Cerrado), as well as the distance in kilometres of each cell to the border between the Amazon and Cerrado. This information is based on a map of the various Brazilian biomes with the scale 1:5,000,000 by the Brazilian Institute for Geography and Statistics (IBGE)[1]. Furthermore, we include data on the amount of carbon stored in the forests in the year 2000 from Baccini et al. (2017). While the first year of deforestation data from the satellite images is 2001, Anderson et al. (2016) also calculate the stock of forest cover in 2000, which allows us to match the carbon data to the forest data and calculate the amount of carbon stored at the end of each year as well as the carbon released in each year.

[1] http://mapas.mma.gov.br/i3geo/datadownload.htm

For our DID analysis, we aggregate the grid cells at the municipal level and match them to the respective biome portions of the municipalities to obtain a more workable dataset[2]. As mentioned previously, we focus on municipalities in the state of Mato Grosso that are divided by the border between the Amazon and the Cerrado and therefore each municipality consists of two biome portions. We therefore exclude municipalities that partly lie in the Pantanal (since this biome is outside of our study area) as well as municipalities that fully lie in either the Amazon or Cerrado. We further exclude municipalities without any remaining forest cover at the end of the year 2002 in at least one biome portion since they do not experience any deforestation during our study period. Consequently, our observation period is limited to the years from 2003 to 2013.

For our graphical RD analysis, we use data at the grid cell level but also exclude cells that lie in the Pantanal or that belong to municipalities that are not divided by the border between the Amazon and the Cerrado. Furthermore, we exclude cells without any remaining forest cover at the end of the year 2002.

Our aggregated dataset is a balanced panel-dataset and comprises of 78 biome-portions in 39 municipalities, observed over eleven years.

Table 1 presents an overview of the data and figure 3 shows the annual deforestation in the Amazon and Cerrado. For a complete list of variables, please refer to appendix A1.

	Amazon		**Cerrado**		**All**	
	2003-2006	2007-2013	2003-2006	2007-2013	2003-2006	2007-2013
Deforestation km² (mean)	64.44	12.06	20.76	2.72	42.60	7.39
Forest Reamining km² (mean)	2,216	2,101	882	852	1,549	1,477
Carbon released Mg (mean)	704,897	130,992	318,223	41,953	511,560	86,472
Carbon stored Mg (mean)	25,141,046	23,751,534	12,264,163	11,766,667	18,702,604	17,759,100
Non-forest % (mean)	0.16		0.48		0.32	
Area km²	168,755		150,580		319,335	
Number of observations	429		429		858	

Table 1: Overview of Sample Data

[2] Since the dataset at the grid cell level contains of roughly 2.8 million observations, it is infeasible for our DID analysis which requires us to perform fixed effects regressions with many dummy variables due to the resulting computational times. We do however use the dataset at the grid cell level to plot RD graphs since this is computationally less demanding.

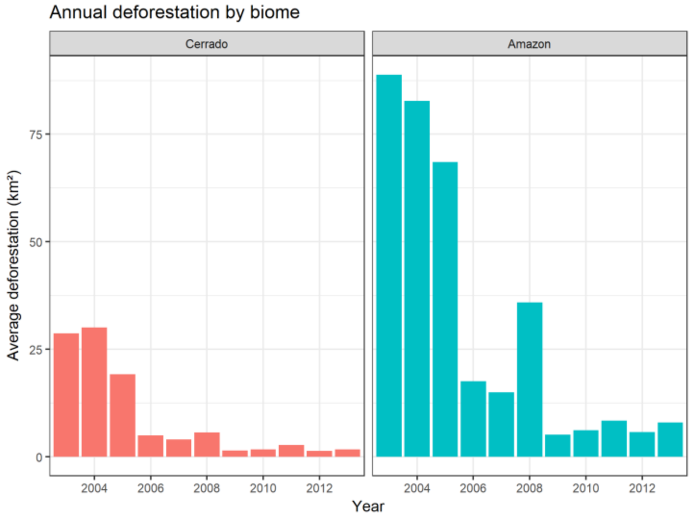

Figure 3: Average deforestation by year in the Cerrado and the Amazon for the biome-border municipalities in Mato Grosso

In line with our expectations, we observe higher levels of deforestation and remaining forest cover in the Amazon compared to the Cerrado. Furthermore, the share of non-forest is lower in the Cerrado, most likely due to the differences in geo-ecological characteristics. Despite of these differences, the annual development in deforestation is similar in both biomes and in line with that of the entire Legal Amazon, where we observe high levels of deforestation until 2005 and low levels from 2009.

Having described the data that our analysis is based on, we outline the empirical strategy in the following section.

5. Empirical Strategy

This section outlines the identification strategy we use in our analysis. We describe the DID approach and the fixed effects model that we use in our estimation. Furthermore, we specify the regression equation we estimate and explain the elements included.

5.1 Difference in Difference Approach

As mentioned previously, the aim of our analysis is to establish whether there is a causal relationship between the SoyM and deforestation in the biome-border municipalities in the state of Mato Grosso. Furthermore, we want to test our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring. We therefore introduce a Difference in Difference (DID) setup that we estimate with a fixed effects estimation model. Furthermore, we complement the DID setup with a graphical analysis of deforestation around the biome border based on a Regression Discontinuity (RD) design in section 8. All computations and data analysis are performed with the statistical software R, using the plm package (Croissant & Millo, 2008). The remainder of this section elaborates further on the DID setup and the fixed effects estimator and outlines the specification of our regression models.

As we have seen in section 4, the levels of deforestation are substantially lower in the Amazon from 2006 to 2013, which is somewhat coincidental with the introduction of the SoyM. However, it would not be a valid approach to establish a causal relationship between the SoyM and the observed decline in deforestation. There could be myriad of factors affecting deforestation simultaneously, such as the other policies that were introduced to curb deforestation. In order to establish causal inference, we need a control group that has not been affected by the SoyM. The idea is that the control group represents the counterfactual sate, which allows us to compare the difference between the actual change in deforestation in the Amazon to what the change in deforestation would have been without the implementation of the SoyM.

As such, the SoyM can be considered as a natural or quasi-experiment, which is defined as an exogenous event that leads to a change in the environment in which individuals, firms or states operate (Wooldridge, 2014). Since the SoyM applies to the Amazon but not the Cerrado, the SoyM determines which observations are treated (affected by the policy) and non-treated (not affected by the policy). Consequently, the Cerrado can serve as the control group to study the SoyM.

Ideally, the SoyM would apply to individual municipalities that are selected randomly from a group of municipalities with similar characteristics, such as the levels of deforestation and remaining forest cover, as well as other unobservable factors. If that was the case, the resulting treatment and control groups would be ideal to study the effect of the SoyM, since we could assume that a potential decrease in the levels of deforestation following the introduction of the SoyM was not caused by any other factors that are inherently different between the two groups.

However, in reality, treatment of the SoyM is not randomly assigned, since it affects all municipalities in the Amazon. As we have seen, the average levels of deforestation are higher in the Amazon than in the Cerrado, which is likely the reason why the Amazon was selected for treatment. Therefore, an analysis in which we compare the levels of deforestation in these two biomes would likely suffer from selection bias and consequently not yield valid results.

However, the DID setup allows us to overcome the potential selection bias and to establish a treatment effect if our control group follows the same deforestation trends as our treatment group (Angrist & Pischke, 2015). Therefore, if the Cerrado is comparable in terms of the change in deforestation, it can serve as a good control group for the Amazon, despite the differences in the average levels of deforestation (Angrist & Pischke, 2015).

As the DID setup adjusts for differences between groups, it allows us to compare two groups that are not identical to one another. Instead of comparing the levels of deforestation in each biome, the DID compares the change in deforestation in the two biomes. This accounts for the fact that in the period prior to the SoyM, the levels of deforestation were higher in the Amazon than in the Cerrado (Angrist & Pischke, 2015). Equation (1) mathematically describes our SoyM DID estimator (Wooldridge, 2014).

$$\hat{\sigma}_{DID} = \left(\overline{DF_{A,Post}} - \overline{DF_{A,Pre}}\right) - \left(\overline{DF_{C,Post}} - \overline{DF_{C,Pre}}\right) \qquad (\mathbf{1})$$

Note: Post = Post SoyM, Pre = Pre SoyM, A = Amazon biome, C = Cerrado biome

$\hat{\sigma}_{DID}$ represents the difference between the average change in deforestation in the treatment group (Amazon) and the average change in deforestation in the control group (Cerrado). Even though the two biomes were initially not the same in terms of levels, this transformation makes them comparable, as we now focus on the slopes or trends across the biomes.

The counterfactual outcome is central in a DID setup, as it allows us to compare the difference between the actual change in deforestation in the Amazon to what the change in deforestation would have been without the implementation of the SoyM (Angrist & Pischke, 2015). Since the Cerrado serves as the counterfactual in the DID setup, it is essential that we observe similar trends in deforestation as in the Amazon prior to the implementation of the SoyM. This is also referred to as the common trends assumption in the context of a DID setup. Violation of the common trends assumption means that we cannot rely on DID as a valid approach to investigate the policy's effect on deforestation in the Amazon. We test for the common trends assumption in section 6. Having introduced the DID setup, we now turn to the fixed effects estimator we use in our analysis.

5.2 Fixed Effects Estimator

We exploit the benefits of panel data by estimating our DID setup with a fixed effects estimator. This allows us to control for the unobserved factors that affect the dependent variable (Wooldridge, 2014). In general, there are two types of unobserved factors, those that change over time (time-variant) and those that are constant (time-invariant) (Wooldridge, 2014). In our case, unobserved, time-variant factors that affect deforestation in all biome-portions could be global prices of soy and timber. Furthermore, unobserved, time-invariant factors could be the quality of the soil and other geographic features in each biome-portion (Wooldridge, 2014). Before we introduce the regression equation we estimate to capture the effect of the SoyM on deforestation in our analysis (equation 4), we illustrate the fixed effects transformation with equations (2) and (3).

$$Deforestation_{it} = \beta_1 x_{it} + I_i + I_t + \varepsilon_{it} \tag{2}$$

i denotes the cross-sectional unit and *t* the time period. In our case, the subscript *i* refers to the biome-portions, and *t* refers to the years from 2003 to 2013. The variable ε_{it} is the time-varying, idiosyncratic, error. It represents unobserved factors that change over time and affect deforestation. The variable that captures all unobserved, time-invariant, factors that affect deforestation is I_i. In our analysis, I_i is the biome-portion fixed effect, which could for example represent the soil quality in biome-portion i (Wooldridge, 2015). Similarly, I_t is the variable that captures all unobserved, time-variant, factors that affect deforestation. In our analysis, I_t is the year fixed effect, which could for example represent the global price of soy.

