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Do forest conservation policies undermine the soybean sector in the Brazilian Amazon? Evidence from the blacklisting of municipalities

Léa Crepin [†] [‡]

Abstract

Minimizing the trade-offs between agricultural production, development and forest conservation is key to ensure that conservation policies can achieve long-term impacts. Taking the case of the Brazilian Amazon in the context of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, we estimate the impact of the blacklisting of municipalities with high deforestation risk on soybean production (a major driver of deforestation), exports and land-use changes. Difference-in-difference regressions and generalised synthetic control method are first used to determine the impacts of the policy. The triple difference strategy is then applied to explore heterogeneity in the production and export changes across municipalities. We find that, although effective to reduce deforestation, the policy is unlikely to have undermined the soybean production and exports. On the contrary, our results suggest that the soybean sector benefited from the changes in land use following the implementation of the blacklist. However, we do not find evidence that land restriction triggered intensification of soybean production, which

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suggests that the soybean sector benefited from intra-crops reallocation.

Key words: PPCDAm; priority list; deforestation;conservation policy; soybean; intensification

1. Introduction

There is a burning need to tackle deforestation since it has large scale impacts on biodiversity losses, climate change and other environmental issues (Lawrence and Vandecar, 2015), with cascading negative effects on human societies. On the other hand, some fear that forest conservation policies could hinder economic development in food producing countries that have heavily based their development strategy on land use. Indeed, because forest loss remains the first driver of global deforestation by far (Pendrill et al., 2019), curbing deforestation also means slowing down agricultural expansion. Identifying the short-term and long-term economic and land use adjustments that follow the implementation of forest conservation policies is crucial for shaping efficient programs that are fair and which do not jeopardise the social and economic development goals.

In the paper, we estimate the impact of conservation programs on the soybean sector focusing on a key conservation measure in Brazil, the priority list of the Action Plan for the Prevention and Control in the Legal Amazon (PPCDAm is the acronym in Portuguese). The priority list, or blacklist, defines a list of the most vulnerable municipalities to deforestation in the Brazilian Legal Amazon to target the prevention and control of deforestation. The measures towards them include enhanced environmental surveillance, severely restricted access to deforestation permits, credits and markets and embargo of illegally cleared areas (Fearnside, 2017). Because the PPCDAm priority list was proven to be an important driver of the slowdown of deforestation in the Amazon (Arima et al., 2014; Assunção et al., 2015; Assunção and Rocha, 2019; Cisneros et al., 2015; Koch et al., 2019), impacts on the decisions of the actors of agriculture as the constraints on the land are modified can be expected.

The PPCDAm has received considerable attention in the recent years. In particular, the priority list is one of the major conservation policies in Brazil and an efficient measure to reduce deforestation (Arima et al., 2014; Assunção et al., 2015; Assunção and Rocha, 2019; Cisneros et al., 2015; Koch et al., 2019), and effective in reducing deforestation due to commodity prices

(Harding et al., 2021). On the consequences of the plan, Koch et al. (2019) examines the collateral effects of the priority list on agricultural productivity, demonstrating that the blacklisted municipalities were paired with increases in cattle production and productivity. They do not find any consistent effect on dairy or crop production. Moffette et al. (2021) also shows that the priority list incites agricultural actors to intensify their cattle production, especially in municipalities with a high proportion of large ranches, however no changes in investments are observed. le Polain de Waroux et al. (2019) is another study which focuses on the impacts of conservation policies on agriculture in South America. They find no evidence of a change in soy or pasture patterns due to changes in regulations, except within the Amazon biome where pasture expansion slowed down and pastures intensified. This paper, more than trying to assess whether there is an intensification in agricultural production, tries to point out whether there is a switch towards more intensive agricultural activities.

le Polain de Waroux et al. (2019) shed light on international trade, another important matter when dealing with land-use change. The case of soybean is particularly relevant, as 70% of the commodity is exported worldwide. Indeed, studies suggest that as openness to trade increases, deforestation also increases in the Amazon (Faria and Almeida, 2016). Our work relates to this literature on trade and the environment through the effects of conservation policies on exports.

The contribution of the paper is to look beyond the direct effect of the policy on forests, to detect what are the indirect effects on the agricultural sector, and in particular on the soybean sector and its exports. To test the relationship between conservation policies, agricultural production and the international trade of soybean, we use national surveys and the TRASE database (Trase (2020)), which trace back the flows of soybean between Brazil and the other nations. We estimate the impact of the blacklist on deforestation, production and exports with two econometric methods. We first adopt classical difference-in-difference strategy with controls and with multiple time periods. Second, we use the generalised synthetic control method to improve the quality of the counterfactual and back up our conclusions. We then explore the heterogeneities of the impacts of the priority list with the help of triple-differences. More specifically, we test whether the agro-climatic conditions, the presence of a developed supply chain and the trade network configuration explain divergent responses of the blacklisted municipalities.

Our findings show that, while the Legal Amazon blacklist was responsible for a decline in the deforestation rates, the slowdown of deforestation was not triggered by a reduction of land use for soybean. On the contrary, the results of the regressions show that the production, the area and the exports of soybean increased with the implementation of the blacklist. This leads us to think that there was a reallocation of agricultural land uses in favour of soybean. Some agricultural activities may have switched to more capital-intensive productions like soybean. This specialisation is corroborated by further results as we notice a shrinkage of some staple food production areas. The largest increase of soybean is observed in the states of Rondônia and Pará, but we do not find evidence of heterogeneous responses of the municipalities with the tested variables. Based on the literature, we find some possible explanations for the positive effects of the blacklisting on the soybean sector. The costs of compliance to the environmental regulation and the scarcity of the land may have motivated farmers to switch from an expansion strategy to an intensification strategy towards more profitable and capital-intensive crops. A crowding out effect of smaller landowners, selling their lands to richer soybean farmers would be plausible as the environmental governance produced economic difficulties for them. The strategy of land management rolled out at the municipality as a response to being blacklisted may also have triggered land use adjustments.

The rest of the paper is organized as follows. Section 2 gives elements of context of the links between deforestation and soybean, in addition to a short presentation of the conservation policies under consideration. Section 3 details the data and empirical methodology. Section 4 presents the land-use changes consecutive to the plan and section 5 details the underlying mechanisms.

Robustness tests can be found in the appendix.

2. Background

2.1 *The priority list of the PPCDAm*

As a response to the skyrocketting rates of deforestation in the early 2000s in the Amazon rainforest, the Brazilian government launched an integrated and coordinated conservation plan called the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (Plano de Prevenção e Controle do Desmatamento na Amazônia Legal, PPCDAm). It covers the Legal Amazon, formed by the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and by the municipalities of the state of Maranhão located west of the 44th meridian, and contains the entire Brazilian Amazon biome and a part of the Cerrado biome. The plan deals simultaneously with monitoring, environmental control and territorial management. It has been through four phases (PPCDAm-I (2004-2008), II (2009-2011), III (2012-2015), and IV (2016-2020)), evolving to address the new patterns of deforestation. The implementation of the plan was followed by a substantial decline of deforestation in the Amazon until 2012, when the rates of deforestation surged again (West and Fearnside, 2021).

We focus here on one of the most emblematic measure of the PPCDAm, the priority list, which aimed at focusing the efforts to mitigate deforestation on the most vulnerable municipalities. The Decree 3621 issued in December 2007 defined 36 priority municipalities, representing 46% of the Amazonian deforestation. They were subject to more intense environmental surveillance and law enforcement, with the Brazilian Environmental Protection Agency having more resources assigned to these locations. More fines were issued and illegaly cleared areas were put on embargo. A series of administrative measures also imposed an additional cost. Licensing and geo-referencing requirements were harsher in the blacklisted municipalities and private land titles were revised, with the objective of gathering data to monitor and prevent the occurrence of new illegal deforestation. Credit from official agencies was prohibited for agricultural and forestry activities related to forests burning and illegal deforestation. This applied also to all services, commercial or industrial activities that acquire, transport or sell product or by-product produced in an embargoed area (Bizzo and de Farias, 2017; Assunção and Rocha, 2019). Additionally, the Arco Verde operation, as part of the PPCDAm, promoted sustainable land-based production models, particularly in the blacklisted municipalities (West and Fearnside, 2021).

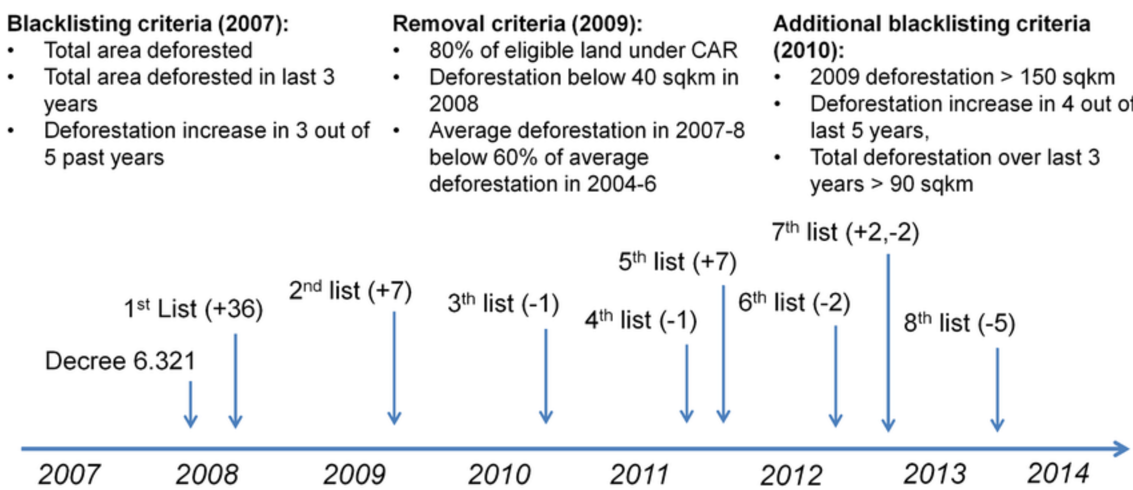


Fig. 1: Evolution of the priority list. Source: Cisneros et al. (2015)

The municipalities were chosen according to criteria mirroring the history of their deforestation ((i) cumulative area of forest loss, (ii) area of forest loss in the last three years, and (iii) increases in deforestation in at least three of the last five years) (Fearnside, 2017). A strict threshold selection rule is followed in practice to select the municipalities, which suggests that the interference of local political influence on the list is unlikely (Assunção and Rocha, 2019). Under the proof of a significant decline of deforestation, the municipalities can exit the list.

The policy is overlapped by other forest protection mechanisms, notably supply chains interventions. They include among others the Amazon Soy Moratorium starting in 2006, which is an agreement by grain traders not to purchase soy grown on recently deforested land (Heilmayr et al., 2020), and the G4 Cattle Agreement, which began in 2010 and excludes suppliers with post-2010 deforestation from selling to signatory slaughterhouses (Moffette et al., 2021). The Amazon Soy Moratorium proved to be complementary with the CAR (”rural environmental registry” or Cadastro Ambiental Rural, legally binding document to clarify land tenures) (Heilmayr et al., 2020) while there is no evidence that the G4 Cattle Agreement was complementary or substitute to the priority list (Moffette et al., 2021).

2.2 *The ties between soybean production and deforestation in the Brazilian Amazon*

From the second half of the twentieth century, soybean has experienced an exceptional and relentless growth of its production, which is a result of both improvements of yields and the expansion of the harvested area. This reflects the ever-growing consumption of this crop around the world which is still expected to rise with the appetite for livestock. Soy is sometimes identified as a ”flexible crop” or a ”cash crop” because of its large range of uses. The crop is used for direct food consumption, biodiesel production and industrial processing but the largest share of soy use is in animal feed, both worldwide and locally (71% of the domestic consumption in Brazil) (De Maria et al., 2020). Brazil recently took first world rank as a producer and exporter of soybean.