The fixed effects estimator allows for correlation between the unobserved fixed effects I_i and the explanatory variables because the fixed effects transformation removes these unobserved fixed effects (Wooldridge, 2015). Equation (3) displays the fixed effects transformation for the biome-portion fixed effect, which subtracts the average of each *i* over time from the original model.

$$DF_{it} - \overline{DF_\iota} = \beta_1(X_{it} - \overline{X_\iota}) + u_{it} - \overline{u_\iota} \tag{3}$$

Equation (3) is the time-demeaned data, in which the average of each observation *i* has been subtracted. In our case, the average deforestation over time in biome-portion *i* is subtracted from the observed values of deforestation for each year in biome-portion *i*. If we compare equation (3) to equation (2), we see that the unobserved fixed effects I_i have been removed. Subtracting the average for each *i* over time will result in the disappearance of this variable because the fixed effects do not vary over time. As such, we are not able to include any time-invariant explanatory variables, as they will disappear in the transformation. Although the fixed effects model allows for correlation between the unobserved fixed effects and the remaining explanatory variables, the model can still be subject to omitted variable bias. If our explanatory variables are correlated with the error term, then we observe endogeneity (Wooldridge, 2014). This can occur if potential factors affecting deforestation that vary both between biome portions and over time, such as the area of soy planted in each biome portion, are excluded from the model. In this example, the potential effect of the area of soy planted on deforestation would then be captured by the error term ε_{it} and consequently bias our estimates.

We have set the foundation of our empirical strategy in describing the DID setup estimated with fixed effects. In the following, we describe our main models and the variables in detail.

5.3 Model Specification

As we first want to study the SoyM in isolation, we specify our initial model with one interaction term that captures the effect of the SoyM on deforestation. Subsequently, we add a second interaction term that captures the effect of satellite monitoring. This allows us to test our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring.

5.3.1 Soy Moratorium

Equation (4) presents the regression equation we estimate to capture the effect of the SoyM on deforestation.

$$\begin{aligned} ln(DF_{it}) = \alpha + \beta_1 biome_i + \ \beta_2 soym_t \\ + \beta_3(biome_i * soym_t) + \beta_4 X_{it-1} + I_i + I_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$ln(DF_{it})$ denotes the dependent variable which is specified as the natural logarithm of deforestation in biome-portion *i* in year *t*. α denotes the constant.

$biome_i$ represents the treatment dummy-variable and takes the value one if the biome-portion of a municipality is located in the Amazon and zero if it is located in the Cerrado. This dummy variable controls for time-invariant differences between the biome portions (Angrist & Pischke, 2015).

$soym_t$ represents the time-dummy variable and takes the value one for the years that the SoyM is active (2007-2013) and zero for all previous years (2003-2006). As mentioned previously, the SoyM was implemented on 24 July 2006. For our analysis, we choose the year 2007 as the cut-off for the SoyM, since it represents deforestation from September 2006 to August 2007 and therefore reflects the first year of the post-period more accurately than the year 2006. $soym_t$ controls for changes in deforestation between the pre- and post-period of the SoyM in all biome-portions (Angrist & Pischke, 2015).

$biome_i * soym_t$ represents the interaction term and is our variable of interest. It is obtained by multiplying the two dummy variables described above. The interaction term takes the value one if biome-portion *i* lies in the Amazon and if the SoyM is active in year *t* (i.e. if *t* >= 2007). The coefficient of this term β_3 can be interpreted as the average treatment effect of the SoyM on deforestation (Wooldridge, 2014).

X_{it-1} denotes the time-varying explanatory variable that we include in our models. We alternate between the one-year lag of deforestation and the one-year lag of remaining forest cover, expressed in natural logarithms. That is, the deforestation and forest remaining from previous year $t\text{-}1$ in biome-portion i, respectively. We do not include both variables simultaneously since they are negatively correlated (i.e. $FR_{t-1} = FR_{t-2} - DF_{t-1}$). Using a lagged dependent variable is common for policy analysis and provides a simple way to account for historical factors of a biome-portion *i* that cause current differences in deforestation, which are difficult to account for in other ways (Wooldridge, 2014). This also makes sense intuitively, since high levels of deforestation in a biome-portion *i* in year *t-1* could indicate that *i* has a tradition of high levels of deforestation and is therefore likely to observe high levels of deforestation in year *t* as well. Regarding lagged forest remaining, we reason that high levels of remaining forest cover in a biome-portion *i* in year *t-1* could imply that *i* is likely to observe high levels of deforestation in year *t*, since there are many trees available to cut down.

I_i and I_t denote the biome-portion fixed effects and year fixed effects respectively.

5.3.2 Satellite Monitoring

In addition to studying the direct effect of the SoyM on deforestation in the Amazon, we also study the effect of satellite monitoring. Therefore, we introduce a second time-dummy, $monitoring_t$ that takes the value one for the years in which satellite monitoring is active

(2009[3]-2013) and zero for all previous years (2003-2008). This time-dummy is then interacted with the same treatment-dummy, $biome_i$ as in the previous DID setup. Equation 5 presents the extended regression equation.

$$ln(DF_{it}) = \alpha + \beta_1 biome_i + \beta_2 soym_t + \beta_3 (biome_i * soym_t) + \beta_4 X_{it-1} + \beta_5 (biome_i * monitoring_t) + I_i + I_t + \varepsilon_{it} \qquad \mathbf{(5)}$$

Now, the coefficient of the interaction term β_5 can be interpreted as the average treatment effect of satellite monitoring on deforestation.

The standard errors for all regressions in this paper are clustered on the biome-portion level to control for potential serial correlation (Croissant & Millo, 2008; Arellano, 1987). To account for potential spatial correlation across neighbouring biome-portions, we include municipality-year fixed effects and two-way clustering in section 8. The following section outlines the potential threats to identification.

6. Threats to Identification

This section describes potential threats to our identification strategy. First, we address the common trends assumption, which is crucial for causal inference. Secondly, we elaborate on the effects of spatial correlation and how we aim to account for this in our analysis.

6.1 Common Trends Assumption

As we have discussed previously, it is essential that the common trends assumption holds in order to establish inference from a DID analysis. In the following, we test the common trends assumption for deforestation in the periods prior to the introduction of the SoyM (2003-2006) and satellite monitoring (2003-2008). We first perform a graphical analysis before we turn to formal testing of the common trends assumption.

[3] Since satellite monitoring was introduced in June 2008 (Brown & Koeppe, 2012), we choose 2009 (September 2008 until August 2009) as the cut-off year.

6.1.1 *Graphical Analysis of the Observed Deforestation Values*

The following graphs display the observed values of deforestation in the Amazon and Cerrado in natural logarithms[4]. Figure (4) refers to the SoyM and figure (5) to the satellite monitoring.

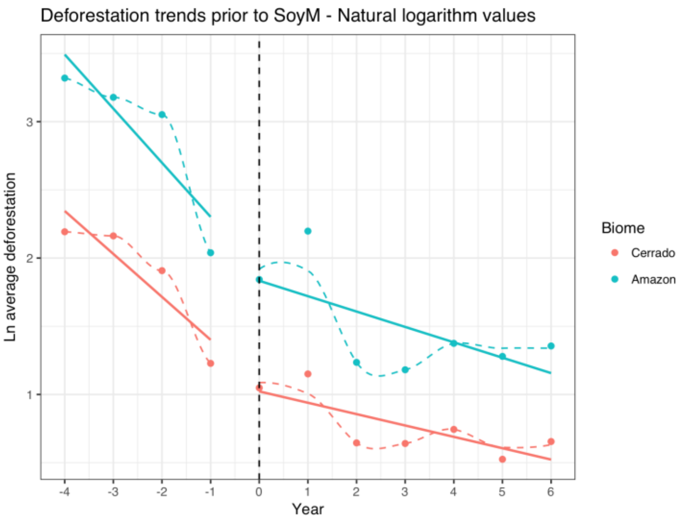

Figure 4: Deforestation trends prior to SoyM

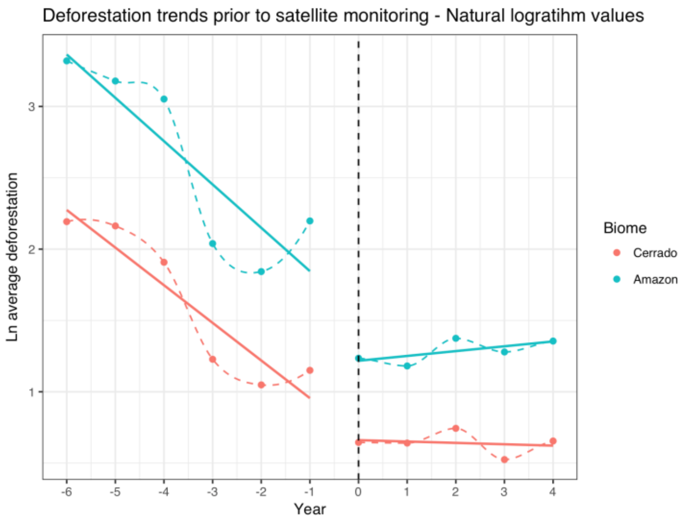

Figure 5: Deforestation trends prior to Satellite Monitoring

We observe parallel deforestation trends in the pre-treatment periods both for the SoyM and satellite monitoring. This indicates that the common trends assumption holds[5].

6.1.2 *Formal Testing of the Pre-Treatment Trends*

In addition to the graphical analysis, we perform a formal test of the deforestation trends in the pre-treatment periods of the SoyM and satellite monitoring to confirm that they do not differ significantly between Amazon and Cerrado. We estimate equation (6) for the SoyM with individual and time fixed effects. The equation for the satellite monitoring follows the same structure but includes the post monitoring dummy instead.

$$ln(DF_{it}) = \alpha + \beta_1 biome_i + \beta_2 soym_t + \beta_3\big(biome_i * ln(trend)\big) + I_i + I_t + \varepsilon_{it} \qquad \textbf{(6)}$$

[4] We also test the common trends assumption for deforestation specified in absolute values and rates (appendices A2-A3) as well as for carbon released (appendix A4). Since we do not observe parallel trends for these specifications, we choose to focus on the specification of deforestation in natural logarithms.

[5] We also plot the average residuals of the fixed effects regression after the individual and time fixed effects have been removed (appendices A5-A6). Since we do not observe parallel trends for the average residuals, we do not elaborate on this approach in this section.

$biome_i * ln(trend)$ represents the interaction term between the biome dummy variable and the natural logarithm of a *trend* variable which captures the change in deforestation in the pre-treatment period. It is constructed in the way that the years 2003-2006 (2003-2008) take the values 1-4 (1-6), respectively. If the coefficient of the interaction term β_3 is insignificant, we can assume that the trends in the pre-treatment period of the SoyM (satellite monitoring) do not significantly differ between the Amazon and Cerrado. The results of the formal test are presented in table 2 below.

Pre-trend test SoyM (1) & satellite monitoring (2)

	Dependent variable:	
	SoyM (1)	Monitoring (2)
ln trend	-0.604^{***}	-0.719^{***}
	(0.106)	(0.105)
ln trend*biome	-0.157	
	(0.151)	
ln trend*monitored		-0.124
		(0.141)
Observations	312	468
R^2	0.267	0.357
F Statistic	42.349^{***} (df = 2; 232)	107.831^{***} (df = 2; 388)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: Pre-trend test SoyM & Satellite Monitoring

Since the coefficients of the interaction terms are insignificant for the SoyM and satellite monitoring, the results confirm that the common trends assumption holds.

6.2 Municipality-Year Specific Shocks and Spatial Correlation

Other policies implemented during our study period, such as the Blacklist, pose two potential threats to identification: municipality-year specific shocks and spatial correlation.

6.2.1 Municipality-Year Specific Shocks

As mentioned previously, there is evidence that the Blacklist was effective in reducing deforestation in the targeted municipalities. As such, the Blacklist can be considered a municipality-year specific shock, since it was implemented on a municipal level in 2008. During our study period, eleven out of 39 of our municipalities were affected by the Blacklist. Therefore, our estimates would likely capture the effect of the Blacklist on deforestation, which could bias our results. To control for this potential bias, we include municipality-year fixed effects to control for the municipality-year specific shocks (Cameron, Gelbach and Miller, 2011). We elaborate on this in section 8.

6.2.2 *Spatial Correlation*

Spatial correlation is an extension of serial correlation (Perasan & Tosetti, 2010). As serial correlation relates to time only, it is one-dimensional. Spatial correlation, however, presents at least two dimensions, one across time and one across space (Perasan & Tosetti, 2010). We observe this in the eleven municipalities that were affected by the Blacklist, since the years during which the municipalities were affected represents a correlation across time and the different municipalities that were affected represents a correlation across space. The presence of spatial correlation in the error term would lead to the standard errors being too small, which could affect the inference of our estimates.

To account for spatial correlation, we follow the two-way clustering approach by Thomson (2011) and calculate standard errors that are robust to simultaneous correlations across two dimensions. In our case, we cluster at both the biome-portion level and the municipality-year level following.

As with the municipality-year fixed effects, we elaborate on the two-way clustering in section 8.

Having addressed the potential threats to identification and established that the common trends assumption for our sample holds, we present our results in the following section.

7. Empirical Results

This section presents the results of our estimations. We first present the results of the regressions related to the SoyM before we turn to the results related to satellite monitoring. Furthermore, we graphically present the year-by-year estimates with the respective cut-off years of the SoyM and satellite monitoring as base years.

7.1 Effect of the Soy Moratorium on Deforestation

Table (3) shows the output for three different models of the fixed effects estimation of equation (4).

DID fixed effects estimation - SoyM

	Dependent variable:		
	Ln deforestation		
	(1)	(2)	(3)
lag ln df		0.347***	
		(0.043)	
lag ln fr			4.605**
			(2.272)
biome*soym	-0.302*	-0.144	-0.215
	(0.178)	(0.107)	(0.175)
Observations	858	780	780
R^2	0.013	0.145	0.063
F Statistic	10.488*** (df = 1; 769)	58.743*** (df = 2; 691)	23.235*** (df = 2; 691)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: DID fixed effects estimation - SoyM

Column (1) presents our most basic model where we only include biome-portion and year fixed effects. The natural logarithm of deforestation is simply regressed on the interaction term $biome_i * soym_t$ (displayed in the third row). The interaction term yields a statistically significant negative coefficient at the ten percent significance level. This is our DID estimate that captures the average treatment effect of the SoyM. It suggests that the municipality portions located in the Amazon experience, on average, 30.2 percent lower deforestation in the period after the introduction of the SoyM (2007-2013) compared to the municipality portions located in the Cerrado during the same time period.

Column (2) presents the model that includes the one-year lag of deforestation in natural logarithms as a time-varying explanatory variable (displayed in the first row). The coefficient of the lagged dependent variable indicates that if the average deforestation was ten percent higher in the previous year, deforestation in the current year is predicted to increase by 3.47 percent (Wooldridge, 2014). As expected, the coefficient of this variable is positive and is significant at the one percent significance level. In this setting, the average treatment effect of the SoyM decreases to 14.4 percent and turns insignificant.

Column (3) presents the model that instead includes the one-year lag of forest remaining in natural logarithms as a time-varying explanatory variable (displayed in the second row). As expected, the coefficient of this variable is positive and statistically significant at the five percent significance level. It suggests that if biome-portion *i* had, on average, ten percent more forest cover in the previous year, deforestation is predicted to increase by 46.6 percent in the current year. In addition, the average treatment effect has declined in magnitude compared to column (1) but increased to 21.5 percent compared to column (2). However, the result is insignificant.

7.2 Effect of Satellite Monitoring on Deforestation

In table (4), we present the regression output from our fixed effects estimation of regression equation (5), in which we add a second interaction term to test our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring. The models are presented in the same order as in the previous subsection but also includes a fourth row with the interaction term $biome_i * monitoring_t$.

DID fixed effects estimation - satellite monitoring

	Dependent variable:		
	Ln deforestation		
	(1)	(2)	(3)
lag ln df		0.345^{***}	
		(0.043)	
lag ln fr			4.632^{**}
			(2.193)
biome*soym	-0.104	0.031	-0.009
	(0.156)	(0.106)	(0.148)
biome*monitoring	-0.277^{**}	-0.246^{**}	-0.288^{**}
	(0.136)	(0.112)	(0.135)
Observations	858	780	780
R^2	0.020	0.151	0.071
F Statistic	7.768^{***} (df = 2; 768)	41.050^{***} (df = 3; 690)	17.687^{***} (df = 3; 690)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: DID fixed effects estimation - Satellite Monitoring

Adding the second interaction term to column (1), in which we only account for biome-portion and year fixed effects, yields a negative coefficient that is significant at the five percent level. Also, the effect of the SoyM turns insignificant. The same effect applies to Columns (2) and (3) when we add deforestation and forest remaining from the previous year, respectively. The second interaction term from model (2) suggests that the portion of municipalities in the Amazon biome on average experienced an additional decline in deforestation of 24.6 percent in the period following the introduction of satellite monitoring, compared to the Cerrado portions of the same municipalities. This result supports our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring.

In the previous regressions, model (2), which includes the one-year lag of deforestation as an explanatory variable is our preferred model, since the inclusion of a lagged dependent variable allows us to account for historical factors (Wooldridge, 2014). Furthermore, the other results we obtain from models (1) and (3) do not contradict the results from model (2). As such, all models indicate the same direction of deforestation. Thus, model (2) is our main model of interest and to the one we relate to with regard to the average treatment effect.

The interaction term from model (2) regression output suggests that about 430 km² of deforestation were avoided in the Amazon biome-portion of our studied municipalities in Mato Grosso due to satellite monitoring, an area approximately the size of Bergen county (Bergen Byleksikon, 2018). This amounts to roughly 4.8 million tons of carbon saved from being released in the atmosphere. The total area deforested after the introduction of satellite monitoring amounts to roughly 1,310 km² in the Amazon and 360 km² in the Cerrado.

7.3 Year-By-Year Estimates

The previous results indicate that the most pronounced decline in deforestation largely occurs after the satellite monitoring was implemented in 2008. To further investigate this, we estimate the year-by-year treatment effect with equation (7). For the regression output, please refer to appendix A7.

$$ln(DF_{it}) = \alpha + \beta_1(year_{2003} * biome_i) + \beta_2(year_{2004} * biome_i) + \\ ... + \beta_9(year_{2013} * biome_i) + I_i + I_t + \varepsilon_{it} \qquad (\mathbf{7})$$

Figure (4) displays the estimates plotted year-by-year with 2006 as the reference year (i.e. the year prior to the introduction of the SoyM). Figure (5) displays the estimates plotted year-by-year with 2008 as the reference year (i.e. the year prior to the introduction of satellite monitoring).