Besides the increased agricultural export revenues, this expansion has been linked with deforestation in the Amazon and in the Cerrado, which questions the sustainability of the soybean supply chain. The most rapid expansion of soybean between 2000 and 2019 occurred in the Brazilian Amazon, where soybean area increased more than tenfold, from 0.4 Mha to 4.6 Mha (approximately equivalent to the area of Denmark) (Song et al., 2021). This expansion of mechanized agriculture altered deforestation dynamics, directly by increasing conversion of forests for soy cultivation and indirectly by replacing existing cattle pasture, some of which moved into other forested regions (Arima et al., 2011). In response, initiatives to improve the sustainability of the soybean supply chains multiplied, and combined with public policy interventions, they triggered a decoupling of soybean expansion and deforestation after 2008 in the Southern Amazon (Macedo et al., 2012).

2.3 *Characteristics of the soybean production in the Legal Amazon*

Soybean is a large-scale mechanized industry which requires high investments, for low on-farm employment in comparison to ranching or other crops (Garrett and Rausch, 2016). Not only are the high levels of inputs (in fertilizers, pesticides, machinery) expensive, but soybean also needs a large number of supporting services (input provision, financing, marketing, distribution and processing). Investing in planting can be risky without long-term investments and secure lands. The expansion of soybean is capital-constrained and is largely driven by capital surpluses during high price years (Richards and Arima, 2018). The other sources of capital are the credits provided by national and international banks or by multinationals, like Cargill or Bunge, providing credits in the form of seed, fertilizer and chemicals in return for the soy harvested (Gollnow and Lakes, 2014; Garrett and Rausch, 2016).

While the soy industry contributes undeniably to growth in national export revenues, and enhances rural incomes and services, the consequence of its expansion is also a decline in rural equity (Gollnow and Lakes, 2014; Garrett and Rausch, 2016). Only farmers with very high levels of savings or leverage for obtaining a loan can afford to engage in soy production. In practice, the large soy landowners are often new South migrants with larger financial resources. Their establishment was in some cases associated with the displacement for smallholders, selling their lands to look for new opportunities in urban areas, or forced departures of vulnerable population (traditional and indigenous landholders) where land tenure are not secure (Schilling-Vacaflor et al., 2020).

2.4 *Assessing the impact of the priority list on the soybean sector*

The previous sections described how the priority list could have disrupted the dynamics of the involved municipalities. We also discussed how the forest dynamics, the soybean expansion, and the socio-economic and political context are intertwined in the Amazon. The next sections present an assessment of the impacts of the plan on the soybean sector. The first step is to replicate the results of the literature which found an impact of the blacklist on deforestation. Once the empirical strategy is validated, we determine how the plan impacted the diverse crops and their allocations. We finally question the heterogeneous responses of the municipalities.

3. Data and empirical strategy

We first describe our main sources of data in 3.1 and we then introduce our methodology in 3.2.

3.1 *Data*

The basis of the analysis is a panel of Brazilian municipalities from 2002 to 2012, gathering data about agriculture, forestry and trade detailed below.

3.1.1 *Main variables*

To measure the changes in the agricultural sector following the implementation of the priority list, we draw primarily on the standard database of the Brazilian Institute of Geography and Statistics (IBGE). The IBGE offers data series enumerating yearly agricultural production, yields and cultivated areas by crops and livestock production in the Brazilian municipalities.

To analyze the changes in the productivity of cattle production and deepen the understanding of the land-use changes, we also exploit the MapBiomas database.[1] Compared to TerraClass, in

[1] The Brazilian Annual Land Use and Land Cover Mapping Project is an initiative relying on Google Earth Engine platform and its loud processing and automated classifiers capabilities. Though, its fully automated methodology results in some inconsistencies (Neves et al., 2020) but this data source is still better suited than TerraClass for a fine analysis of land-use transitions.

which we can find areas for LULCC only for a few years (2004, 2008, 2014), MapBiomas has the advantages of providing yearly areas on land cover and land uses as well as the land-use and land-cover transitions. The stocking rate is calculated by dividing the number of cattle heads (from IBGE) with the pasture areas by municipalities (from MapBiomas)[2]. The pasture area for the calculation is defined only by the land class ”pasture” and does not include the land class “mosaic of pasture and agriculture” because it was not possible to disentangle cropland from pasture land in that class. The intensity of the livestock may therefore be underestimated and its trend inaccurate.

We complement the IBGE series with trade data using the most recent Brazil-soybean dataset of the TRASE database (Trase, 2020).[3] Annual data of production, exports and associated risks at the sub-national level is linked to individual companies that export, ship and import a traded commodity. From these sources, we rebuild the yearly volumes and values of exports for each municipality[4].

The newly deforestated area comes from the INPE, based on the PRODES project, which carries out satellite monitoring of clear-cut deforestation in the Legal Amazon.

3.1.2 *Other data*

Table A1 synthetizes the sources and definitions of the other variables of the study, used as controls in our regressions. We rely extensively on the data provided by Koch et al. (2019). Their choice reflects the changes in land management (protected areas, indigenous territories, settlements) and in local economic conditions (local prices of timber and soybean, GDP).

[2]Its correlation is low with the stocking rates provided by Cisneros et al. (2015) and Koch et al. (2019), but these authors already had very low correlation between their data. These differences can be attributed to the difficulty of classifying land cover as pastures and the choice of the kind of pastures to calculate the stocking rates.

[3]TRASE is a research project aiming at increasing transparency of the supply chains of some commodities by revealing environmental and social risks in tropical forest regions. Its core principle is to track the supply chains at the subnational level with a Spatially Explicit Information on Production to Consumption Systems (SEI-PCD) model.

[4]In TRASE, the exports include soybeans, cake oil and soy sauce, but they do not include more processed products such as animal feed or biodiesel (because they involve other raw product and the tracking of the supply chain would involve many other actors, which is hard to retrace). Also, 14.5% were not attributed to a municipality successfully.

To explore the heterogeneities and mechanisms, we test for the influence of other variables also listed in Table A1. We use the Suitability index range for soybean from GAEZ[5] to account for the agro-climatic conditions. As a second indicator, we use a proxy of the climatic conditions by multiplying the 2006 mean annual temperature, averaged by municipality by the 2006 mean annual precipitation, averaged by municipality.

Other variables were generated to account for the connection to infrastructures to reflect the presence of an agribusiness cluster. We also compute the mean cost of transport towards the nearest soy export port.

The state of the connection to markets is depicted with a dummy for the most exporting municipalities and an Herfindahl-Hirschmann index to our variables to measure the market concentration of soybean traders at the municipality or state level.

3.1.3 *Estimation sample*

The sample contains municipalities located in the Brazilian Legal Amazon. The period under study goes from 2004 to 2012. We choose this time window in order to keep enough years before and after the implementation of the blacklist in 2008.

We follow some exclusion rules to end with a sample better suited for the evaluation of the interaction between forest conservation policies and soybean expansion. First, following the criterion of Cisneros et al. (2015) and Koch et al. (2019), municipalities with less than 10% of forest cover remaining in 2002 (114 municipalities, none of them being blacklisted) are excluded. This leaves us with some municipalities located mainly at the frontier of the Amazon biome as illustrates Figure 2. Then, we exclude municipalities that do not produce soybean at least once in our time frame. The total "treated group" is at that stage composed of 28 municipalities

[5]The Global Agro-Ecological Zoning, developed by the Food and Agriculture Organization of the United Nations (FAO) in collaboration with the International Institute for Applied Systems Analysis (IIASA), provides a standardized framework for the characterization of climate, soil and terrain conditions relevant to agricultural production. It identifies crop-specific limitations of climate, soil and terrain resources in a consistent and empirically founded way.

blacklisted in 2008, 5 in 2009 and 5 in 2011. For the main specification, we keep only the 2008 treated group (by far the largest group) and exclude of the control group the municipalities treated later so that they do not serve as comparison for the 2008-blacklisted municipalities in the regressions. The main final sample contains 161 municipalities in the Legal Amazon, among which 28 municipalities blacklisted in 2008. In the following sections, "treated municipalities" will refer to the municipalities onto the priority list, and "control municipalities" will refer to the municipalities of the rest of the sample under consideration.

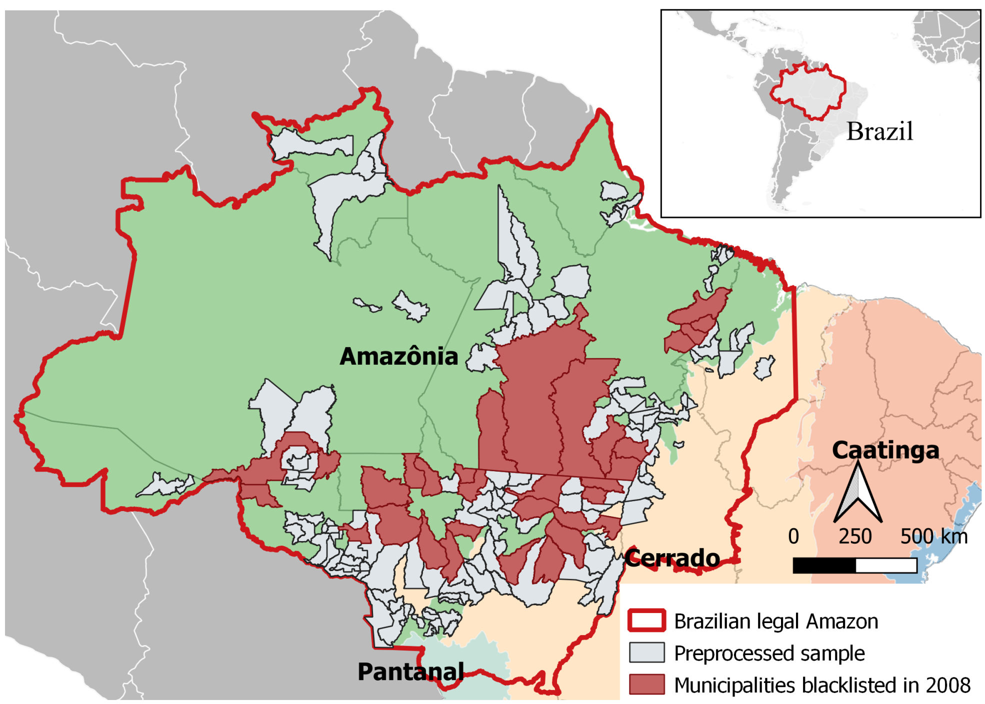


Fig. 2: Processed sample. Priority municipalities in red and control municipalities in grey.

3.1.4 *Comparison of the treated versus control municipalities*

Table 1 summarises the statistics of some main land uses, agricultural and economic variables in 2007, right before the implementation of the blacklist. The main point on which they differ are their size. The treated municipalities are considerably larger than the control municipalities.

They also had more remaining vegetation before the implementation of the policy, but their rates of deforestation were substantially higher, in line with the selection criteria of the priority list. The treated municipalities tend to have a smaller agricultural area, both for soybean, other crops and pasture relatively to their total area than the control municipalities. The pastures are less intensive. There are no striking differences in the implementation of environmental policies (considering protected areas), GDP, or suitability for soybean cultivation. The priority municipalities are more integrated in the international soybean sector and display a more concentrated soybean market.

While the levels of deforestation are different, the trends of deforestation of the two groups before the treatment show some similarities as illustrates Figure 3. Both groups have experienced a decline in deforestation rates in 2004, consecutive to the implementation of the first phase of the PPCDAm in the Legal Amazon. In the regressions, we transform the increments of deforestation with an Inverse Hyperbolic Sine function (IHS). The evolution of the IHS-transformed variable (Figure 4) shows even more similar trends between the two groups. After 2008, the deforestation rates decline again, with a more pronounced pattern in the priority municipalities. We do not detect any anticipation effect before 2008. Figure 3 also shows in parallel the changes of variations of areas of soybean and pasture. Before 2008, the increase in pasture follows the decrease in the deforestation rates for both groups, suggesting that slowing down deforestation also slowed down the pasture expansion. After 2008, the treated group even shows a net decrease of the pasture area. The variation in soybean area also follows the deforestation rates with a decrease of the rates between 2005 and 2007. Nevertheless, the soybean expansion seems to speed up again in 2008, with a steeper increase for the treated group.

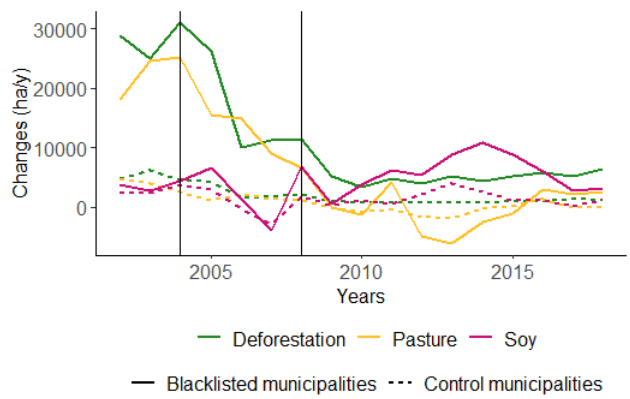


Fig. 3: Time series of the variations of areas of deforestation, pasture and soybean

The solid lines is the group of the priority municipalities and the dotted lines is the control group.

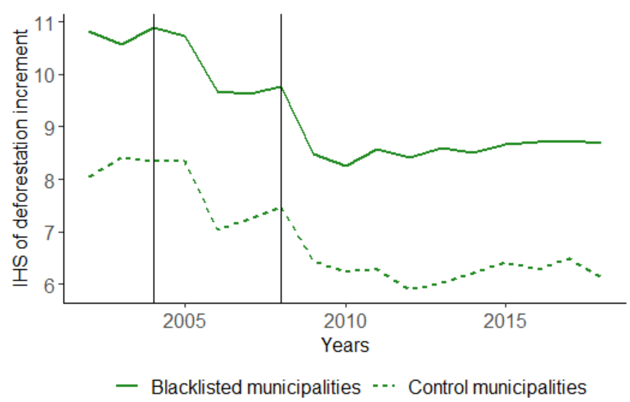


Fig. 4: Time series of the deforestation rates, with the inverse hyperbolic sine transformation

The solid lines is the group of the priority municipalities and the dotted lines is the control group.

3.2 *Empirical strategy*

Main difference-in-difference

The goal of the identification strategy is to estimate the effects of the priority list on deforestation, agricultural production and agricultural exports. We rely on a difference-in-difference strategy to leverage our quasi-natural experimental design where only a few municipalities are "treated" by the environmental measures. Indeed, the aim of the paper is to analyse whether there is a causal effect from the environmental measures on the agricultural sector, and the difference-in-difference is one of the most practical way to identify causal effects.[6] [7].

We estimate how the blacklist affects the production and exports of soybean using the following general specification (3.1). We look at different outcomes Y_{it} that characterise the sector (e.g. land use, production, production exported) and deforestation.

$$Y_{it} = \gamma + \tau_{DiD}(MP_i.Post_t) + \gamma_i + \delta_t + \sum_k \gamma_k X_{it} + \epsilon_{it} \tag{3.1}$$

In Equation (3.1), Y_{it} is the outcome variable for municipality i and year t. MP_i is the dummy variable taking 1 if i belongs to the treated group. $Post_t$ is the dummy variable taking 1 if year t is after the year of treatment. The policy effect is estimated by obtaining the coefficient τ_{DiD}.

We control the bias from the fixed unobservable variables correlated with the policy and the outcome variables (mining, vegetation type, slope, altitude, roads, economic shock affecting the entire region, etc) by adding municipality fixed effects and year fixed effects in all the specifications (γ_i and δ_t). The other issue that may arise from the difference-in-difference approach is the existence of time varying variables correlated to our outcome variables and with blacklisting. We use covariates related to land management, agricultural and socio-economic characteristics detailed in Table A1 based on the previous literature of the priority list to control this bias. They are represented by the vector of covariates X_{it} in equation (3.1). Though not reported here, the results are robust to various combinations of covariates.

The main hypothesis to use the difference-in-difference method is to make sure that there are no unobservable variables that would influence changes in the outcome variables and the

[6] Regression discontinuity design would have been another approach, but there are too few observations close to the threshold frontier. Moreover, the regression discontinuity would estimate the average treatment effects at the cutoff frontier which is not the parameter we are interested in.

[7] The propensity-score matching approach is not retained because the resulting matched units were not convincing (very different propensity score of the matched and treated sample, lack of robustness to the different type of matching). This may be due to the fundamentally different characteristics of our treated and control units.

probability to be blacklisted. To support this hypothesis, we show that the trends of most of the outcome variables for the treated and control groups on the pre-treatment period are parallel (Figure 4 and Figure 6).

Heterogenous effects of the policy between the municipalities

After demonstrating the effects of the priority list, we seek to demonstrate heterogeneous effects of the policy across municipalities. To do so, we use a triple difference model with two periods[8]. Like in the first-stage estimation, we keep only the largest treated group, the blacklist from 2008. This allow us to quantify heterogeneity in the impacts of the priority list to help identify mechanisms that could explain the different responses to the program.

The triple difference estimator can be computed as the difference between two difference-in-differences estimators. Though, the triple difference estimator does not require two parallel trend assumptions, but only one: the relative outcome of the two groups in the treated state must trend in the same way as the relative outcome of the two groups in absence of treatment.

The specification is the following:

$$\begin{aligned} Y_{it} = \gamma + \tau_{DiD}(MP_i.POST_t) + \beta_1(MP_i.d_i) + \beta_2(POST_t.d_i) + \tau_{TD}(MP_i.POST_t.d_i) \\ + \gamma_i + \delta_t + \sum_k \gamma_k X_{it} + \epsilon_{it} \end{aligned} \tag{3.2}$$

Where d_i is a dummy defining the group. The parameter of interest is τ_{TD}, which isolates the deviation in deforestation rates (or soybean production, exports, or land use) that occurs on the blacklisted municipalities presenting the characteristic d.

This can be interpreted as the average treatment effect of the PPCDAm on municipalities with d.

[8] To our knowledge, the triple difference is not yet adapted to a setup with multiple time periods

4. Impacts of the priority list on the soybean sector

In this section, we present our main empirical results for the Legal Amazon and investigate their robustness.

4.1 *Impact of the policy on the deforestation dynamics*

As an initial check on our data and empirical approach, we test the effect of the priority list on deforestation which has already been demonstrated in several studies. Some specificities of our approach could explain different results. First, our sample is generally more restricted than what was published before as the focus is here on the municipalities that produced soybean. Second, we transform the variables with high values with an IHS function, in order to avoid problems with log transforming null values.

The first column of Table 2 shows the results of the regression. Consistent with the literature, we find that the plan triggered a decrease of 41% of deforestation rates with a simple difference-in-difference with controls. This result is in line with the estimates in Assunção and Rocha (2019) who finds -44.7% of reduction of deforestation for the period 2008-2011, with Assunção et al. (2015) who estimated a reduction between -39.7% and -37.6% for 2008-2012, and Koch et al. (2019) who finds a reduction between -49.9 and -55.8% from 2008 to 2014.

4.2 *Effects on the main complementary land uses*

The previous results show a change in the dynamics of deforestation in the priority municipalities. The story is incomplete without inquiring the complementary land uses. We explore in this section the changes of areas in agriculture, by far the most land consuming activity, focusing on the impacts in the soybean sector specifically.

Table 2 assesses the effects on the pasture, the crops and soybean. The regressions are performed on the areas transformed with IHS. The third column is the regression results for the total

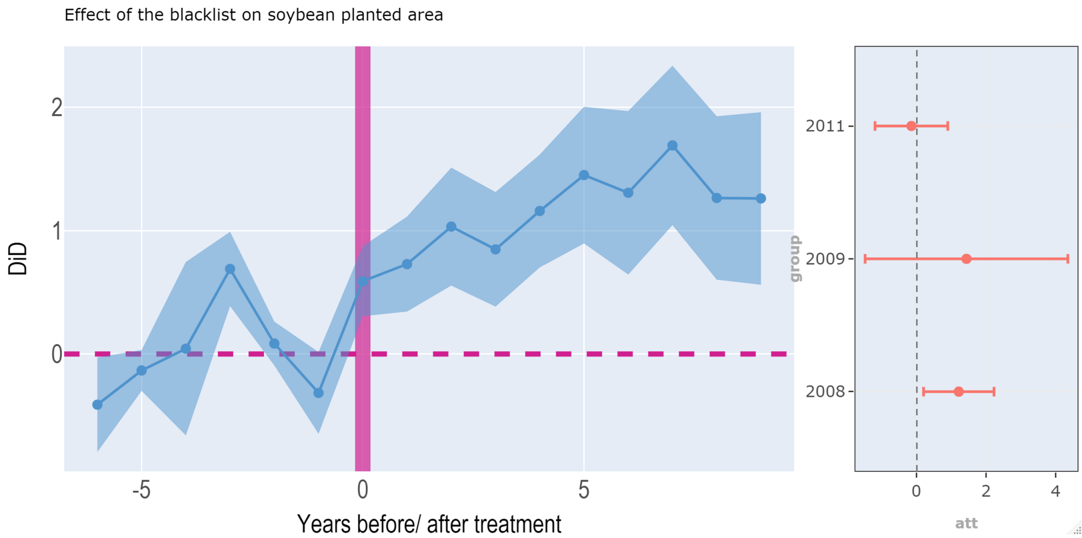


Fig. 5: Average treatment effect on soybean surface across time and treated groups (with Callaway and Sant'Anna (2020) estimator)

cultivated area, approximated by the sum of the six crops (cotton, rice, sugarcane, cassava, corn, soja) while column 4 refers to the total area of crops without soybean (soybean alone represented 25% of the cultivated area on average in 2007). The coefficients are all not statistically significant, except for soybean in column 5. Column 5 estimate implies that a priority municipality experiences on average an additional expansion of its soybean cultivated area of 73% compared to the non-listed municipalities (significant at 10%).

4.3 *Effects on the other crops*

How can the decrease of the deforestation rates and the increase in the soybean cultivated area both be explained? The implication of those two patterns is that soybean encroaches upon some other land uses, as shown in Table 3.

The average treatment effects are statistically significant for cotton (decrease of 37% of the area relatively to the control group) and sugarcane (decrease of 76% of its area relatively to the control group).

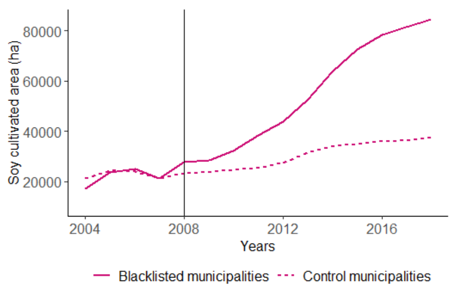
These relative decreases may suggest that soybean benefited from a reallocation of land inside the crops following the implementation of the blacklist. The policy would have spurred farmers to switch towards more intensive crops, like soybean. Indeed, the priority list makes deforestation less attractive by increasing the costs of clearing land (no credit available, risks of fines) and by reducing the benefits of clearing land (embargoes, no opening for products stemming from illegal deforestation). In doing so, the priority list is expected to reduce deforestation and cause a substitution from land to capital, hence from land-intensive crops to capital-intensive ones (Richards and Arima, 2018).