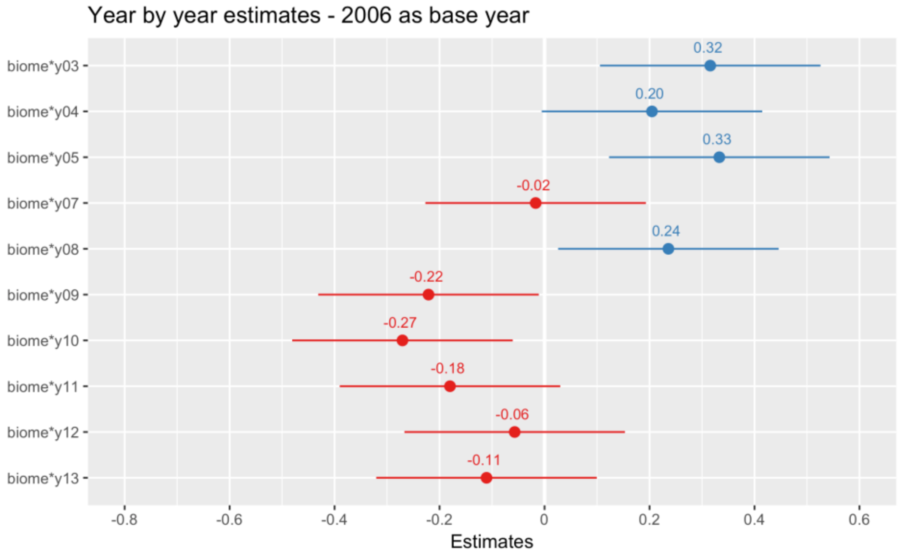

Figure 6: Year by year estimates - 2006 as base year

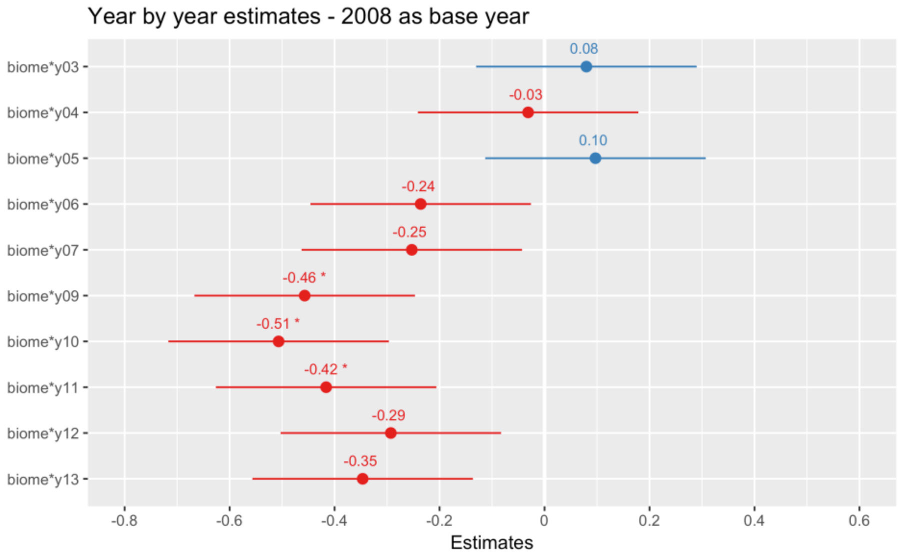

Figure 7: Year by year estimates - 2008 as base year

The results above coincide with the estimates from the previous regressions presented in tables (3) and (4). In figure (6) and (7), the respective pre-trends are insignificant, which further shows the common trends assumption is satisfied. Figure (6) shows that none of the yearly estimates yield statistically significant coefficients, which confirms the results displayed in table (3) and suggests that the SoyM itself does not have a significant effect on deforestation. Figure (7) provides further evidence that the satellite monitoring was the main driver in the decrease in deforestation in the Amazon since the yearly estimates from 2009 to 2011 yield statistically significant coefficients at the one percent significance level. Furthermore, they show an additional decrease in deforestation of 42 to 51 percent in the Amazon compared to the Cerrado.

The results from the regressions presented in tables (3) and (4) as well as the year-by-year estimates displayed in figures (6) and (7) supports our hypothesis that the SoyM only had a significant impact on deforestation in the Amazon after it was enforced with satellite monitoring. In the next section, we test if our estimates are robust by controlling for spatial correlation.

8. Robustness

This section presents a robustness test with regards to municipality-year specific shocks and spatial correlation.

As mentioned previously, we account for municipality-year specific shocks, such as the Blacklist, by including municipality-year fixed effects in our regressions (Cameron, Gelbach and Miller, 2011). Consequently, we include one fixed effect for each municipality for each year (eleven fixed effects per municipality). This allows us to control for unobserved effects that affect each municipality individually and that vary over time.

Furthermore, to account for potential spatial correlation, we follow the two-way clustering approach by Thompson (2011) and calculate standard errors that are robust to simultaneous correlations across two dimensions. In our case, we cluster at both the biome-portion level and the municipality-year level.

The double cluster covariance estimator is obtained by adding the estimator that clusters by group (biome-portion) to the estimator that clusters by time (municipality-year) and subtracting the heteroskedasticity-robust OLS covariance matrix (Thompson, 2011. Table (5) presents the regression output for the SoyM with municipality-year fixed effects and includes the two-way clustering. Table (6) includes the second interaction term for the satellite monitoring.

Municipality-year fixed effects - SoyM

	Dependent variable:		
	(1)	(2)	(3)
lag ln df		0.313***	
		(0.065)	
lag ln fr			3.025
			(2.359)
biome*soym	-0.302***	-0.156*	-0.233**
	(0.112)	(0.086)	(0.117)
Observations	858	780	780
R^2	0.041	0.134	0.060
F Statistic	15.115*** (df = 1; 351)	23.960*** (df = 2; 311)	9.996*** (df = 2; 311)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Municipality-year fixed effects - SoyM

As table (5) shows, the estimates of the interaction term turn significant when we account for spatial correlation. The change in the magnitude of the average treatment effects are marginal.

Municipality-year fixed effects - satellite monitoring

	Dependent variable:		
	Ln deforestation		
	(1)	(2)	(3)
lag ln df		0.306***	
		(0.065)	
lag ln fr			3.089
			(2.231)
biome*soym	-0.104	0.020	-0.029
	(0.108)	(0.092)	(0.108)
biome*monitoring	-0.277***	-0.250***	-0.285***
	(0.095)	(0.084)	(0.094)
Observations	858	780	780
R^2	0.061	0.152	0.085
F Statistic	11.337*** (df = 2; 350)	18.571*** (df = 3; 310)	9.584*** (df = 3; 310)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Municipality-year fixed effects - Satellite Monitoring

In table (6), all coefficients of the interaction terms are significant at the one percent significance level and the change in the magnitude of the estimates are negligible.

Overall, we conclude that our estimates are robust when municipality-year fixed effects are taken into account and when we cluster the standard errors two-ways. Although there are some discrepancies in terms of magnitude and significance levels for the different models, it does not affect our main model (2) substantially, nor the conclusion of this paper. In the following section, we discuss our results and elaborate on limitations that could affect our study.

9. Discussion of Results and Limitations

In this section, we discuss the findings from our analysis and relate them to previous studies on the SoyM. Furthermore, we address limitations that could potentially influence our results.

9.1 Results

The results from our analysis indicate that the Amazon and Cerrado still follow similar trends in deforestation in the two years following the introduction of the SoyM (2007 and 2008). Only after the introduction of satellite monitoring, the Amazon experiences an additional decrease in deforestation that is significantly different from the decrease in the Cerrado. Furthermore, while we observe a decrease in deforestation in both biomes immediately after the introduction of the satellite monitoring, our estimates indicate that the decrease between 2008 and 2009 is statistically significant and 46 percent greater in the Amazon compared to the Cerrado. Consequently, we draw the following conclusions from our analysis:

1. *The SoyM had little or no effect on deforestation in the Amazon until it was enforced with satellite monitoring.*
2. *In conjunction with satellite monitoring, the SoyM contributed to the observed decline in deforestation in the Amazon.*
3. *It is unlikely that the SoyM was the sole driver of the observed decline in deforestation, since we observe lower levels of deforestation in both biomes after the introduction of the satellite monitoring.*

In the following, we discuss these findings in further detail before we address limitations of our analysis that could potentially influence our results.

1. The SoyM had little or no effect on deforestation in the Amazon until it was enforced with satellite monitoring.

Our first finding is contrary to Kastens et al. (2017), who observe a substantial decline in deforestation rates in the Amazon immediately after the introduction of the SoyM in 2006.

Furthermore, they find that the average deforestation rates were roughly six times higher in the period prior to the introduction of the SoyM compared to the period following the introduction. However, since Kastens et al. (2017) do not perform a counterfactual analysis, their findings might not be comparable to ours.

Other studies find that satellite monitoring and enforcement are the main contributors to the decrease in deforestation, which is in line with our first finding (Assunção, Gandour & Rocha, 2013; Assunção & Rocha, 2014; Burgess, Costa & Olken, 2012).

Assunção & Rocha (2014) study the impact of the Blacklist on deforestation and isolate the effect of stricter monitoring and law enforcement and from the effect of the restriction of credit. Their findings suggest that the main contributor to the decrease in deforestation after the introduction of the Blacklist was the stricter monitoring and law enforcement, not the restriction of credit.

Furthermore, Assunção, Gandour & Rocha (2013) study the impact of the DETER satellite monitoring system on deforestation in the Legal Amazon. As such, they isolate the effect of the monitoring and enforcement component of the PPCDAm. Their findings suggest that that the DETER-based monitoring contributed to the preservation of 59,500 km² of forest cover in the Legal Amazon between 2007 and 2011. They further conclude that the DETER satellite monitoring system significantly raised IBAMA's ability to penalise illegal deforestation.

Moreover, Burgess, Costa & Olken (2012) employ a spatial Regression Discontinuity Design in order to study the impact of command and control policies between the years 2000 and 2014 around the national border between Brazil and its Amazon-neighbouring countries. They find that prior to the gradual rollout of the PPCDAm policies from 2004 to 2006, deforestation rates were four times higher in Brazil than in the neighbouring countries, whereas deforestation rates drop to similar levels on both side of the border in 2006. They argue that this drop is due to the enhanced enforcement in protecting the forests.

Lastly, Gibbs et al. (2015) acknowledge that the success of the SoyM was due to numerous factors, including satellite monitoring.

2. In conjunction with satellite monitoring, the SoyM contributed to the observed decline in deforestation in the Amazon.

Our second finding complements Gibbs et al. (2015) who find that the SoyM effectively reduced deforestation directly related to soy expansion. However, as mentioned previously, they neither establish a causal relationship between the SoyM and the observed decline in overall deforestation during their study period, nor do they quantify the amount of deforestation that was avoided by the SoyM.

With our counterfactual analysis, we confirm that the SoyM, in conjunction with satellite monitoring, had a significant impact on deforestation in the Amazon. Furthermore, we find that deforestation decreased by an additional 24.6 percent in the Amazon compared to the Cerrado, which preserved about 430 km^2 of forest cover in our study area.

3. It is unlikely that the SoyM was the sole driver of the observed decline in deforestation, since we observe lower levels of deforestation in both the Amazon and Cerrado after the introduction of the satellite monitoring.

Our third finding suggests that the sharp decline in deforestation between 2008 and 2009 has likely been caused by other exogenous events. In other words, while the SoyM and satellite monitoring can explain why the observed decline in deforestation between 2008 and 2009 is more pronounced in the Amazon than in the Cerrado, they cannot explain why we observe a decline in both biomes.

One exogenous event that could potentially explain the sharp decline in deforestation between 2008 and 2009 in both biomes is the introduction of the Blacklist, as it was coincidental with the introduction of the satellite monitoring. Furthermore, as eight out of 39 municipalities in our sample were affected by the Blacklist from 2008[6], it is likely that we observe the effect of the Blacklist on deforestation in our data. Since we control for the effect of the Blacklist in our regressions through the inclusion of municipality-year fixed effects, it should however not bias our estimates.

[6] This number increases to nine municipalities for the years 2009 and 2010 and to eleven municipalities for the years 2011 until 2013.

An alternative hypothesis for why we observe lower levels of deforestation in both biomes after the introduction of satellite monitoring is that there are positive spillover effects of the SoyM.

As the border between the Amazon and Cerrado is a natural border, it might not be clearly visible in reality, which can cause difficulties when trying to establish whether a property lies within the Amazon or Cerrado biome. We consider three possibilities how this could influence the effect of the SoyM on deforestation.

First, the authorities could enforce the SoyM on properties within the Cerrado if they falsely assume that the property is located in the Amazon. Secondly, soy producers in the Cerrado could falsely assume that their property lies in the Amazon and comply with the SoyM although they are not required to. Thirdly, soy producers in the Cerrado could voluntarily comply with the SoyM to avoid the risk of losing market access if their property is falsely classified as being located in the Amazon.

Brown and Koeppe (2012) provide support for the hypothesis of positive spillover effects and state that in the area near the biome border, it is often not possible to clearly distinguish between forest and savannah. Furthermore, they point out that the GTS does not specify how properties in transition areas are treated with respect to the monitoring of the SoyM. Lastly, they state that the classification of transitional areas largely depends on the political and economic agenda of the respective authorities, such as IBAMA. While the authorities in one municipality might classify these areas as forest and thereby maximise conservation, the authorities in another municipality might classify these areas as savannah, which is less protected by the forest code and not within the scope of the SoyM.

Since we do not have any information on how the SoyM is enforced in practice and whether individual soy producers are aware of whether they need to comply with the SoyM, this presents an interesting research question for potential future field studies in the area around the biome border.

We further investigate the hypothesis of positive spillover effects with a graphical Regression Discontinuity (RD) analysis in section 10. However, we first address limitations of our analysis that could potentially influence our results in the following subsection.

9.2 Limitations

This subsection discusses potential limitations that could bias the results from our DID analysis.

9.2.1 Overestimation of the Treatment Effect due to Leakage of Deforestation

The effect of the SoyM and satellite monitoring could be overestimated if deforestation in our counterfactual (Cerrado) increases in the post-treatment period. This could for example occur if there is leakage of deforestation from the Amazon to the Cerrado. For clarity, we illustrate this with a numerical example. Assume that deforestation in the Amazon and the Cerrado in year *t* is 10 km². If 1 km² of deforestation is moved from the Amazon to the Cerrado in year *t+1*, this results in deforestation of 9 km² in the Amazon and 11 km² in the Cerrado. Our DID estimator would capture this change as (9 km² - 10 km²) - (11 km² - 10 km²) = -2 km². In other words, the actual decrease in deforestation in the Amazon would be overstated by 100% due to the simultaneous increase in deforestation in the Cerrado.

Gibbs et al. (2015) acknowledge the risk of potential deforestation leakage of soy into the Cerrado as a result of the SoyM. However, as our analysis shows, deforestation has decreased both in the Amazon and Cerrado in the post-treatment period. As such, we are confident that this effect should not affect our estimates significantly. Despite of that, we cannot rule out that the Cerrado was affected by the SoyM and this should be taken into consideration when interpreting our results.

9.2.2 Overestimation of the Treatment Effect due to Other Policy Implementation

As mentioned previously, several other policies and supply chain interventions have been implemented with the aim of reducing deforestation during our observed period from 2003 to 2013. All of these policies are not specifically targeted towards the Amazon biome alone but are implemented at either municipal or property level. While we are able to control for policies that target entire municipalities, such as the Blacklist, by including municipality-year fixed effects, we cannot control for policies that are implemented at the property level. The latter policies might have led to an additional decrease in deforestation that could bias our estimates if their assignment is correlated with the timing of the SoyM and satellite monitoring as well as the biome border. We therefore address these concerns below.

PPCDAm: DETER satellite monitoring and Conservation Zones (CZs)

The PPCDAm is the action plan presented in 2004 by the Brazilian government in an effort to reduce the soaring deforestation rates in the Legal Amazon (Assunção et al., 2015; Nepstad et al., 2014). The plan comprises of a set of policies, such as the DETER satellite monitoring system and the expansion of conservation zones (CZs).

Assunção et al. (2015) study the effect of the policies in the PPCDAm framework on deforestation in the Legal Amazon. Based on counterfactual simulations, they find that these policies had a significant impact on deforestation rates in the period from 2002 to 2009. However, Assunção et al. (2015) do not distinguish between the effects of the DETER satellite monitoring and the CZs in the PPCDAm framework. As such, it is difficult to isolate the effect of the command and control component (DETER) from the territorial management component (CZs) on deforestation.

Assunção, Gandour & Rocha (2013) find evidence that the command and control component of the PPCDAm (DETER) was efficient in reducing deforestation rates in the Legal Amazon. In contrast, Anderson et al. (2016) states that the CZs had no significant impact in reducing deforestation, with the exception of CZs within blacklisted municipalities. They explain that the majority of CZs are located in areas where agricultural activity (and deforestation) would be unprofitable even in the absence of these CZs. The results from these studies suggests that it is the command and control component (DETER) rather than the territorial management component that is the main driver in declining deforestation.

Nevertheless, as the PPCDAm applies to the entire Legal Amazon, it should affect the Amazon and Cerrado equally in our study. Therefore, we do not expect these policies to bias the results of our study.

CAR Environmental Property Registration

The CAR mandates all landholders to register the boundaries of their properties and outline how they will satisfy the FC requirements. Mato Grosso introduced the property registration in 2009 on a voluntary basis (Alix- Garcia et al., 2017). Since the CAR is linked to land use on the property level (Gibbs et al., 2015), we cannot account for its potential effect on deforestation in our analysis.

Alix-Garcia et al. (2017) investigate the impact of the CAR in the states Mato Grosso and Pará between 2005 and 2014. Their results suggest that in the absence of the property registration, deforestation would have been 10 percent higher in the studied area. However, they stress that other CAR-related policies, such as threats to market access (e.g. SoyM and Blacklist) had a greater impact on deforestation.

Gibbs et al. (2015) also stress that the CAR alone does not prevent deforestation. They find that almost 25 percent of Amazon deforestation in Mato Grosso occurred on registered properties, although half of these deforested areas were meant to be conserved under the FC.

We acknowledge that the CAR might have had an impact on deforestation, which could be captured by our estimates. However, as Alix-Garcia et al. (2017) and Gibbs et al. (2015) note, other policies had a larger impact on deforestation. Furthermore, since property registration was only introduced on a voluntary basis in Mato Grosso, we do not expect the CAR to affect our estimates significantly.

Cattle Moratorium

The cattle moratorium was introduced in 2009 and stipulated that the major beef processing companies in Brazil would no longer purchase beef from slaughterhouses that had deforested illegally on their properties (Gibbs et al., 2016).

As the cattle moratorium was implemented at the property level, we cannot account for its potential effect on deforestation in our analysis. However, Alix-Garcia & Gibbs (2017) find that the cattle moratorium did not have a significant impact on deforestations in areas surrounding slaughterhouses. Furthermore, Gibbs et al. (2016) state that the narrow application of the cattle moratorium limits its impact on deforestation, since it can be undermined by leakage and laundering. For example, cattle can be reared on non-compliant ranches to then be moved to compliant ranches for slaughter (Gibbs et al., 2016).

As such, we do not expect the cattle moratorium to bias our estimates significantly.

9.2.3 Overestimation of the Treatment Effect due to Exogenous Factors

In our analysis, we study the impact of the SoyM on deforestation in conjunction with satellite monitoring. However, we focus on areas that are subject to satellite monitoring at the time when the government supported the SoyM in monitoring compliance with the SoyM. As such, we merely study the monitored area, not the monitoring itself. Therefore, there might be other exogenous occurrences that affect deforestation in the areas that are subject to satellite monitoring, which could bias our estimates and be mistaken for the average treatment effect of the SoyM. There could be a myriad of factors that could have influenced deforestation in our study area over the time period.

For example, the substantial decline in deforestation that we observe between 2008 and 2009 could have been driven by the coincidental occurrence of the financial crisis in 2008, which could have affected the demand for commodities (Arima et al., 2014; Cisneros et al., 2015). However, we do not expect this to affect our results significantly due to three reasons.

First, although it is acknowledged that deforestation and commodity prices were highly correlated from 1995 to 2007 (Assunção et al., 2015; Arima et al., 2011; Macedo et al., 2012; Nepstad et al., 2014), the commodity price-effect weakened after 2007 (Arima et al., 2011; Nepstad et al., 2014). Therefore, as the satellite monitoring was introduced in 2008, we do not expect the price-effect to bias our results substantially.

Secondly, since we study municipalities where we observe one Amazon portion and one Cerrado portion in the same municipality, we do not expect the price to affect the two biomes within the same municipality differently.

Lastly, as we include municipality-year fixed effects in our regression, we take into account municipality-year specific shocks, which allows us to control for all unobserved effects that affect each municipality individually and that vary over time.

Although we cannot entirely rule out that some exogenous factor affects deforestation in the Amazon portions of the municipalities, we consider our estimates to be robust in this regard.

Having addressed potential limitation that could bias the results from our DID analysis, we perform the graphical RD analysis in the next section to study the effect of the SoyM and satellite monitoring at the biome border.

10. Graphical RD Analysis of Deforestation

To complement our DID analysis of the effect of the SoyM and satellite monitoring on deforestation in the Amazon biome, and to investigate the hypothesis of positive spillover effects, we further analyse the spatial dimension of deforestation by zooming in on 1 km² grid cells in close proximity to the border between the Amazon and Cerrado. This allows us to investigate whether the levels of deforestation change significantly on either side of the biome border following the introduction of the SoyM and satellite monitoring. Our approach is based on the methodology of a Sharp Regression Discontinuity (RD) design (Angrist & Pischke, 2015). However, as a comprehensive RD analysis is beyond the scope of this thesis, we limit our analysis to graphical investigation.

In the following subsections, we first outline our RD approach, before we present the results and relate them to the previous discussion.

10.1 Approach

In general, sharp RD designs are used to analyse natural experiments in which treatment is determined by a set of known rules and changes once an observable variable exceeds a threshold (Angrist & Pischke, 2015). In the context of the SoyM and satellite monitoring, the biome border represents the threshold and the distance of each grid cell to the biome border represents the observable variable that determines treatment. We should therefore be able to observe the treatment effect of the SoyM and satellite monitoring as a discontinuity at the biome border, given that the adjacent grid cells in the Cerrado are comparable to the adjacent grid cells in the Amazon (Lee & Lemieux, 2010).

As our approach is limited to a graphical analysis, we are not able to establish a causal relationship between any observed effects and the SoyM or satellite monitoring. Therefore, we will not elaborate on the assumptions that need to be satisfied in order to pursue a valid RD analysis in detail. However, we present arguments to support our assumption that the grid cells on the Cerrado side of the biome border are a suitable counterfactual.