4.4 *Intensification*

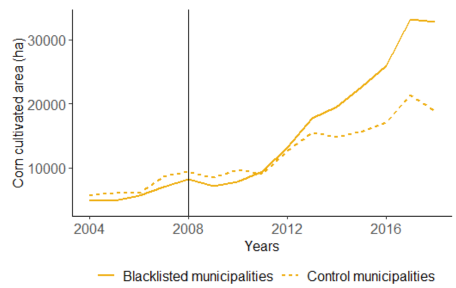
Literature has emphasised the potential intensification effect of the implementation of conservation policies (Garrett et al., 2018). Given that we study the collateral effects on the soybean sector of a conservation policy, we cannot neglect to explore this option. In the case of the priority list, a potential substitution from land to capital could lead to intensification processes, although it was not proven to be the case for crops (Koch et al., 2019; Moffette et al., 2021). We use three measures of the intensification processes. The productivity of pastures is measured as the number of cattle heads per hectare. Crop productivity is measured as the yields of the six main crops in tonnes per hectare. We also consider soy-corn double-cropping as a form of intensification and measure it with a cropping frequency ratio.

Pasture and crops intensification

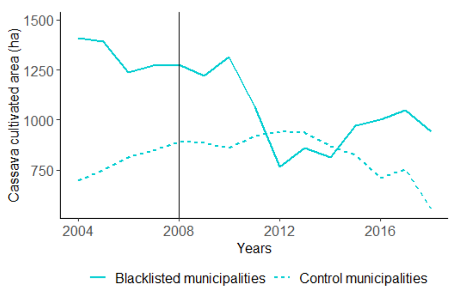
When land clearing is no longer an option, agricultural producers are likely to intensify their production. As reveals Table 4, the plan indeed triggered an increase of 2% of the productivity of pastures, while the total area of pasture remained stable. For the yields of the other crops, we find no robust evidence that the policy led to substantial increases of productivity. These conclusions are in line with the results in Moffette et al. (2021) and Koch et al. (2019), but



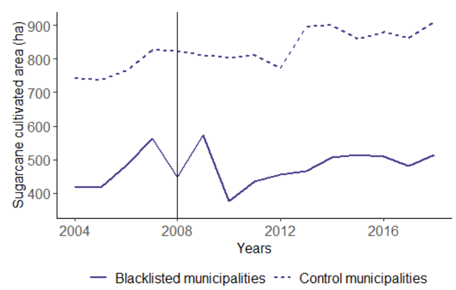
(a) Soybean



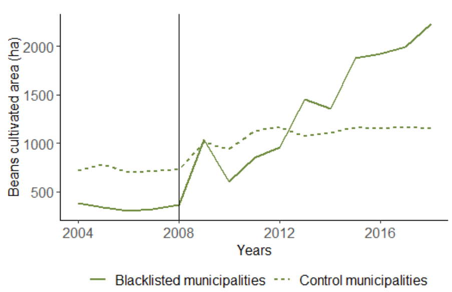
(b) Corn



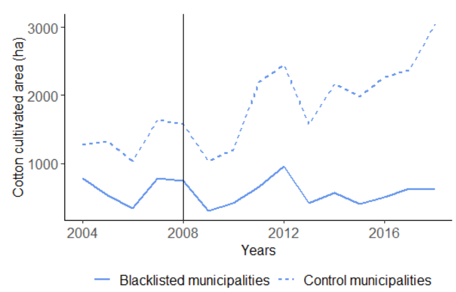
(c) Cassava



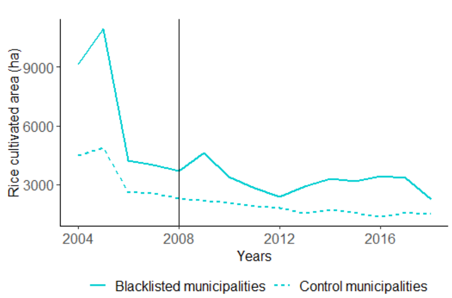
(d) Sugarcane



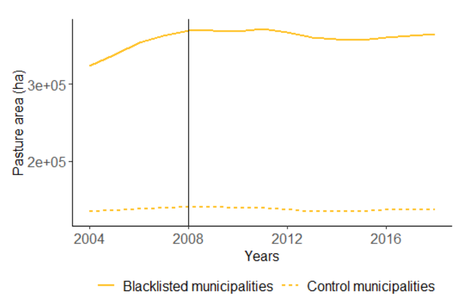
(e) Beans



(f) Cotton



(g) Rice



(h) Pasture

Fig. 6: Cultivated areas and pasture area over time in blacklisted municipalities in 2008 (solid line) and control municipalities (dotted line)

our magnitude of the pasture intensification is much lower. Full regression results are given in appendix (Table A14).

Intensification through double-cropping

The additional increase in the soybean cultivated land in the blacklisted municipalities could hide an intensification of the agriculture through double-cropping instead of a soybean land expansion in forests, pastures or other crops as in the official records the area in case of double-cropping is double-counted. This is worth looking at this phenomenon for three main reasons. First, because there is evidence that while cropland expansion was still the primary driver for the Brazilian grain boom, its influence has a general decreasing trend in favour of double-cropping [9] Second, previous research has established that crop intensification with double-cropping was linked with increasing forest conservation and broader supply chain development (Garrett et al., 2018). Thirdly, the results of our regressions suggest a positive impact of the plan on the soybean production area, but no significant impact on the corn area, which represents the second main crop area after soybean in our sample. An expansion of double-cropping would be consistent with these results.

We focus on soy-corn double-cropping, the most common double-cropping in Brazil, and consider the other types of double-cropping negligible as in Xu et al. (2021). In this configuration, soybean is the main crop and is planted first. Corn is planted on the same land, after soybean and on a shorter period of time. We use the same data (the IBGE-PAM dataset) and method as in Xu et al. (2021) to build our variables to quantify the impact of the plan on soy-corn double-cropping. No double-cropping is observed on about half of the municipalities in 2010 (42 municipalities on 119), among which 8 are priority municipalities[10].

The difference-in-difference regressions show no significant effects of the plan on the outcomes

[9] The quantitative importance of double-cropping is such as soybean-corn double-cropping would have offset 76.6 million ha of Brazilian arable land for grain production from 2003 to 2016 (Xu et al., 2021).

[10] Figure A3 in appendix compares the cropping frequencies (number of harvest each year) by municipality in 2004 and 2012.

characterizing the double cropping (surface of second-season corn, cropping frequency, area increment induced by cropland expansion and area increment induced by double-cropping).

4.5 *Empirical challenges*

4.5.1 *Placebo tests* Our identifying assumption requires that in a counterfactual world without the priority list, trends in the outcome variables are the same in the treatment and control group. One important objection is that the priority municipalities are put on the list because of particularly high deforestation rates, which suggests that the land use dynamics between the control and the treated municipalities are indeed different. A few years after the peak of deforestation, the municipalities are likely to naturally transform the new pastures into crops, and in that way catching up the municipalities with a longer history of intensive deforestation. Would it be the case, the effects on soybean production described in the previous sections would be overestimated.

We first run a placebo test to deal with this concern. We check for diverging trends in outcomes before the implementation of the policy by imposing a fictitious treatment on priority municipalities. Results are displayed in appendix (Table A3, Table A4, Table A5, Table A6). They show no evidence supporting different pretreatment trends (absence of correlation of the outcome variables with the placebo treatment).

4.5.2 *Generalised synthetic control* We also double-check the estimated treatment effects with the generalised synthetic control method (Xu, 2017) with panel data until 2014. This is a generalisation to multiple treated units of the synthetic control, a common method in empirical economics to relax the assumption of the parallel trends but which requires a single, or very few, treated units. Its core principle is to use the control group information to impute a synthetic counterfactual for each treated unit. Overall, the conclusions are the same than with the difference-in-difference method (see Table A7, Table A8, Table A10, Table A11).

4.5.3 *Land-use transitions* The differences of levels of the output variables before the treatment is usually not a threat to identification when using difference-in-difference. However in our case they may become a concern. A well-known practice is indeed to deforest for pastures first, and then to sell for high prices to soybean growers a few years later. One could thereby argue that the municipalities with high stocks of new pastures (typically the priority municipalities) would see an increase of soybean after a few years in any case. To identify whether we indeed capture the effect of the policy, or solely a different stage in the land-use chain, we investigate deeper the land-use transitions (see Table A9).

4.5.4 *Multiples time periods* Our setup deviates from the canonical difference-in-difference setup because there are four time periods instead of only two, and potential treatment effect heterogeneity. In our case, it is worth looking at these heterogeneities to have an idea of the intensity through time of the effects of the policy and across the different waves of priority lists. Simply extrapolating the previous methodology to the setup with the multiple groups (with a two-way-fixed-effects event-study regression for instance) would create biases both pre and post treatment, as Sun and Abraham (2020) demonstrate. The literature field of difference-in-difference has been dynamic these last years and found new estimators to circumvent these limitations (Athey and Imbens, 2021; Borusyak and Jaravel, 2016; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020). The estimator proposed in Callaway and Sant'Anna (2020) suits our needs, as their method accounts for weighting issues and has the advantages of allowing for covariates in a flexible form, proposing different estimation procedures based on outcome regression, inverse probability weighting and doubly robust methods, proposing different aggregation schemes to further summarize the effects of the treatment and intervals of confidence, and makes minimal parallel trends assumptions. Figure 5 reports the regression estimates. The effect of the blacklisting on the soybean area is only significant for the group treated in 2008, which is not very surprising as the two other lists are composed of very few units. We also see that this effect intensifies over time. The increasing magnitude could be explained by the fact that the transition from forest requires a few years to be accomplished. On the contrary, the effect on deforestation rates weakens over time.

This section illuminated certain facts about the reactions of farmers to the priority list. First, the policy was efficient in reducing the pressure on forests. As a result, we observe an increase of the soybean areas, production and even exports concurrent to a decrease in the dynamics of other crops like cotton or sugarcane. These changes of dynamics did not occur hand to hand with intensification processes, except for pasture. This leads us to think that the main response of the agricultural sector to the priority list was the substitution across crops towards the capital-intensive culture of soybean. These results were not documented previously to our knowledge and remain puzzling. Thus we explore the potential mechanisms of this shift and heterogeneities of responses of the municipalities in the next section.

5. Discussion

5.1 *Potential mechanisms*

Standard microeconomic analysis looks at the maximisation of profits to explain the behaviors of economic actors. Producers choose the combination of inputs and methods of combining them that maximises their profits. In our case, environmental policies can increase the cost of access to land because the cost of clearing new land increases (no cheap credits, fines and risks of embargoes) and new land is scarcer. In order to maximise their profits in these new conditions, farmers choose either to increase the level of the other inputs depending on their relative prices, either to change their production portfolio. In the previous section, apart from livestock farming, we do not find signs of improvement of yields that would corroborate the increase of inputs (capital for machines, fertilizers, genetic improvement of cultivars, etc). This may be due to difficulties to access some technologies to improve yields, or due to to the fact that yields are already optimized, leaving little room for improvement. Our intuition is that switching to soybean may have been a rational choice of farmers facing higher costs of access to land.

Rational economic decisions shape behaviors, but so do social forces and institutions. Two mechanisms can take place. First, farmers can reallocate their land from one crop to another. Second, there might be some land transfer towards soybean producers. Indeed, we described earlier both how the policy made the access to credits harsher and how soy is a relatively expensive crop to grow. Sufficient capital and experience is necessary to engage in soy production (Garrett et al., 2022). Reduction of economic support for farmers may induce difficulties for smaller producers to invest in seeds, fertilisers, pesticides and equipment. At the same time, increased cost of access to land where land, especially with title, is scarce and soy production profitable, can encourage smallholders to sell their land to capitalized soy farmers to find new occupations. This was pointed out in the municipality of Santarem, where smallholders were replaced by soy farmers after the construction of the Cargill port (Weinhold et al., 2013; Steward, 2007; Baletti, 2014) and in the case of the priority list in the municipality of São Félix. The environmental compliance produced economic stress pushing small and medium landowners to sell their properties (Thaler et al., 2019). The neighbors are then jointly more disposed to sell as their social network are broken and their production can be affected by the neighboring practices (Baletti, 2014). To sum up, the winners of the priority list could be the capitalized soy farmers who would have seized the opportunity to buy the land of smallholders growing staple food (rice, beans, cassava) in order to expand their own production. This mechanism would be difficult to test given that the agrocensus, which collects the information on the sizes and densities of the farms is only available in 2010 on our period of analysis.