As mentioned previously, we generally observe lower average levels of deforestation and remaining forest cover in the Cerrado than in the Amazon in our sample at the municipality level. Therefore, one could expect to observe a discontinuity in forest cover at the border between the two biomes. However, since biome border is a natural border and not clearly visible (Brown & Koeppe, 2012), we assume that the vegetation is similar across grid cells in close proximity to the biome border. To verify this, we plot the share of non-forest around the biome border. As displayed in figure 8, the share of non-forest decreases linearly when crossing the border from the Cerrado to the Amazon and we do not observe any discontinuity, meaning a jump or drop in these levels, at the border.

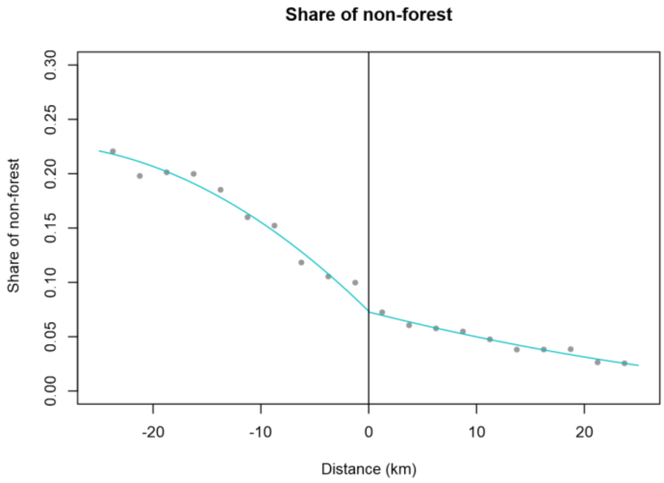

Figure 8: Share of non-forest

Cerrado on the left, Amazon on the right,
Bandwidth of 25km, 10 evenly spaced bins with size 2.5 km, lines show second-order polynomials.

Another concern with regards to spatial RD analyses is the possibility of *compound treatment* (Keele & Titiunik, 2015). In our case, grid cells could be affected by compound treatment if crossing the border from the Cerrado to the Amazon was associated with an additional treatment other than the SoyM that could affect deforestation. However, other policies aimed at reducing deforestation are either implemented at the municipal or property level, such as the blacklisting of municipalities or the cattle moratorium. Since the biome border does not follow any political or administrative borders, we assume that compound treatment is unlikely when crossing the biome border.

Since we can assume that the Amazon and Cerrado are similar in vegetation near the biome border, we would expect to observe similar levels of deforestation and remaining forest cover in both biomes in the respective pre-treatment periods of the SoyM and satellite monitoring. As the results of our DID analysis suggest that the SoyM led to a decrease in deforestation that is significantly higher in the Amazon than in the Cerrado after it was enforced with satellite monitoring, we would expect to observe a discontinuity in the level of deforestation at the biome border in the period following the introduction of satellite monitoring. However, if we do not observe a discontinuity at the biome border, this could support for our hypothesis of positive spillover effects of the SoyM.

We test this hypothesis graphically by utilising the grid data, which contains information on the distance of each cell to the biome border. To distinguish the cells that lie in the Amazon from those that lie in the Cerrado, we assign positive distance values to the Amazon cells and negative distance values to the Cerrado cells. The resulting distance variable is referred to as the running variable in RD analyses (Angrist & Pischke, 2015), which allows us to aggregate the cells to different bins of observations. For each bin, we calculate the average deforestation and remaining forest cover and plot the resulting values against the running variable. In doing so, we can observe how the levels of deforestation and remaining forest cover vary when approaching the biome border. Furthermore, we can observe whether there is a discontinuity at the border for the periods after the introduction of the SoyM and satellite monitoring. In contrast to our DID analysis in which we study deforestation over a period of eleven years, we either compare two individual years or aggregate several years to one pre and one post period in the RD analysis. To plot the graphs, we use the *rdrobust* package in R (Calonico et al., 2018).

For the RD analysis, we choose a bandwidth of 25 kilometres as the two biomes appear to be relatively similar with regards to the observed levels of deforestation, remaining forest cover as well as the number of observations within this bandwidth.

As mentioned previously, the map used to assign grid cells to the respective biomes is available only at a scale of 1:5,000,000. This might lead to some of the cells in close proximity to the border to be assigned to the wrong biome. Furthermore, the biome border might in reality cut through the grid cells, which is not reflected in the data since each cell is assigned to only one biome. We therefore choose to exclude observations that lie within one kilometre of the biome border to account for these inaccuracies.

10.2 Results

In the following, we display the graphs for our sample at the grid cell level. For all graphs, the observations are aggregated up to 10 evenly spaced bins with a size of 2.5 kilometres. The number and distribution of observations are equal for all graphs, with 30,104 observations in the Cerrado, displayed on the left-hand side, and 46,644 observations in the Amazon, displayed on the right-hand side. The lines show second-order polynomials while the blue lines relate to the pre-treatment periods and the red lines to the post-treatment periods.

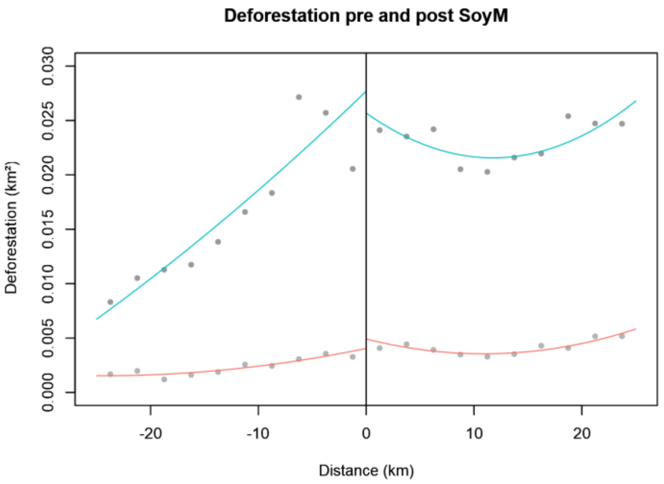

Figure 9: Deforestation pre (03-06) and post (07-13) SoyM

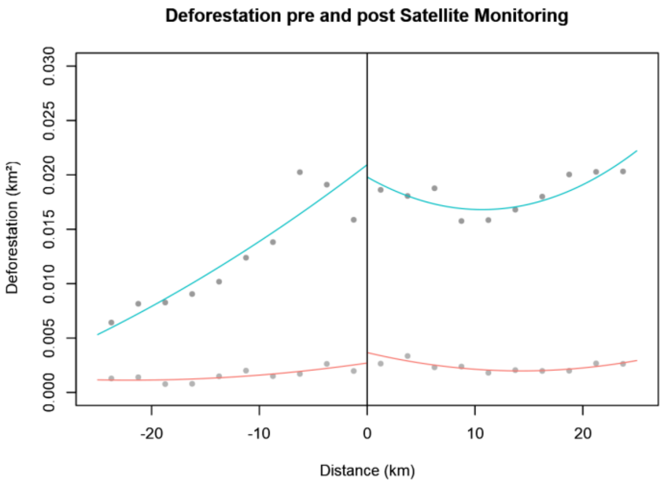

Figure 10: Deforestation pre (03-08) and post (09-13) Satellite Monitoring

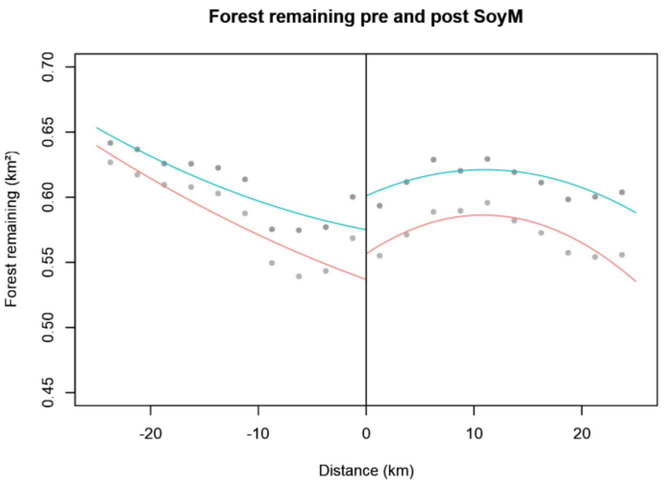

Figure 11: Forest remaining pre (03-08) and post (09-13) SoyM

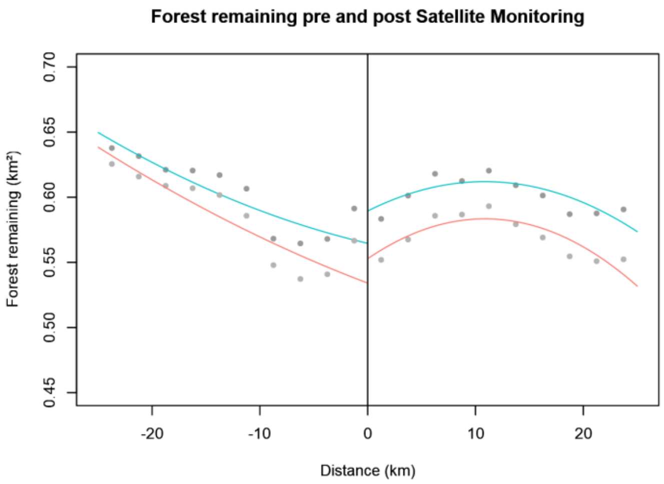

Figure 12: Forest remaining pre (03-08) and post (09-13) Satellite Monitoring

In line with our expectations, we observe higher levels of deforestation and remaining forest cover prior to the introduction of the SoyM and satellite monitoring than in the respective periods following their introduction. Furthermore, we observe that the levels of deforestation increase in the Cerrado with closer proximity to the biome border and peak at a distance of roughly five kilometres before decreasing again slightly. In contrast, deforestation in the Amazon seems to be more stable within the observed bandwidth in the same periods. Despite of the slight dip in the levels of deforestation in the Cerrado close to the biome border, we do not observe a clear discontinuity at the border in the periods prior to the introduction of the SoyM and satellite monitoring, which is also in line with our expectations.

However, we neither observe a discontinuity at the biome border in the respective periods following the introduction of the SoyM and the satellite monitoring. Instead, the levels of deforestation are very stable across the two biomes with slightly higher levels in the Amazon. While the levels of deforestation increase slightly when moving further into the Amazon after the introduction of the SoyM, this trend is no longer visible after the introduction of satellite monitoring.