Local governments and the private sector have also a role to play in the orientation of the agriculture in the municipalities. Farmers require adequate access to dynamic input markets, dryers and silos, and transportation systems to compete in the global economy. Thus, the profitability and the expansion of soybean is intertwined with the emergence of agglomeration economies (Garrett, 2013) which depends on the local politics. It could be hypothesized that the the strategies of the local governments in response to the blacklisted benefited soybean in some cases. Indeed, it is worth noting that some local governments did not stand idly by when their municipalities were placed on the list. The strategy of the 2008-blacklisted municipality of Paragominas in Pará soon paid off and became emblematic, as the municipality became the first to exit the priority list. The mayor formed an alliance with the local landowning elite and seized the opportunity of the disruption of the priority list to promote at the same time environmental compliance and agribusiness (Viana et al., 2016). A pact "Zero deforestation" was negotiated and signed by the main sectors, which was also the opportunity to attract new markets and investors with this Green re-branding. Although the environmental and economic objectives were reached through a boost of the capitalized agricultural production, along with an expansion of the soybean production, the small producers found themselves marginalized. They still relied on deforestation-dependent activities (charcoal and slash-and-burn agriculture) with few other alternatives and felt no need to register under the CAR ("rural environmental registry" or Cadastro Ambiental Rural, legally binding document to clarify land tenures) (Viana et al., 2016; Laurent et al., 2017). The strategy of Paragominas inspired the "Green Municipality Program" (or Programa Municipios Verdes) launched by the governor of Pará in 2011. It aimed at improving the local environmental governance capacity and this way, at helping the other priority municipalities of the state to exit the blacklist or stay off it (Sills et al., 2020). There is little evidence that the program reduced further deforestation but it benefited the economic activity.

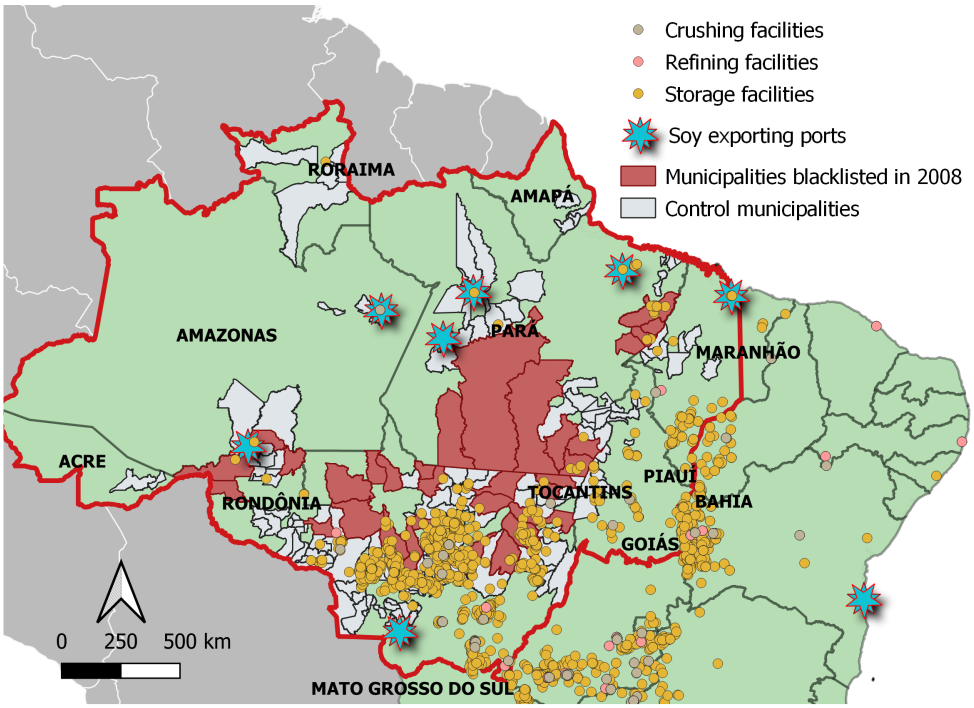


Fig. 7: Ports and facilities of the soybean sector in the Legal Amazon

5.2 *Heterogeneous responses of the municipalities*

Finding empirical evidence of the mechanisms mentioned above is made complicated by the lack of data. However, the conditions influencing the expansion of soybean can be better understood by taking a closer look at the potentially divergent land-use responses of the municipalities to the policy. The soybean sector also present some sources of heterogeneity, in terms of production concentration, as well as allocation between local use and international trade. Hence looking for heterogeneous responses to the policy across the municipalities makes sense, all the more that there is a substantial level of uncertainty around the average treatment effect for most tested variables (Figure 5). Moreover, further statistical tests at the state level reveal that the increase in the soybean area is particularly significant in the states of Rondônia and Pará whereas we do not observe the same statistically significant effect in the state of Mato Grosso. We investigate these heterogeneous responses using triple differences to helps us to identify on which population we can detect a causal effect of the policy.

More specifically, we examine the differences of responses in the light of three broad categories of characteristics: the potential for soybean development, the presence of agro-business clusters and finally of the openness to trade. Those potential heterogeneities are tested both upon soybean area (Table 5), but also on other soybean development characteristics, such as production, yields and exports.

Taken together, these results suggest that there is no association between the land characteristics, the supply chain development or the trade network organisation and the soybean expansion generated by the priority list. However, the explicative power of such regressions is limited due to the low number of municipalities and the lack of heterogeneity of our sample.

6. Conclusion

The blacklist curbed deforestation rates of 36% to 41% compared to the other municipalities of the Legal Amazon. This was made possible by more intense environmental surveillance, restrictions on the issuance of deforestation permits, embargo of illegally cleared areas, and limited access to credit and markets. This disruption suggests that the soybean sector, vastly established in the Brazilian Amazon and often associated with deforestation, may have been exposed to the policy. Much previous work have studied the effects of the blacklisting on deforestation, ranching and agriculture. By analysing the response of the soybean sector and considering the trade effects, our paper deepens the analyses of the consequences of blacklisting beyond the already discussed processes of intensification. Specifically, we relate the implementation of the policy with changes in soybean production, land use and productivity and compare it to the evolution of the other crops and pastures, using difference-in-difference and generalised synthetic control method. Because the soybean sector presents some sources of heterogeneity that shaped its previous development, we analyse the responses of the sector according to initial patterns of agro-climatic conditions, supply chain infrastructures development and trade network configuration.

Surprisingly, our analysis finds that the soybean sector benefited from the policy in terms of land-use, production and exports. The blacklisting triggered a shrinkage of the production of some staple food production areas, suggesting a reallocation inside the agricultural sector towards more capital-intensive activities. Soybean expanded mainly on other crops and pastures. The largest increase is noted in the states of Rondônia and Pará, but we do not find evidence of heterogeneous responses of the municipalities with the tested variables. There are several possible explanations for the development of the soybean sector concomitant with the blacklisting. To comply with the environmental regulation and confronted to higher costs of deforestation, medium and large farms may have switched from an expansion strategy to an intensification strategy towards more profitable and capital-intensive crops. A crowding out effect of smaller landowners, selling their lands to richer soybean farmers is also likely to have happened as the environmental governance produced economic difficulties. In some cases, it has also been reported that the strategy of the priority municipalities to exit the blacklist favoured the agribusiness.

The literature suggests that the soybean development in Amazonia is associated with a rise of the rural inequalities, land grabbing, concentration of tenure and land disputes. Further research could be undertaken to investigate the distributive consequences of the blacklisting, on employment wages, and sustainable development indicators.

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Table 1: Summary statistics for 2007*

	Treated group N = 31		Control group (N = 160)		Comparison
	Mean	SD	Mean	SD	t-test
Land uses					
Area of the municipality	19220	28820	6360	7100	2.347 **
Remaining natural vegetation	0.6568	0.1451	0.5677	0.2253	2.644 **
Increment of deforestation	0.7728	0.5168	0.3516	0.4004	4.063 ***
Soy area	0.01571	0.03492	0.03311	0.09903	-1.607
Other crops area	0.01306	0.01594	0.03194	0.06064	-3.116 **
Soy yields	1.906	1.471	1.63	1.44	0.9035
Pasture area	0.3036	0.1578	0.3707	0.2575	-1.8
stocking rate	0.8783	0.3641	1.137	0.5309	-3.129 **
indigenous land	0.1185	0.1784	0.08075	0.1594	1.036
rural settlement area	0.08609	0.1179	0.1598	0.194	-2.642 **
strictly protected area	0.02685	0.05492	0.03277	0.09021	-0.4557
multiple uses protected area	0.0357	0.09178	0.07319	0.1911	-1.563
Other variables					
gdp per capita	9.951	0.422	9.888	0.6051	0.6544
GDP of the municipality (ihs)	12.94	0.848	12.43	1.187	2.717 **
Soybean suitability index	0.4301	0.08048	0.4464	0.104	-0.9225
Crushing facility	0.07143	0.2623	0.08271	0.2765	-0.2048
Storage facility	0.3214	0.4756	0.3459	0.4774	-0.2469
High share of exports	0.4545	0.5096	0.3786	0.4874	0.6389
HHI by municipality	2007	3471	1490	3212	0.7258

* This table reports the means and standard deviation of the main variables in 2007, just before the implementation of the policy.
The treated group comprises the 2008-blacklisted municipalities.
The areas are expressed in % of the area of the municipalities, the yields in tonnes per ha, the stocking rates in cattle heads per ha.
GDP per capita is in reais while the GDP of the municipalities are expressed in 1000 Reais.

Table 2: Regression of IHS-transformed deforestation rates and cultivated areas of the main crops

	Dependent variable: cultivated area									
	Def	Pasture	Crops	Other crops	Soybean	Cotton	Rice	Sugarcane	Cassava	Corn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
treatment effect	**−0.410*****	**0.020**	**0.022**	**−0.091**	**0.734***	**−0.374****	**0.082**	**−0.762****	**−0.258***	**0.056**
	(0.113)	(0.021)	(0.095)	(0.084)	(0.385)	(0.169)	(0.132)	(0.364)	(0.156)	(0.216)
indigenous area	2.067	0.029	−0.125	0.377	−2.891	0.480	1.354	0.075	0.234	−1.089
	(0.641)	(0.086)	(0.312)	(0.269)	(1.376)	(0.861)	(0.695)	(1.386)	(0.339)	(0.853)
settlement area	1.828*	0.010	−0.005	0.053	−0.323	−0.166	−0.227	−1.387	0.554*	−0.096
	(0.859)	(0.118)	(0.329)	(0.271)	(1.825)	(0.361)	(1.012)	(1.027)	(0.294)	(0.525)
strictly protected area	2.198	0.524	−0.431	−0.249	−5.815	0.313	3.810	−0.980	−0.595	−0.607
	(1.221)	(0.330)	(0.566)	(0.568)	(5.996)	(0.435)	(1.692)	(1.385)	(0.740)	(0.777)
multiple uses protected area	1.165*	0.065	−0.133	−0.151	−2.515	−0.209	−1.095	−1.345	−0.273	−0.415
	(0.445)	(0.089)	(0.194)	(0.228)	(1.570)	(0.230)	(0.761)	(1.223)	(0.315)	(0.383)
soy price lagged	0.320***	0.028***	0.221**	0.118	3.051***	0.045	0.339**	−0.090	−0.113	0.094
	(0.105)	(0.010)	(0.094)	(0.080)	(0.451)	(0.120)	(0.163)	(0.276)	(0.111)	(0.129)
timber price lagged	−0.034*	0.002	0.021*	0.009	0.037	0.023	0.025	0.043	−0.028	0.034
	(0.019)	(0.002)	(0.011)	(0.012)	(0.063)	(0.050)	(0.025)	(0.058)	(0.018)	(0.029)
GDP per capita lagged	−0.051	−0.004	0.043	−0.109	−0.642*	−0.449	0.077	−0.166	−0.015	−0.198
	(0.140)	(0.022)	(0.105)	(0.104)	(0.362)	(0.323)	(0.251)	(0.258)	(0.112)	(0.187)
party affiliation	0.044	−0.018	−0.130	−0.028	−0.914*	0.354	−0.368*	0.507	0.147	−0.004
	(0.120)	(0.018)	(0.185)	(0.131)	(0.523)	(0.331)	(0.210)	(0.534)	(0.114)	(0.196)
municipality GDP	0.318**	−0.015	0.648***	0.834***	0.241	0.921**	0.377	0.133	0.203*	0.664***
	(0.134)	(0.015)	(0.109)	(0.121)	(0.376)	(0.414)	(0.279)	(0.236)	(0.118)	(0.178)
Observations	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449
Adjusted R^2	0.851	0.994	0.940	0.917	0.862	0.878	0.775	0.820	0.894	0.839

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates.
Robust standard errors in parentheses are clustered at the municipality level.

Table 3: Regression of IHS-transformed cultivated areas of the main crops

	Dependent variable: cultivated area					
	Cotton	Rice	Sugarcane	Cassava	Corn	Soy
	(1)	(2)	(3)	(4)	(5)	(6)
treatment effect	**−0.374***	**0.082**	**−0.762****	**−0.258*****	**0.056**	**0.734***
	(0.163)	(0.098)	(0.185)	(0.086)	(0.102)	(0.250)
indigenous area (%)	0.480	1.354***	0.075	0.234	−1.089**	−2.891***
	(0.551)	(0.408)	(0.630)	(0.209)	(0.430)	(0.913)
settlement area (%)	−0.166	−0.227	−1.387	0.554**	−0.096	−0.323
	(0.262)	(0.642)	(0.986)	(0.224)	(0.408)	(1.413)
strictly protected area (%)	0.313	3.810**	−0.980	−0.595	−0.607	−5.815*
	(0.375)	(1.805)	(1.280)	(0.507)	(0.806)	(3.032)
multiple uses protected area	−0.209	−1.095	−1.345	−0.273	−0.415	−2.515**
	(0.162)	(1.106)	(0.931)	(0.250)	(0.305)	(1.165)
soy price lagged	0.045	0.339***	−0.090	−0.113	0.094	3.051***
	(0.110)	(0.121)	(0.170)	(0.075)	(0.092)	(0.381)
timber price lagged	0.023	0.025	0.043	−0.028*	0.034	0.037
	(0.036)	(0.027)	(0.031)	(0.015)	(0.025)	(0.042)
GDP per capita lagged	−0.449	0.077	−0.166	−0.015	−0.198	−0.642**
	(0.326)	(0.237)	(0.237)	(0.113)	(0.164)	(0.327)
party affiliation	0.354*	−0.368***	0.507**	0.147**	−0.004	−0.914***
	(0.208)	(0.129)	(0.251)	(0.074)	(0.130)	(0.297)
municipality GDP	0.921***	0.377*	0.133	0.203*	0.664***	0.241
	(0.327)	(0.201)	(0.234)	(0.119)	(0.153)	(0.303)
Observations	1,449	1,449	1,449	1,449	1,449	1,449
Adjusted R^2	0.878	0.775	0.820	0.894	0.839	0.862

*p<0.1; **p<0.05; ***p<0.01
Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates.
Robust standard errors in parentheses are clustered at the municipality level.

Table 4: Average Treatment Effect using difference-in-difference and the generalised synthetic control method. Dependent variables: IHS-transformed stocking rates and IHS-transformed yields of the main crops.

	Dependent variable: productivity	
	Difference-in-difference	GSC
Pasture	0.0233*	0.0223
(1)	(0.0133)	(0.0236)
Soybean	0.103	0.111
(2)	(0.0973)	(0.105)
Cotton	-0.0948	-0.085*
(3)	(0.0605)	(0.0501)
Rice	0.0268	-0.0320
(4)	(0.0393)	(0.0438)
Sugarcane	-0.514	-0.566*
(5)	(0.328)	(0.311)
Beans	-0.0534	-0.0589
(6)	(0.0503)	(0.0507)
Cassava	0.00214	0.0317
(7)	(0.0394)	(0.0371)
Corn	-0.091	0.0704
(8)	(0.0845)	(0.0474)

*p<0.1; **p<0.05; ***p<0.01

Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates. Robust standard errors, in parentheses, are clustered at the municipality level both in the difference-in-differences and in the generalised synthetic control method.

Table 5: Average Treatment Effects using difference-in-difference with interaction. Dependent variable: Soybean area

	Dep. Var: IHS of soybean area					
Interaction term	(1)	(2)	(3)	(4)	(5)	(6)
Treatment x post	2.33	0.838	0.494	6.14	0.741	0.540
	(1.99)	(0.596)	(0.400)	(7.68)	(0.753)	(0.529)
Treatment x post x inter.	-3.74	-0.269	-0.747*	-0.505	-0.351	-1.52.10-5
	(4.25)	(0.599)	(0.409)	(0.723)	(0.816)	(8.67.10-5)
R2	0.862	0.861	0.874	0.862	0.816	0.867
# Obs.	1449	1449	1288	1449	1125	1449

*p<0.1; **p<0.05; ***p<0.01

Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates. Robust standard errors, in parentheses, are clustered at the municipality level. (1) Suitability index for soybean (2) Dummy indicating the presence of a storage facility (3) Dummy indicating the presence of a crushing facility (4) Cost of transport to soy exporting ports (5) Dummy indicating that the municipality is open to international soybean trade (6) Hirschmann Herfindahl index, reflecting the trade network concentration

7. Supplementary Material

7.1 *Data*

Suitability index. We use the Suitability index range for soybean from GAEZ (Fischer et al., 2012)[11] to account for the agro-climatic conditions. The index, initially defined for 30 arc-second pixel is averaged at the municipality level and because it is initially ranging from 0 to 1000, we divide it by 1000. More specifically, the database that is used is the GAEZ v4 dataset suitability index, with the climate data source CRUTS32 on the time period 1981-2010 for soybean, rainfed and with high input level. Variables where also computed for the same database for rainfed crops but the results are not displayed here.

Precipitation and temperature. Temperatures and precipitation are the year (in 2006) and municipality averages.

Infrastructures of the soy supply chain. We account for the presence of infrastructures in the neighborhood in order to represent the presence of agribusiness clusters. It has been previously observed that the soy processing facilities are correlated with other soy supply chain variables(Garrett et al., 2018). They can therefore be used as indicators of the presence of a well-developed soy cluster. Here, we compute dummies for each municipalities across time that take value 1 if there is any facility within 100km of each polygon based on the storage facilities (to store the soybean grains) and crushing facilities (to process soybean into soybean meal or soybean oil) mapped in TRASE.

Cost of transport to ports. The mean distance through roads from the centroid of each municipality to the nearest active soybean port is computed as a proxy of the transportation costs. The distance is calculated for the years 2000, 2005 and 2010, based on the costs of transportation

[11] The Global Agro-Ecological Zoning, developed by the Food and Agriculture Organization of the United Nations (FAO) in collaboration with the International Institute for Applied Systems Analysis (IIASA), provides a standardized framework for the characterization of climate, soil and terrain conditions relevant to agricultural production. It identifies crop-specific limitations of climate, soil and terrain resources in a consistent and empirically founded way.

from Victoria et al. (2021). The initial maps in Victoria et al. (2021) were calculated taking into account the evolution of the road network and differential costs for paved roads, unpaved roads and the absence of network. More information on their methodology can be found here https://data.mendeley.com/datasets/6xbjzyz3th/2.

Openness to trade. We differentiate the municipalities the most integrated in the international soybean trade with a dummy variable taking 1 if the municipality under consideration has a highest share of export than the median of the municipalities in 2006.

Herfindahl-Hirschmann index. This variable is used to measure the market concentration of soybean traders at the municipality or state level. The higher the index is, the more the market is concentrated in the hands of a few traders. Both variables are calculated from the TRASE database.

Table A1: Description and data sources of the variables used in the model

Variable	Description	Unit	Time frame	Source
MPi	Intercept dummy for the presence in the priority list	-	-	MMA
Def_area	Yearly increment of deforestation	m2	2002-2012	INPE/PRODES
Planted_area	Area planted with soybean, corn, cassava, rice, sugarcane, cotton, beans		2002-2012	IBGE/PAM
Prod_vol	Volume of production for the seven main crops	t	2002-2012	IBGE/PAM
Yield	Yields for the seven main crops	t/ha	2002-2012	IBGE/PAM
Cattle_heads	Number of heads of cattle	-	2002-2012	IBGE/PPM
Stocking_rate	Number of heads of cattle per hectare	heads/ha	2002-2012	IBGE/PPM and MapBiomas
Exp_soja	Volume of exports for soybean	t/yr	2004-2012	TRASE
Exp_soja_large	Volume of exports for soybean through large trading firms	t/yr	2004-2012	TRASE
upi_parea	Share of district area covered by strictly protected reserves	-	2002-2012	Cisneros et al. (2015)
uus_parea	Share of district area covered by multiple use protected reserves	-	2002-2012	Cisneros et al. (2015)
ind_parea	Share of district area covered by indegenous territory	-	2002-2012	Cisneros et al. (2015)
settle_parea	Share of district area covered by settlement projects	-	2002-2012	Cisneros et al. (2015)
soy_price_l1	lagged real local soy price	Reais	2002-2012	Cisneros et al. (2015)
timber_price_l1	lagged real rimber price	Reais	2002-2012	Cisneros et al. (2015)
gdpcc_l1	lagged GDP per capita of the previous year	Reais	2002-2012	Cisneros et al. (2015) (IBGE)
muni_GDP	Municipal GDP	1000 Reais	2002-2012	Koch et al. (2019) (IBGE)
SI_soy	Suitability index for Soybean	-	-	GAEZ v4
PT	Precipitation x Temperature	mm/an.°C	-	
d_storage	Intercept dummy for the presence of soy storage facility within 100km	-	2004-2014	TRASE
d_crushing	Intercept dummy for the presence of soy crushing facility within 100km	-	2004-2014	TRASE
dist_ports	Cost of transport to the nearest port	-	2000, 2005, 2010	Victoria et al. (2021)
d_open	Intercept dummy for the municipalities exporting the most	-	2006	TRASE
HHI	Herfindahl-Hirschmann index	-	2004-2014	TRASE

Table A2: Summary statistics for 2007 - firms and workers

	Treated group (N = 31)		Control group (N = 160)		Comparison
	Mean	SD	Mean	SD	t-test
#firms	660.8	1371	392.8	714.8	1.006
#firms, agriculture	16.57	18.56	6.91	10.98	2.659 **
#firms, soybean	0.1429	0.4484	0.2782	0.9951	-1.119
#firms, temporary crops	0.4286	0.6901	0.6466	1.372	-1.235
#firms, permanent crops	2.429	11.31	0.188	0.5923	1.048
#firms, livestock	4.714	4.537	1.932	3.367	3.072 **
% firms, agriculture	4.442	3.891	2.515	2.804	2.489 **
% firms, soybean	0.07786	0.2294	0.09496	0.4154	-0.3035
% firms, temporary crops	0.1343	0.2585	0.2062	0.5131	-1.088
% firms, permanent crops	0.2443	1.196	0.05075	0.2218	0.8533
% firms, livestock	1.944	3.143	1.049	1.857	1.455
#workers	7047	21850	3523	9916	0.8355
#workers, agriculture	153.3	198.6	139.8	412.3	0.2384
#workers, soybean	0	0	15.73	169.3	-1.005
#workers, temporary crops	0	0	28.46	192.2	-1.525
#workers, permanent crops	0	0	2.773	27.7	-1.092
#workers, livestock	73.69	79.98	26.79	65.84	2.204 **
% workers, agriculture	6.27	6.972	4.322	7.456	1.252
% workers, soybean	0	0	0.1794	1.92	-1.011
% workers, temporary crops	0	0	0.5223	3.019	-1.781
% workers, permanent crops	0	0	0.1945	2.103	-1.009
% workers, livestock	4.126	8.457	0.7683	1.922	1.58

7.2 *Multiple time periods*

We run the difference-in-difference with multiple time periods using as the control group the "not-yet-treated units" instead of "never-treated units" to leverage the most of our sample, meaning the the municipalities blacklisted in 2009 and 2011 belong to the control group before their year of treatment.