With regards to remaining forest cover, we again do not observe a clear discontinuity at the biome border, neither before nor after the introduction of the SoyM and satellite monitoring. The slight dip in the levels of remaining forest cover in the Cerrado at a distance of roughly five kilometres from the border mirrors the observed peak in the levels of deforestation and does not indicate a discontinuity in remaining forest cover.

While our DID analysis suggests that the decrease in deforestation in the Amazon following the introduction the satellite monitoring is significantly higher than the decrease in the Cerrado, the graphical RD analysis indicates that this additional decrease does not occur close to the biome border. Instead, the introduction of the satellite monitoring has led to a decrease in deforestation that is similar in magnitude across the two biomes in areas close to the border. This also suggests that there has been little or no leakage of deforestation from the Amazon to the Cerrado following the introduction of the SoyM and the Monitoring within close proximity to the biome border.

To analyse further whether we observe discontinuity in the levels of deforestation immediately after in the introduction of the SoyM and satellite monitoring, we plot the graphs for the respective cut-off years, namely 2006/2007 for the SoyM and 2008/2009 for satellite monitoring.

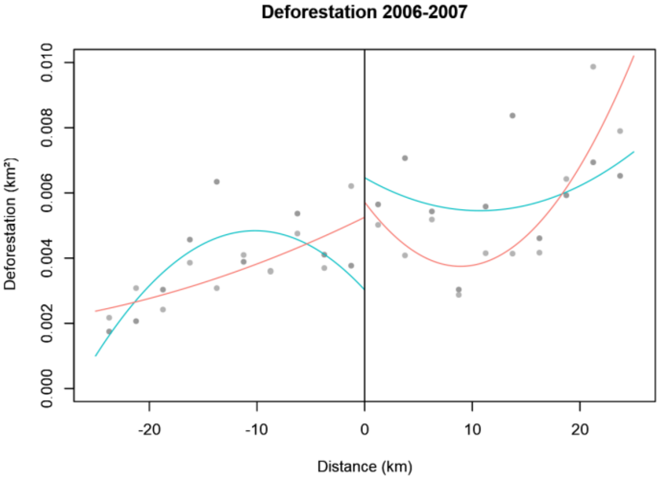

Figure 13: Deforestation pre and post SoyM

Blue lines show the pre-period, red lines show the post-period

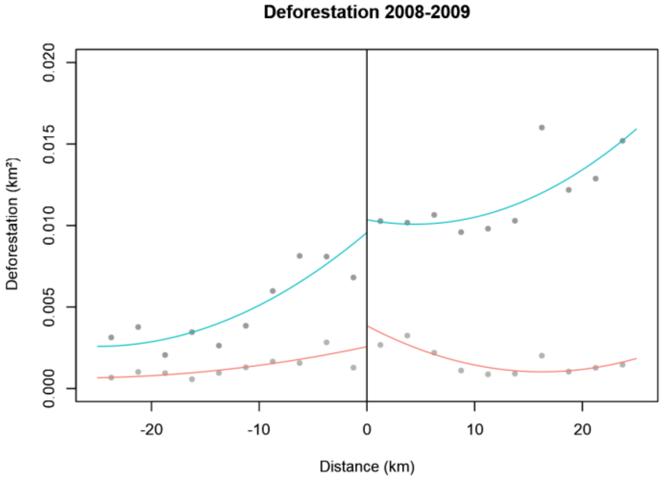

Figure 14: Deforestation pre and post Satellite Monitoring

Blue lines show the pre-period, red lines show the post-period

Since we now observe even higher levels of deforestation after the introduction of the SoyM in the Amazon at a distance of roughly 20 kilometres from the border (figure 13), this indicates that the SoyM itself did not lead to a decrease in deforestation.

Conversely, we observe lower levels of deforestation following the introduction of the satellite monitoring (figure 14). This indicates that the decrease in deforestation is more pronounced after the introduction of the satellite monitoring than after the SoyM. However, we again do not observe a clear discontinuity at the biome border after the introduction of satellite monitoring.

10.3 Discussion

The observations from the graphical RD analysis support our finding from the DID analysis that the SoyM itself had little or no effect on deforestation. However, the observations do not support our finding that the SoyM effectively reduced deforestation after it was enforced with satellite monitoring. Therefore, this raises concerns as to whether the Cerrado serves as a valid counterfactual for the Amazon to study the effectiveness of the SoyM, at least in areas close to the biome border.

Furthermore, the observations support our hypothesis that positive spillover effects could explain the lower levels of deforestation on both sides of the biome border. As discussed previously, while the SoyM should in theory only apply to the Amazon biome, it might in practice also be enforced in parts of the Cerrado, since the biome border is not clearly visible.

However, as we exclude observations within one kilometre of the biome border, this implies that the biome border is even “thicker” in reality, if positive spillover effects explain the decrease in deforestation in the Cerrado.

Despite of the evidence in favour of the hypothesis of positive spillover effects, we cannot rule out that the decrease in deforestation in both biomes could have been caused by other exogenous events, such as the blacklisting of municipalities. As discussed previously, the blacklisting of municipalities affects both the Amazon and the Cerrado biome and was coincidental with the introduction of the SoyM. While we control for the effect of the Blacklist in our DID analysis through the municipality-year fixed effects, we cannot control for this effect in the graphical RD analysis.

In conclusion, the observations from the graphical RD analysis do not support the finding from our DID analysis, that in conjunction with satellite monitoring the SoyM contributed to the observed decline in deforestation in the Amazon, since we do not observe a discontinuity in deforestation at the biome border. It remains however unclear whether this can be explained by a thick biome border and positive spillover effects of the SoyM to the Cerrado or if other exogenous events drove the observed decline in deforestation in both biomes. Further research and a thorough RD analysis could provide insights into this question.

11. Conclusion

In this paper, we analysed the effect of the SoyM and satellite monitoring on deforestation in the Brazilian Amazon. We studied municipalities in Mato Grosso that are divided by the border between the Amazon and Cerrado and performed DID regressions to establish whether there is a causal relationship between the SoyM, satellite monitoring and the observed decline in deforestation in the Amazon between 2006 and 2013. Our findings suggest that the SoyM itself did not have a significant impact on deforestation before it was enforced with satellite monitoring from 2008. In the following years, deforestation in the Amazon decreased by an additional 24.6 percent compared to the Cerrado which avoided about 430 km² of deforestation in our study area and saved 4.8 million tons of carbon from being released. Although we observed a higher decrease in deforestation in the Amazon, the Cerrado also experienced a substantial decrease after the introduction of satellite monitoring. This could suggest that the SoyM had positive spillover effects on the Cerrado or that other factors than the SoyM were the main driver of the observed decrease in deforestation. We further investigated this by performing a graphical RD analysis but did not observe a discontinuity in deforestation at the biome border after the introduction of the SoyM and satellite monitoring. This does not support the results from the DID analysis and instead suggests that the SoyM and satellite monitoring did not have a significant impact on deforestation in the area close to the biome border. Further research could help to clarify whether this is due to positive spillover effects of the SoyM or other factors that affected deforestation during the observed period.

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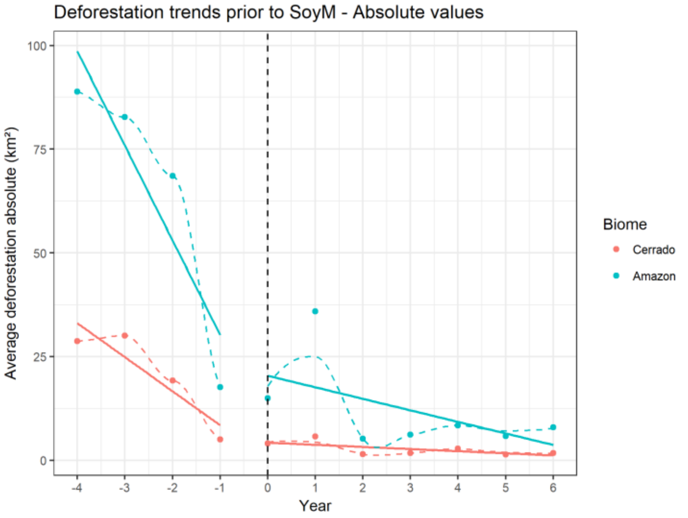
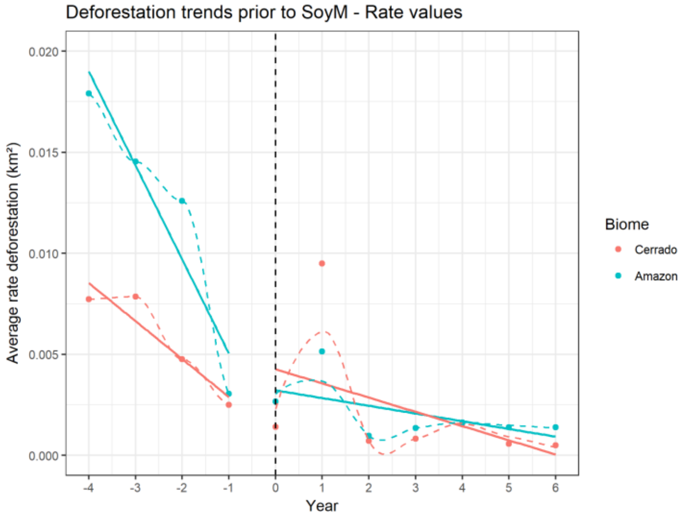
Appendix

A1: List of Variables

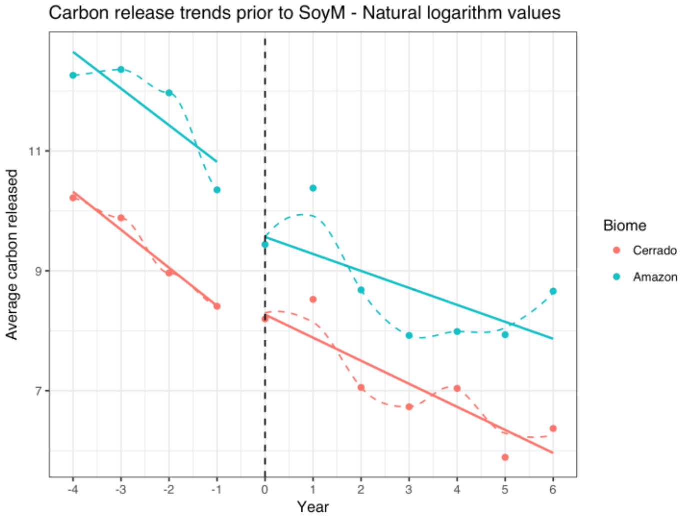
Municipality dataset				
Abbreviation	**Description**	**Unit**	**Time variant**	**Source**
year	Period for which the deforestation data is recorded (September in year t-1 to August in year t)	-	Yes	-
code	IBGE municipality code	-	No	-
biome	Dummy that indicates whether a biome portion of a municipality lies in the Amazon (1) or the Cerrado (0) biome	-	No	Calculated based on IBGE biome map
code_biome	Dummy for biome portion individual fixed effects (obtained by merging the code and biome variables)	-	No	-
code_year	Dummy for municipality year fixed effects (obtained by merging the code and year variables)	-	No	-
soym	Dummy that indicates the treatment period of the Soy Moratorium (1 for the years 2007-2013)	-	Yes	-
monitoring	Dummy that indicates the treatment period of the satellite monitoring (1 for the years 2009-2013)	-	Yes	-
municipality	Name of the municipality	-	No	Anderson et al. (2016)
state	Name of the state that the municipality belongs to	-	No	Anderson et al. (2016)
sum_df	Sum of the deforestation in a respective biome portion in a given year (obtained by calculating the sum of the deforestation of all grid cells in a biome portion)	Km^2	Yes	Anderson et al. (2016)
sum_fr	Sum of the remaining forest cover in a respective biome portion at the end of a given year (obtained by calculating the sum of the deforestation of all grid cells in a biome portion)	Km^2	Yes	Anderson et al. (2016)
rate_df	Mean of the deforestation in a respective biome portion in a given year (obtained by calculating the mean of the deforestation of all grid cells in the respective biome portion)	Km^2	Yes	Anderson et al. (2016)
rate_fr	Mean of the remaining forest cover in a respective biome portion at the end of a given year (obtained by calcualating the mean of the deforestation of all grid cells in the respective biome portion)	Km^2	Yes	Anderson et al. (2016)
sum_carbon	Sum of the carbon stored in the respective biome portion at the end of a given year	Mg	Yes	Baccini et al. (2015)
sum_carbon_release	Sum of the carbon released in a respective biome portion in a respective year	Mg	Yes	Baccini et al. (2015)
non_forest	Share of a respective biome portion that is not covered by forest	Km^2	No	Anderson et al. (2016)
grid_km2	Area of a respective biome portion (obtained by calculating the sum of grid cells in a respective biome portion)	Km^2	No	Anderson et al. (2016)
Grid dataset				
OID	Unique code of a grid cell	-	No	-
dist_biome_border	Distance of a cell to the border between the Amazon and Cerrado biomes	Km	No	Calculated based on IBGE biome map

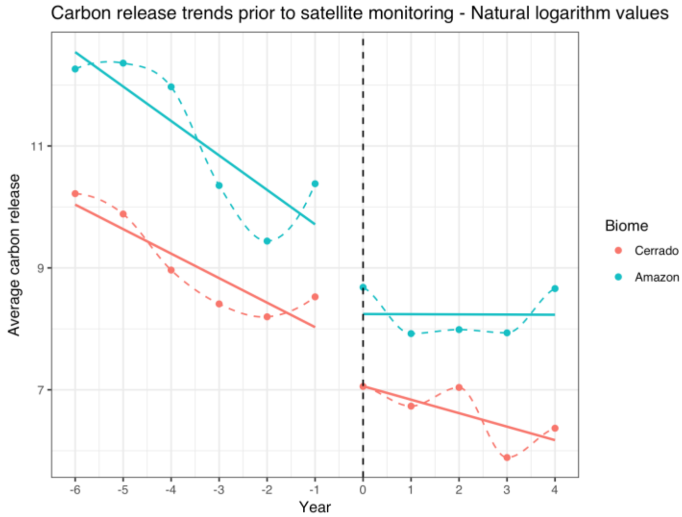
A2-A3: Pre-trends – Deforestation in Absolute Values and Rates





A4: Pre-trends - Carbon Released



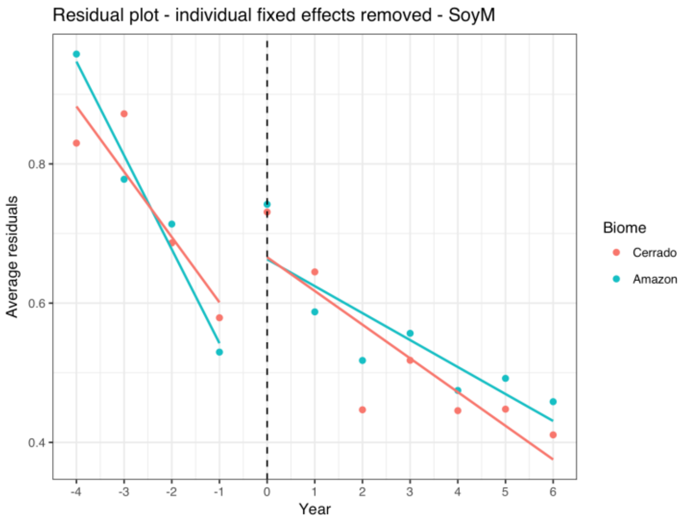


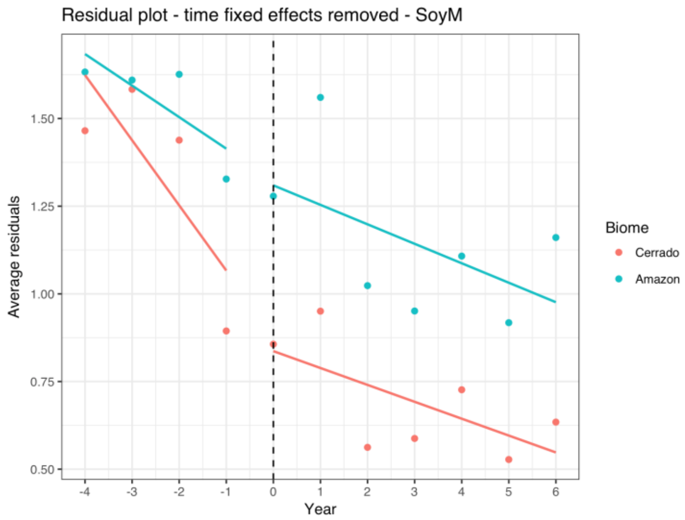
A5-A6: Pre-trends – Residual Plots

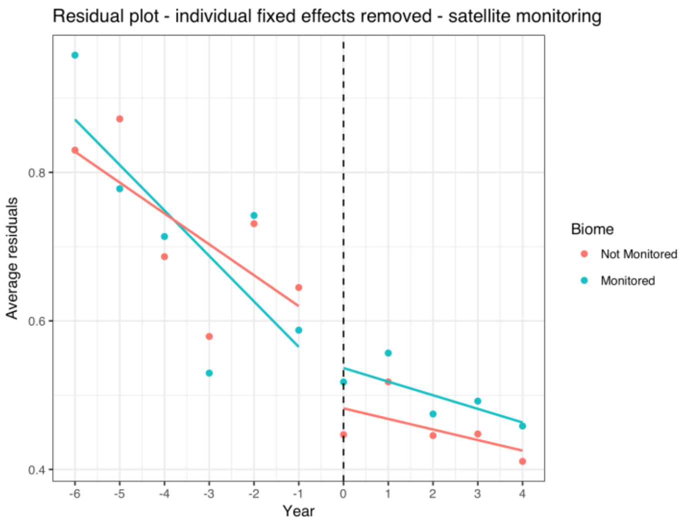
An alternative approach to plotting the observed values is to plot the average residuals of the fixed effects regression after the individual and time fixed effects have been removed. The equation below presents our basic fixed effects model for the SoyM without the interaction term. The $biome_i * post\ soym_t$ equation for the Monitoring follows the same structure but includes the post monitoring dummy instead.

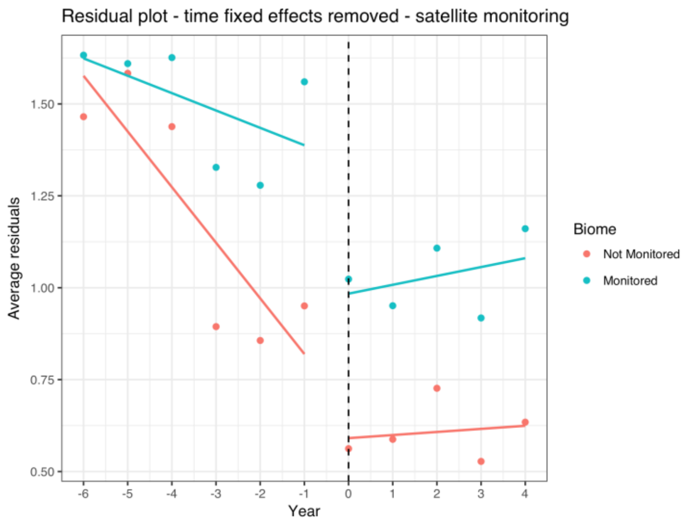
$$\ln(DF_{it}) = \alpha + \beta_1 biome_i + \beta_2 soym + I_i + I_t + \varepsilon_{it}$$

By plotting the average residuals in absolute terms of the over the years for each biome, we obtain the variation that is explained by our interaction term. If the trends of the residuals prior to the SoyM (Monitoring) are parallel, the common trends assumption holds. However, this is not the case for our sample, as displayed below.









A7: Year-By-Year Estimates – Regression Output

Year by year estimates - 2006 as base year

	Dependent variable:
	Ln deforestation
biome*03	0.316
	(0.225)
biome*04	0.205
	(0.234)
biome*05	0.333*
	(0.195)
biome*07	-0.017
	(0.139)
biome*08	0.236
	(0.165)
biome*09	-0.221
	(0.167)
biome*10	-0.271
	(0.190)
biome*11	-0.180
	(0.173)
biome*12	-0.057
	(0.175)
biome*13	-0.111
	(0.174)
Observations	858
R^2	0.027
F Statistic	2.145** (df = 10; 760)
Note:	*p<0.1; **p<0.05; ***p<0.01

Year by year estimates - 2008 as base year

	Dependent variable:
	Ln deforestation
biome*03	0.080
	(0.224)
biome*04	-0.031
	(0.245)
biome*05	0.097
	(0.197)
biome*06	-0.236
	(0.165)
biome*07	-0.253
	(0.174)
biome*09	-0.457**
	(0.197)
biome*10	-0.507**
	(0.204)
biome*11	-0.416**
	(0.184)
biome*12	-0.293
	(0.196)
biome*13	-0.347*
	(0.178)
Observations	858
R^2	0.027
F Statistic	2.145** (df = 10; 760)
Note:	*p<0.1; **p<0.05; ***p<0.01