In the case of the difference-in-difference with multiple time periods, the identifying assumptions are (Callaway and Sant'Anna, 2020):

— irreversibility of the treatment. In our case, this does not hold as there is the possibility to be removed from the blacklist. This is the case for 6 municipalities from the 2008 group.

One is removed in 2010, one is removed in 2011 and four others are removed in 2011. However, we can suppose that once a municipality is removed from the blacklist, there is still an enhanced monitoring from the local authorities to prevent going back in the list. Also, to get out of the list, the licensing and geo-referencing requirements were already accomplished, and may have lasting effects. Finally, the potential supplementary measures taken by governments, like local plans for sustainable production are likely to be still up to date., random sampling, limited treatment anticipation [12]

— Conditional Parallel Trends based on a "Never-Treated" Group or based on a "Not-yet-Treated" Group (which is is a generalisation of the two-period parallel trend assumption). It states that, conditional on covariates, the average outcomes for the group first treated in period g and for the never-treated / not yet treated group would have followed parallel paths in the absence of treatment

— overlap. A positive fraction of the population starts treatment in period g, and that, for all g and t, the generalized propensity score is uniformly bounded away from one.

7.3 *Placebo tests*

Beyond the visual support for the parallel trends assumption, we employ a more formal approach to have additional support. A placebo treatment test is conducted on the pre-policy data on all the tested outcomes. The policy timing is falsified and imposed in 2005, 2006 or 2007. Apart from that, the specification is the same as in the difference-in-difference exposed earlier, using fixed effects and covariates. There should be no significant treatment effect to ensure that the trends between the two groups were the same before the policy intervention. For all variables except pasture area and rice area, we fail to reject the parallel

[12] The criteria are based on the past three years so there is little room for anticipation. Moreover the trends of the rates of deforestation do not suggest any anticipation effect.

trends in the pre-period. Of course, this is not enough to establish the validity of the parallel trends assumption. But we have other reasons to think that there is no factors that could have differentially affected each group. Besides the levels of deforestation, the municipalities are not that different. The restriction to the municipalities producing soybean in the Legal Amazon region is likely to have selected more similar municipalities and they are mostly all located in the Arc of deforestation. The main concern that remain is the stock of pasture which is likely to be higher in the blacklisted municipalities and could affect the future dynamics of land uses. Especially, there is a higher potential in blacklisted municipalities for soybean expansion. To account for that, we run the same difference-in-difference regression and add initial conditions interacted with time linear trend. As initial conditions, we use the soil suitability to grow soybean and the shares of land used as pastures and soybean in 2006. We find consistent results (Table A12 and Table A13 in appendix).

Table A3: Pre-Treatment 'Common Trends' Test, 2005-2007*

	Deforestation	Soybean area	Soybean volume	Soybean exports	Soybean yields
Treated Group x Year=2005	-0.0643	0.76	0.818	0.594	0.096
	(0.128)	(0.533)	(0.533)	(1.08)	(0.131)
Treated Group x Year=2006	0.00704	0.56	0.582	0.691	0.0579
	(0.129)	(0.425)	(0.481)	(1.49)	(0.1)
Treated Group x Year=2007	-0.126	0.0221	-0.0044	0.686	-0.0338
	(0.149)	(0.558)	(0.641)	(1.03)	(0.143)
Nobs	644	644	644	644	644

Table A4: Pre-Treatment 'Common Trends' Test, 2005–2007*

	Pasture area	Crops area	Crops without soybean area
Treated Group x Year=2005	0.0514***	0.0301	-0.047
	(0.0159)	(0.0914)	(0.101)
Treated Group x Year=2006	0.04***	0.00633	-0.12
	(0.0129)	(0.0901)	(0.102)
Treated Group x Year=2007	0.0283**	-0.0215	-0.0755
	(0.0128)	(0.081)	(0.0812)
Nobs	644	644	644

Table A5: Pre-Treatment 'Common Trends' Test, 2005–2007*

	Cotton	Rice	Sugarcane	Cassava	Corn
Treated Group x Year=2005	0.0789	-0.19	0.0574	-0.049	0.127
	(0.298)	(0.124)	(0.185)	(0.197)	(0.15)
Treated Group x Year=2006	-0.17	-0.294**	0.318	-0.108	0.132
	(0.267)	(0.129)	(0.265)	(0.182)	(0.144)
Treated Group x Year=2007	0.104	-0.222*	0.27	-0.123	0.106
	(0.27)	(0.114)	(0.247)	(0.161)	(0.122)
Nobs	644	644	644	644	644

*Planted areas

Table A6: Pre-Treatment 'Common Trends' Test, 2005–2007*

	Pasture	Cotton	Rice	Sugarcane	Cassava	Corn
Treated Group x Year=2005	-0.00838	0.0514	0.00428	-0.0124	0.0349	-0.0175
	(0.0243)	(0.0668)	(0.0488)	(0.136)	(0.0619)	(0.0379)
Treated Group x Year=2006	-0.00597	-0.0493	-0.0322	0.0768	0.0416	0.00653
	(0.026)	(0.0769)	(0.0424)	(0.21)	(0.0488)	(0.0376)
Treated Group x Year=2007	-0.00885	0.0296	-0.0355	0.144	0.0417	0.011
	(0.0382)	(0.0751)	(0.0421)	(0.12)	(0.047)	(0.037)

*Yields

7.4 *Comparison with the Generalized Synthetic Control method*

Table A7: Average Treatment Effect using difference-in-difference, difference-in-difference with multiple groups and timings and the generalised synthetic control method. Dependant variable: IHS-transformed deforestation increments

Average Treatment Effects: Deforestation			
	DD	Multiple time DD	GSC
ATT 2008-2012	-0.410***	-0.358*	-0.372***
	[-0.502, -0.301]	[-0.598, -0.118]	[-0.594, -0.150]
ATT 2008-2014		-0.2896*	
		[-0.5166, -0.0615]	

*p<0.1; **p<0.05; ***p<0.01.

Covariates, time and municipality fixed effects included and not reported.

Standard errors are robust and clustered at the municipality level.

Table A8: Average Treatment Effects using difference-in-difference and generalised synthetic control. Dependent variable: Agricultural areas

		Dependent variable: agricultural areas			
		Pasture	Crops	Soybean	Other crops
		(1)	(2)	(3)	(4)
Difference-in-difference		**0.0200**	**0.0223**	**0.734***	**-0.091**
		(0.0214)	(0.0948)	(0.385)	(0.0845)
	R2	0.994	0.94	0.862	0.917
	Obs	1449	1449	1449	1449
GSC		**0.0485****		**0.782***	
		(0.0245)		(0.400)	

*p<0.1; **p<0.05; ***p<0.01.
Regressions with controls, municipality fixed effects and year fixed effects.
Robust standard errors in parentheses are clustered at the municipality level.

7.5 *Land use transitions*

Table A9: Statistics of the land-use and land-cover change transitions*

	Control group			Treated group		
	(1)	(2)	(3)	(1)	(2)	(3)
2000-2005						
Crops	0.01	0.12	13.33	0.03	0.60	32.08
Pasture	0.03	0.37	42.31	0.03	0.53	28.41
Other natural vegetation	0.01	0.14	15.65	0.02	0.43	22.90
Forest Formation	0.02	0.25	28.21	0.02	0.29	15.46
Other land cover	0.00	0.00	0.50	0.00	0.02	1.14
2005-2010						
Crops	0.02	0.69	38.36	0.02	0.73	40.73
Pasture	0.03	0.85	47.17	0.02	0.67	37.54
Other natural vegetation	0.00	0.11	6.21	0.01	0.26	14.51
Other land cover	0.00	0.05	2.76	0.00	0.07	3.68
Forest Formation	0.00	0.10	5.51	0.00	0.06	3.54
2010-2015						
Pasture	0.08	2.46	74.72	0.07	2.11	67.28
Crops	0.02	0.59	17.87	0.02	0.74	23.50
Other natural vegetation	0.00	0.10	3.15	0.01	0.23	7.23
Forest Formation	0.00	0.13	3.86	0.00	0.05	1.69
Other land cover	0.00	0.01	0.40	0.00	0.01	0.31
2015-2020						
Pasture	0.05	1.54	66.15	0.05	1.52	63.26
Crops	0.02	0.59	25.14	0.02	0.64	26.60
Other natural vegetation	0.00	0.06	2.66	0.01	0.18	7.38
Forest Formation	0.00	0.14	5.92	0.00	0.06	2.65
Other land cover	0.00	0.00	0.12	0.00	0.00	0.11

* Net transitions to soybean
(1) share of the group area
(2) share of the net land-use change
(3) share of the net land-use changes to soybean

7.6 *Effect on deforestation*

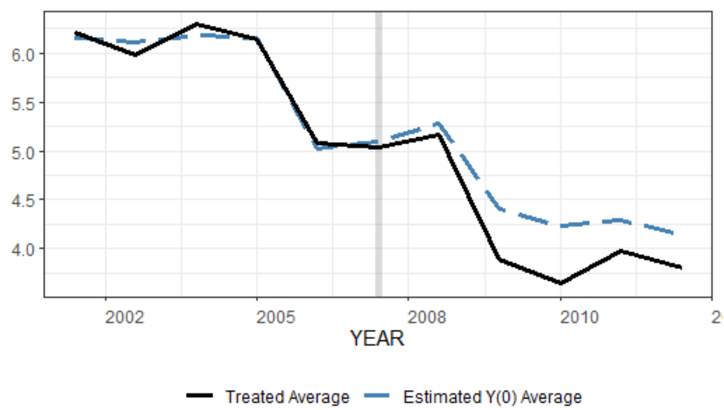


Fig. A1: Generalised synthetic control counterfactual for deforestation rates, computed with the matrix completion method

Table A10: Regression of IHS-transformed deforestation rates and cultivated areas of the main crops - Generalized Synthetic Control method

	Def	Pasture	Crops	Other crops	Soy	Cotton	Rice	Sugarcane	Cassava	Corn
ATT	-0.372***	0.049**	0.068	-0.024	0.782*	-0.341**	0.072	-0.820**	-0.254	0.088
	(0.113)	(0.024)	(0.130)	(0.116)	(0.399)	(0.140)	(0.140)	(0.343)	(0.158)	(0.218)

*p<0.1; **p<0.05; ***p<0.01
Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates.
Regressions are run with the matrix completion algorithm.

Table A11: Regression of IHS-transformed yields of the main crops and stocking rates - Generalized Synthetic Control method

	Cotton	Rice	Sugarcane	Cassava	Corn	Soy	Stocking rate
ATT	-0.085*	0.032	-0.566**	0.032	0.070	0.111	0.022
	(0.048)	(0.044)	(0.285)	(0.038)	(0.046)	(0.097)	(0.024)

*p<0.1; **p<0.05; ***p<0.01
Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates. Regressions are run with the matrix completion algorithm.

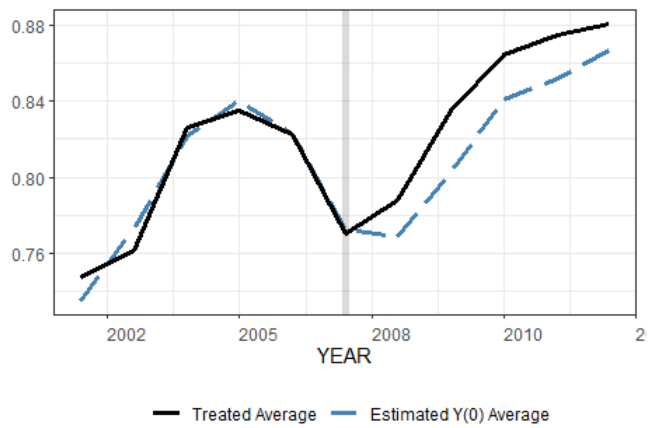


Fig. A2: Generalised synthetic control counterfactual for stocking rates, computed with the matrix completion method

Double-cropping. We use the same data (the IBGE-PAM dataset) and method as in Xu et al. (2021) to build our variables to quantify the impact of the plan on soy-corn double-cropping. The IBGE-PAM dataset contains separate records for first season and second season corn. We preprocess the dataset by (1) excluding the municipalities with more than three years of repeated values, because we consider that there might contain artificial data (2) by selecting only the municipalities with more than 4 years consecutive records (for the validity of linear regression) (3) we exclude second season corn from municipalities where soybean is not planted (because considered not to be soybean-corn) (4) in the North-East, double-cropping is not possible due to unfavourable climate conditions, and the cropping season is late, so we move their second season corn recordings to the first season corn recording. Cropland expansion is defined as the increase in the harvested areas of main-season crops (soybean and first-season corn).

Table A12: Regression of IHS-transformed deforestation rates and cultivated areas of the main crops - with time linear trend correction

	Def	Pasture	Crops	Other crops	Soy	Cotton	Rice	Sugarcane	Cassava	Corn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
did	−0.498***	0.008	0.039	−0.077	0.798**	−0.383**	0.036	−0.738**	−0.275*	0.060
	(0.114)	(0.021)	(0.092)	(0.078)	(0.388)	(0.176)	(0.131)	(0.371)	(0.155)	(0.198)
Observations	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449	1,449
Adjusted R^2	0.856	0.994	0.942	0.923	0.862	0.879	0.777	0.820	0.894	0.847

Note: *p<0.1; **p<0.05; ***p<0.01

Table A13: Regression of IHS-transformed yields of the main crops and stocking rates - with time linear trend correction

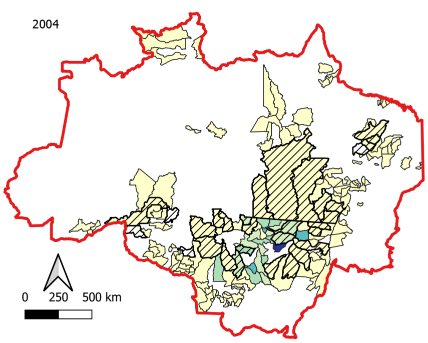
	Cotton	Rice	Sugarcane	Cassava	Corn	Soja	Stocking rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
did	−0.099	0.024	−0.530	0.008	0.075	0.108	0.026
	(0.062)	(0.040)	(0.331)	(0.039)	(0.049)	(0.099)	(0.024)
Observations	1,449	1,449	1,449	1,449	1,449	1,449	1,449
Adjusted R^2	0.822	0.649	0.768	0.744	0.772	0.733	0.918

Note: *p<0.1; **p<0.05; ***p<0.01

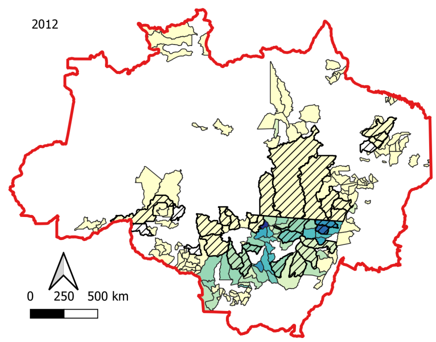
Table A14: Regression of IHS-transformed yields of the main crops and stocking rates

	Dependent variable: yields and stocking rates (IHS-transformed)						
	Cotton	Rice	Sugarcane	Cassava	Corn	Soja	Stocking rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treatment effect	**−0.095**	**0.027**	**−0.514**	**0.002**	**0.059**	**0.103**	**0.023***
	(0.061)	(0.039)	(0.328)	(0.039)	(0.048)	(0.097)	(0.013)
indigenous area	0.110	0.184	0.019	0.149	−0.370	−0.295	0.001
	(0.171)	(0.261)	(1.614)	(0.174)	(0.159)	(0.283)	(0.087)
settlement area	0.008	−0.435	−0.574	0.045	−0.243	−0.088	0.201*
	(0.081)	(0.331)	(1.065)	(0.108)	(0.225)	(0.462)	(0.103)
strictly protected area	0.135	0.428	1.967	0.083	0.231	−0.958	0.296
	(0.123)	(0.635)	(1.587)	(0.257)	(0.428)	(1.652)	(0.215)
multiple uses protected area	−0.054	−0.134	−1.326	−0.090	−0.114	−1.376*	−0.123
	(0.059)	(0.156)	(1.448)	(0.087)	(0.127)	(0.425)	(0.092)
soy price lagged	0.019	0.086**	−0.159	−0.015	0.076*	0.766***	−0.027**
	(0.033)	(0.043)	(0.243)	(0.041)	(0.040)	(0.107)	(0.014)
timber price lagged	0.003	0.003	0.008	0.007	0.004	−0.002	0.001
	(0.010)	(0.009)	(0.051)	(0.010)	(0.009)	(0.016)	(0.003)
GDP per capita lagged	−0.102	−0.071	−0.091	0.019	−0.150***	−0.163**	−0.005
	(0.065)	(0.063)	(0.218)	(0.041)	(0.045)	(0.082)	(0.030)
party affiliation	0.053	−0.071*	0.279	0.026	0.012	−0.173	−0.015
	(0.067)	(0.039)	(0.274)	(0.044)	(0.048)	(0.118)	(0.022)
municipality GDP	0.183*	0.019	0.019	0.070	0.106**	0.025	0.028
	(0.101)	(0.083)	(0.209)	(0.051)	(0.042)	(0.081)	(0.031)
Observations	1,449	1,449	1,449	1,449	1,449	1,449	1,449
Adjusted R^2	0.822	0.649	0.767	0.744	0.768	0.733	0.915

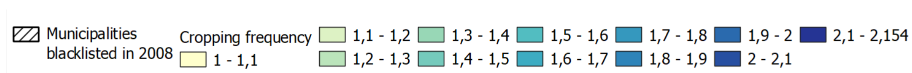
*p<0.1; **p<0.05; ***p<0.01
Difference-in-difference with municipality fixed effects, time fixed effects and time-varying covariates.
Robust standard errors in parentheses are clustered at the municipality level.



(a) Cropping frequency in 2004 1



(b) Cropping frequency in 2012 2



(c) 2

Fig. A3: Soy-corn cropping frequency in 2004 and 2012. A cropping frequency of 1 means that there was no double cropping, while a cropping frequency of 2 means that the entire soy production was in double cropping systems.

7.8 *Heterogeneity*

Land characteristics and potential for soybean development. We suspect that our previous results on soybean are driven by some municipalities particularly suitable for the production of soybean. Indeed, since 90% of soy is planted in locations meeting specific soil and climatic suitability conditions, the expansion should be concentrated on the most suitable municipalities (Heilmayr et al., 2020). The triple-differences model isolates the changes in soybean expansion occurring on soy-suitable portions of the sample relative to non-soy-suitable locations of the sample. While the average of the suitability index is very similar between the treated group and the control group of municipalities (Table 1), there is a large heterogeneity of soy suitability within the groups as illustrates Table 1 (ranging from 0.30 to 0.55 for the treated group). The most suitable municipalities for soybean production are located in the South of Mato Grosso, South Rondônia, Acre and Roraima.

Table 5 displays the results for the regression on the soybean area, with the interaction with the soy suitability index in column (1). The interacted term is not statistically significant (row 2). The results of the tests with other outcome variables describing the soybean sector (production, yields and exports) and other indicators of soil and climatic suitability (suitability classes of soybean, suitability index for rainfed crops, also from the GAEZ database) show similar results. These findings suggest that the priority municipalities do not respond differently to the policy according to their suitability for soybean. Because the expansion may also depend on the previous land uses in the municipalities, we try as variables of interaction the share of the remaining vegetation and the initial share of pastures in 2007 (the results are available in appendix). They are meant to represent respectively the limits and the potential of expansion of soybean. Again, no evidence was found of differential effects with these variables. It can therefore be assumed that the land characteristics do not lead to different responses on the soybean expansion, at least on the tested variables.

Influence of supply chain development.

"Agglomeration economies" (i.e., positive spillovers produced by agribusiness clusters) affect agricultural innovation, profits, area expansion (Garrett et al., 2013) and land-use intensity (Garrett et al., 2018). Thereby, the presence of a supportive agribusiness environment is decisive for the land-use response to a conservation policy. We measure the divergent land-use responses to the blacklist depending on the agribusiness environment using the presence of facilities to store and crush soybean as a proxy for a developed supply chain. The cost of transport to the nearest port which exports soybean is used as a second indicator to account for a dynamic supply chain. Because it reflects the cost to export soybean to other countries, this variable is more directly linked to the exports than to the total production. Column (3) in Table 5 shows no statistically significant effect of the presence of the storage facilities nearby. By contrast, in column (4) a small but significant negative effect of the presence of crushing facilities was detected. This means that the increase of soybean area is less pronounced where the soybean supply chain is already developed. A possible explanation for this might be that the municipalities close to crushing facilities are already mature for the development of soybean and there is few margin for expansion.

Trade network configuration. Finally, we investigate the role of the configuration of trade network to explain the land-use responses of the municipalities. We believe that the expansion of soybean area will depend on the exposure to the international demand because soybean production in Brazil is very often intended for export[13]. Since openness to trade is linked with agricultural expansion and deforestation (Faria and Almeida, 2016), there could be more expansion of soybean in the municipalities well connected to the trade network. We distinguish export-orientated municipalities from domestic-orientated municipalities. We also account for market concentration of the soybean trading sector with the Hirschmann Herfindahl index. The results indicate that the area expansion of soybean was not influenced by the openness to trade. Turning now to the results on exports, a significant effect of the openness to trade and of the Hirschmann Herfindhl index is revealed. Overall these results indicate that the soybean response to the policy is not led by the exposition to international markets. By contrast, the exports repond less to the policy when the market was already export-orientated when there is a variety of trading firms on the territory.

7.9 *Leakages*

The program may lead to leakage to neighbouring municipalities. The programme could either deter deforestation because it could be more easily detected by the authorities, or it could push deforestation pressure back into neighbouring municipalities. The accompanying

[13]Soybean is the first exported agricultural commodity with exports accounting for 42.7 billion dollars in 2018 (De Maria et al., 2020).

effect on soybeans could also go both ways. Leakages need to be measured to ensure the effectiveness of the policy and to verify that our estimates are not over- or underestimated by these potential effects. This is done by using the neighbouring communes of the target communes as the treated units, and by removing the blacklisted municipalities from the sample. The results are presented in Table A15. No significant effect is found. It can therefore be assumed that the policy did not lead to a leakage effect.

Table A15: Estimations of the leakages of IHS-transformed deforestation rates and cultivated areas of the main crops - with time linear trend correction

	Def	Pasture	Crops	Other crops	Soy	Cotton	Rice	Sugarcane	Cassava	Corn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
did	0.037	0.003	0.066	−0.014	0.114	0.349	−0.444	0.033	0.007	0.382^{*}
	(0.149)	(0.020)	(0.125)	(0.106)	(0.349)	(0.363)	(0.286)	(0.238)	(0.113)	(0.206)
Observations	1,197	1,197	1,197	1,197	1,197	1,197	1,197	1,197	1,197	1,197
Adjusted R^2	0.813	0.993	0.942	0.927	0.861	0.886	0.773	0.840	0.904	0.860

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$